ISSN: 3068-1774
Research Article
Journal of Material Sciences & Applied Engineering

# Opportunities and Risks Based on Food Safety and Nutrition Ai: A Mathematical Approach

**Pragna A Vadher[1], Gunamani B Deheri[2], Dhinesha Ruwanthi Perera[3], Sanjay Chaudhary[4] & Rakesh Manilal Patel[5]***

[1]*Principal, Government Science College, Idar, India*
[2]*Retired Asso. Prof. of Mathematics, Dept. of Maths, S. P. Univ., V. V. Nagar, India*
[3]*Senior lecturer, GSJKD University, Sri Lanka*
[4]*Dept. of Mathematics, IBS, DRBAU, Agra, India*
[5]*Department of Mathematics, Government Science College, Gandhinagar*

***Corresponding author:** Rakesh Manilal Patel, Department of Mathematics, Government Science College, Gandhinagar India. Ph No: +919426530263.

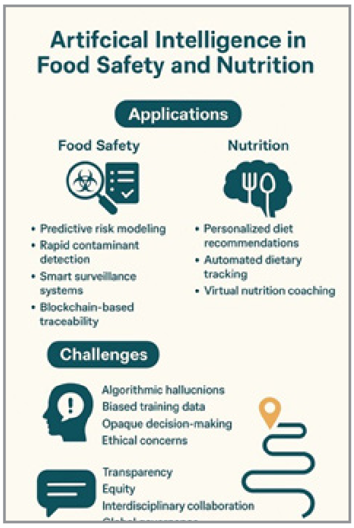
**Submitted:** 25 September 2025 **Accepted:** 04 October 2025 **Published:** 09 October 2025

https://doi.org/10.63620/MKJMSAE.2025.1057

***Citation:*** *Vadher, P. A., Deheri, G. B., Perera, D. R., Chaudhary, S., & Patel, R. M. (2025). Opportunities And Risks Based on Food Safety and Nutrition Ai: A Mathematical Approach. J Mat Sci Apl Eng, 4(5), 01-13.*

***Abstract***

*Artificial intelligence (AI) is reshaping food safety and nutrition practices by delivering 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 supports personalized diet recommendations, automated dietary tracking, and virtual nutrition coaching by integrating data from genomics, the microbiome, and behavioral inputs. Despite these advancements, AI introduces significant risks, including algorithmic hallucinations, biased training data, opaque decision-making, and ethical concerns related to data privacy and consent. Additionally, the absence of robust regulatory frameworks and unequal access to AI tools may widen existing health disparities. This narrative review synthesizes current developments in AI-based food and nutrition applications, examines emerging challenges, and highlights ethical, technical, and policy considerations. It also proposes a roadmap for the responsible integration of AI into food systems, emphasizing transparency, equity, interdisciplinary collaboration, and global governance. While AI holds immense potential to enhance safety and nutrition worldwide, its success ultimately depends on how thoughtfully and ethically it is designed, implemented, 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, Blockchain Traceability, Dietary Tracking, Data Ethics, Public Health, Algorithmic Bias

**Subject Classification:** Depending on the indexing system (Scopus, Web of Science, PubMed, IEEE, etc.), these categories would fit: Scopus ASJC (All Science Journal Classification) codes, 1702 – Cognitive Neuroscience / Artificial Intelligence, 1706 – Computer Science Applications, 1705 – Health Informatics, 1106 – Food Science, 1110 – Nutrition and Dietetics, 2102 – Agricultural and Biological Sciences (Applied), 2209 – Industrial and Manufacturing Engineering (for food systems/ traceability).

**Web of Science Categories:** Computer Science, Artificial Intelligence, Food Science & Technology, Nutrition & Dietetics, Health Care Sciences & Services, Ethics / Medical Ethics, Public, Environmental & Occupational Health.

**Medical Subject Headings (MeSH, PubMed-style):** Artificial Intelligence, Food Safety, Nutrition Assessment, Diet, Food, and Nutrition, Public Health Informatics, Ethics, Research, Health Equity.

## 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 such as disease burden, health equity, and socioeconomic stability. As global food systems grow more complex and interconnected, ensuring their safety and nutritional adequacy poses new challenges that demand innovative solutions [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 for digital innovation in food systems has been underscored 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 seen as a strategic tool for enhancing resilience and enabling proactive, data-driven interventions in both food safety and personalized nutrition [5].

### This Review Addresses Three Guiding Questions

1. What are the contemporary applications of AI 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?

## Methods

We searched PubMed and Scopus for literature published between 2018 and 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.

### From Reactive to Predictive Systems

Traditionally, food safety relied on reactive approaches such as microbial testing, physical inspection, and batch sampling. In contrast, AI enables predictive modeling using real-time data streams from 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 populations rather than individuals. With the rise of personalized nutrition and precision health, these limitations have become apparent. AI now supports individualized dietary recommendations by integrating genetic, metabolic, microbiome, and lifestyle data, improving both efficacy and user engagement [7– 9].

### The Rise of Ai in Food and Nutrition Research

Recent years have witnessed increasing use of machine learning (ML), natural language processing (NLP), and neural networks in food-related research. In food safety, AI has been applied to contaminant detection via image analysis, optimization of storage conditions, and blockchain-based enhancement of product recalls [10]. In nutrition, AI supports automated food logging, dietary pattern recognition, virtual coaching, and predictive modeling of disease risks based on diet quality indices [11]. AI-powered "digital dietitians" are also emerging, offering continuous dietary support in settings with limited access to healthcare professionals. While promising, these tools raise concerns regarding accuracy, equity, privacy, and accountability. Without rigorous governance and transparent design, risks such as misinformation, data mismanagement, and algorithmic bias may undermine trust and exacerbate health disparities.

### Objectives of This Review

Despite growing enthusiasm for AI in food systems, few critical syntheses examine both its promises and pitfalls. This review seeks to fill that gap by offering a structured overview of AI applications in food safety and nutrition, while also addressing risks, ethical concerns, and future directions. Specifically, our objectives are to: Summarize current AI applications in food safety (e.g., contaminant detection, predictive surveillance). Review AI-enabled tools in nutrition practice (e.g., personalization, digital dietary counseling).

Highlight benefits for efficiency, accessibility, and data-driven decision-making. Discuss limitations and risks, including algorithmic hallucinations, privacy concerns, and regulatory gaps. Provide recommendations for the responsible integration of AI into food systems. As a narrative review, we identified literature through PubMed, Scopus, and Google Scholar searches between 2019 and 2025. Search terms included "AI in nutrition," "food safety AI," and "AI ethics in health." Eligible sources included peer-reviewed articles, technical reports, and relevant policy documents in English. Editorials and non-scholarly commentaries were excluded.

**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 results in nearly 600 million cases of foodborne disease and 420,000 deaths annually [12]. Traditional approaches—such as microbial testing, physical inspection, and batch sampling—are often reactive, labor-intensive, and limited in scope. By contrast, AI offers scalable, data-driven, and predictive alternatives that can improve both the reliability and efficiency of food safety systems.

**Ai-Based Contaminant Detection and Quality Control**

AI has been successfully applied to identify physical, chemical, and microbial contaminants across 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 images, spectral data, or chemical signatures to classify food quality and detect anomalies [13]. For example, hyperspectral imaging (HSI) combined with deep learning has achieved high accuracy in detecting foreign objects in processed foods, including plastic fragments and insect parts [14]. Similarly, near-infrared (NIR) spectroscopy paired with convolutional neural networks (CNNs) enables real-time identification of adulterants in milk, oils, and flours [15]. In microbial detection, AI algorithms trained on genomics and metagenomics datasets can differentiate pathogenic from non-pathogenic bacterial strains based on DNA sequences, expediting identification of high-risk contaminants such as Listeria monocytogenes and Salmonella enterica [16].

