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Artificial intelligence applications in nutrition science: A brief thematic overview

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REVIEW PAPER

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ABSTRACT

Artificial intelligence (AI) and machine learning (ML) methods are increasingly applied across various domains of nutrition science and dietetics. This paper provides a thematic overview of the key research and practical applications, including image- and sensor-based tools for dietary intake assessment, predictive models used in food production and safety, public health and epidemiological applications, and precision nutrition strategies in clinical diagnostics and therapy. It also addresses the integration of diverse data sources and the recognition of complex biological patterns, while also highlighting ethical, legal, and data protection challenges.

KEYWORDS

artificial intelligence, machine learning, applications, nutrition science

1. INTRODUCTION

The emergence of artificial intelligence (AI) in nutrition science marks one of the most significant innovations of the past decade. AI technologies are becoming increasingly sophisticated and accessible, playing a pivotal role in the development of novel models for dietary data

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processing, prediction, and personalisation. The aim of this paper is to provide a thematic – not exhaustive – overview of the principal applications of artificial intelligence in nutrition science. The review is based on keyword searches conducted in PubMed and Google Scholar, as well as publications retrieved *via* the natural language search engine Scite.ai in July 2025, using the most frequent and thematically central keywords identified in the literature (Fig. 1), such as 'nutrition', 'diet', 'precision nutrition', 'obesity', 'microbiome', 'metabolism', 'prediction', 'machine learning', and 'artificial intelligence'. It briefly summarises current findings and outlines directions for future research and practical implementation, drawing on the most relevant sources from these searches.

2. OVERVIEW OF ARTIFICIAL INTELLIGENCE IN HEALTH AND NUTRITION

Artificial intelligence is an umbrella term encompassing various machine-based algorithms capable of learning from data, making predictions, and supporting complex decision-making

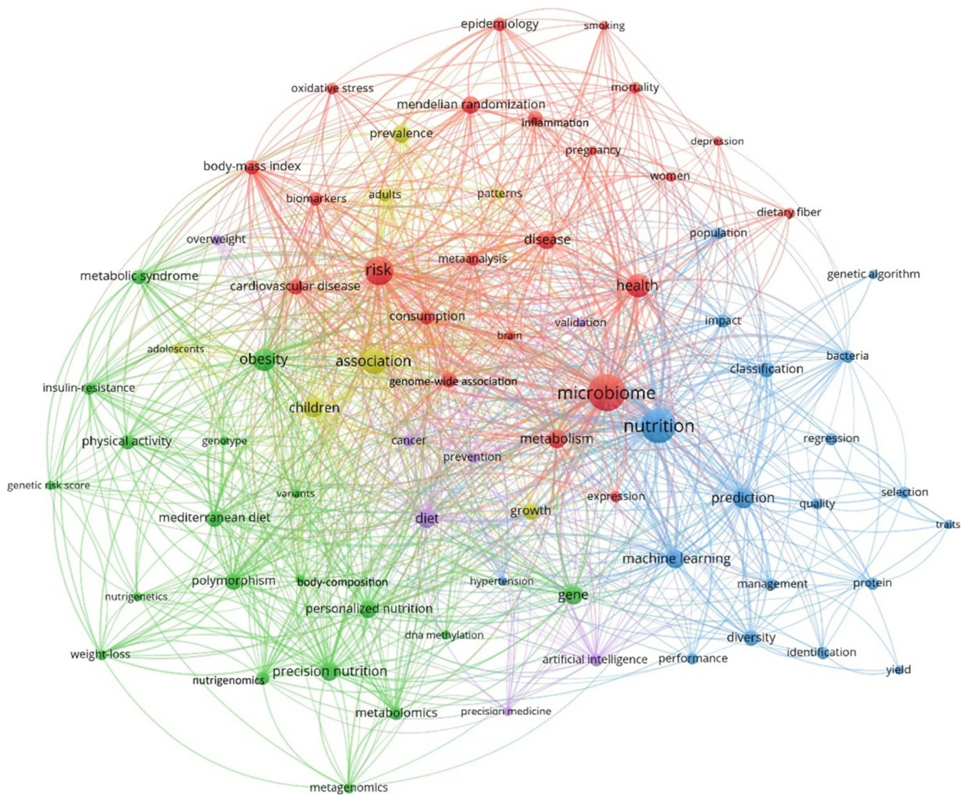

Fig. 1. Keyword co-occurrence network of AI in nutrition science.
Nodes represent keywords, with node size proportional to frequency of occurrence; links indicate co-occurrence relationships, and clusters denote thematic groupings in the literature (adapted from Ferreira et al., 2025)

processes. In nutrition science, AI tools primarily employ machine learning (ML) techniques – including supervised, unsupervised, and reinforcement learning – alongside deep learning (DL) based on artificial neural networks, and natural language processing (NLP) methods for a range of dietetic, research, and healthcare purposes. AI can extract interpretable patterns from unstructured data, providing a foundation for predictive nutritional modelling. These systems complement traditional tools in nutrition science, supporting real-time monitoring of health status and optimisation of dietary decisions (Miyazawa et al., 2022).

