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COMPREHENSIVE REVIEW

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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

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Abstract

To enhance the resilience of food systems to food safety risks, it is vitally important for national authorities and international organizations to be able to identify emerging food safety risks and to provide early warning signals in a timely manner. This review provides an overview of existing and experimental applications of artificial intelligence (AI), big data, and internet of things as part of early warning and emerging risk identification tools and methods in the food safety domain. There is an ongoing rapid development of systems fed by numerous, real-time, and diverse data with the aim of early warning and identification of emerging food safety risks. The suitability of big data and AI to support such systems is illustrated by two cases in which climate change drives the emergence of risks, namely, harmful algal blooms affecting seafood and fungal growth and mycotoxin formation in crops. Automation and machine learning are crucial for the development of future real-time food safety risk early warning systems. Although these developments increase the feasibility and effectiveness of prospective early warning and emerging risk identification tools, their implementation may prove challenging, particularly for low- and middle-income countries due to low connectivity and data availability. It is advocated to overcome these challenges by improving the capability and capacity of national authorities, as well as by enhancing their collaboration with the private sector and international organizations.

KEYWORDS
data sharing, digital tools, machine learning, proactive system, risk prediction

1 | BACKGROUND

Ensuring food safety has been and remains a key objective for governments and policymakers, food industry, and researchers worldwide. Nevertheless, new challenges may be posed by, inter alia, the increasing complexity of food supplies, accelerating climate change, intensifying international food trade, new food sources and technologies, circular economy, and sprawling urban agriculture. Effective tools and methods for early warning and emerging risk identification form a solid basis for achieving food systems that are resilient to food safety risks, a priority for national and international authorities and organizations dealing with food safety, enabling their preparedness for emerging food risk prevention, mitigation, and response (Food and Agriculture Organization [FAO], 2022).

There are many early warning and monitoring systems in operation that can contribute to emerging risk identification system. These include systems that focus on foodborne disease outbreaks and animal disease related to feed or food safety risks, as in the European Commission's Rapid Alert System for Food and Feed (RASFF). The World Health Organization's (WHO) Global Strategy for Food Safety notes that Member States' food safety systems should become forward-looking in order to make them more effective (World Health Organization [WHO], 2022). Such systems should monitor for the emerging drivers of change and trends that ultimately contribute to the emergence of food safety hazards (WHO, 2022). The FAO/WHO International Food Safety Authorities Network (INFOSAN) Strategic Plan 2020–2025 has also emphasized the need for a proactive approach to emerging risk identification and supports the countries to develop this capability (FAO, 2022). Information from different electronic information systems can be integrated to make better predictions. In the public health sector, the epidemic intelligence from open sources initiative adopts the One Health principle, which allows early detection of health threats and conducting subsequent interventions (Abdelmalik et al., 2018).

A review based on bibliometric analyses of artificial intelligence (AI) and machine learning applied to food safety reveals that historically, the field has been progressively advancing from 2012 on, covering different domains across the production chain, including crop breeding, agricultural production, food processing and distribution, and human nutrition (Liu et al., 2023). AI can be useful for food safety practitioners in both the industry and the public service, for example, with regards to safe raw material selection, and their processing and packaging. The use of AI for food safety surveillance and hazardous source tracking purposes enables the identification of critical points and processes that are susceptible toward the introduction of contaminants or unsafe elements into the food supply chain. For microbiological hazards, AI can be used the identification and characterization of microbes and the modeling of microbial population dynamics and growth (Qian et al., 2023). Also at the retail stage, both staff and customers can be targeted by AI applications with the aim of enhancing food safety. For example, besides predictive analytics, staff could be trained to use augmented or virtual reality and be assisted in their safety routines by robotics. AI could help guard over the consistency of information and practices, such as consumer information about and staff handling of allergens. Consumers could also benefit from directions and advice given by personal food safety assistants (Friedlander & Zoellner, 2020). Practical examples of AI applications in industry and government include AI-assisted detection of *Escherichia coli* with optical imaging, vegetable growers' management of potential problems in leafy greens produce based on weather, location, and water quality data; and food workers' behavioral data in the workplace; as well as the US FDA's AI-supported identification of potentially problematic lots of imported seafood such as shrimps (Miller, 2023). Yet an in-depth review of the use of these techniques for the identification of prospective *emerging* risks is still lacking.

This article aims to provide a comprehensive overview of the existing applications of AI, big data, and internet of things (IoT) in developing early warning and emerging food safety risk identification tools and methods, based on data gathered from different sources (i.e., Scopus, Science Direct, and Google Scholar). Details of the approach followed are provided in the Supplementary Materials. In brief, 40 original research articles and 57 reviews had been retained after several rounds of selection. These items and in some cases documents referred to by them were used as input for this review.