**Predictive Surveillance and Outbreak Forecasting**

One of AI's major contributions to food safety is the shift from retrospective testing to predictive surveillance. Predictive models can assess the likelihood of contamination or spoilage based on variables such as temperature, humidity, supply chain interruptions, and consumer feedback. For example, AI models integrating satellite and weather data have been used to forecast aflatoxin contamination in maize crops in sub-Saharan Africa [17]. In the United States, the FDA has piloted AI models that analyze import records, supplier risk histories, and inspection outcomes to assign dynamic risk scores to imported goods, enabling more targeted inspections and resource allocation [18]. Emerging applications also include natural language processing (NLP) for social media mining. Early studies demonstrate that NLP algorithms can scan user complaints and reviews on delivery platforms to detect potential foodborne illness clusters before formal reporting [19].

**Blockchain and AI: Enhancing Traceability**

Blockchain provides a decentralized, tamper-proof ledger for recording transactions across the food supply chain. When combined with AI, blockchain enables real-time verification of food provenance, reducing traceability times from days to minutes. For example, an IBM– Walmart collaboration applied blockchain–AI systems to track leafy green vegetables from farms to store shelves, reducing the traceability time for contaminated batches from seven days to under three seconds [20]. In the meat and dairy industries, blockchain–AI platforms are being tested to integrate cold-chain sensor data, automatically alerting retailers if temperature thresholds are breached during transport [21].

**Smart sensors and IoT Integration**

The integration of AI with Internet of Things (IoT) sensors in warehouses, transport vehicles, and retail environments is another critical development. These sensors collect continuous data on temperature, humidity, $CO_2$ levels, and microbial counts. AI models analyze these streams to assess spoilage risk in real time and recommend corrective actions [22]. In seafood logistics, AI systems analyzing packaging environment data predict histamine development in tuna—a common food safety concern. When thresholds are exceeded, automated alerts trigger rerouting or removal of shipments [23]. This approach also enables adaptive shelf-life estimation, replacing static expiry dates with dynamic predictions based on actual storage conditions. Such systems simultaneously improve food safety and reduce waste.

**Applications in Developing Countries**

AI holds particular promise for low- and middle-income countries where food safety regulations are often under-resourced. Mobile AI apps that analyze smartphone images can assess produce freshness, detect bruising, and evaluate contamination risks, making safety tools more accessible to farmers, vendors, and consumers [24]. For example, a Kenyan startup has developed a mobile platform that uses machine vision to detect mold growth in grains stored in rural silos, allowing farmers to act before toxic mycotoxins develop—a major cause of liver cancer in Africa [25]. Cloud-based AI platforms can thus function as "digital inspectors," bridging inspection gaps in resource-limited settings.

**Challenges in Implementation and Interpretation**

Despite its potential, several challenges limit the broad application of AI in food safety.

**Interpretability:** Deep learning models often function as "black boxes," providing little transparency for decision-making, which is problematic for regulatory compliance [26].

**Data Quality:** High-quality, labeled datasets are often scarce, fragmented, or proprietary, limiting model development and validation [27].

**Infrastructure Gaps:** Many AI tools require continuous internet access, cloud computing, or advanced sensors, which may be infeasible in rural or low-resource settings [28].

Regulatory Readiness: Agencies often lack the technical capacity to evaluate AI-based systems. Without harmonized standards or certification mechanisms, adoption may remain inconsistent [29].

**Scalability and Sustainability:** While blockchain–AI systems show promise, issues of data integrity, scalability, and the environmental footprint of computationally intensive models remain unresolved [30, 31].

**Ethical Concerns:** Data ownership, consent for IoT-based collection, and potential misuse of predictive models to stigmatize specific populations must be addressed. Current frameworks, such as the EU Data Act, offer general principles but lack sector-specific standards tailored to high-risk AI applications in food safety and nutrition.

**AI in Nutrition Practices:** Personalized Diets and Health Monitoring

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

**Personalized Nutrition Through Data Integration**

Conventional dietary recommendations are typically population-based, relying on generalized guidelines such as the Mediterranean diet or USDA's MyPlate. While valuable, these approaches often fail to account for individual differences in genetics, metabolism, gut microbiota, cultural practices, and psychological factors [33]. AI enables precision nutrition by integrating multi-dimensional data sources, including genomic information, phenotypic biomarkers, metabolomics, microbiome composition, lifestyle behaviors, and even geolocation-based food access [34].

Algorithms can synthesize these datasets to generate highly individualized dietary recommendations that adapt dynamically to 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, enabling more effective dietary management of insulin resistance and type 2 diabetes [36]. Similarly, microbiome-informed AI models have been shown to improve predictions of weight loss outcomes during dietary interventions.

**Ai-Powered Dietary Assessment Tools**

One of the earliest and most widely adopted applications of AI in nutrition is automated dietary intake tracking. Traditional methods—such as 24-hour recalls, food frequency questionnaires (FFQs), and dietary records—are time-intensive, 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 photograph meals, and deep learning algorithms identify food items, estimate portion sizes, and calculate nutrient content [38]. Several consumer-facing platforms already employ these features for automated meal logging and nutrient estimation. More advanced systems integrate AI with continuous glucose monitors (CGMs) and wearable fitness trackers, contextualizing food intake within broader physiological data. This enables real-time feedback and adaptive nutrition recommendations [39]. However, accuracy remains a challenge. Comparative studies show moderate agreement between AI-estimated nutrient intake and dietitian-reviewed records, underscoring the need for larger training datasets and culturally diverse food image libraries [40].

**Conversational Ai and Digital Nutrition Coaching**

AI-driven chatbots and virtual coaches represent a new frontier in behavior-focused dietary interventions. These tools combine NLP with established behavior change frameworks (e.g., the transtheoretical model, cognitive behavioral therapy) to deliver tailored feedback, motivational interviewing, and habit-tracking support [41]. Randomized controlled trials suggest that AI-assisted nutrition coaching can yield modest improvements in dietary quality, particularly in populations with limited access to nutrition professionals [42]. However, effectiveness varies depending on chatbot design, personalization capacity, and sustained user engagement. Large language models (LLMs) such as ChatGPT are also being piloted for nutrition education and client engagement. While promising, these systems are susceptible to "hallucinations" (confident but incorrect outputs) and lack grounding in validated nutrition databases unless externally constrained [43].

**Predictive Analytics for Population Nutrition**

AI extends beyond individual guidance to applications in public health nutrition, where it supports surveillance, modeling, and policy evaluation. Machine learning models can analyze large-scale dietary survey data to identify nutrient deficiencies, emerging dietary trends, and vulnerable populations. For instance, AI models trained on national health and nutrition datasets have been used to predict future prevalence of obesity and hypertension based on current dietary patterns, thereby informing proactive policy simulations [44]. Such insights can guide resource allocation, subsidy design, and the targeting of nutrition campaigns more effectively than traditional epidemiological methods. AI is also being applied to assess the environmental and sustainability impacts of dietary patterns by linking nutrition outcomes with climate projections. This integration is central to the emerging planetary health framework [45].

Real-World Case Studies in Low- and Middle-Income Countries (Lmics)

Practical applications of AI in LMICs illustrate its potential for scalable, context-sensitive solutions.

