

Artificial intelligence in food safety and nutrition practices: opportunities and risks

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Abstract

Artificial intelligence (AI) is transforming food safety and nutrition practices by offering scalable, real-time, and personalized solutions. In food safety, AI enables predictive risk modeling, rapid contaminant detection, smart surveillance systems, and blockchain-based traceability. In nutrition, AI facilitates personalized diet recommendations, automated dietary tracking, and virtual nutrition coaching through data integration across genomics, microbiome, and behavioral inputs. Despite these promising applications, AI introduces notable risks, including algorithmic hallucinations, biased training data, opaque decision-making processes, and ethical concerns regarding data privacy and consent. Furthermore, the lack of regulatory frameworks and unequal access to AI tools may exacerbate existing health disparities. This narrative review synthesizes the current developments in AI-based food and nutrition applications; explores emerging challenges; and highlights ethical, technical, and policy considerations. This paper also presents a roadmap for the responsible integration of AI into food systems, emphasizing transparency, equity, interdisciplinary collaboration, and global governance. AI holds great promise to enhance safety and nutrition at a global scale, but its success depends on how thoughtfully and ethically it is designed, deployed, and evaluated. This review aims to guide researchers, policymakers, and practitioners in aligning technological innovation with public health priorities.

Keywords: *artificial intelligence, food safety, nutrition practices, personalized nutrition, predictive modeling*

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1. Introduction

Food safety and nutrition are fundamental pillars of global public health. The integrity, traceability, and nutritional quality of the food supply affect not only individual well-being but also population-level outcomes, including disease burden, health equity, and socioeconomic stability. As global food systems become more complex and interconnected, ensuring their safety and nutritional adequacy presents new challenges that require innovative approaches [1, 2].

In parallel, artificial intelligence (AI) is transforming multiple domains by processing large datasets, recognizing patterns, and making predictions at a speed and scale beyond human capacity. AI refers to computer systems designed to simulate human cognitive functions such as learning and problem solving. From agriculture and logistics to medicine and education, AI is reshaping traditional practices. Its integration into food safety and nutrition science is therefore both likely and potentially transformative [3].

The urgency of digital innovation in food systems has been highlighted by recurring global crises, including pandemics, climate change, and geopolitical disruptions. These events expose vulnerabilities in food security, supply chain resilience, and nutritional adequacy [4]. Within this context, AI is increasingly viewed as a strategic tool for strengthening resilience and enabling proactive, data-driven interventions in both food safety and personalized nutrition [5].

This review addresses three guiding questions: (1) What are contemporary AI applications in food safety and nutrition? (2) What ethical, infrastructural, and regulatory barriers limit their effectiveness? (3) How can the responsible use of AI advance public health goals?

1.1. Methods

We searched PubMed and Scopus from 2018 to 2025 using keywords such as “AI AND food safety” and “nutrition AND machine learning”. We included peer-reviewed empirical studies and policy documents in English, excluding editorials and commentaries.

1.2. From reactive to predictive systems

In contrast to the past, AI enables predictive modeling based on real-time data streams, including environmental sensors, supply chain analytics, microbial genomics, and consumer behavior tracking. These tools allow authorities and producers to detect and prevent hazards before they escalate [6].

Similarly, nutritional interventions have historically been based on generalized dietary guidelines designed for population-wide applicability. However, with the emergence of personalized nutrition and precision health, the limitations of this approach

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have become apparent. AI now supports individualized dietary recommendations that integrate genetic, metabolic, microbiome, and lifestyle data, thereby improving both efficacy and user engagement [7–9].

1.3. The rise of AI in food and nutrition research

In recent years, research on food-related domains has increasingly applied machine learning (ML), natural language processing (NLP), and neural networks. In food safety, AI has been used for contaminant detection through image analysis, the optimization of storage conditions, and the enhancement of recall systems through blockchain integration [10]. In nutrition, AI supports automated food logging, recognition of dietary patterns, virtual diet coaching, and predictive modeling of disease risks based on diet quality indices [11].

AI-powered “digital dietitians” are being developed to provide continuous dietary support, especially in contexts with limited access to healthcare professionals. While promising, these tools also raise concerns regarding accuracy, equity, privacy, and ethical accountability. Without rigorous governance and transparent design, risks such as misinformation, data mismanagement, and algorithmic bias could undermine trust and widen health disparities.