Machine learning – particularly supervised learning – is well-suited for monitoring dietary habits, nutrient intake, and predicting health risks. Deep learning models, especially convolutional neural networks (CNNs), are especially effective in image-based food recognition and portion size estimation (Dalakleidi et al., 2022). These technologies enhance the accuracy and reproducibility of dietary data, particularly in the context of mobile applications and digital food diaries. However, so-called "black box" models – whose inner workings and decision-making logic are opaque or not readily interpretable by humans – are of limited use in clinical settings, which is driving a growing demand for explainable AI (XAI) techniques (Kassem et al., 2025).

AI-based systems are capable of processing large and complex datasets (e.g., dietary records, biological markers, images), uncovering associations, making predictions, and automating personalised decision support. While most such systems are currently in the research and development phase, they hold considerable future potential. Nevertheless, clinical applicability is limited by the frequent lack of interpretability and by data privacy concerns, which present significant regulatory and ethical challenges (Sosa-Holwerda et al., 2024).

AI and ML technologies enable automated identification of dietary patterns and prediction of health status, opening new horizons in preventive nutrition. Although predictive models are typically tested on validated datasets (e.g., National Health and Nutrition Examination Survey – NHANES 2007–2010), these often underrepresent cultural diversity within populations, and dataset biases pose a major challenge to the generalisability of models (Theodore Armand et al., 2024).

3. DOMAINS OF APPLICATION IN NUTRITION SCIENCE

This section provides an overview of the principal domains in which artificial intelligence is applied in nutrition science, with particular emphasis on those research and practice areas where AI technologies show considerable developmental potential.

3.1. AI in nutrition science and research

AI technologies offer a wide range of novel opportunities in nutrition research, from improving dietary assessment and food recognition to advancing microbiome analysis. The following subsections outline the key applications and related challenges.

3.1.1. Dietary assessment and food recognition. Traditional methods for assessing food and nutrient intake – such as 24-h dietary recalls or food diaries – are often prone to bias. AI technologies offer promising alternatives, particularly through real-time, image-based, and sensor-based monitoring and documentation, which reduce human intervention and enhance the objectivity and accuracy of estimating actual food consumption (Zheng et al., 2024).

Dietary assessment tools designed for specific target populations (e.g., children, adolescents, healthy adults, pregnant women) may vary considerably in both functionality and language to accommodate age- or physiology-specific needs. Image-based systems (e.g., food recognition using mobile photographs) and sensor-based tools (e.g., motion, jaw movement, or voice recognition) are effective in tracking food consumption and nutrient intake (Phalle and Gokhale., 2025).

The direct relationship between AI-based dietary estimations and health outcomes remains underexplored, limiting their use in clinical and public health practice. Further research and the development of standardised validation protocols are needed. Most AI systems developed thus far focus on estimating intake of macronutrients, with micronutrient intake less frequently assessed, and biomarkers rarely incorporated to enhance the reliability of intake estimates (Cofre et al., 2025).

Accurately determining the quantity and quality of consumed foods and meals is essential for calculating energy and nutrient intake. Estimating food volume using reference objects, stereo cameras, or 3D reconstruction algorithms is technically promising, but practical application – particularly on mobile devices – remains challenging and often lacks sufficient accuracy (Tahir and Loo, 2021).

Image-based food recognition systems typically estimate portion size through a combination of image segmentation, classification, and volume estimation, often relying on 3D reconstruction or reference objects. Public food databases are crucial for training AI-based systems, but their heterogeneity and cultural limitations may reduce the reliability of dietary assessments (Dalakleidi et al., 2022). Nevertheless, recent advances in deep learning techniques have significantly improved food recognition accuracy, even for heterogeneous food types (Konstantakopoulos et al., 2024).

3.1.2. Nutrigenomics, metabolomics, and biomarker integration. Nutrigenomics investigates how genetic variations influence individual responses to nutrients, offering a framework for uncovering complex relationships among dietary factors, particularly in the context of neurological disorders. The gut microbiota contributes to the regulation of cognitive function through neural, endocrine, and immune mechanisms. Personalised dietary interventions targeting gene expression and the gut–brain axis may enhance cognitive performance and reduce the risk of neurodegenerative diseases. Future directions in this field will be shaped by the joint advancement of omics technologies (genomics, epigenomics, metabolomics, proteomics) and artificial intelligence, enabling integrated analysis of large biomarker datasets (Waheed et al., 2024).

AI-driven analysis of omics data can identify metabolite patterns that support early detection, prediction, and monitoring of metabolic diseases such as type 2 diabetes, obesity, and non-alcoholic fatty liver disease (NAFLD). Pharmacometabolomics focuses on the relationship between metabolic profiles and pharmacological responses, facilitating the prediction of treatment outcomes and optimisation of individualised drug dosing (Singh et al., 2023). This principle is illustrated in Fig. 2, which contrasts the conventional "one size fits all" model with a personalised, omics-driven approach that integrates AI-based analysis to enhance efficacy and reduce toxicity.

Beyond genetic characteristics, complex data derived from diverse biological matrices (e.g., blood, urine, saliva, stool, tissues) can be interpreted as biological fingerprints reflecting an individual's current physiological state. AI-based analysis of metabolite profiles presents new opportunities for applying precision nutrition (PN) in clinical settings (Catussi et al., 2024).