**Agricultural Risk Prediction:** In East Africa, researchers combined satellite data with machine learning to map aflatoxin risk in maize-growing regions. An ensemble gradient boosting model trained on 907 pre-harvest maize samples from Kenya, Uganda, Malawi, and Tanzania achieved a balanced accuracy of 62% and generalized well to external datasets, demonstrating feasibility for field-level risk prediction.

**Digital Diet Assistants:** In India, the fintech–wellness company HealthifyMe has deployed its AI nutrition assistant, Ria, at scale. Ria manages around 80% of user queries and provides personalized dietary advice using regional food databases and local dietary habits. Its image recognition feature can identify culturally specific meals, enhancing relevance and scalability across India's diverse linguistic and dietary landscapes.

**Opportunities:** Efficiency, Precision, and Scalability

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

### Automation and Real-Time Decision Support

AI can automate tasks that are traditionally time-consuming and prone to error. In food safety, AI systems process visual, chemical, and sensor data to detect contaminants, monitor storage conditions, and trigger alerts for unsafe batches—functions that would otherwise require manual inspection or laboratory testing [39]. In many industrial settings, this automation already reduces labor costs, minimizes inspection delays, lowers error rates, and enables more frequent and detailed quality control [46]. In nutrition, automation powered by AI supports real-time dietary tracking and interventions. Rather than relying solely on occasional check-ins with healthcare professionals, users now benefit from continuous feedback through mobile applications, wearables, and voice assistants. This shift fosters stronger adherence and engagement in dietary interventions [47].

### Improved Personalization and Predictive Capabilities

AI systems excel at detecting patterns in large, heterogeneous datasets. This capability enables personalized nutrition models that incorporate genomics, metabolomics, microbiome profiles, and behavioral data to predict individual responses to specific foods or dietary patterns [48]. Such predictive precision holds particular promise for managing chronic conditions including diabetes, obesity, cardiovascular disease, and irritable bowel syndrome (IBS) [8]. AI can also simulate long-term health scenarios, projecting how today's dietary choices may influence future disease risk. These predictive insights support earlier interventions and more meaningful counseling in both clinical and public health contexts [49].

### Expanded Access and Equity in Underserved Populations

Globally, shortages of nutrition professionals pose barriers to equitable care, particularly in rural and low-income regions. Validated AI tools can serve as digital nutrition coaches, delivering evidence-based guidance in multiple languages, adapted for cultural relevance, and integrated into accessible platforms such as messaging apps or government health portals [50, 51]. In food safety, AI-based mobile applications empower farmers, small vendors, and frontline workers to assess risks without requiring advanced training or laboratory resources. For example, smartphone-based image recognition tools can detect signs of spoilage, mold, or pest infestation [52]. If deployed responsibly, these tools can reduce inequities by democratizing access to knowledge. However, implementation in low-resource contexts depends on infrastructure investment, supportive policies, and localized adaptation. Without these measures, outcomes observed in high-income countries may not be replicated.

### Optimization of Supply Chains and Sustainability

Food systems often suffer from inefficiencies, waste, and loss. AI supports optimization by modeling supply flows, predicting demand, and adjusting production or distribution in real time. For instance, algorithms can analyze purchasing patterns, weather forecasts, and logistics data to reduce overproduction and minimize spoilage during transport [53]. These optimizations directly improve food safety by reducing time spent in high-risk stages of distribution, while also preserving the nutritional value of perishable foods such as fruits, vegetables, dairy, and meat [54]. AI is increasingly applied to assess the environmental impacts of dietary patterns—including greenhouse gas emissions, water use, and land degradation—alongside nutritional outcomes. This dual analysis enables dietary recommendations that promote both health and environmental sustainability [55].

### Supporting Public Policy and Regulatory Innovation

AI enhances evidence-based policymaking by analyzing large-scale dietary surveillance data and simulating outcomes of regulatory interventions (e.g., sugar taxes, front-of-pack labeling, food fortification strategies) [56]. Such tools enable more flexible decision-making that adapts to local and global trends. Regulatory agencies can also leverage AI to identify high- risk imports, detect food fraud, and prioritize inspection schedules based on predicted violation risks. This approach improves efficiency and effectiveness in resource-limited regulatory environments [57]. In this way, AI serves not only as a technological innovation but also as a policy enabler, strengthening both food safety and nutrition security at population levels.

### Enhanced Research and Knowledge Discovery

AI accelerates research in nutrition and food safety by facilitating large-scale data synthesis. Natural language processing (NLP) tools can scan thousands of scientific articles, highlight emerging patterns, identify contradictions, and pinpoint gaps in the literature. This accelerates meta-analyses and contributes to the development of more robust evidence-based guidelines [58]. In food safety, AI supports discovery by screening molecular datasets to identify new antimicrobial compounds, detection methods, and biomarkers of food safety. Hypotheses generated through AI analysis can then be validated in laboratory studies. As summarized in Table 1, AI-powered tools are already being applied across multiple domains of food safety and nutrition, offering a roadmap for further innovations.

### Risks and Ethical Challenges: Hallucinations, Bias, and Data Privacy

While artificial intelligence (AI) holds significant promise for advancing food safety and nutrition, its use also raises critical limitations and ethical concerns. Issues such as hallucinations, algorithmic bias, lack of transparency, accountability gaps, and privacy risks can undermine both individual health and public trust. Without appropriate governance, these risks may outweigh potential benefits, especially for vulnerable populations.

### Hallucinations and Misinformation

One of the most serious limitations of generative AI, particularly large language models (LLMs), is their tendency to produce "hallucinations"—confidently stated but factually incorrect outputs [59]. In nutrition, such errors can manifest as unsafe dietary advice, misinterpretations of health conditions, or endorsements of fad diets without scientific basis. Studies show that LLMs asked for dietary recommendations sometimes provide answers that sound authoritative yet contradict established guidelines [60,61]. For instance, an AI system might recommend ketogenic diets for renal patients or underreport nutrient deficiencies, exposing users to serious risks. These dangers increase when such systems are integrated into consumer apps without professional oversight.

### Algorithmic Bias and Inequitable Recommendations

AI models reproduce the characteristics of their training data. When datasets are incomplete or culturally unrepresentative, models can reflect and amplify existing biases [62]. In nutrition, where dietary patterns and cultural norms vary widely, this poses particular risks. For example, food recognition apps trained primarily on Western diets may misidentify traditional dishes from Africa, Asia, or the Middle East, producing inaccurate nutrient estimates [63]. Similarly, models that exclude indigenous or low-income communities risk widening health disparities [64]. Bias can also arise from optimization criteria—for instance, prioritizing calorie reduction over nutrient quality, or weight loss over metabolic health. A Southeast Asian nutrition app once mislabeled fermented foods such as tempeh and kimchi as spoiled, illustrating the risks of cultural misinterpretation.

**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, while anonymized datasets 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 heighten surveillance risks. Sensors in kitchens, stores, or supply chains may monitor consumers or workers without explicit consent, raising ethical concerns about autonomy and workplace rights [67].

**Lack of Transparency and Explainability**

Most high-performing AI models, particularly deep learning systems, operate as "black boxes" whose decision-making processes are opaque even to developers. In food safety and nutrition, this lack of explainability is problematic: regulatory and clinical decisions must be auditable [68]. For example, if an AI system labels a food batch as unsafe, regulators need to understand the rationale. Similarly, clinicians require insight into the evidence behind chatbot-generated recommendations [69]. Without explainability, accountability and trust are undermined.