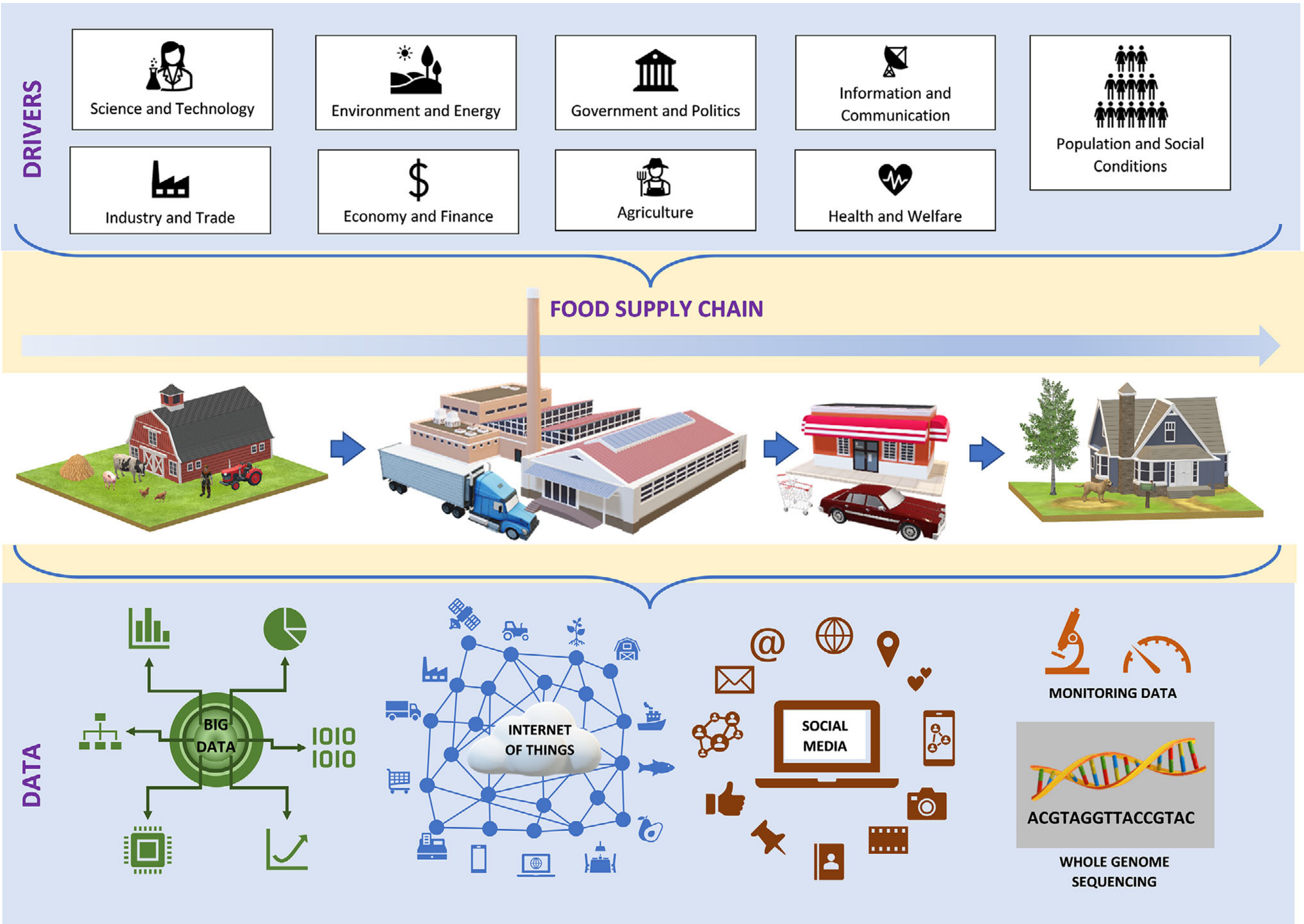

FIGURE 1 The food supply chain, the drivers for change within influential sectors [as defined by Noteborn (2006)] acting on it, and the various types of data coming from it which can be used for emerging risk identification.

2 | EMERGING FOOD SAFETY RISKS, AND THE DRIVERS AND INFLUENTIAL SECTORS DRIVING THEIR EMERGENCE

A holistic approach toward emerging risk identification within the food chain was developed at European Food Safety Authority (EFSA's) and national authorities almost two decades ago through projects such as Per-Apt and EMRISK and has been adopted and pursued by many others since (Noteborn, 2006). This approach is based on the insight that "drivers" give impetus to trends and other phenomena within "influential sectors" surrounding the food production chain, which could ultimately lead to the emergence of a risk [see the glossary of The European Food Safety Authority [EFSA] (2023)]. This need not necessarily be only new risks but could also be known risks that reemerge (e.g., from new food sources) or for which the vulnerability has increased, amongst others. Examples of sectors are culture and demographics; agriculture and fisheries; economy; energy, nature and environment; science, technology, and industry; government and politics; information and media; and public health and welfare (Figure 1). Within the sectors, indicators are measures that are associated with these changes and that therefore indicate the occurrence of a hazard. Monitoring of indicators, particularly if they rise above a threshold level that would trigger an alert requiring follow-up assessment of its relevance, would be part of an emerging risk identification system (Noteborn, 2006). For example, certain weather anomalies (e.g., heavy rainfall) could be indicative of eventual crop contamination with mycotoxins or pathogens.

3 | MODERN SYSTEMS FED BY NUMEROUS, REAL-TIME, AND DIVERSE DATA

There is a concurrence of innovations in both data gathering, data storage and sources, and the ways to process the vast amount of data. This allows for the holistic real-time measurement of many data such as indicators of drivers (e.g., climate change, weather conditions, trade flows, new food sources and food production systems, and

TABLE 1 Summary of the various data sources and data processing technologies.

Technology category	Technology name	Purpose	Advantages	Disadvantages (and barriers to adoption)
Data sources	IoT	Situational awareness in real time	Extends beyond conventional monitoring data	Need to be combined with other data for meaningful emerging risk prediction
	Unstructured data (e.g., social media)	Gauge unofficial channels for early reports of issues with food safety of products and establishments	Public opinion can help government formulate policies addressing societal needs	Data unification needed
	Blockchain	Traceability	Full, internal traceability of food commodities throughout the production chain; transparency	Elements incompatible with legislation on personal data protection
	Whole-genome sequencing	Outbreak monitoring; clade discernment	Comprehensive information allowing for establishing relationships otherwise not possible	Lack of technical facilities in LMICs
Data processing	Text mining	Prediction of hazards based on correlations within text	Handling of large amounts of data; identification of hazards overlooked	Still needs expert judgment
	AI, machine learning	Prediction of food safety issues based on circumstantial data	Handles both structured and unstructured data	Reproducibility challenging

Abbreviations: AI, artificial intelligence; IoT, internet of things; LMICs, low- and middle-income countries.

consumption patterns) for emerging hazards within influential sectors, complementing monitoring data, which can also be complex, such as for genomics of food pathogens. An impression of how these various data is integrated is provided by Figure 1 and Table 1.

3.1 | Data sources

3.1.1 | Digital devices

Information sources, which are currently used for food safety early warning and as emerging risk identification tools, are not limited to the conventional monitoring data collected by food inspectors and companies. For example, precision agriculture, radiofrequency identification (RFID), and wireless sensor networks allow for the real-time gathering of food safety or quality data in primary production, which can be further processed by early warning and emerging risk tools.

The meat production and dairy chains are examples of technologically advanced environments where various digital devices (e.g., RFID tags and readers, GPS tracking devices) can add to the surveillance of potential food safety hazards. For example, both in the production chain and on the farm, biosensors can be used to measure the presence of certain pathogens (e.g., through antibody binding). These devices could be attached to smart phones. In addition, camera surveillance in slaughterhouses could be used to monitor carcasses for pathological conditions such as lesions (Farag et al., 2021; Nastasijević & Vesković Moračanin, 2021). Notably, biosensor technology is a means to assist with rapid information at points of care. Biosensor technologies include, for example, lateral flow devices and RFID technology. They could be used to detect, qualitatively, semiquantitatively, and quantitatively, pathogens (e.g., *Salmonella*), toxins (e.g., mycotoxins), and bacteriophages (indirect indicator for certain pathogens). Biosensors could also be incorporated into packaging materials (Neethirajan et al., 2018). Such biosensors within "Intelligent packaging" could also serve as a compliance tool for food safety management systems based on HACCP (Hazard Analysis and Critical Control Points), measuring tens of data in critical control points in real-time (Yam et al., 2005).