1.4. The objectives of this review

Despite the growing enthusiasm for AI in food systems, there remains a lack of critical syntheses examining both its promises and perils. This review seeks to fill this gap by providing a structured overview of the applications of AI in food safety and nutrition while also addressing the associated risks, ethical concerns, and future directions.

Specifically, we aim to

- Summarize current AI applications in food safety (e.g., contamination detection, predictive surveillance);
- Review AI-enabled tools in nutrition practice (e.g., personalization, digital dietary counseling);
- Highlight the benefits of AI for efficiency, accessibility, and data-driven decision-making;
- Discuss the limitations and risks, including algorithmic hallucinations, privacy issues, and regulatory gaps;
- Provide recommendations for the responsible development and integration of AI technologies into food systems.

By offering a comprehensive synthesis of these dimensions, we aim to support researchers, practitioners, and policymakers in navigating the complex landscape of AI adoption in food and nutrition sciences. As this is a narrative review, literature works were identified using searches in PubMed, Scopus, and Google Scholar from 2019 to 2025. The search terms included “AI in nutrition”, “food safety AI”, and “AI ethics in health”. Peer-reviewed articles, technical reports, and relevant policy documents in English were included. Editorials and non-scholarly commentaries were excluded.

2. AI in food safety: from contaminant detection to predictive risk modeling

Food safety remains one of the most critical components of public health, as foodborne illnesses continue to cause significant morbidity and mortality worldwide. According to the World Health Organization, unsafe food leads to nearly 600 million cases of foodborne disease and 420,000 deaths each year [12]. Traditional approaches to ensuring food safety, including microbial testing, physical inspection, and batch sampling, are often reactive, labor-intensive, and limited in scope. In contrast, artificial intelligence (AI) provides scalable, data-driven, and predictive alternatives that can improve both the reliability and the speed of food safety systems.

2.1. AI-based contaminant detection and quality control

AI has been successfully applied in identifying physical, chemical, and microbial contaminants throughout the food production and distribution chain. Machine learning (ML) algorithms, particularly supervised learning models such as support vector machines (SVMs), random forests (RFs), and artificial neural networks (ANNs), can be trained on large datasets of image, spectral, or chemical signatures to classify food quality and detect anomalies [13].

For instance, hyperspectral imaging (HSI) combined with deep learning has been used to detect foreign objects in processed foods, such as plastic fragments or insect parts, with remarkable accuracy [14]. Similarly, near-infrared (NIR) spectroscopy analyses through convolutional neural networks (CNNs) can identify adulterants in milk, oils, and flours in real time [15].

In microbial detection, AI algorithms trained on genomics and metagenomics data can differentiate between pathogenic and non-pathogenic bacterial strains based on DNA sequences, accelerating the identification of high-risk contaminants such as *Listeria monocytogenes* and *Salmonella enterica* [16].

2.2. Predictive surveillance and outbreak forecasting

A major innovation introduced by AI in food safety is the shift from retrospective testing to predictive surveillance. Predictive models can assess the probability of contamination or spoilage based on environmental variables such as temperature, humidity, supply chain interruptions, and consumer feedback data.

For example, AI models analyzing satellite data and weather patterns have been used to forecast aflatoxin contamination in maize crops in sub-Saharan Africa [17]. By integrating remote sensing with crop phenology data, AI systems can predict which geographic areas are most at risk, thus allowing for preemptive interventions.

In the United States, the FDA has piloted the use of AI models that detect patterns in food import records, supplier risk histories, and inspection outcomes to assign dynamic risk scores to imported goods [18]. This has enabled more targeted inspections and resource allocation, replacing outdated random inspection models.

Moreover, social media mining using natural language processing (NLP) is an emerging application. Early studies show that NLP algorithms can scan user complaints and reviews on food delivery

platforms or social media to detect signals of potential foodborne illness clusters before they are formally reported [19].

2.3. Blockchain and AI: enhancing traceability

Blockchain technology provides a decentralized, tamper-proof ledger for recording transactions across the food supply chain. When coupled with AI, blockchain enables real-time verification of food provenance, reducing the time required to trace contaminated products from days to minutes.