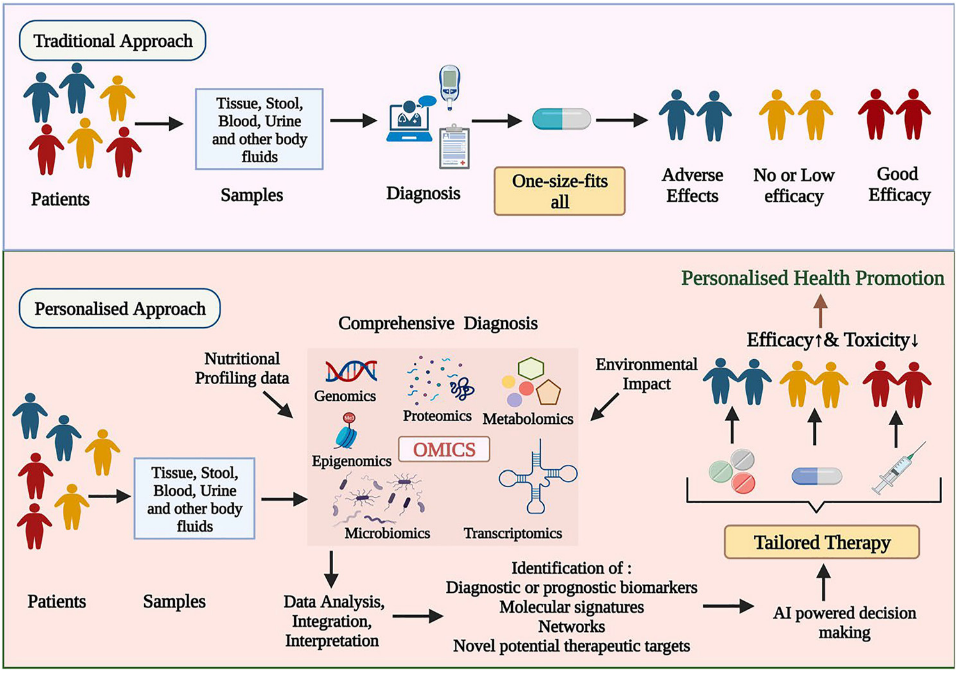

Fig. 2. From conventional "one size fits all" to personalized nutrition and medicine.
The figure contrasts uniform conventional care with individualised approaches supported by omics data and AI (adapted from Singh et al., 2023)

3.1.3. Gut microbiome analysis. The gut microbiome is closely linked to nutrition, health status, and numerous metabolic processes. Leveraging big data and bioinformatics tools, artificial intelligence – often referred to in this context as Biomedical Industry 4.0 – enables integrated evaluation of microbiome and dietary data, and supports targeted microbiome modulation to develop individualised nutritional strategies. This approach may contribute to maintaining optimal health as well as to the prevention and treatment of diet-related chronic diseases, although its effective implementation still requires substantial technological advancement (Yeşilyurt et al., 2022).

Microbiota composition is influenced by a range of factors (e.g., diet, medications, environmental exposures) and directly impacts nutrient metabolism, immune responses, and inflammatory processes. Dysbiosis, or microbial imbalance, has been associated with obesity and chronic diseases. The gut microbiome can modulate food intake and metabolic homeostasis by affecting hormonal regulation of hunger and satiety. Artificial intelligence enables analysis of the microbiome's composition and its complex interactions with the host, providing a foundation for the next generation of personalised dietary recommendations (Saxena et al., 2024).

3.1.4. Nutrient–drug interaction studies. Drug–food interactions (DFIs) represent a critical yet underexplored area. Advanced AI algorithms (e.g., XGBoost, neural network-based models), trained on specialised food and drug databases such as DrugBank and FooDB, can classify compounds based on their chemical structures and effectively predicting potential DFIs. This facilitates the generation of clinically relevant warnings (Kha et al., 2023).

Graph-based DFI network analysis, applied to large-scale data sources, can reveal complex interactions – such as molecular communications spanning diet–microbiome–drug–food–drug pathways – within a pharmacomicrobiome framework. This provides a valuable tool for more precise mapping of clinically significant interactions and supports safer decision-making in personalised medicine (Roy et al., 2022).

3.2. AI in food production and food sciences

Food production and food sciences are rapidly integrating artificial intelligence (AI) technologies, which offer new opportunities for optimising production, improving quality and safety, and achieving sustainability and economic goals. AI enables complex analysis of large and heterogeneous datasets, the development of predictive models, and automated decision support, thereby increasing the efficiency of food system processes. The following subsections review the role of AI in food production, safety and quality control, and its influence on innovation and market trends.

3.2.1. Food production optimisation and development. In food production, rising population demands pose significant challenges to the efficiency and sustainability of conventional agricultural systems, compounded by climate change, environmental degradation, and pest pressures. AI supports predictive modelling and data-driven optimisation to improve the efficiency and adaptability of agri-food systems. During the pre-production phase, AI can optimise soil quality, seeding schedules, and weather forecasting. It also supports pest and disease detection (e.g., *via* drone technology), autonomous harvesting, reduced energy use and waste during processing, and improved logistics and product traceability throughout distribution. In the food industry, AI facilitates predictive quality control (e.g., through next-generation sequencing), product development, and analysis of consumer demand. Specific AI applications in food production include 3D food printing and the use of "electronic nose" and "electronic tongue" algorithms (Aghababaei, 2025).