Biosensors and other types of sensors would create a "situational awareness," enabling the detection of anomalous behavior, such as in the physical activity of livestock. Although biosensors for humans have been experimentally tested for a range of ailments, the application of biosensors to animals is limited by affordability and the extent to which it is possible to interpret animal functions. Besides common parameters such as body temperature, breath, sweat, and movement, biosensors worn by livestock could also be employed to measure biochemical parameters such as glucose levels in blood (Zhang et al., 2021). These items would complement the video and audio surveillance methods already used in "precision livestock farming." These include cameras, sound systems, and audio in pig farming to track feeding and drinking behaviors and movement, amongst others (Tzanidakis et al., 2021). In addition, computer vision systems are also used in abattoirs to detect pathological lesions and fecal contamination on carcasses (Nastasijević & Vesković Moračanin, 2021). Ren et al. (2022) noted that the IoT is being applied in meat cold chain logistics, such as RFID based tracking plus humidity sensors, as well as digital twins, particularly hydrodynamic fluid modeling. RFID tags would allow to trace pigs individually during their productive life up to the slaughterhouse (Xu et al. (2013). Another example of behavioral observations used to safeguard food safety is that of the AI system developed by a Japanese company to monitor the behavior of staff in slaughterhouses (i.e., adherence to and consistent application of good hygiene and sanitation practices) and handwashing in kitchens (Saxena & Gautam, 2021).

The costs for these different types of device can vary widely (Tekin et al., 2021). For example, a reader of electronic identification tags of dairy cows may cost up to $1425, which may act as a barrier to their adoption by less affluent communities and end-users. Other challenges linked to IoT are those of high energy consumption and the incompatibility of different datasets. Maksimovic et al. (2019) contended that the solution for these problems would be the use of nanodevices that could help spanning the Internet of Nano Things by incorporating nanodevices such as nanosensors into food packaging that will enable the sensing of signals at a nanoscale within the environment. For example, an "intelligent" food packaging containing nanobiosensors could contain information for consumer and allow for measurement of the quality of the packaged food.

Hill et al. (2017) raised doubts on the usefulness of the reliance on big data alone for food safety surveillance. The possibilities of machine learning for the prediction of food infections from pork consumption have been explored by these authors using simulations based on a hypothetical food chain model, similar to one previously used by the EFSA for *Salmonella* in pigs. They observed that certain anomalies can be detected by using whole-genome sequencing (WGS) and supply chain data from critical control points as inputs into early detection algorithms as predictive models, yet the rare true cases will be overwhelmed by false positives. The best, although not optimal, performance was achieved if the machine learning was applied to individual cases, with 3 out of 4 true cases correctly predicted yet still amongst many other false positives, which reduced the predictability to 0.01. It showed that variance in food supply chain characteristics; for example, processing temperature and contamination burden had more impact on the decision outcomes than pathogen genotype, for example (Hill et al., 2017).

3.1.2 | Unstructured data

The extent to which unstructured data (e.g., text data from websites, blogs, and social media) are being utilized in managing food safety issues has been reviewed by Wang et al. (2021). Specifically, the review considers the application of mobile phones as food safety detecting devices, and the use of social media as an early warning system for food safety issues. Despite the advantage of using social media data for disclosing hidden patterns, poor data quality and privacy concerns need to be addressed. A study using Twitter as input for a text mining machine learning model showed a good correspondence with true incidence of a romaine lettuce food poisoning in the USA in 2018 (Tao et al., 2021). The most frequently used sources of unstructured data related to food safety can be found in the review published recently by Jin et al. (2020), where the option of using smartphones and handheld devices for food safety data collection is discussed. The data from social media, satellite images, IoT, and blockchain technology are current ongoing developments for obtaining data for smart food safety monitoring systems to manage food safety issues.

Various unstructured data sources that are relevant for the food safety domain involve the use of image data (from food packaging, vegetable, and animal products), sensor data (primarily from spectroscopy and electronic noses), and text data derived from online media, reports, and emails. Besides data on food safety, other data sources on, for example, climate and trade statistics provide added value to increase the accuracy of the prediction of food safety issues through application of a food system approach that takes into account social, economic, and environmental factors as drivers and consequences of food safety issues (Wang, Bouzembrak, Lansink, et al., 2022). In addition, a combination ("triangulation") of the outputs from these data sources with, for example, expert and consumers' knowledge helps improving model validity (Hadjigeorgiou et al., 2022).

Li et al. (2021) considered the importance of unifying the management of data from multiple sources for a tool that the group had developed for the detection of food safety hazards and early warning. Whilst data from food inspections were to feed into the associated database, both professionals and the public at large are the prospective users and sources of information for this tool, in future possibly also via a mobile phone application.

Wang et al. (2021) identified combinations of social media analysis and big data being deployed to ensure food safety. These include data from surveillance systems and surveillance of devices involved in hygiene control; food buying patterns, and the integrative food safety collaborative platform (FOSCOLLAB) of WHO.

3.1.3 | Blockchain

Blockchain may be an attractive tool to comply with food traceability requirements, such as full traceability and transparency (also toward consumers), and the speed with which products and data can be traced back and data retrieved in case of recalls. Other advantages of blockchain technology include reducing probability in changing or tampering data that have been entered into the system, and the independent verification of data packages. It does not require central entity for oversight. Moreover, “smart contracts” developed within the blockchain can specify the requirements for food safety that the products need to be checked against (Singh et al., 2022). A great variety of options is available for the data and documents that can be included depending on the design and acceptable volume of data, which does not have to be exhaustive for providing relevant information. It has been suggested that the inclusion of traceability and safety data into the record of the blockchain should be pilot tested in an isolated, protected area for software development (“sandbox”), using data representative for the real-world scenario (Hernandez San Juan & González-Vaqué, 2020). A number of challenges still may have to be overcome if such systems are to be implemented, such as those associated with scalability, security, privacy, and storage capacity. The interoperability of the blockchain models and regulations used, as well as their public availability, will be key to ensuring that an operator with a distributed technology can join any supply chain of its preference. Various strides toward this end are already made, such as rules for identifying items across different platforms supported by various collaborative initiatives (Bhat et al., 2022).

