Holistic artificial intelligence for food safety

Floor van Meer[1], Eva Korenjak Lalovič[2], Bas H.M. van der Velden[1]

Main takeaways

- AI can support food safety decision-making.
- Food safety requires a holistic food systems perspective.
- Integrated, large-scale datasets are essential for holistic AI.
- Holistic AI models can predict contaminant risks.
- AI in food safety operates within an evolving EU legal framework.
- Trustworthiness, explainability and data governance are central.

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Introduction

Artificial intelligence (AI) offers promising opportunities to improve food safety. To be adopted responsibly, AI tools must be *trustworthy and compliant with legal requirements.* Furthermore, AI for food safety should be *holistic,* integrating information across the food chain and from multiple data sources to reflect the full range of drivers that influence food safety risks.

Artificial intelligence is a general term for computer systems that can perceive information, learn from data, and support decision-making. In food safety, AI most often refers to machine learning: algorithms that learn patterns from data to make predictions or classifications, such as estimating contamination risk or prioritizing samples for testing. A more advanced form of machine learning is deep learning. Deep learning learns patterns directly from large amounts of raw data (e.g., images, sensor signals, or text) without requiring experts to first manually instruct which details are important.

More recently, generative AI (GenAI) has emerged, referring to models that can create new content such as text and images, or synthetic data for lab tests. The best-known examples of GenAI are large language models like ChatGPT. While GenAI is gaining attention, current food safety research and applications still largely rely on traditional machine learning approaches, with deep learning and GenAI used more selectively and often in emerging or exploratory use cases (van Meer et al., 2025).

Issue description

When using AI for food safety, it is important to appreciate the complexity of food systems. According to Food and Agriculture Organization (FAO) of the United Nations, a food system encompasses all actors and activities involved in producing, processing, distributing, consuming, and disposing of food, embedded within broader economic, social, and natural environments. Hence, one needs to understand what drives these food systems to understand what potential food safety hazards might occur or might emerge in case these drivers change.

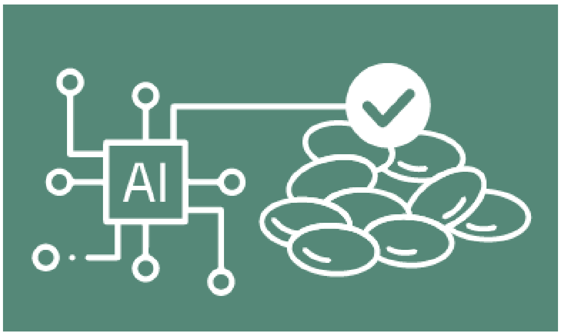

Figure 1 – AI and food safety representation.

The HOLIFOOD project assessed which drivers of change are relevant for food safety hazards. Examples of such drivers include weather or climate, (socio)economics, political status, and others. To develop AI using these drivers, the drivers are captured with numerical variables. Examples of such numerical variables are the maximum temperature in a given region at a certain timepoint, the human development index, and the corruption index. In total, over 300 of such numerical variables are identified in HOLIFOOD as input for AI models.

Key messages for policy makers

Recommendation #1: To enable holistic AI-driven food safety assessments, large-scale, integrated datasets are essential

AI models require diverse and longitudinal data across hazards, food products, countries, and drivers (e.g., environmental, trade, and production factors) to capture the complexity of modern food systems.

A recent example is the CompreHensive European Food Safety (CHEFS) database (Kızılilsoley et al., 2026), which consolidates decades of official EU monitoring data into a unified and structured dataset comprising hundreds of millions of analytical results across thousands of food products. This resource developed within the HOLiFOOD project was recently published and made publicly available (https://github.com/WFSRDataScience/CHEFS), providing an unprecedented foundation for AI-based trend analysis, risk prediction, and early warning systems in food safety.

Other parts of the dataset such as those describing the previously mentioned numerical variables that describe the drivers of change are derived from the United Nations, the World Bank, FAOstat, satellites such as Copernicus, and many more. These are preferably automatically updated via an Application Programming Interface (API).

Van den Bulk et al. (2025) demonstrated how to develop a holistic AI model. They predicted potential presence of food safety hazards in animal feed in an accurate and timely manner. The authors modeled relations between direct and indirect drivers of contaminant emergence across countries and feed types, using extensive historical monitoring data covering multiple contaminant groups (mycotoxins, heavy metals, dioxins, and pesticides), enriched with socioeconomic and weather indicators to emphasize the holistic design. By incorporating this broad range of external features, the model could estimate the probability that a given feed sample would exceed predefined safety thresholds, achieve high sensitivity and specificity and supporting risk-based decision-making through a decision support system interface.