AI also contributes to sustainability objectives by optimising water usage, improving harvest timing, enhancing resource efficiency, and reducing the ecological footprint of production. As a result, it can help make agricultural systems more sustainable and resilient, while strengthening global food security (Raliya, 2024).

3.2.2. Food safety and quality control. The chemical composition of food extends far beyond currently known nutrients and bioactive non-nutrient compounds. Of the more than 26,000 identified components (records of FooDB open-access database), the majority remain unquantified and are considered part of the so-called "nutritional dark matter." The complex food matrix – including novel compounds formed during processing – can influence physiological effects through synergistic or antagonistic interactions. Using data from published food chemistry studies, machine learning enables "foodome"-based mapping strategies that can function as a form of chemical barcode. When linked to individual genetic variation and medical history, such data open new avenues for personalised and therapeutic applications of nutrition (Barabási et al., 2020).

The fourth category of the NOVA food classification system includes products that contain chemically modified ingredients and specialised additives (e.g., flavour enhancers, colorants, emulsifiers) typically absent from home-prepared meals. With the exception of infant formulas, which are produced and controlled according to extremely strict requirements, ultra-processed foods not only have poor nutritional profiles but also contribute – when overconsumed – to the development of numerous diet-related conditions such as obesity, metabolic syndrome, and certain cancers. The core issue lies not in processing *per se*, but in the extent of ultra-processing, which displaces whole foods and generates public health, economic, and cultural harm (Monteiro et al., 2019).

Processing significantly alters the nutrient content and structural complexity of foods. Machine learning analyses based on objective measurements can predict the degree of processing. The FoodProX algorithm, together with a calculated index based on nutrient and metabolite content, classifies foods into the four NOVA categories, enabling reproducible and objective classification. The analysed metabolites include both polar (e.g., amino acids, nucleotides) and nonpolar compounds (e.g., fatty acids, carotenoids); mass spectrometry-based profiling also detects numerous unannotated features, reflecting the exploratory nature of untargeted metabolomics despite the use of extensive reference libraries (e.g., METLIN, MoNA). Epidemiological analyses (e.g., from NHANES 1999–2006 and 2007–2010 data) show that consumption of foods with high FPro index values – indicating greater ultra-processing – is positively associated with increased risk of various metabolic diseases, particularly when accounting for the individual gram-weighted contribution of such foods to total intake ($iFPro_{WG}$) (Menichetti et al., 2023, 2024).

Climate change, globalisation, and emerging technologies have introduced novel food-related risks that traditional risk assessment systems are often unable to detect or predict in time. Machine learning models that integrate meteorological, microbiological, sensory, and commercial data can greatly improve the reliability of risk forecasting and support proactive, predictive protection of the food supply chain. Effective implementation requires international collaboration among regulatory authorities, private-sector actors, and stakeholders across the food production and distribution sectors (Mu et al., 2024).

In the food industry, AI supports the detection of chemical, biological, and physical contaminants, enables rapid and accurate interventions when combined with real-time sensing technologies, and helps identify functional properties such as antioxidant capacity or probiotic activity, thereby supporting the development of health-promoting foods (Yang et al., 2025a). Food fraud represents a serious global challenge, as conventional inspection methods are time-consuming and expensive. Advanced analytical and sensor technologies – such as spectroscopy, chromatography, DNA barcoding, and biosensors – combined with AI-based data analysis enable rapid and sensitive detection of adulteration. These algorithms enable automated, high-resolution pattern recognition, risk prediction, and anomaly detection, thus contributing to proactive protection of the food system (Sharma et al., 2024).

Barriers to the widespread adoption of AI-based systems in the food industry include high initial investment costs, concerns about data security, and unresolved ethical and regulatory challenges. Successful implementation depends on interdisciplinary collaboration and the establishment of transparent technological protocols (Zatsu et al., 2024).

Conventional food research and development processes are often time-intensive, costly, and resource-demanding. AI, by leveraging large datasets, enables predictive modelling of new foods, flavours, textures, and nutrient profiles *via* "*in silico*" experimentation. This accelerates innovation and makes food system development more accessible, including for smaller research groups and enterprises (Kuhl, 2025).

AI also exerts a notable economic impact on the food sector. It supports consumer preference analysis, sales trend forecasting, product development, inventory management, quality assurance, and food safety. It can even analyse the emotional content of social media posts to predict consumer behaviours. The Industry 5.0 paradigm emphasises the synergy between AI and biotechnology, enabling the use of biological sensors for monitoring and controlling production processes, thereby enhancing food safety and quality (Nikolola-Alexieva, 2024).

3.3. AI in public health nutrition

In the field of public health nutrition, artificial intelligence offers a range of innovative solutions. It supports nutritional epidemiological research, facilitates the planning and monitoring of personalised dietary interventions, enhances the effectiveness of educational and interventional programs, and contributes to improvements in food security and global nutritional equity. AI-based systems enable complex data analysis, predictive modelling, and decision support, providing new tools to address public health challenges.

3.3.1. Nutritional epidemiology. Nutritional epidemiology aims to identify associations between diet and disease using large-scale data. Traditional statistical methods are often inadequate for capturing complex, nonlinear relationships between variables or for managing confounding factors. Artificial intelligence and machine learning approaches offer promising ways to overcome these limitations – for example, by imputing missing data or developing predictive models. However, their application requires careful design and validation to ensure scientific reliability and interpretability of results. More advanced deep learning models may also be suitable for analysing nutritional image data (Russo and Bonassi, 2022).