A prominent example is the collaboration between IBM and Walmart, where AI-driven blockchain systems track leafy green vegetables from farms to store shelves. In trial runs, the traceability time for contaminated batches decreased from seven days to under three seconds [20]. AI is used here not only to manage the ledger but also to detect anomalies in supply chain data such as missing checkpoints or delayed entries, which could indicate mishandling or fraud.

In the meat and dairy industries, blockchain–AI systems are being tested to integrate sensor data from cold-chain logistics, alerting retailers in real time if temperature thresholds are breached during transport [21].

2.4. Smart sensors and IoT integration

Another important development is the integration of AI with Internet of Things (IoT) sensors deployed in warehouses, vehicles, and retail environments. These sensors continuously collect data on temperature, humidity, CO₂ levels, and microbial counts. AI models then analyze these data streams to assess spoilage risk in real time and recommend corrective actions [22].

In seafood logistics, for example, AI systems process sensor data from packaging environments to predict histamine development in tuna, a common food safety concern [23]. When thresholds are exceeded, alerts are automatically generated, and shipments can be rerouted or removed from circulation.

This integration enables adaptive shelf-life estimation by replacing static expiry dates with dynamic predictions that reflect actual storage conditions. This is a major step toward both improved safety and reduced food waste.

2.5. Applications in developing countries

AI holds particular promise for improving food safety in low- and middle-income countries, where regulatory systems may be under-resourced. Mobile AI apps that analyze smartphone images of produce can assess freshness, bruising, and contamination risks, making food safety more accessible to farmers, vendors, and consumers alike [24].

For instance, a Kenyan startup has developed a mobile platform that uses machine vision to detect mold growth in grains stored in rural silos. This allows farmers to take preventive action before toxic mycotoxins develop, which are a major cause of liver cancer in Africa [25].

In these settings, cloud-based AI tools can serve as “digital inspectors”, bridging gaps where in-person inspections are unfeasible.

2.6. Challenges in implementation and interpretation

While the potential of AI in food safety is clear, several challenges limit its broad implementation. A central issue is the interpretability of AI models. Deep learning systems, although often highly accurate, typically function as “black boxes” and provide little insight into how decisions are made. This creates difficulties for regulatory compliance, where transparency and reproducibility are essential [26].

Many AI applications also depend on high-quality labeled datasets for training. In food safety, such datasets are frequently scarce, fragmented, or proprietary. The absence of standardized data collection practices across regions and industries complicates model development and validation further [27].

Infrastructure is another limiting factor, particularly in rural or underdeveloped settings. AI tools that rely on continuous internet access, cloud computing, or advanced sensors may not be feasible unless supported by substantial public or international investment [28].

Integrating AI into existing food safety frameworks presents additional challenges. Regulatory bodies often lack the technical capacity to evaluate AI-based systems. Without harmonized standards or certification mechanisms, their adoption may remain inconsistent, and trust among stakeholders may be weakened [29].

Although blockchain–AI integration shows promise for traceability, issues of data integrity and scalability remain unresolved [30]. High computational costs and energy demands also raise concerns about the environmental sustainability of large-scale AI applications, highlighting the need for energy-efficient architectures [31].

Finally, ethical concerns must be addressed. These include data ownership, informed consent for data collected via IoT sensors, and the risk of predictive models being misused to stigmatize specific regions or populations. The EU Data Act provides general principles of fairness and portability, but it does not adequately address the specific requirements of high-risk AI applications in food safety and nutrition. Without targeted enforcement and sector-specific standards, unregulated AI-based dietary tools could operate without the proper oversight, posing risks to both public health and data security.

3. AI in nutrition practices: personalized diets and health monitoring

Artificial intelligence (AI) is redefining the landscape of nutrition science, particularly in the domains of dietary assessment, personalized nutrition, behavior modification, and population health surveillance. With the rising prevalence of diet-related chronic diseases and growing awareness of interindividual variability in dietary responses, the demand for precise, scalable, and real-time nutrition guidance has never been higher [32]. AI, when integrated with digital health platforms, offers unprecedented capabilities to meet these demands.