**Over-Reliance and De-Skilling**

As AI tools become embedded in food and health systems, there is a risk of over-reliance. Dietitians may defer too heavily to algorithmic outputs, while inspectors may prioritize automated risk scores over contextual expertise [70]. End-users may also assume AI recommendations are infallible, especially when marketed as "smart" solutions. Without adequate training, such reliance can weaken professional judgment and critical thinking [71].

**Regulatory Gaps and Ethical Ambiguity**

Most countries still lack clear frameworks for regulating AI in food and nutrition. Existing guidance for medical AI often does not cover consumer apps or agricultural systems [72]. Ethical ambiguity also persists around questions such as: Should AI nudge users toward specific 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.

**Toward Responsible AI in Food Systems**

Maximizing the benefits of AI while minimizing risks requires responsible innovation grounded in technical rigor, ethical foresight, interdisciplinary collaboration, regulatory reform, and active community engagement.

**Principles of Ethical AI**

AI in food systems should adhere to five core principles: transparency, accountability, equity, privacy, and inclusiveness [73].

**Transparency Requires Algorithms to be Explainable**

Accountability demands clear assignment of responsibility in cases of harm. Equity ensures fair access across diverse cultural and socioeconomic groups. Privacy calls for strict safeguards around sensitive health and personal data.

Inclusiveness emphasizes the involvement of underrepresented communities in both design and governance [74,75].

**Multidisciplinary Collaboration**

Safe and effective AI cannot be developed by engineers alone. Progress requires input from nutritionists, food safety experts, epidemiologists, ethicists, legal scholars, and community stakeholders. For example, dietitians ensure evidence-based recommendations, while ethicists and legal experts address fairness and compliance issues [74, 76]. Co- development with local communities—especially in low-resource settings—enhances cultural acceptance and trust.

**Validation and Certification**

AI systems must undergo external validation across diverse datasets and populations to ensure generalizability, detect bias, and minimize harm [77]. Regulatory bodies should establish certification pathways similar to those governing medical devices. Ethical impact assessments and algorithm audits can provide additional safeguards for the public interest.

**Strengthening Policy and Global Governance**

Most national frameworks are inadequate for regulating AI in food systems. International organizations such as WHO, FAO, and Codex Alimentarius should play a leading role in setting global standards, supporting open-source tool development, and maintaining shared data repositories [78]. Coordinated governance would reduce fragmentation and increase scalability of safe AI solutions.

**Building AI Literacy**

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

**Open Science and Equitable Access**

To prevent deepening inequalities, AI datasets and models should be made openly available where feasible. Proprietary systems often limit access, particularly in low-resource settings [81]. Open-source platforms and global collaborations can promote equitable innovation [82]. Localization is also critical—AI systems must adapt to local languages, dietary practices, and technological infrastructures.

## Limitations

As a narrative review, this paper is limited to English-language sources and lacks a systematic synthesis protocol. Future work should expand to include multilingual literature, broader databases, and systematic review methodologies.

**Fruitful and Feasible Conclusions**

Artificial intelligence is rapidly becoming integral to food safety and nutrition systems. From contaminant detection to personalized diet planning, AI technologies offer tools to improve efficiency, responsiveness, and scalability. When responsibly developed, they can enhance food system resilience and strengthen public health outcomes. At the same time, AI introduces substantial challenges—including risks related to data privacy, algorithmic bias, misinformation, and regulatory uncertainty. Without robust oversight, such risks may exacerbate health inequalities and erode public trust in digital health solutions. To fully realize AI's potential in food systems, development must be guided by ethics, equity, and transparency. This entails inclusive design processes, interdisciplinary collaboration, validation across diverse populations, and training programs that empower professionals and communities to engage critically with AI tools. As food and nutrition sciences evolve alongside technological innovation, responsibility lies with researchers, developers, policymakers, and practitioners to ensure that AI is deployed not only for its capabilities but also for its appropriateness, safety, and fairness. The future of AI in food systems will depend as much on ethical governance as on technological advancement.

**Let**

F = Food system variables (e.g., contamination detection, supply chain, nutritional planning) AI = AI technologies applied to food systems

P = Public health outcomes (e.g., safety, nutrition, resilience) R = Risks associated with AI (R = {r1, r2, r3, r4}

r1 = Data privacy

r2 = Algorithmic bias r3 = Misinformation

r4 = Regulatory uncertainty

G = Governance and oversight functions (ethical, equitable, transparent policies) U = Utility function representing the benefit of AI in food systems

AI impact on food systems:

F′ = F + AI(F)

Where F′ represents improved food system performance under AI intervention. Public health outcomes as a function of AI and risks:

$$P = U(F') - \sum_{i=1}^{i=4} \lambda_i r_i$$

Where:

$\lambda_i$ = weight or severity of each risk $r_i$

U(F′) = utility (benefit) of AI-enhanced food systems

Risk mitigation through governance:

$$r_i^{effective} = r_i * [1 - g_i(G)]$$

Where $g_i(G) \in [0,1]$ represents the mitigation factor from governance GGG for each risk ri.

Maximizing responsible AI utility:

$$\max_{AI,G} P = U\{F + AI(F)\} - \sum_{i=1}^{i=4} \lambda_i r_i * [1 - g_i(G)]$$

**Subject to**

i=1

AI satisfies ethical design constraints (E(AI) = 1)

**G Ensures Equity, Transparency, And Interdisciplinary Oversight Interpretation**

AI (AI) improves food system outcomes (F′), which increases public health utility (P). Risks (R) reduce utility if unmitigated.

**Governance (G) Acts as a Control Mechanism, Reducing Effective Risks.**

The objective is to maximize public health and food system benefits while minimizing risks, constrained by ethics and equity.


## Declarations

Funding: The authors received no financial support for the research, authorship, or publication of this article.


## Author Contributions

All authors contributed equally to this work.

## Conflict of Interest

The authors declare no conflicts of interest.

## Data Availability Statement

The data used in this study were obtained from publicly available online sources.

## Institutional Review Board Statement

Not applicable.

## Informed Consent Statement

Not applicable.

## Ethics Statement

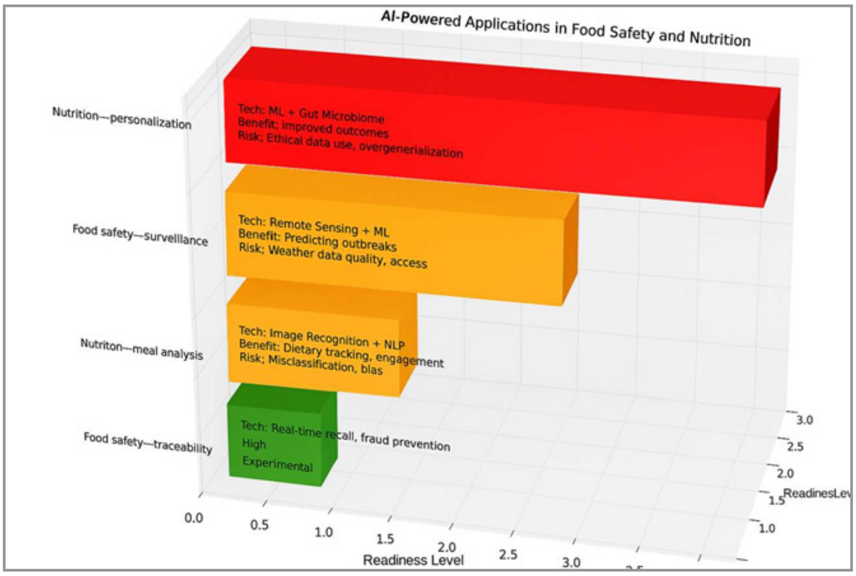
This manuscript does not involve any ethical concerns.