Soon (2022) investigated the application of blockchain concept and digitization of food chain to enhance food traceability, which can contribute to food integrity and authenticity (i.e., positive attributes beyond safety and quality, such as origin country, sourcing, distribution, and fairness). Consideration was given to recent development using portable and smartphone-based food diagnostic technologies as a new generation of miniaturized equipment for food fraud detection (Soon, 2022).

Manning and Kowalska (2021) extolled the potential benefits of blockchain for traceability and product recall, covering the whole chain and reducing opportunities for fraud. Vimalajeewa et al. (2020) described how a combination of blockchain, IoTs, and nanotechnology can be exploited for sensing chemicals in the environment. They elaborate this concept in a case study in which pesticides are applied on the farm and data are transmitted through the chain via blocks, whilst the amount of chemicals used is traceable as the farmer uses tokens, that is, digital assets stored securely on the blockchain, in this case a colored token with the color representing the level of a chemical in the soil (Vimalajeewa et al., 2020).

3.1.4 | Whole-genome sequencing data

As regards WGS data from microbial pathogens, Allard et al. (2019) featured an example of how this technology helped the authorities to link sporadic food poisoning events to a contaminated product, identify the causative pathogen of foodborne disease, and formulate actionable risk management measures. In this case, food safety inspectors had collected environmental samples including hundreds of swabs from food contact surfaces and other spots within a particular ice-cream manufacturing plant during 2 years period. Based on clustering of related single-nucleotide-polymorphism (SNP) genotypes of *Listeria monocytogenes* pathogen with less than 20 SNPs difference, the results demonstrated that some strains were “resident” within the plant, persisting throughout the sampling period. In addition, the similarity of some strains with those involved in previously reported food poisoning events was established, and the causative link was further corroborated by observable insanitary conditions and exposure data. This triggered a voluntary product recall by the company and subsequently its suspension by the US federal administration. The authors note that this would have previously not been possible without the WGS technology (Allard et al., 2019). WGS has replaced the technique of pulse-field gel electrophoresis in various networks for monitoring of specific pathogens, such as PulseNet (Allard et al., 2019).

A strategy proposed by O’Brien (2019) is to obtain “actionable insights from combining microbiological monitoring and predictive analytics.” Through this approach, the content of actionable information can be further increased by extending the mere detection of pathogens with more data on the context, for example, metagenomics of the microbiome in which it occurs (O’Brien, 2019). This is already being conducted in the USA (Kovac, 2019).

3.2 | Data processing: text mining and artificial intelligence

The EFSA explored the possibility of deploying a text mining tool for identification of emerging risks in seafoods (salmons and oysters). In abstracts from two scientific bibliographies (medical and food science and technology), the text mining tool identified the concurrence of certain concepts within the same sentence. These concepts belonged to different categories according to a customized hierarchical ontology. These were initially used for retrieving abstracts (e.g., on biological and chemical hazards) and subsequently utilized in further in-depth exploration, using ontologies with commonly used names and synonyms for chemical hazards, and human and animal pathogens and health impacts. The automatically generated outputs were scrutinized by experts to obtain a final selection for follow-up. This way, various seafood-related emerging risks could be identified (Lucas Luijckx et al., 2016).

Two recent publications further advance the concept of text mining into the detection of unknown food safety hazards. In the first study, the European Media Monitor and scientific literature served as data sources for the successful identification of the occurrence of illegal stimulants in food supplements. This approach was based on the use of AI involving a word-embedding model. The latter had been trained to recognize the context surrounding the mention of stimulants within a given text (Gavai et al., 2021). The second study explored the possibility of predicting chemical hazards in milk based on possible correlations with changes in economic, environmental, social, and technological factors within six major dairy-producing countries. The chemical hazards reported through RASFF within the studied period included mycotoxins and veterinary drug residues in particular, besides industrial contaminants, allergens, composition, organoleptic properties, food additives, and other contaminants. The results showed that anomalies in drivers of change (e.g., milk price) may precede food safety problems (RASFF notifications) with significant statistical correlations and a lag time from the peak in milk price until that in RASFF notifications of up to 2 years, that is, 10–13 months in The Netherlands and Germany and 20–32 months in France and Italy (Liu, Bouzembrak, et al., 2022).

In addition, new and emerging forms of data have been witnessed, for example, social media data have been used as an alternative to traditional survey data and used to identify peoples' opinions and trends in priorities and concerns about emerging food risks. Moreover, various types of multimedia data (e.g., transaction, registration, tracking, and images) have been combined in making AI models (Radanliev & De Roure, 2023). Tao et al. (2020) reviewed the data sources (mainstream news media, government websites, specialty blogs, social media platforms like Twitter, Facebook, and Instagram), computational methods, and applications of text data in food industry and showed that application of text data analysis can be beneficial for improving food safety and food fraud surveillance by checking different types of information for trends and patterns, such as food safety and fraud surveillance, dietary patterns, consumer-opinions, new-product development, and feedback to online food services.

Yang and Liu (2021) proposed a framework for data mining for food safety risks. This entails a system for storing inspection and enterprise data, plus a food risk model to predict occurrence of hazards. Seven categories of hazards are included, with different hazards being relevant for different types of product, such as *Salmonella* and nitrite for dairy products (Yang & Liu, 2021).

Recent breakthrough developments in the machine learning and AI field have enabled the identification of early warning signals and emerging risks made possible by using various data sources. Bayesian networks, neural networks, random forests, and decision-trees have been identified as the most used ML methods in the food safety domain. For instance, Bayesian networks were used successfully to predict the occurrence of chemical food hazards, such as pesticide residues and mycotoxins in fruits and vegetables from three geographically distinct countries. The machine learning approach applied system drew upon open-access data from EU food law enforcement alerts, agricultural economic and agronomic statistics [Food and Agriculture Organization Corporate Statistical Database (FAOSTAT)], and meteorological data [National Oceanic and Atmospheric Administration (NOAA)] (Bouzembrak & Marvin, 2019). In addition, two examples of successful machine learning approaches applied to the dairy sector have been provided, namely, the detection of unknown hazards using word embedding (Gavai et al., 2021), and the ability to predict hazards based on altered behavior in drivers of change (Liu, Bouzembrak, et al., 2022).