3.1. Personalized nutrition through data integration

Traditional dietary recommendations are typically population-based, relying on generalized guidelines such as the Mediterranean diet or USDA’s MyPlate. While useful, these guidelines

often fail to accommodate individual differences in genetics, metabolism, gut microbiota, cultural practices, and psychological factors [33].

AI facilitates precision nutrition by integrating multi-dimensional data sources: genomic information, phenotypic biomarkers, metabolomics, gut microbiota composition, lifestyle behaviors, and even geolocation data on food access [34]. Algorithms can synthesize this information to generate highly individualized dietary recommendations that evolve over time based on user feedback and physiological changes [35].

For example, decision-tree-based AI models have been used to predict individual postprandial glycemic responses to identical meals, allowing for more effective dietary management of insulin resistance and type 2 diabetes [36]. AI models trained on gut microbiota profiles have also been associated with better predictions of weight loss success during dietary interventions.

3.2. AI-powered dietary assessment tools

One of the most immediate applications of AI in nutrition is the automation of dietary intake tracking. Manual dietary recall methods, such as 24 h recalls, food frequency questionnaires (FFQs), and dietary records, are time-consuming, prone to recall bias, and difficult to scale [37].

AI-based mobile applications now use image recognition and natural language processing (NLP) to automate food logging. Users can take photos of their meals, and deep learning algorithms identify food items, estimate portion sizes, and calculate nutrient content [38]. Several consumer-facing mobile applications already implement these technologies for automated meal logging and nutrient estimation.

More advanced platforms integrate AI with continuous glucose monitors (CGMs) and wearable fitness trackers to place food intake in a broader physiological context. This allows for real-time feedback and adaptive recommendations [39].

Despite these advances, accuracy remains a concern. Studies comparing AI-estimated nutrient intake with dietitian-reviewed records report moderate agreement but emphasize the need for larger training datasets and culturally diverse food image libraries [40].

3.3. Conversational AI and digital nutrition coaching

The development of AI-driven chatbots and virtual coaches marks an important step in behavior-based dietary interventions. These systems combine NLP with behavior change frameworks (e.g., the transtheoretical model, cognitive behavioral therapy) to deliver tailored feedback, motivational interviewing, and habit-tracking support [41].

Recent randomized trials suggest that AI-supported coaching can produce modest improvements in dietary quality, particularly in populations with limited access to nutrition professionals [42]. However, outcomes vary depending on the chatbot design, personalization capacity, and user engagement.

Large language models (LLMs) such as ChatGPT are also being tested for nutrition education and client engagement. While promising, these models are prone to “hallucinations” (confident

but incorrect outputs) and lack grounding in validated nutrition databases unless externally constrained [43].

3.4. Predictive analytics for population nutrition

Beyond individual interventions, AI is increasingly used in public health nutrition for surveillance, modeling, and policy evaluation. Machine learning models can analyze large dietary survey datasets to identify nutrient deficiencies, emerging dietary trends, and at-risk populations.

In one study, AI models trained on national health and nutrition datasets predicted the future prevalence of obesity and hypertension based on current dietary habits. This approach enabled proactive policy simulations [44]. Such insights support targeted campaigns, subsidy design, and resource allocation in ways that extend beyond traditional epidemiological tools.

AI has also been applied to assessing the environmental and sustainability impacts of dietary patterns by integrating nutrition outcomes with climate projections. This intersection is gaining importance within the planetary health framework [45].

3.5. Real-world case studies in LMICs

In Kenya, researchers recently combined satellite data with machine learning techniques to map the aflatoxin risk levels in maize-growing regions across East Africa. An ensemble gradient boosting model trained on 907 pre-harvest maize samples from Kenya, Uganda, Malawi, and Tanzania achieved a balanced accuracy of about 62% and generalized well to external test data. These results demonstrate the feasibility of AI-supported risk prediction for aflatoxin contamination in real-world agricultural settings.

In India, the fintech–wellness company HealthifyMe has deployed its AI nutrition assistant, Ria, at scale. Ria handles around 80% of user queries and provides personalized dietary advice using regional food databases and user habits. Its image recognition capability can identify local Indian meals for calorie and nutrient tracking, making the tool both culturally relevant and scalable across diverse linguistic settings.