## Disclosure of AI Use

Artificial intelligence (AI) tools (e.g., ChatGPT) were used to a limited extent, solely for language refinement and formatting assistance.

**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 |




**Pictorial form of Table 1** as a horizontal bar chart:

Each application area is shown on the y-axis, Readiness levels are color-coded: High = Green, Medium = Orange, Experimental = Red, inside each bar, AI technology, potential benefits, and key risks annotated.

“Materials to read”

Mathematical models provide a structured framework for analyzing the opportunities and risks of AI in food safety and nutrition. These models use statistical, probabilistic, and optimization techniques to transform AI's function from a reactive measure into a proactive, predictive tool. Applications range from predicting microbial growth to creating personalized diets based on complex biological data.

**Opportunities: Mathematical modeling and AI**

Mathematical approaches leverage vast datasets collected through IoT sensors, advanced imaging, and genomic sequencing to enhance food safety and nutrition across the supply chain.

**Predictive Analytics for food Safety**

Microbial risk modeling: Mathematical kinetic models, such as the Gompertz or Baranyi- Roberts equations, are combined with AI to forecast the growth or inactivation of microorganisms under specific environmental conditions (e.g., temperature, pH). This moves food safety from a reactive system to a predictive, preventative one.

**Contamination Source Identification:** AI models using Bayesian networks or support vector machines (SVMs) analyze data from historical outbreaks and the supply chain to identify and predict potential contamination sources. For example, by monitoring livestock feed, water, and environmental factors, AI can predict the likelihood of a pathogen like Salmonella proliferating.

**Automated Visual Inspection:** Computer vision, powered by convolutional neural networks (CNNs), analyzes images from production lines to detect defects, foreign objects, or spoilage in real-time. Mathematical models help optimize the CNN's architecture and performance for specific applications like fruit ripeness grading.

**Personalized and Public Nutrition**

Dietary optimization: Linear programming (LP) is used to mathematically optimize diets based on user-defined constraints, such as cost, dietary preferences, and nutritional targets.

**Disease Risk Prediction:** Machine learning (ML) models analyze multi-modal datasets, including genetic information, dietary intake, and biochemical markers, to predict individual health outcomes. A neural network model can forecast an individual's obesity risk and predict weight-loss progress with high accuracy by analyzing a person's age, BMI, and biochemical attributes.

**Public Health Surveillance:** AI uses natural language processing (NLP) to analyze social media data and online health forums, tracking dietary trends and monitoring for foodborne illness outbreaks. Mathematical models quantify the potential spread of pathogens and provide early warning systems for public health agencies.

**Supply Chain optimization and Transparency**

Food waste reduction: AI-driven optimization models forecast demand based on historical sales, weather patterns, and social media trends, leading to smarter inventory management and reduced food waste.

**Blockchain Integration:** Mathematical algorithms, particularly in the consensus mechanisms of blockchain, ensure a tamper-proof and transparent record of a food product's journey from "farm to fork". AI and ML algorithms analyze this data to detect anomalies that may indicate food fraud or safety breaches.

**Traceability Systems:** Graph theory is applied to model the complex, interconnected nature of the food supply chain, enabling quick and efficient tracing of contaminated products during a recall.

**Risks: Mathematical and Systematic Challenges**

While the opportunities are significant, the mathematical and systemic risks of implementing AI in food and nutrition must be addressed.

**Data and Algorithmic Limitations**

**Data quality and bias:** AI models are only as good as their training data. Biased, inconsistent, or incomplete datasets can lead to flawed models that produce inaccurate or inequitable results. A model trained on data from one region, for example, may not be applicable in another with different food safety standards or dietary habits.

**The "Black Box" Problem:** Complex deep learning models are often opaque, making it difficult for regulators or operators to understand how they arrive at a particular decision. The lack of interpretability can undermine trust, especially in high-stakes areas like food safety recalls.

**False Positives and Negatives:** AI systems must be validated thoroughly to prevent false alerts (unnecessary product recalls) or missed detection (hazardous products reaching consumers). Mathematical metrics like accuracy, precision, and recall are used to measure and minimize these errors, but they can never be entirely eliminated.

**Operational and Implementation Challenges**

**High Costs and Infrastructure Barriers:** Implementing AI, IoT sensors, and blockchain requires substantial investment in infrastructure, which can be prohibitive for small and medium-sized enterprises (SMEs) and developing countries. This could exacerbate existing socio-economic disparities.

**Need for Specialized Skills:** The food industry lacks a workforce with the necessary data science, AI, and engineering skills to effectively deploy and manage these advanced systems.

**Regulatory Gaps:** The fast pace of AI development has outstripped the ability of regulatory frameworks to keep up, creating uncertainty around liability and the governance of AI-based food safety decisions.

**Ethical and Social Implications**

**Privacy and Data Security:** The collection of vast amounts of consumer health data for personalized nutrition raises significant privacy concerns. Secure and ethical data-sharing protocols are essential to build and maintain public trust.

**Equity of Access:** Unequal access to AI-powered personalized nutrition could widen health disparities. Without intervention, advanced dietary planning may only be available to affluent populations, leaving others to rely on less effective, "one-size-fits-all" approaches.

**Consumer Trust and Misinformation:** Overreliance on AI could lead to public skepticism or be exploited by bad actors to spread misinformation about food safety. Transparent and explainable AI algorithms are needed to build confidence in these new systems.

**Future Scopes of Visual Analytics Techniques in Food Safety Risk Assessment and Prediction (RAPW)**

Over the last decade, visual analytics has been widely applied in food safety to support risk monitoring, assessment, prediction, and fraud detection. Applications span various food safety risks, including:

Microbial contamination (using sensor data; analyzed via association analysis)

Pesticide and veterinary drug residues (using online databases; analyzed through risk assessment)

Heavy metal contamination (using satellite imagery; analyzed via risk prediction)

Illegal additives and food fraud (using social media; analyzed via food fraud identification)

**Data Characteristics & Sources:**

**Dimensions:** Multiple, hierarchical, relational, and spatial-temporal structures

**Sources:** Sensors, online databases, satellite imagery, social media

**Analysis Methods**

**Traditional Methods:** Correlation analysis, regression, qualitative and quantitative approaches Machine Learning: Shallow and deep neural networks, extreme learning machines, convolutional neural networks Probabilistic /Rule-based: Bayesian networks, association rule mining Comprehensive methods combining multiple approaches for robust risk analysis

**Visualization Methods:** Data types: Multidimensional, hierarchical, relational, and spatial- temporal Techniques: Scatterplots, scatterplot matrices, parallel coordinates, node-linked graphs/trees, adjacency matrices, maps, timelines, and space-filling methods.

**Interactive features:** Select, filter, navigate, overview + detail, focus + context, and spatial- temporal correlation Key Insight: Visual analytics integrates heterogeneous data, advanced analysis methods, and interactive visualizations to enhance understanding and management of food safety risks, supporting timely decision-making and fraud detection [83].