Wang, Bouzembrak, Lansink et al. (2022) reviewed the application of machine learning techniques to monitor and predict food safety issues. Various machine learning algorithms for both unstructured and structured data in the food safety domain were identified. Of these, Bayesian network analysis is the most frequently used algorithm for analyzing structured data as it allows easy incorporation of expert knowledge, which can be obtained, for example, through brainstorming and other elicitation events. Moreover, the model structure is relatively easy to understand. The neural network is the main algorithm for analyzing unstructured data because of its ability to handle both image and text data.

AI focused on narrow tasks ("weak artificial intelligence") and machine learning approaches are also being applied in the field of food safety. They can handle different types of data, such as text, transactional, and trade data. For example, machine learning has been applied experimentally to predict the minimum inhibitory concentration of antibiotics to microbial pathogens (e.g., non-typhoidal *Salmonella*) based on genomic data (Deng et al., 2021).

In the field of toxicology, Pérez Santín et al. (2021) identified a departure from animal experimentation (as demanded by regulations in, e.g., EU and USA), which has occurred via computational methodologies toward the current usage of AI algorithms (e.g., machines learning and deep learning). Combined with nondestructive methodologies (e.g., spectroscopic technologies), this trend reduces the analysis time and costs.

Chen et al. (2021) identified food hygiene as one of the main indicators for a risk prediction tool for possible incidents at large-scale youth events. This tool is based on random forest using 10fold cross-validation, reaching an accuracy of 86%, random forest, and outperforming other learning methods tested in the same study (Chen et al., 2021). Liu and Hu (2017) used a serial combination of three tools to enhance the ability to predict damage to strawberries during transportation of this perishable product. The first step consisted of a neural network, which has a high accuracy (90%) in terms of predicting spoilage but lacks stability and interpretability. It is followed by the robust classification and regression tree algorithm and then by Bayesian Modeling with good stability and interpretability. The temperature, humidity, and mechanical damage of strawberries were the variables which were measured regularly (at 15-min intervals) during transportation in the case study considered, with metamorphism as end point. If 70% of data were used for training and 30% for testing, the combined model outperformed all single ones, reaching 95% accuracy, thereby helping to avoid perishing of foods before they reach the market (Liu & Hu, 2017). Wu and Weng (2021) explored the use of "ensemble learning," that is, using multiple machine-learning methods in parallel. They tested these on historic data for three types of problematic foodstuffs whilst considering 125 factors. Ensemble learning applied to three different datasets improved the accuracy of predictions (85.5%–95.8%) over the use of single machine-learning methods in all but one (i.e., 14) comparisons (78.7%–96.7%). The hit rate of inspections, if guided by the ensemble model, would increase by 3.5–9.3 times over that of random inspections. The outcomes hence enable more efficient use of food inspections. Kong et al. (2021) used a "deep stacking network" approach with relatively modest memory requirements, which managed a high accuracy (94.88%–97.62%) for prediction of various mycotoxins, chemicals (heavy metals), and microbial risks in China within the grain supply chain used as case study.

Deep learning based on feature representation could offer stronger ability than traditional learning methods, as well as the possibility to transfer its learning outcomes to other systems, thereby reducing training time for other models (Zhou et al., 2019). Liu (2021) outlined a deep-learning system to be developed for the food safety of urban agriculture products, extending the methodology applied in the area of medical imaging. Such a system should include big data technology, encompassing the rapid collection of data from all segments of the supply chain, barcode technology for identification of products, and technology for product traceability based on data exchange (Liu, 2021). The use of AI, particularly machine learning, in developing countries would allow to cope with constraints of limited data and other resources (De-Arteaga et al., 2018).

4 | CASE STUDIES ILLUSTRATING THE POTENTIAL CONTRIBUTIONS OF BIG DATA AND AI (MACHINE LEARNING) TO EARLY WARNING AGAINST CLIMATE-CHANGE-RELATED FOOD SAFETY HAZARDS

Scientific evidence is increasing on the importance of climate change as a driver of emerging food safety risks that should be considered when designing food safety systems (EFSA, 2020; FAO, 2022; Tirado et al., 2010). The early identification of climate-change-related problems through surveillance of environmental health parameters, food safety, and human and animal disease could help formulate and implement solutions for mitigation of its impacts caused by diminished productivity, increased irrigation, changed agronomic practices, reduced crop land arability, and increased pest pressure, in a timely manner (Gomez-Zavaglia et al., 2020). Talari et al. (2021) made the case for the use of big data analytics combined with decision-support systems for the prediction of climate-change related hazards and decision-making to prevent these from developing into real risks. These authors suggest various cases that would be particularly amenable to future development of such a system, such as (i) the dairy chain, which is prone to climate-change-related impacts on the safety and quality of its products and in which, at the same time, a wealth of data is collected along the production chain, which, as big data, could feed into decision-support systems informing potential measures to control them, and (ii) environmental contaminants and toxins, such as those polluting soils caused by heaving flooding of agricultural land with contaminated water containing, for example, chemical contaminants such as PCBs, heavy metals, or pesticide residues, of which food safety competent authorities keep track (Talari et al., 2021).

Marvin et al. (2013) reviewed the impacts of climate extremes on food safety issues and proposed to develop approaches for proactive early warning of food safety hazards induced by climate-driven natural disasters by consolidating information on environmental conditions combined with a One-Health approach that takes stock of monitoring data on plant, animal, and human disease and considers their interrelation. Two examples of such a system mentioned in their review have indeed evolved since, namely, warning systems for harmful algal blooms (HABs) and for mycotoxins (naturally occurring toxins formed by certain fungi, often under warm and humid conditions, and capable of causing disease in humans and animals), which will be reviewed in more detail in the following subsections.