4. Opportunities: efficiency, precision, and scalability

The integration of artificial intelligence (AI) into food safety and nutrition offers opportunities to overcome persistent limitations in both domains. By automating complex processes, improving precision, and supporting interventions at scale, AI has the potential to transform how food systems operate and how individuals manage their nutritional health.

4.1. Automation and real-time decision support

One immediate advantage of AI is its ability to automate tasks that are traditionally time-consuming and error-prone. In food safety, AI can process visual, chemical, and sensor data to detect contaminants, monitor storage conditions, and trigger alerts for unsafe batches. These are functions that would otherwise require manual inspection or laboratory testing [39]. In many industrial settings, such automation already reduces labor costs, inspection

delays, and error rates while enabling more frequent and detailed quality control [46].

In nutrition, AI-powered automation allows for real-time dietary tracking and intervention. Instead of relying on occasional check-ins with healthcare professionals, users can now receive continuous dietary feedback through mobile apps, wearables, or voice assistants. This fosters improved adherence and engagement [47].

4.2. Improved personalization and predictive capabilities

AI systems excel at identifying patterns in large, heterogeneous datasets. This ability enables highly personalized recommendations that adapt over time. Personalized nutrition models that incorporate genomics, metabolomics, microbiome profiles, and behavioral data are now capable of predicting individual responses to specific foods or dietary patterns [48]. This predictive capacity is especially promising for managing chronic conditions such as diabetes, obesity, cardiovascular disease, and irritable bowel syndrome (IBS) [8].

AI can also simulate long-term scenarios based on current data, making it a valuable tool for proactive interventions. For example, machine learning models can project how today's dietary habits may influence future disease risk, supporting more meaningful counseling and early prevention [49].

4.3. Expanded access and equity in underserved populations

Globally, healthcare systems face a shortage of dietitians, particularly in rural and low-income regions. Validated AI tools can help bridge this gap by acting as digital nutrition coaches and providing evidence-based guidance [50]. These tools can be translated into multiple languages, adapted for cultural relevance, and embedded into widely used platforms such as messaging applications or government health portals [51].

In food safety, AI-based mobile applications can empower farmers, small vendors, and frontline workers to assess risks without advanced training or laboratory access. For example, image recognition tools can identify signs of spoilage, mold, or pest infestation using a simple smartphone scan [52].

By democratizing access to knowledge and technology, AI has the potential to improve health equity. However, its successful implementation in low-resource settings requires investment in infrastructure, supportive policies, and culturally relevant adaptation. Without these elements, the outcomes observed in high-income countries may not be replicated.

4.4. Optimization of supply chains and sustainability

Food systems are complex networks that often suffer from inefficiencies, waste, and loss. AI helps optimize these systems by modeling the flow of goods, predicting demand, and adjusting production or distribution in real time. For instance, AI algorithms can analyze purchasing patterns, weather forecasts, and logistics data to prevent overproduction or spoilage during transport [53].

These optimizations directly enhance food safety by reducing the time spent in high-risk stages of distribution. They also support nutrition by maintaining the quality of perishable foods such as fruits, vegetables, dairy products, and meat [54].

AI has also been applied to assessing the environmental impact of diets, including greenhouse gas emissions, water use, and land degradation, alongside their nutritional value. This dual analysis allows for dietary recommendations that are both health-promoting and environmentally sustainable [55].

4.5. Supporting public policy and regulatory innovation

AI provides new tools for evidence-based policymaking. Public health authorities can apply machine learning to large-scale dietary surveillance data and simulate the outcomes of regulatory interventions (e.g., sugar taxes, front-of-pack labeling, or food fortification strategies) [56]. This approach enables more informed and flexible decision-making that can adapt to local and global trends.

Regulatory agencies can also use AI to identify high-risk imports, monitor food fraud, and prioritize inspection schedules based on the predicted likelihood of violations. In this way, limited resources are deployed more effectively [57].

Such data-driven governance can strengthen both food safety and nutrition security at the population level, positioning AI not only as a technological tool but also as a policy enabler.