## References


1. Nicolétis, É., Caron, P., El Solh, M., Cole, M., Fresco, L. O., Godoy-Faúndez, A., ... & Zurayk, R. (2019). Agroecological and other innovative approaches for sustainable agriculture and food systems that enhance food security and nutrition. A report by the High-Level Panel of Experts on Food Security and Nutrition of the Committee on World Food Security.
2. El Bilali, H., Callenius, C., Strassner, C., & Probst, L. (2019). Food and nutrition security and sustainability transitions in food systems. Food and Energy Security, 8(2), e00154. https://doi.org/10.1002/fes3.154.
3. Khan, N., Ray, R. L., Kassem, H. S., Hussain, S., Zhang, S., Khayyam, M., ... & Asongu, S. A. (2021). Potential role of technology innovation in transformation of sustainable food systems: A review. Agriculture, 11(10), 984.
4. Iqbal, B., Alabbosh, K. F., Jalal, A., Suboktagin, S., & Elboughdiri, N. (2024). Sustainable food systems transformation in the face of climate change: Strategies, challenges, and policy implications. Food Science and Biotechnology, 34, 871–883. https://doi.org/10.1007/s10068-024-01712-y.
5. Mu, W., Kleter, G. A., Bouzembrak, Y., Dupouy, E., Frewer, L. J., Radwan Al Natour, F. N., & Marvin, H. J. P. (2024). Making food systems more resilient to food safety risks

by including artificial intelligence, big data, and internet of things into food safety early warning and emerging risk identification tools. Comprehensive Reviews in Food Science and Food Safety, 23(1), e13296.
6. Dhal, S. B., & Kar, D. (2025). Leveraging artificial intelligence and advanced food processing techniques for enhanced food safety, quality, and security: A comprehensive review. Discover Applied Sciences, 7(1), 1–46. https://doi.org/10.1007/s42452-025-06472-w
7. Prasad, G., Padhiary, M., Hoque, A., & Kumar, K. (2025). AI-driven personalized nutrition apps and platforms for enhanced diet and wellness. In Food in the metaverse and Web 3.0 era: Intersecting food, technology, and culture (pp. 125–158). Hershey, PA: IGI Global Scientific Publishing.
8. Rouskas, K., Guela, M., Pantoura, M., Pagkalos, I., Hassapidou, M., Lalama, E., ... & Argiriou, A. (2025). The Influence of an AI-Driven Personalized Nutrition Program on the Human Gut Microbiome and Its Health Implications. Nutrients, 17(7), 1260.
9. Arslan, S. (2024). Decoding dietary myths: The role of ChatGPT in modern nutrition. Clinical Nutrition ESPEN, 60, 285–288. https://doi.org/10.1016/j.clnesp.2024.02.022.
10. Dimitrakopoulou, M. E., & Garre, A. (2025). AI's intelligence for improving food safety: Only as strong as the data that feeds it. Current Food Science and Technology Reports, 3(1), 1–13. https://doi.org/10.1007/s43555-025-00060-0.
11. Tsolakidis, D., Gymnopoulos, L. P., & Dimitropoulos, K. (2024). Artificial intelligence and machine learning technologies for personalized nutrition: A review. Informatics, 11(3), 62. https://doi.org/10.3390/informatics11030062.
12. Owusu-Apenten, R., & Vieira, E. (2022). Microbial foodborne disease outbreaks. In Elementary food science (pp. 171–196). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-65433-7_8.
13. Gbashi, S., & Njobeh, P. B. (2024). Enhancing food integrity through artificial intelligence and machine learning: A comprehensive review. Applied Sciences, 14(8), 3421. https://doi.org/10.3390/app14083421.
14. Kang, Z., Zhao, Y., Chen, L., Guo, Y., Mu, Q., & Wang, S. (2022). Advances in machine learning and hyperspectral imaging in the food supply chain. Food Engineering Reviews, 14(4), 596–616. https://doi.org/10.1007/s12393-022-09322-2.
15. Sitorus, A., & Lapcharoensuk, R. (2024). Exploring deep learning to predict coconut milk adulteration using FT-NIR and micro-NIR spectroscopy. Sensors, 24(7), 2362. https://doi.org/10.3390/s24072362.
16. Karanth, S. (2021). Development of machine learning and advanced data analytical techniques to incorporate genomic data in predictive modeling for Salmonella enterica [Doctoral dissertation, University of Maryland].
17. Keller, B., Russo, T., Rembold, F., Chauhan, Y., Battilani, P., Wenndt, A., et al. (2022). The potential for aflatoxin predictive risk modelling in sub-Saharan Africa: A review. World Mycotoxin Journal, 15(2), 101–118. https://doi.org/10.3920/WMJ2021.2683.
18. Rahman, M. S., Hossain, M. S., Rahman, M. K., Islam, M. R., Sumon, M. F. I., Siam, M. A., & Debnath, P. (2025). Enhancing Supply Chain Transparency with Blockchain: A Data-Driven Analysis of Distributed Ledger Applications. Journal of Business and Management Studies, 7(3), 59-77.
19. Salaris, S., Ocagli, H., Casamento, A., Lanera, C., & Gregori, D. (2025). Foodborne event detection based on social media mining: A systematic review. Foods, 14(2), 239. https://doi.org/10.3390/foods14020239.
20. Kamath, R. (2018). Food traceability on blockchain: Walmart's pork and mango pilots with IBM. Journal of the British Blockchain Association, 1(1), 1–6. https://doi.org/10.31585/jbba-1-1-(10)2018.
21. Kaur, A., Potdar, V., & Agrawal, H. (2023). Industry 4.0 adoption in food supply chain to improve visibility and operational efficiency—a content analysis. IEEE Access, 11, 73922–73958. https://doi.org/10.1109/access.2023.3295780.
22. Ding, Y., Jin, M., Li, S., & Feng, D. (2021). Smart logistics based on the Internet of Things technology: An overview. International Journal of Logistics Research and Applications, 24(4), 323–345. https://doi.org/10.1080/13675567.2020.1757053.
23. Wang, B., Liu, K., Wei, G., He, A., Kong, W., & Zhang, X. (2024). A review of advanced sensor technologies for aquatic products freshness assessment in cold chain logistics. Biosensors, 14(10), 468. https://doi.org/10.3390/bios14100468.
24. Altaf, Q. S., & Ksouri, R. (2025). Application of machine learning in the food industry. In Artificial intelligence in the food industry (pp. 23–55). Boca Raton, FL: CRC Press.
25. Gachoki, S., Muthoni, F., Mahuku, G., Atehnkeng, J., Njeru, N., Kamau, J., & Tripathi, L. (2025). Predicting aflatoxin risk in maize using machine learning and satellite data in East and Southern Africa. World Mycotoxin Journal, 18(2-3), 101-120.
26. Esna-Ashari, M. (2025). Beyond the black box: A review of quantitative metrics for neural network interpretability and their practical implications. International Journal of Sustainable Applied Sciences and Engineering, 2(1), 1–24.
27. Trienekens, J., & Zuurbier, P. (2008). Quality and safety standards in the food industry, developments and challenges. International Journal of Production Economics, 113(1), 107–122. https://doi.org/10.1016/j.ijpe.2007.02.050.
28. Mahmood, H. S., Abdulqader, D. M., Abdullah, R. M., Rasheed, H., Ismael, Z. N. R., & Sami, T. M. G. (2024). Conducting in-depth analysis of AI, IoT, web technology, cloud computing, and enterprise systems integration for enhancing data security and governance to promote sustainable business practices. Journal of Information Technology and Informatics, 3(2), 297–322.
29. Zavatin, I., Popescu, I. M., Lupu, R., & Orloschi, A. E. (2024). AI regulation vs. AI standardization. Revista de Economie, 76(3), 113–126. https://doi.org/10.56043/reveco-2024-0030.
30. Kuznetsov, O., Sernani, P., Romeo, L., Frontoni, E., & Mancini, A. (2024). On the integration of artificial intelligence and blockchain technology: A perspective about security. IEEE Access, 12, 3881–3897. https://doi.org/10.1109/ACCESS.2023.3349019.
31. Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. International Journal of Information Management, 53, 102104. https://doi.org/10.1016/j.ijinfomgt.2020.102104.
32. Yahya Rayat, D. (2024). Longitudinal monitoring of physi-