4.1 | Harmful algal blooms

HABs in marine environments may arise under favorable weather conditions, such as warmer temperature, extreme rainfall) and a surplus of nutrients (eutrophication) dissolved in the seawater, for example, phosphorus and nitrogen originating from run-offs from agricultural lands into waterways. These blooms threaten especially aquaculture operations because of the exposure of the trapped aquaculture stocks (fish, molluscs, and crustaceans) to toxin-producing microalgae. These microalgae and their biotoxins are not only toxic to the cultured aquatic animals (e.g., salmon and trout) but may also be consumed by them and transferred to foods for human consumption, particularly in the case of filter-feeding species (e.g., mussels). Both monitoring and forecasting systems are in place in various parts of the world, monitoring for the presence of associated biotoxins in bivalve species, or the prediction based on modeling outcomes imputing known growth characteristics of toxin-producing algal, weather conditions, seawater temperature, and so on (U.S. National Office for Harmful Algal Blooms, 2019). Longer-term HAB forecasting, with a view on protection of public health and food safety in particular, would entail the collaboration between local and coastal observational programs on one hand and food safety monitoring activities on the other. In addition, this would be further supported by extension of the physicochemical and biological parameters measured by existing observation stations with HAB-relevant parameters (species, community composition, and toxicity). Moreover, these networks should be extended to less common latitudes (Wells et al., 2020). Notably, the Intergovernmental Oceanographic Commission under UNESCO has started an initiative into this direction, the Harmful Algal Information System, including a database of algal toxins, information on algal species and their biogeographies, a resource of experts, and global HAB status reports being produced on a regular basis (The Intergovernmental Oceanographic Commission of UNESCO [IOC UNESCO], 2022).

A case in point are the devastating "red tides" caused by the toxin-forming unicellular dinoflagellate *Margalefidinium polykrikoides* (formerly known as *Cochlodinium polykrikoides*) being responsible for an unusually prolonged (over 10-month) and sprawling event in the Arabian Gulf (2008–2009), causing death of fish and blockage of water desalination plants, amongst others (Richlen et al., 2010). The contribution of climate change to HABs in this oceanic area is yet unclear, whilst fouling by ballast water and seasonal impacts of cyclones (e.g., upwelling) may also be implicated, amongst others (Lincoln et al., 2021). *M. polykrikoides* is also known to cause red tides impacting on aquaculture elsewhere, such as in Korea in 2014 (Shim et al., 2021). Red tides are also caused by many other species wreaking havoc in other parts of the world, such as *Karenia brevis* in the Gulf of Mexico (Tominack et al., 2020). Satellite data of oceanic and coastal waters measuring spectral data related to the chlorophyll content (a pigment produced by the algae) as well as nutrient levels and other relevant parameters from water samples have proven valuable in red tide detection and forecasting, such as in a regional program in the Arabian Gulf for phytoplankton and red tide monitoring and management (United Arab Emirates Ministry of Climate Change and Environment [MOCCAE], 2017). Recent improvements have been achieved in the knowledge and understanding of HAB formation and improved spatial resolution and detection algorithms using satellite data (Jeong et al., 2017; Liu, Xiao, et al., 2022).

For the prediction of HABs in Western Scotland, Davidson et al. (2021) described how satellite data applied to measuring phytoplankton density are combined with meteorological data and monitoring data on shellfish toxins produced by HABs. The resulting predictions are used by experts to forecast the risks of toxin contamination of cultured shellfish for the next week in Western Scotland, particularly the Shetland islands, where most of the UK shellfish industry is located. Based on weekly reports, the annual success rates for expert interpretations over a 3-year period varied between 50% and 97% of total predictions for shellfish toxin poisoning syndromes [*Dinophysis*-associated diarrhetic shellfish poisoning; *Alexandrium*-associated paralytic shellfish poisoning; and *Pseudo-nitzschia*-associated amnesic shellfish poisoning], with 3%–47% false positives and 0%–3% false negatives (Davidson et al., 2021).

Similarly, Liao et al. (2021) achieved a good prediction of algal growth, measured as chlorophyll, in a freshwater river and hydraulic lake using a random forest model. Training and testing the system with data from a 12-year period of chlorophyll measurements resulted in prediction accuracy r consistently exceeding 0.6, which the authors judged to be sufficient in the light of the high variability of chlorophyll within the natural environment.

Fernandes-Salvador et al. (2021) identified machine learning as a future method to predict the threat to European aquaculture from HABs, with the caveat that machine learning combines data from different information sources with different formats and purposes, and that therefore data consolidation is a challenge. This also holds true for changes in toxic marine algae species that are emerging under climate change, and the different geographies within Europe. These authors also noted that the current HAB prediction methods are already sufficient for weekly reports currently used within the sector to alert growers to HAB risks in the week ahead (Fernandes-Salvador et al., 2021; Leadbetter et al., 2018).

Mateus et al. (2019) pointed out various issues in relation to the use of HAB forecasting for shellfish aquaculture based on for example, monitoring data and computer models. Although it is possible to predict the blooms occurrence, forecasting may be more difficult for that of biotoxins and/or consortia of toxin-producing microalgae. If it is the case that blooms migrate along coast lines, crossing political borders, cooperation, and exchange amongst national authorities would be needed. In addition, the environmental parameters underlying the predictive models may shift due to accelerating climate change (Mateus et al., 2019).

A recent study explored the applicability of Bayesian networks to the prediction of toxin concentrations in mussels from a particular growing area in Ireland during a 5-year period. Bayesian networks involve the use of probabilistic acyclic graphs representing conditional dependencies between the nodes (variables). An advantage of these networks, including for low- and middle-income countries (LMICs), is that these models can also work with limited data as inputs. The model was based on data that included sea surface temperature in the coastal marine waters, the phytoplankton densities, and toxin concentrations in mussels from 8 to 9 locations other than the target area. It was able to predict with 82% accuracy the occurrence of toxins in mussels from a specific growing site, increasing to 96% accuracy when only toxin concentrations up to 0.16 μg/g was considered, that is, the maximum limit posed by EU regulation (EC) No 853/2004 for okadaic acid and its metabolites in shellfish meat (Wang, Bouzembrak, Marvin, et al., 2022).

4.2 | Mycotoxins and fungal growth

The development and use of predictive models for fungal infestation and mycotoxin contamination of crops is envisaged to have multiple impacts in sub-Saharan Africa. In addition to enhanced food safety, increased value and productivity of the crop may result, which will in turn improve economic return and demand within various markets. Several models are amenable for use in Africa. Keller et al. (2021) listed 15 methods for mycotoxin prediction that would be suitable for application in sub-Saharan Africa, that is, AFLA-maize, AFLA-maize + carryover, AFLA-pistachio, APHLIS+, APSIM+ Risk Model, AVHRR-based, CROPGRO, drought index (ARID), Maxent2, multilevel modeling, multivariate regression, risk in storage, spatial Poisson profile regression, and stacked Gaussian. Their accuracies varied between 54% and 99% for 10 methods (with the remaining ones being not predictive, future projections, or unvalidated). These models have been validated for peanut, maize, and wheat crops and use varying input data, including temperature, rainfall, wind speed, soil temperature and moisture, and crop phenology. A limiting factor to their application in sub-Saharan Africa is the availability of African data on occurrence of aflatoxins and associated climatological and agronomic data. Such data would be needed to recalibrate the empirical part of the model. The Partnership for Aflatoxin Control in Africa is currently collecting data and establishing an information management system, which could help provide relevant warning (Keller et al., 2021).