A key concern among health professionals is that data from nutrition-related mobile applications are often inaccurate or self-reported, leading to deviations and biases when compared with measured data, thereby limiting clinical applicability. For these tools to evolve into practical decision-support systems, it is essential to base them on scientifically validated principles, use appropriate local databases, and ensure secure data handling (Vasiloglou et al., 2020).

In 2020, a smartphone-based dietary diary application was introduced that uses artificial intelligence to analyse food images and automatically generate corresponding nutrient profiles. The app also enables both qualitative and quantitative corrections of detected foods, thereby improving data accuracy. Test participants reported positive experiences regarding the simplicity, speed of data entry, and user-friendliness of the app. Although statistical differences were observed between the app results and those of a conventional three-day food diary, these differences were considered moderate in practical terms, and user preference for the app was clearly favourable (Ji et al., 2020).

3.3.2. Personalised nutrition and precision diet planning. Digital technologies in precision nutrition can be categorised into three main areas. The first involves food photography and AI-based food recognition, which facilitate dietary logging, enable real-time data capture, and improve recall accuracy. The second comprises various sensors that automate the tracking of eating behaviour and the estimation of nutrient intake. These include physical sensors such as electromyographic glasses, piezoelectric and acoustic detectors for monitoring eating movements, chewing, and swallowing, as well as smart utensils and environmental cameras. The third area comprises AI-driven personalised nutrition programs that integrate genetic information, biochemical markers, and gut microbiome data (Mortazavi and Gutierrez-Osuna, 2021).

A paradigm shift is underway in nutrition science, moving from generalised dietary guidelines toward personalised diet planning. Algorithms that incorporate individual preferences, habits, and health goals can generate tailored dietary recommendations that dynamically adapt to user feedback. Such systems are already widely used in areas like fitness apps, activity tracking platforms, and diet-planning tools. However, designing personalised diet planning tools for children presents specific challenges due to age- and nutrition-specific requirements (Sharma and Gaur, 2024).

Chemical sensors – including continuous glucose monitoring (CGM) systems, breath analysers, sweat and saliva detectors – estimate nutrient intake through biomarkers, allowing for the generation of personalised dietary advice. Systems based on computer vision and neural networks can identify foods and estimate nutrient content *via* image processing, which may be further refined through integration with mobile apps and wearable data collection tools. However, such AI nutritionist systems can only be ethically deployed if developed according to professionally validated protocols and strict data protection standards (Liang et al., 2024; Ferreira et al., 2025).

Precision nutrition systems are most commonly used to predict and manage metabolic disorders such as diabetes and obesity. AI's predictive and pattern recognition capabilities are also particularly valuable in cardiovascular disease and certain cancers, such as colorectal cancer. However, broad clinical validation is generally still lacking, and equitable application requires attention to minority and cultural considerations (Wu et al., 2025).

In recent years, the use of large language models has further expanded the potential for automated personalised diet planning. Algorithms based on fuzzy logic – a form of reasoning that allows for degrees of truth rather than binary yes/no decisions – can account for uncertainty in nutritional parameters (e.g., "moderately high fat intake"), perform rule-based food prescreening and refinement, and optimise meal plans by integrating individual preferences with omics data. This enables greater efficiency and flexibility than manual diet planning, even when multiple objectives – health, nutritional, or preference-related – must be considered simultaneously (Amiri et al., 2023).

Natural language models can also be used to generate structured dietary plans. For example, variational autoencoders (VAEs) can create digital profiles by transforming user data into a latent space – a compressed feature representation that captures meaningful patterns in individual health characteristics and dietary-nutrient targets. This structured representation serves as input for generating personalised meal plans. ChatGPT integration allows the system to express dietary recommendations in natural language and offer equivalent meal alternatives, thereby enhancing user experience and practical applicability (Papastratis et al., 2024).

3.3.3. Nutrition education and intervention. AI-based interactive platforms provide opportunities for delivering personalised nutrition education aligned with WHO guidelines. These tools enhance user engagement and learning outcomes, while also fostering positive changes in nutritional attitudes. More advanced applications can be integrated into school curricula, supporting long-term health promotion – particularly when they incorporate age-appropriate gamification features, virtual advisors, and feedback systems. However, for both children and adult users – especially those from disadvantaged populations – it is essential to address the digital divide, algorithmic bias, data security, and ethical compliance (Ojo et al., 2025).

Generative AI is playing an increasingly prominent role in dietetics education and the development of communication skills. Traditional training with human patients is costly and time-intensive. The Authentic Teaching and Learning Application Simulation (ATLAS) platform enables students to practice realistic scenarios with voice-controlled, AI-based virtual patients. These virtual patients are programmed based on clinical cases and incorporate personality traits, communication styles, and nonverbal cues. The system can provide feedback on a lack of empathy or even simulate a "disengagement" response, thereby enhancing the realism of the learning experience (Barker et al., 2024).

3.3.4. Food security and global nutrition. Achieving global, sustainable food production, transforming dietary habits, and developing high-quality diets tailored to diverse population needs require multidisciplinary approaches and advanced technologies. Artificial intelligence supports the optimisation of soil and water management, increases crop yields, reduces environmental impact, and mitigates damage from weather, pests, and disease. In the distribution and consumption chain, it enables real-time quality control, food labelling, consumer information, and behavioural analysis, while in waste management, it helps reduce losses through predictive modelling and sensor-based solutions (Namkhah et al., 2023).