ological, psychological and molecular responses to different dietary interventions: A precision health approach [Master's dissertation, University of Alberta]. University of Alberta, Edmonton, AB.
33. Roman, S., Campos-Medina, L., & Leal-Mercado, L. (2024). Personalized nutrition: The end of the one-diet-fits-all era. Frontiers in Nutrition, 11, 1370595. https://doi.org/10.3389/fnut.2024.1370595.
34. Nienaber-Rousseau, C. (2025). Understanding and applying gene–environment interactions: A guide for nutrition professionals with an emphasis on integration in African research settings. Nutrition Reviews, 83(2), e443–e463. https://doi.org/10.1093/nutrit/nuae015.
35. Kolodziejczyk, A. A., Zheng, D., & Elinav, E. (2019). Diet–microbiota interactions and personalized nutrition. Nature Reviews Microbiology, 17(12), 742–753. https://doi.org/10.1038/s41579-019-0256-8.
36. Choudhry, N. K., Priyadarshini, S., Swamy, J., & Mehta, M. (2025). Use of machine learning to predict individual postprandial glycemic responses to food among individuals with type 2 diabetes in India: Protocol for a prospective cohort study. JMIR Research Protocols, 14(1), e59308. https://doi.org/10.2196/59308.
37. Whitton, C., Healy, J. D., Collins, C. E., Mullan, B., Rollo, M. E., Dhaliwal, S. S., ... & Kerr, D. A. (2021). Accuracy and cost-effectiveness of technology-assisted dietary assessment comparing the automated self-administered dietary assessment tool, intake24, and an image-assisted mobile food record 24-hour recall relative to observed intake: protocol for a randomized crossover feeding study. JMIR Research Protocols, 10(12), e32891.
38. Sahoo, D., Hao, W., Ke, S., Xiongwei, W., Le, H., Achananuparp, P., ... & Hoi, S. C. (2019, July). FoodAI: Food image recognition via deep learning for smart food logging. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (pp. 2260-2268).
39. Han, M., Chen, J., & Zhou, Z. (2024). NutrifyAI: An AI-powered system for real-time food detection, nutritional analysis, and personalized meal recommendations. arXiv. arXiv:2408.10532. https://doi.org/10.48550/arXiv.2408.10532.
40. Cofre, S., Sanchez, C., Quezada-Figueroa, G., & López-Cortés, X. A. (2025). Validity and accuracy of artificial intelligence-based dietary intake assessment methods: A systematic review. British Journal of Nutrition, 133(9), 1241–1253. https://doi.org/10.1017/S0007114525000520.
41. Zhang, J., Oh, Y. J., Lange, P., Yu, Z., & Fukuoka, Y. (2020). Artificial intelligence chatbot behavior change model for designing artificial intelligence chatbots to promote physical activity and a healthy diet. Journal of Medical Internet Research, 22(9), e22845. https://doi.org/10.2196/22845.
42. Singh, B., Olds, T., Brinsley, J., Dumuid, D., Virgara, R., Matricciani, L., ... & Maher, C. (2023). Systematic review and meta-analysis of the effectiveness of chatbots on lifestyle behaviours. NPJ Digital Medicine, 6(1), 118.
43. Balloccu, S., Reiter, E., Kumar, V., Recupero, D. R., & Riboni, D. (2024). Ask the experts: Sourcing high-quality datasets for nutritional counselling through human-AI collaboration. arXiv. arXiv:2401.08420. https://doi.org/10.48550/arXiv.2401.08420.
44. Jeong, J. H., Lee, I. G., Kim, S. K., Kam, T. E., Lee, S. W., & Lee, E. (2024). DeepHealthNet: Adolescent obesity prediction system based on a deep learning framework. IEEE Journal of Biomedical and Health Informatics, 28(4), 2282–2293. https://doi.org/10.1109/JBHI.2024.3356580.
45. Debnath, R., Creutzig, F., Sovacool, B. K., & Shuckburgh, E. (2023). Harnessing human and machine intelligence for planetary-level climate action. NPJ Climate Action, 2(1), 20. https://doi.org/10.1038/s44168-023-00056-3.
46. Clarifresh. (2024). Speed up produce QC: AI solutions for inspection bottlenecks. Clarifresh Blog. Retrieved August 27, 2025, from https://clarifresh.com/blog/quality-control-process-slowing-you-down-speed-up-produce-inspection/.
47. Jiang, Z., Zhao, R., Lin, L., Yu, Y., Chen, H., Zhang, X., ... & Ngai, E. C. (2025). DietGlance: dietary monitoring and personalized analysis at a glance with knowledge-empowered AI assistant. arXiv preprint arXiv:2502.01317.
48. National Institutes of Health. (2022). Nutrition for precision health, powered by the All of Us Research Program. Bethesda, MD: NIH Common Fund. Retrieved August 27, 2025, from https://commonfund.nih.gov/nutritionforprecisionhealth.
49. Huang, L., Huhulea, E. N., Abraham, E., Bienenstock, R., Aifuwa, E., Hirani, R., ... & Etienne, M. (2025). The role of artificial intelligence in obesity risk prediction and management: approaches, insights, and recommendations. Medicina, 61(2), 358.
50. Nourish. (2025). Nourish raises $70M to bring affordable nutrition to millions of Americans. San Francisco, CA: AIM Research. Retrieved August 27, 2025, from https://aimresearch.co/ai-startups/nourish-raises-70m-to-bring-affordable-nutrition-to-millions-of-americans.
51. Krish, S. (2022). Mobile phone device can measure food spoilage. San Diego, CA: BusinessChief's Insight. Retrieved August 27, 2025, from https://businesschiefsinsight.com/mobile-phone-device-can-measure-food-spoilage/.
52. Wu, T. Y., Xu, Z., Yang, X. D., Hodges, S., & Seyed, T. (2021, May). Project tasca: enabling touch and contextual interactions with a pocket-based textile sensor. In Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (pp. 1-13).
53. Ghosh, T. (2025). Combating the bullwhip effect in rival online food delivery platforms using deep learning. arXiv. arXiv:2503.22753. https://doi.org/10.48550/arXiv.2503.22753.
54. Spitalleri, A., Kavasidis, I., Cartelli, V., Mineo, R., Rundo, F., Palazzo, S., ... & Giordano, D. (2023, June). BioTrak: A blockchain-based platform for food chain logistics traceability. In 2023 International Conference on Intelligent Computing, Communication, Networking and Services (ICCNS) (pp. 105-110). IEEE.
55. Hirvonen, K., Bai, Y., Headey, D., & Masters, W. A. (2020). Affordability of the EAT–Lancet reference diet: A global analysis. The Lancet Global Health, 8(1), e59–e66. https://doi.org/10.1016/S2214-109X(19)30447-4.
56. Edwards, K. M., Song, B., Porciello, J., Engelbert, M., Huang, C., & Ahmed, F. (2024). ADVISE: Accelerating the creation of evidence syntheses for global development using natural language processing-supported human-artificial intelligence collaboration. Journal of Mechanical Design, 146(5), 051404. https://doi.org/10.1115/1.4064245.
57. Food Standards Agency. (2021). FSA shares how it is