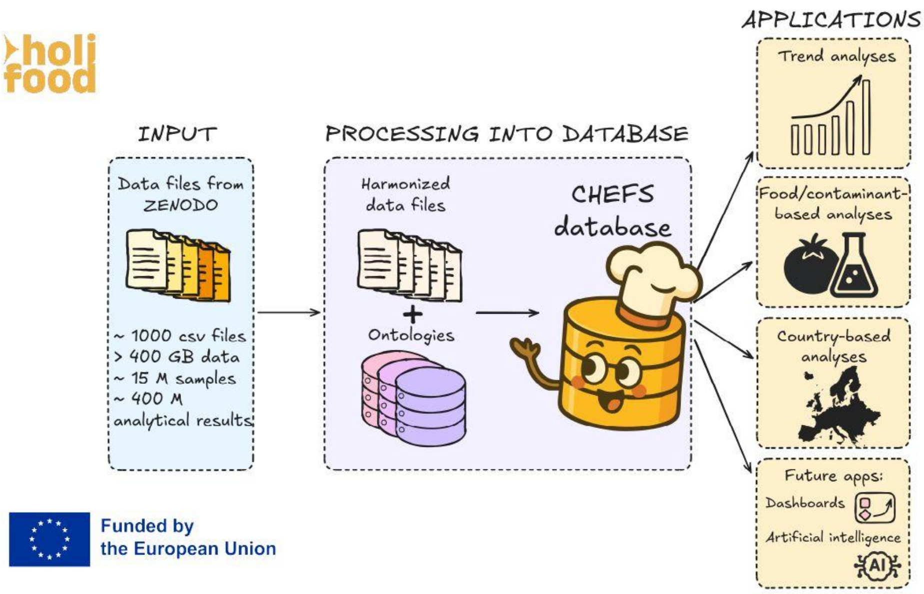

Figure 1 – CHEFs Database representation.

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Recommendation #2: To ensure that AI applications in food safety comply with regulatory requirements, it is essential to address risks related to opacity and bias throughout the AI lifecycle

The use of AI is subject to an increasingly comprehensive legal framework in the European Union. Central to this is the EU Artificial Intelligence Act (AI Act; EU, 2024), which entered into force in August 2024 and is being implemented in phases. Some provisions, such as those on prohibited AI systems, apply already from February 2025, general applicability is expected by August 2026, and most rules on high-risk AI systems will apply from August 2027. The AI Act establishes the world's first comprehensive, risk-based regulatory framework for AI and applies to both public and private actors that develop or use AI systems within the EU, regardless of where the provider is located. While the AI Act includes a research exemption, according to which it does not apply to AI systems developed solely for scientific research or to pre-market testing, real-world testing or deployment after the research phase remove this exemption.

AI Act classifies AI systems into four risk categories: unacceptable, high, limited, and minimal risk. AI systems posing unacceptable risks to fundamental rights and safety, such as harmful manipulation, exploitation of vulnerabilities, or certain biometric or emotional recognition, are strictly prohibited. High-risk systems include safety-critical components, those covered by EU health and safety legislation, or systems used in the eight areas listed in Annex III of the AI Act (biometrics, critical infrastructure, education, employment, essential services, law enforcement, migration, justice).
The use of AI in food safety is also governed by existing legislation, most notably the General Data Protection Regulation (GDPR), which imposes strict requirements on the lawful, transparent, and secure processing of personal data, and copyright law, which is relevant when AI systems are trained on protected texts, images, or scientific publications. Together, these legal frameworks underline that AI for food safety must not only be innovative and effective, but also compliant, transparent, and respectful of fundamental rights. Beyond legal requirements, ethical considerations are crucial, particularly those related to trustworthy AI (see Ethics Guidelines for Trustworthy AI, European Commission, 2019), guided by principles such as human agency and oversight, technical robustness and safety, privacy and data governance, transparency, diversity, non-discrimination and fairness, societal and environmental wellbeing, and accountability. While many of these principles are already reflected in laws such as the AI Act, their full implementation may go beyond existing legal obligations
To ensure that AI applications in food safety comply with these regulatory requirements, it is essential to address risks related to opacity and bias throughout the AI lifecycle. Many advanced AI models, particularly deep learning systems, operate as so-called "black boxes," making it difficult to understand how decisions are reached and to detect hidden biases that may affect outcomes. Explainable AI (XAI) provides a key mechanism to meet these requirements by enabling insight into how models use input data and which factors drive predictions, thereby supporting bias detection, validation, and meaningful oversight (Mutlu et al., 2025). Equally important is data transparency and governance: AI systems can only be trustworthy if the data used are well-documented, representative, and traceable. Applying principles such as FAIR (Findable, Accessible,

Interoperable, Reusable) data helps reduce the risk of biased or misleading results and strengthens reproducibility and auditability. Together, the use of XAI and robust data governance not only supports legal and ethical compliance but also ensures that AI-based food safety tools produce outputs that can be clearly explained to end users, which is essential for trust, acceptance, and responsible deployment. The HOLiFOOD project uses explainable AI to ensure trustworthy models.
Ultimately, AI has the potential to meaningfully strengthen food safety by being legally compliant, trustworthy, and grounded in a holistic understanding of risks across the entire food system.

Authors' affiliations

[1] Wageningen Food Safety Research, Wageningen, The Netherlands
[2] University of Vienna, Vienna, Austria

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