4.6. Enhanced research and knowledge discovery

AI also accelerates research in both basic and applied nutrition sciences. Natural language processing tools can analyze thousands of scientific articles to highlight emerging patterns, contradictions, and gaps in the literature. This facilitates faster meta-analyses and supports the development of evidence-based guidelines [58].

In food safety, AI supports the discovery of new antimicrobial compounds, detection methods, and safety biomarkers by screening large molecular datasets and proposing hypotheses that can later be validated in laboratory studies. As summarized in **Table 1**, AI-powered tools are being applied across diverse domains of food safety and nutrition.

Table 1 • Summary of AI-powered applications in food safety and nutrition.

Application area	AI technology used	Readiness level	Potential benefits	Key risks
Food safety—traceability	Blockchain + ML	High	Real-time recall, fraud prevention	Data burden, scalability
Nutrition—meal analysis	Image Recognition + NLP	Medium	Dietary tracking, engagement	Misclassification, bias
Food safety—surveillance	Remote Sensing + ML	Medium	Predicting outbreaks	Weather data quality, access
Nutrition—personalization	ML + Gut Microbiome	Experimental	Improved outcomes	Ethical data use, overgeneralization

5. Risks and ethical challenges: hallucinations, bias, and data privacy

While artificial intelligence (AI) has significant potential in food safety and nutrition, its use raises important limitations and ethical concerns. Issues such as hallucinations, dataset bias, a lack of transparency, accountability gaps, and privacy risks threaten both individual health and public trust. Without the appropriate governance, these risks may outweigh the potential benefits, particularly for vulnerable populations.

5.1. Hallucinations and misinformation

One of the most serious limitations of generative AI models, especially large language models (LLMs), is their tendency to produce “hallucinations”, meaning confidently stated but factually incorrect outputs [59]. In nutrition, such errors may appear as unsafe dietary advice, misinterpretation of health conditions, or the endorsement of fad diets without a scientific basis.

Studies have shown that LLMs asked for dietary recommendations sometimes produce answers that sound authoritative but contradict established guidelines [60, 61]. For example, a system might suggest ketogenic diets for renal patients or underreport nutrient deficiencies, exposing users to significant risk. These dangers increase when tools are embedded into consumer apps without human oversight.

5.2. Algorithmic bias and inequitable recommendations

AI models reproduce the data on which they are trained. If training data are incomplete or culturally unrepresentative, models will reflect and even amplify existing biases [62]. This is problematic in nutrition, where diets, food access, and cultural norms differ across populations.

For example, food recognition apps trained mainly on Western diets may misidentify traditional dishes from Africa, the Middle East, or Asia, producing inaccurate nutrient estimates [63]. Similarly, models that exclude indigenous or low-income communities risk widening health disparities [64]. Bias can also appear in the optimization criteria—for instance, emphasizing calorie reduction over nutrient quality or weight loss over metabolic health. A nutrition app in Southeast Asia even mislabeled fermented foods such as tempeh and kimchi as spoiled, illustrating how cultural misunderstanding can create harmful recommendations.

5.3. Data privacy and surveillance

AI systems often require sensitive personal data, including eating habits, biometric measures, geolocation, and microbiome profiles. This raises major concerns about privacy, consent, and data ownership [65]. Some commercial platforms collect such data with limited transparency, and anonymized data can often be re-identified [66]. In weak regulatory environments, health data may even be sold to insurers or advertisers.

Wearables and IoT devices also pose surveillance risks. Sensors in kitchens, stores, or supply chains may monitor workers or consumers without their explicit consent, raising ethical concerns about autonomy and workplace rights [67].

5.4. A lack of transparency and explainability

Most high-performing AI models, particularly deep learning systems, are “black boxes” whose decision-making processes are not transparent, even to developers. In food safety and nutrition regulation, this lack of explainability is problematic: compliance decisions and health advice must be auditable [68].

For example, if an AI system labels a food batch as unsafe, regulators must understand the reasoning. Similarly, clinicians need to know the evidence behind chatbot recommendations [69]. Without explainability, accountability and trust are undermined.

5.5. Over-reliance and de-skilling

As AI becomes embedded into food and health systems, there is a risk of over-reliance. Dietitians may defer too heavily to algorithmic outputs, while inspectors may focus on automated risk scores at the expense of contextual expertise [70]. End-users may also assume AI recommendations are infallible, particularly when tools are marketed as “smart”. Without training, this could weaken professional judgment and critical thinking [71].