Modern food bank systems allow for the dynamic alignment of food surpluses with social need. Such advanced AI-driven platforms can play a crucial role in reducing social inequalities, particularly in addressing undernutrition, poverty, and food waste. AI can forecast demand, optimise donation opportunities, and increase donor confidence through transparent systems (Yang et al., 2025b).

Artificial intelligence and natural language processing tools can also rapidly identify geographic patterns of food insecurity by analysing social media data. Such analysis can reveal needs for aid and the mental health impacts linked to gaps in food access – such as anxiety, stress, or changes in eating behaviour. This can offer actionable insights for decision-makers and support the development of complex intervention strategies (Martin et al., 2022).

3.4. AI in diagnosis and treatment of nutrition-related diseases

Clinical applications of artificial intelligence provide new opportunities for more accurate risk prediction and personalised therapeutic strategies for nutrition-related diseases.

3.4.1. Disease risk prediction and early detection. Artificial intelligence and machine learning offer promising tools for personalised risk estimation of coronary artery disease (CAD), particularly when accounting for the interaction between dietary factors and gut microbiome composition. Combined AI/ML models – given sufficient data quality and standardisation – may outperform current prediction systems such as the Framingham Risk Score (FRS) or the Systematic Coronary Risk Evaluation (SCORE). These data-intensive, personalised approaches can integrate complex multivariable inputs – including nutritional, genetic, and microbiome data – thereby supporting more effective clinical decision-making (Vilne et al., 2022; Kasartzian and Tsiampalis, 2025).

In patients with type 2 diabetes (T2DM) and diabetic kidney disease (DKD), the risk of end-stage renal disease (ESRD) has traditionally been estimated using general clinical parameters such as age, sex, glycaemic control, and blood pressure. However, a machine learning-based model has demonstrated that key additional predictors include nutritional status, anaemia, and renal function indicators – parameters that, when combined, enhance the predictive accuracy for ESRD risk (Zou et al., 2022).

3.4.2. Precision nutrition for disease management. Maintaining long-term motivation is one of the main challenges in weight management programs. An empathy-enabled chatbot (SlimMe), which combines calorie estimation based on nutritional databases with behaviour change techniques, has shown promise in facilitating personalised weight management. One study found it to be a useful tool in personalised, empathic nutrition counselling, particularly in fostering user engagement and behaviour modification (Rahmanti et al., 2022).

In another study, personalised weight-loss meal plans generated by ChatGPT (4.0) for hypothetical patients were compared with control diets used at two major clinical institutions. According to evaluations by dietitians, physicians, and nurses, the AI-generated plans generally met expectations for effectiveness, balance, variety, and practical applicability. However, in more complex dietetic cases – such as those involving multiple comorbidities – or in situations requiring precise individual dosing, the limitations of AI-based dietary decision support became more apparent, reinforcing the indispensable role of clinical dietitians (Kim et al., 2024).

Malnutrition remains an underdiagnosed and complex condition. Automated systems based on machine learning can provide valuable support in its recognition and management. With adequate clinical validation, these models may help identify malnutrition risk early, analyse clinical documentation, and support personalised nutritional interventions (Janssen et al., 2024).

While general dietary guidelines are useful for the majority of the population, they often fail to account for individual needs and psychological factors that influence dietary behaviour. This limits their applicability for individuals living with obesity. There is an urgent need for targeted, specific recommendations and advanced tools aligned with these to improve the effectiveness of nutritional interventions (Marsall et al., 2023).

Childhood obesity is increasing worldwide, yet due to the heterogeneity of individual dietary responses, standard recommendations are often inadequate. Artificial neural networks (ANNs) may more accurately model the relationship between the microbiome and glycaemic responses than traditional prediction formulas, thereby improving disease risk prediction and enabling personalised dietary interventions. However, relevant data for paediatric populations are limited, and further research is needed to develop effective AI models. This conclusion was reinforced by a later review focusing on precision nutrition algorithms for managing obesity in children and adolescents (0–19 years) (Milani et al., 2021; Huey, 2025).

Pathogenesis of inflammatory bowel diseases (IBD) – particularly ulcerative colitis and Crohn's disease – involves complex interactions between genetic, environmental, and immunological factors, with gut dysbiosis playing a critical role. Precision nutrition and targeted dietary strategies based on genetic and microbiome differences can reduce inflammation, improve clinical status, enhance predictive disease monitoring, and support the design of individualised nutritional interventions (Baldi et al., 2025). Machine learning models can support the identification of malnutrition, predict enteral feeding intolerance (EFI), and detect early-stage sarcopenia (Singer et al., 2023).

Early identification of metabolic syndrome (MetS) and cardiometabolic diseases, along with accurate risk stratification, is essential for effective intervention. AI-based tools enable the integrated analysis of multisource data–including clinical parameters, genetic and omics information, and environmental factors – resulting in more sensitive prediction models. Liu et al. (2025) highlight that although these models are promising, they often operate as “black boxes,” which limits their clinical acceptance and underscores the need for population-specific validation. Guasch-Ferré et al. (2025) further emphasise that AI- and big data–driven systems can uncover complex interactions between genotype and environment, identify epigenetic changes and diet-modifiable gene expression patterns, and elucidate the role of the gut microbiome in modulating metabolic and inflammatory responses. This significantly enhances prediction accuracy and validity for both prevention and treatment.