Chen et al. (2022) applied a new predictive modeling method for microbial growth to wheat infection with *Helminthosporium* and *Alternaria Fungi*. This was based on the "Wiener process," which had previously been successfully applied to estimate the remaining useful life of other (technical) products from different industries and was adapted to estimate the "remaining safety life," predicting the time left until the safety threshold will be exceeded. In the tested scenario, the exponential growth of mildew, that is, the hazardous fungus, during wheat storage was offset against the diminishing degree of food safety, and the time until a safety threshold would be exceeded for the first time was predicted. It demonstrated that the new model performed better than the more traditional tertiary models based on kinetic parameters. Moreover, the prediction became more accurate as time progressed, so the later the intervention, the more reliable were the data underlying it (Chen et al., 2022).

Research amongst stakeholders in China showed that, in addition to the technical implementation and improvement of models for the prediction of occurrence of fungal diseases (and hence mycotoxins), the understanding amongst farmers, traders, and other stakeholders of the utility of the models used and the implications of their outcomes is important, as is the sharing of protocols for data gathering, sharing, and disclosure and their implementation without identifying and hence stigmatizing individual farmers which mycotoxins have compromised food safety of crop, for example (Leslie et al., 2020).

5 | DISCUSSION AND SYNTHESIS

Although there are many developments in the field of food safety early warning and emerging risk identification, several challenges/conditions should be addressed regarding their implementation that may be particularly demanding for LMICs.

A prime challenge is to obtain rich and reliable data. Appropriate infrastructure and skilled personnel are required for collecting monitoring data. Information and data obtained through new channels such as social media and crowdsourcing should be processed with caution as there is a lack of assurance of data quality. Despite its appeal for LMICs, crowdsourcing has so far been mainly confined to high-income countries (van Niekerk et al., 2020). For crowdsourcing, another, general challenge is the lack of crowd participation and loss of control, as well as selecting the right "crowd" to ensure the reliability of information obtained (Soon & Saguy, 2017). In addition, when obtaining the training data for AI models, the data collection strategy should come before or simultaneously with the development of the algorithms. This will help ensuring representativeness of data in terms of demographic and geographic considerations, amongst other things. This allows the model to reflect real-world situations and to avoid biased results, as well as to enhance the ethical responsibility in AI development, for example, by ensuring inclusiveness toward subpopulations at risk (Radanliev & De Roure, 2022).

To enable automated data collection, good internet and/or wireless connectivity in rural areas of LMICs is required. For example, a survey amongst Zimbabwean farmers showed that those using IoT had issues with connectivity to the internet. In addition, a large computational infrastructure is needed to handle the long computational time for processing big data (Zengeya et al., 2021). The use of IoT technology in food safety is limited and the data produced today by IoT devices can be difficult to interpret, communicate, and share due to lacking standardized communication protocols for the food supply chain. The facilitation of information and data sharing with developing nations would help to reduce the digital gap between LMICs and resource rich countries. With the fast development of big data applications in developed countries, data privacy and security issues remain a challenge and should be further addressed (Sapienza & Palmirani, 2018). With the increasing digitalization of the systems, cyber risks may emerge concurrently, which makes it imperative to ensure strong cybersecurity. The possibility of cyberattacks in edge devices (e.g., IoT devices and drones) and their impacts should therefore be taken into consideration when designing the digital system (Radanliev & De Roure, 2022).

Some of the tools developed in relation to food hazard identification focus specifically on the conditions that prevail in LMICs. For example, a recurrent neural network-based system identifying food hazards from Arabic texts in social media, technical reports, and websites would be particularly suitable for use in the Middle East and North Africa region (Harrag & Gueliani, 2008). Niu et al. (2021) successfully tested a neural network model for the prediction of carcinogenicity risk of contaminated edible oil, which could aid risk management in countries with less developed food safety control systems. Tools have also been developed to work with nonstructured data from social media, such as decision-support tools that act as portals to data analysis and that summarize and visualize data to enable decision-making (Chen et al., 2020; Talari et al., 2021).

The rapid development of modern systems fed by numerous, real-time, and diverse data in identification of early warning and emerging food safety risks has been witnessed in the literature. The concepts of big data (e.g., text data from social media, image data), IoT, blockchain, and WGS data have been further implemented in data collection process, meanwhile recent breakthrough developments in machine learning and AI field have enabled the successful application of techniques (e.g., Bayesian network and neural network) on processing structured and unstructured data sources in the food safety domain. Big achievements have been made with moving toward more proactive early warning systems by establishing automatic food safety early warning systems that take into account not only food safety-related indicators but also socioeconomic indicators that are linked with drivers of change. Accelerating climate change, dietary shifts, and new technologies may cause more emerging food safety risks and pose threats to public health. The One Health principle has been considered for predicting future food safety risk and this provides a comprehensive approach that allows for more effective early detection of health threats and to take measures in time so that the food systems can be more resilient to food safety risks. Although these developments increase the feasibility and effectiveness of early warning and emerging risk tools in practice, several challenges/conditions should be addressed for their implementation that may be particularly demanding for

LMICs. Nevertheless, through improving the capability and capacity of national authorities and with international organizations' support to identify emerging food safety risks and to provide on-time early warning signals, the resilience of food systems to food safety risks can be enhanced.

6 | RECOMMENDATIONS

Based upon the findings in this review, a number of recommendations can be made addressed to the various parties involved in food safety governance internationally, nationally, and corporately to promote the accommodation of AI and big data in early warning and emerging food risk identification so as to enhance food systems' resilience toward safety threats.