5.6. Regulatory gaps and ethical ambiguity

Most countries still lack clear frameworks for regulating AI in food and nutrition. The existing guidance for medical AI rarely addresses consumer apps or agricultural systems [72]. Ethical ambiguity remains over questions such as should AI nudge users toward certain diets? Is biased AI acceptable in underserved regions if it is the only available option? Who is liable when harm occurs?

Without robust oversight, commercial incentives may dominate, leading to unregulated deployment that prioritizes profit over public health.

6. Toward responsible AI in food systems

To maximize the benefits of AI while minimizing risks, responsible innovation is essential. This requires technical rigor, ethical foresight, interdisciplinary collaboration, regulatory reform, and active community engagement.

6.1. Principles of ethical AI

AI in food systems should follow five core principles: transparency, accountability, equity, privacy, and inclusiveness [73]. Transparency requires algorithms that are explainable. Accountability demands clear responsibility for harm. Equity ensures access across diverse cultural and socioeconomic groups. Privacy requires strict safeguards for sensitive data. Inclusiveness calls for the involvement of underrepresented communities in design and governance [74, 75].

6.2. Multidisciplinary collaboration

Safe and effective AI cannot be built by engineers alone. Development must involve nutritionists, food safety experts, epidemiologists, ethicists, legal scholars, and community stakeholders. For example, dietitians can ensure evidence-based recommendations,

while ethicists and legal experts address fairness and compliance [74, 76]. Co-development with communities, particularly in low-resource settings, strengthens cultural acceptance and trust.

6.3. Validation and certification

AI systems must undergo external validation across different datasets and populations to ensure generalizability, detect bias, and avoid harm [77]. Regulatory agencies should establish certification pathways similar to those for medical devices. Ethical impact assessments and algorithm audits can safeguard public interest further.

6.4. Strengthening policy and global governance

Few national frameworks adequately regulate AI in food systems. International organizations such as WHO, FAO, and Codex Alimentarius should coordinate global standards, open-source tool development, and data repositories [78]. Such cooperation would reduce fragmentation and improve the scalability of safe AI solutions.

6.5. Building AI literacy

AI tools are only effective if users understand their limits. Training programs for dietitians, inspectors, and public health workers should include AI literacy and critical thinking. For example, a pilot study in China tested an AI-based nutritionist for type 2 diabetes patients, showing promising alignment with dietitian recommendations [79]. Education helps professionals interpret AI outputs, recognize bias, and integrate human judgment [80].

6.6. Open science and equitable access

To avoid deepening inequality, AI datasets and models should be openly available where possible. Proprietary systems restrict access, especially in low-resource settings [81]. Open-source platforms and global collaborations can ensure equitable innovation [82]. Localization is also crucial, as AI systems must be adapted to local languages, diets, and technological infrastructure.

6.6.1. Limitations

As a narrative review, this paper is limited to English-only sources and lacks a systematic synthesis protocol. Future work should consider broader databases, the multilingual literature, and systematic review methods.

7. Conclusions

Artificial intelligence is rapidly becoming an integral part of food safety and nutrition systems. From contaminant detection to personalized diet planning, AI technologies provide tools for improving efficiency, responsiveness, and scalability. When developed responsibly, these innovations can strengthen food system resilience and contribute to better public health outcomes.

At the same time, AI introduces significant challenges, including risks related to data privacy, algorithmic bias, misinformation, and regulatory uncertainty. Without careful oversight, such risks

may deepen existing health inequalities or reduce public trust in digital health solutions.

To realize AI's potential in food systems, its development must be guided by principles of ethics, equity, and transparency. This requires inclusive design processes, interdisciplinary collaboration, validation across diverse populations, and training for professionals and communities to engage critically with AI tools.

As food and nutrition sciences evolve alongside technological progress, responsibility rests with researchers, developers, policy-makers, and practitioners to ensure that AI is applied not only due to its capabilities but also its appropriateness, safety, and fairness. The future of AI in food systems will depend as much on ethical deployment as on technological advancement.

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