Precision nutrition has become indispensable for prevention, risk prediction, clinical therapy, and the management of healthy aging in diet-related chronic diseases. It is grounded in nutritional omics, which integrates the fields of nutrigenomics, nutrigenetics, nutri-epigenetics, metagenomics, and metabolomics (Singh et al., 2024).

4. CHALLENGES AND ETHICAL CONSIDERATIONS

The application of artificial intelligence in the public health sector undeniably enhances diagnostic accuracy and improves the efficiency of healthcare delivery. At the same time, it raises serious ethical concerns – particularly regarding the protection of patient data, algorithmic bias, and legal accountability. Ning et al. (2024) explored the ethical dimensions of generative artificial intelligence (GenAI) in healthcare through a comprehensive scoping review, which resulted in the development of the Transparent Reporting of Ethics for Generative AI (TREGAI) checklist. This framework is designed to support the responsible and safe use of GenAI, with specific applicability to both clinical practice and research contexts. The authors identified nine ethical principles that are relevant in all healthcare settings involving the implementation of GenAI: accountability, autonomy, equity, integrity (in medical education and quality of clinical research), non-maleficence, privacy, security, transparency, and trust. Systematic integration of these principles and consistent application of the framework are essential prerequisites for the responsible deployment of generative AI in healthcare. The analysis emphasises that while GenAI offers new opportunities – such as strengthening personal data protection through synthetic data – it also introduces novel risks. These are particularly evident in the case of large language models, where issues such as inaccuracy, bias, and lack of transparency may pose a threat to patient safety (Ning et al., 2024).

Although it is not possible to completely eliminate concerns related to AI use, they can be mitigated through appropriate oversight. Effective implementation in healthcare requires a strong partnership between clinicians and informaticians, the establishment of clear legal and regulatory frameworks, the systematic incorporation of ethics and AI education into all training programs, and a commitment to reducing inequality (Kooli and Al Muftah, 2022).

5. CONCLUSION

The application of artificial intelligence in nutrition science and dietetics constitutes a major advancement in both research methodology and practical implementation. From measuring and monitoring dietary intake to enhancing food chain safety and quality, supporting public health programs, and developing predictive models and personalised therapeutic strategies, advanced machine learning and analytical tools are playing an increasingly central role. However, ethical, legal, and data protection concerns, together with the challenges of methodological validation, underscore the need to ground future developments in interdisciplinary collaboration and the establishment of professional standards.

6. LIMITATIONS

This study aimed to provide a thematic overview of the major domains of artificial intelligence application in nutrition science, rather than a systematic literature review. The selection of topics was based primarily on relevance and the representativeness of the cited scientific publications; consequently, some emerging or underexplored subfields may have been omitted. Given the rapid evolution of AI technologies, some of the approaches or tools presented may become outdated or be replaced by newer, more effective methods. Finally, although the study touches on ethical, data protection, and regulatory issues, an in-depth analysis of these aspects was beyond its scope and merits further investigation.

REFERENCES

Aghababaei, A., Aghababaei, F., Pignitter, M., and Hadidi, M. (2025). Artificial intelligence in agro-food systems: from farm to fork. *Food*, 14(3): 411, https://doi.org/10.3390/foods14030411

Amiri, M., Li, J., and Hasan, W. (2023). Personalized flexible meal planning for individuals with diet-related health concerns: system design and feasibility validation study. *JMIR Formative Research*, 7: e46434, https://doi.org/10.2196/46434

Baldi, S., Sarikaya, D., Lotti, S., Cuffaro, F., Fink, D., Colombini, B., Sofi, F., and Amedei, A. (2025). From traditional to artificial intelligence-driven approaches: revolutionizing personalized and precision nutrition in inflammatory bowel disease. *Clinical Nutrition ESPEN*, 68: 106–117, https://doi.org/10.1016/j.clnesp.2025.05.012

Barabási, A.-L., Menichetti, G., and Loscalzo, J. (2020). The unmapped chemical complexity of our diet. *Nature Food*, 1: 33–37, https://doi.org/10.1038/s43016-019-0005-1

Barker, L.A., Moore, J.D., and Cook, H.A. (2024). Generative artificial intelligence as a tool for teaching communication in nutrition and dietetics education – a novel education innovation. *Nutrients*, 16(7): 914, https://doi.org/10.3390/nu16070914

Catussi, B.L.C., Lo Turco, E.G., Pereira, D.M., Teixeira, R.M.N., Castro, B.P., and Massaia, I.F.D. (2024). Metabolomics: unveiling biological matrices in precision nutrition and health. *Clinical Nutrition ESPEN*, 64: 314–323, https://doi.org/10.1016/j.clnesp.2024.10.148

Cofre, S., Sanchez, C., Quezada-Figueroa, G., and 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/s0007114525000522

Dalakleidi, K.V., Papadelli, M., Kapolos, I., and Papadimitriou, K. (2022). Applying image-based food-recognition systems on dietary assessment: a systematic review. *Advances in Nutrition*, 13(6): 2590–2619, https://doi.org/10.1093/advances/nmac078