6.1 | International organizations

Progress has recently been made with the adoption of revised guidelines on the paperless, digital exchange of food safety certificates, as published by the Codex Committee on Food Import and Export Inspection and Certification Systems (Codex Alimentarius Commission, 2021). This is also seen as an opportunity to link these electronic documents with modern methods based on digital tools for food safety inspections and management (United Nations Economic Commission for Europe [UNECE], 2021). Moreover, international organizations such as UNIDO facilitate the dialogue between stakeholders with a stake in food safety from countries worldwide by hosting events and initiatives to share their experiences with electronic food safety data for public health protection and trade enhancement (United Nations Industrial Development Organization [UNIDO], 2022). Another example is the 2021 annual Global Summit on Regulatory Science hosted by the Global Coalition for Regulatory Science Research. In this conference, international regulatory experts discussed the significance of AI and real-world data for the regulatory science surrounding medicines and food safety. These could support regulatory work in different ways, such by improvement of the review of a product's safety, provision of data driving decision-making, and accessible data that support regulation and enforcement, for example, through improved traceability and rapid detection of hazards. Examples include the timely identification of trends potentially indicating risks and horizon scanning. Real-world data have already found uses in daily practice, whereas AI could help agencies to improve their operation. Data standardization will be key in this regard (Thakkar et al., 2023).

International organizations should therefore continue to facilitate the exchange of data and collaboration between member state authorities, for example, through the harmonization of data formats and collection methods and the establishment of collaboration platforms and databases. In addition, they should foster capacity building amongst LMICs and to promote the establishment of adequate infrastructure through international aid.

6.2 | National authorities

National governments have been incentivized by international organizations such as the United Nations to implement digitalization of food safety certification of agricultural consignments traded across borders (United Nations Economic and Social Commission for Asia and the Pacific [ESCAP], 2018). There are examples of national initiatives for the establishment of platforms and harmonized data requirements to improve the exchange and sharing of food safety data amongst national stakeholders, such as the U.S. Food and Drug Administration's Integrated Food Safety System and China's Food Safety Improvement Project (U.S. Food and Drug Administration [FDA], 2023a, 2023b; World Bank, 2021). These include, amongst others, practical instructions such as sampling plans, good hygiene practices, procedures for routine tasks, guidance for authorities, inspectors, and industry, and public health alerts (from surveillance laboratory networks to authorities, amongst authorities, and from authorities to consumers), as well as materials for awareness raising, training, and capacity building, amongst others. The platforms could be a place for exchange between food safety professionals from public and business parties, food business operators, and consumers (Corby et al., 2015). Besides initiatives targeting food production chain actors, it is notable that authorities like the European Commission's Directorate-General for Research and Technology Development foster citizen science. This would involve consumers as source of self-measured or reported data on the healthiness and sustainability of foods, employing AI for the analysis of their inputs whilst at the same time respecting their privacy. This is in line with the Commission's policy toward co-creation and responsible research and innovation (European Commission, 2023).

National authorities should therefore be encouraged to continue implementing national strategies toward proactive emerging risk identification as part of their national food safety policy. Moreover, they should share data and collaborate with other national authorities and foster data generation and sharing within the private sectors, as well as public private cooperation. For this, they should also prioritize the establishment of adequate infrastructure

(ICT, mobile communications, and connectivity) and an enabling environment (adequate legislation on food safety data, data protection).

6.3 | Private sector

“Industry 4.0” with the use of modern tools, such as AI, big data, and IoT, is not only forethought to bring potential benefits in terms of food quality and safety but could also increase operational efficiency and environmental sustainability of food business operations (Romanello & Veglio, 2022). Digitalization of food safety data in the food industries has already found many applications, both for data-driven food manufacture and catering. These applications can range from the collection of consumption data to product traceability and recording of analysis data from critical control points and a swath of sensors, RFID devices, and so on from across the food production chain. Data collection can be harmonized either prospectively (before data are being collected) or retrospectively, that is, analyzing data already gathered. Prospective applications are usually more extensive and require stringent rules. Besides collection of data, also the means of data integration, that is, “extract, transform, load” should be harmonized. Various initiatives of EUROFIR, INFOODS, and EFSA have provided food-related ontologies such as FoodOn and the Meat Supply Chain Ontology (Zeb et al., 2021). In addition, data mining tools are used to support decision making (Romanello & Veglio, 2022). Various electronic tools are available for food business operators for their food risk management, including not only tools for hazard identification and characterization and risk characterization but also monitoring of hazards and emerging risk identification, such as the FOODAKAI platform (Stoitsis et al., 2023). Data-generating tools that are already being used in the food industries include advanced multi- and hyperspectral imaging besides the more conventional ultraviolet- near-infrared, and visual-wavelength spectroscopic sensors, as well as electronic noses and tongues. These and other sensors can be used in combination through IoT technology so that their signals can be processed in real-time and transferred to repositories. This can helps to create situational awareness and ensure compliance with analysis at critical controls points under a HACCP strategy and good transportation practices. Next-generation sequencing is already being applied to detect pathogens such as *Campylobacter jejuni* and *L. monocytogenes*. Although big data appear to remain underutilized in the food industries, the FOSCOLLAB is a large accessible repository of food safety monitoring data, whilst government websites in the US, EU, and China provide details of official monitoring (Nychas et al., 2021).

Corporate parties should therefore be encouraged to allow openness of data for use for the public good, to enhance traceability systems to enhance data transparency, and to strengthen supply chain networks and data sharing among supply chain partners (e.g., block chain technology, where applicable). In addition, they should further pursue the adoption of and compliance with international standards and collaborate with governmental agencies and research organizations on co-development of the tools for identifying early warning signal and emerging food safety risks.

7 | CONCLUSION

This literature review focused on existing and experimental applications of AI, big data, and IoT in the development of early warning and emerging risk identification tools and methods used in the food safety domain. Discussion and synthesis have been provided on the challenges/conditions that need to be addressed regarding the implementation of the developments in the field of food safety early warning and emerging risk identification. AI, IoT, and big data hold great potential as tools supporting an efficient and effective food safety management by the public and private sectors in nations across the globe. Recommendations have been proposed for the actors and stakeholders involved in both national and international food safety governance and in the industrial sectors. International cooperation and capacity building amongst food safety authorities, as well as access to data and tools through data standards harmonization, collaboration with industrial sectors, and the establishment of the proper infrastructure and platforms, for exchange, are needed particularly in LMICs to promote public health protection and prevent trade disruption.

AUTHOR CONTRIBUTIONS

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DISCLAIMER

The views expressed in this article are those of the authors and do not necessarily reflect the views or policies of the Food and Agriculture Organization of the United Nations or any other party.

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