using data to monitor food risks. Food Safety News. Retrieved August 27, 2025, from https://www.foodsafetynews.com/2021/05/fsa-shares-how-it-is-using-data-to-monitor-food-risks/.
58. O'Connor, A. M., Tsafnat, G., Gilbert, S. B., Thayer, K. A., Shemilt, I., Thomas, J., ... & Wolfe, M. S. (2019). Still moving toward automation of the systematic review process: a summary of discussions at the third meeting of the International Collaboration for Automation of Systematic Reviews (ICASR). Systematic reviews, 8(1), 57.
59. Tonmoy, S. M. T. I., Zaman, S. M., Jain, V., Rani, A., Rawte, V., Chadha, A., & Das, A. (2024). A comprehensive survey of hallucination mitigation techniques in large language models. arXiv preprint arXiv:2401.01313, 6.
60. Barlas, T., Altinova, A. E., Akturk, M., & Toruner, F. B. (2024). Credibility of ChatGPT in the assessment of obesity in type 2 diabetes according to the guidelines. International Journal of Obesity, 48(2), 271–275. https://doi.org/10.1038/s41366-023-01410-5.
61. Schwartz, I. S., Link, K. E., Daneshjou, R., & Cortés-Penfield, N. (2024). Black box warning: Large language models and the future of infectious diseases consultation. Clinical Infectious Diseases, 78(4), 860–866. https://doi.org/10.1093/cid/ciad633.
62. Koçak, B., Ponsiglione, A., Stanzione, A., Bluethgen, C., Santinha, J., Ugga, L., ... & Cuocolo, R. (2025). Bias in artificial intelligence for medical imaging: fundamentals, detection, avoidance, mitigation, challenges, ethics, and prospects. Diagnostic and interventional radiology, 31(2), 75.
63. Li, X., Yin, A., Choi, H. Y., Chan, V., Allman-Farinelli, M., & Chen, J. (2024). Evaluating the quality and comparative validity of manual food logging and artificial intelligence-enabled food image recognition in apps for nutrition care. Nutrients, 16(15), 2573. https://doi.org/10.3390/nu16152573.
64. Gyawali, B., Mkoma, G. F., & Harsch, S. (2024). Social determinants influencing nutrition behaviors and cardiometabolic health in indigenous populations: A scoping review of the literature. Nutrients, 16(16), 2750. https://doi.org/10.3390/nu16162750.
65. Thapa, C., & Camtepe, S. (2021). Precision health data: Requirements, challenges and existing techniques for data security and privacy. Computers in Biology and Medicine, 129, 104130. https://doi.org/10.1016/j.compbiomed.2020.104130.
66. Mostert, M., Bredenoord, A. L., Biesaart, M. C., & Van Delden, J. J. (2016). Big data in medical research and EU data protection law: Challenges to the consent or anonymise approach. European Journal of Human Genetics, 24(7), 956–960. https://doi.org/10.1038/ejhg.2015.239.
67. Bader, F., & Jagtap, S. (2020). Internet of things-linked wearable devices for managing food safety in the healthcare sector. In Wearable and implantable medical devices (pp. 229–253). Cambridge, MA: Academic Press. https://doi.org/10.1016/B978-0-12-815369-7.00010-0.
68. Moorthy, U. M. K., Muthukumaran, A. M. J., Kaliyaperumal, V., Jayakumar, S., & Vijayaraghavan, K. A. (2025). Explainability and regulatory compliance in healthcare: Bridging the gap for ethical XAI implementation. In Explainable artificial intelligence in the healthcare industry (pp. 521–561). Hoboken, NJ: John Wiley & Sons, Inc.
69. Markus, A. F., Kors, J. A., & Rijnbeek, P. R. (2021). The role of explainability in creating trustworthy artificial intelligence for health care: A comprehensive survey of the terminology, design choices, and evaluation strategies. Journal of Biomedical Informatics, 113, 103655. https://doi.org/10.1016/j.jbi.2020.103655.
70. Gerlich, M. (2025). AI tools in society: Impacts on cognitive offloading and the future of critical thinking. Societies, 15(1), 6. https://doi.org/10.3390/soc15010006.
71. Chatelan, A., Clerc, A., & Fonta, P. A. (2023). ChatGPT and future artificial intelligence chatbots: What may be the influence on credentialed nutrition and dietetics practitioners? Journal of the Academy of Nutrition and Dietetics, 123(11), 1525–1531. https://doi.org/10.1016/j.jand.2023.08.001.
72. Salim, A. Jr., Allen, M., Mariki, K., Masoy, K. J., & Liana, J. (2023). Understanding how the use of AI decision support tools affect critical thinking and over-reliance on technology by drug dispensers in Tanzania. arXiv. arXiv:2302.09487. https://doi.org/10.48550/arXiv.2302.09487.
73. Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. Nature Machine Intelligence, 1(9), 389–399. https://doi.org/10.1038/s42256-019-0088-2.
74. Turner Lee, N., Simmons, M., & Crawford, M. (2025). Health and AI: Advancing responsible and ethical AI for all communities. Washington, DC: Brookings Institution. Retrieved August 27, 2025, from https://www.brookings.edu/articles/health-and-ai-advancing-responsible-and-ethical-ai-for-all-communities/.
75. Dignum, V. (2023). Responsible artificial intelligence—from principles to practice: A keynote at The Web Conf 2022. ACM SIGIR Forum, 56(1), 1–6. https://doi.org/10.1145/3582524.3582529.
76. Manning, L., Brewer, S., Craigon, P. J., Frey, J., Gutierrez, A., Jacobs, N., ... & Pearson, S. (2022). Artificial intelligence and ethics within the food sector: Developing a common language for technology adoption across the supply chain. Trends in Food Science & Technology, 125, 33-42.
77. Winter, P. M., Eder, S., Weissenböck, J., Schwald, C., Doms, T., Vogt, T., ... & Nessler, B. (2021). Trusted artificial intelligence: Towards certification of machine learning applications. arXiv preprint arXiv:2103.16910.
78. Eruaga, M. A. (2024). Enhancing global food safety standards through international collaboration and policy harmonization. International Journal of Scholarly Research in Multidisciplinary Studies, 4(1), 20–32. https://doi.org/10.56781/ijsrms.2024.4.1.0027.
79. Sun, H., Zhang, K., Lan, W., Gu, Q., Jiang, G., Yang, X., ... & Han, D. (2023). An AI dietitian for type 2 diabetes mellitus management based on large language and image recognition models: preclinical concept validation study. Journal of medical Internet research, 25, e51300.
80. Vegesna, V. V., Adepu, A., & Whig, P. (2024). IT for healthcare and food safety: Enhancing public health through technology integration. In Nutrition controversies and advances in autoimmune disease (pp. 525–546). Hershey, PA: IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-55282.ch020.
81. Wolfe, R., Slaughter, I., Han, B., Wen, B., Yang, Y., Rosenblatt, L., ... & Howe, B. (2024, June). Laboratory-scale ai: Open-weight models are competitive with chatgpt even in low-resource settings. In Proceedings of the 2024 ACM

Conference on Fairness, Accountability, and Transparency (pp. 1199-1210).
82. Di Bitonto, P., Magarelli, M., Novielli, P., Romano, D., Diacono, D., De Trizio, L., ... & Tangaro, S. (2024). From data to nutrition: the impact of computing infrastructure and artificial intelligence. Exploration of Foods and Foodomics, 2, 810-829.
83. Arslan, S. (2025). Artificial intelligence in food safety and nutrition practices: Opportunities and risks. Academia Nutrition and Dietetics, 2. https://doi.org/10.20935/AcadNutr7904.

***Copyright:*** *©2025 Rakesh Manilal Patel, et al. This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.*