Ferreira, D.D., Ferreira, L.G., Amorim, K.A., Delfino, D.C.T., Ferreira, A.C.B.H., and Souza, L.P.C.E. (2025). Assessing the links between artificial intelligence and precision nutrition. *Current Nutrition Reports*, 14: 47, https://doi.org/10.1007/s13668-025-00635-2

Guasch-Ferré, M., Wittenbecher, C., Palmnäs, M., Ben-Yacov, O., Blaak, E.E., Dahm, C.C., Fall, T., Heitmann, B.L., Licht, T.R., Löf, M., Loos, R., Patel, C.J., Quarta, C., Redman, L.M., Segal, E., Segata, N., Snyder, M., Sun, Q., Tobias, D.K., Hu, F.B., Franks, P.W., Landberg, R., Sargent, J.L., and Merino, J. (2025). Precision nutrition for cardiometabolic diseases. *Nature Medicine*, 31(5): 1444–1453, https://doi.org/10.1038/s41591-025-03669-9

Huey, S.L., Mehta, N.H., Steinhouse, R.S., Jin, Y., Kibbee, M., Kuriyan, R., Finkelstein, J.L., and Mehta, S. (2025). Precision nutrition-based interventions for the management of obesity in children and adolescents up to the age of 19 years. *Cochrane Database of Systematic Reviews*, 2025(1): CD015877, https://doi.org/10.1002/14651858.cd015877

Janssen, S.M., Bouzembrak, Y., and Tekinerdogan, B. (2024). Artificial intelligence in malnutrition: a systematic literature review. *Advances in Nutrition*, 15(9): 100264, https://doi.org/10.1016/j.advnut.2024.100264

Ji, Y., Plourde, H., Bouzo, V., Kilgour, R.D., and Cohen, T.R. (2020). Validity and usability of a smartphone image-based dietary assessment app compared to 3-day food diaries in assessing dietary intake among Canadian adults: randomized controlled trial. *JMIR mHealth and uHealth*, 8(9): e16953, https://doi.org/10.2196/16953

Kasartzian, D.-I. and Tsiampalis, T. (2025). Transforming cardiovascular risk prediction: a review of machine learning and artificial intelligence innovations. *Life*, 15(1): 94, https://doi.org/10.3390/life15010094

Kassem, H., Beevi, A., Basheer, S., Lutfi, G., Cheikh Ismail, L., and Papandreou, D. (2025). Investigation and assessment of AI's role in nutrition – an updated narrative review of the evidence. *Nutrients*, 17(1): 190, https://doi.org/10.3390/nu17010190

Kha, Q.-H., Le, V.-H., Hung, T.N.K., Nguyen, N.T.K., and Le, N.Q.K. (2023). Development and validation of an explainable machine learning-based prediction model for drug–food interactions from chemical structures. *Sensors*, 23(8): 3962, https://doi.org/10.3390/s23083962

Kim, D.W., Park, J.S., Sharma, K., Velazquez, A., Li, L., Ostrominski, J.W., Tran, T., Seitter Peréz, R.H., and Shin, J.-H. (2024). Qualitative evaluation of artificial intelligence-generated weight management diet plans. *Frontiers in Nutrition*, 11: 1374834, https://doi.org/10.3389/fnut.2024.1374834

Konstantakopoulos, F.S., Georga, E.I., and Fotiadis, D.I. (2024). A review of image-based food recognition and volume estimation artificial intelligence systems. *IEEE Reviews in Biomedical Engineering*, 17: 136–152, https://doi.org/10.1109/RBME.2023.3283149

Kooli, C. and Al Muftah, H. (2022). Artificial intelligence in healthcare: a comprehensive review of its ethical concerns. *Technological Sustainability*, 1(2): 121–131, https://doi.org/10.1108/TECHS-12-2021-0029

Kuhl, E. (2025). AI for food: accelerating and democratizing discovery and innovation. *Npj Science of Food*, 9: 82, https://doi.org/10.1038/s41538-025-00441-8

Liang, Y., Xiao, R., Huang, F., Lin, Q., Guo, J., Zeng, W., and Dong, J. (2024). AI nutritionist: intelligent software as the next generation pioneer of precision nutrition. *Computers in Biology and Medicine*, 178: 108711, https://doi.org/10.1016/j.compbiomed.2024.108711

Liu, J., Liu, Z., Liu, C., Sun, H., Li, X., and Yang, Y. (2025). Integrating artificial intelligence in the diagnosis and management of metabolic syndrome: a comprehensive review. *Diabetes/Metabolism Research and Reviews*, 41(4): e70039, https://doi.org/10.1002/dmrr.70039

Marsall, M., Engelmann, G., Teufel, M., and Bäuerle, A. (2023). Exploring the applicability of general dietary recommendations for people affected by obesity. *Nutrients*, 15(7): 1604, https://doi.org/10.3390/nu15071604

Martin, N.M., Poirier, L., Rosenblum, A.J., Reznar, M.M., Gittelsohn, J., and Barnett, D.J. (2022). Enhancing artificial intelligence for twitter-based public discourse on food security during the COVID-19 pandemic. *Disaster Medicine and Public Health Preparedness*, 1–25, https://doi.org/10.1017/dmp.2022.207

Menichetti, G., Barabási, A.-L., and Loscalzo, J. (2024). Decoding the foodome: molecular networks connecting diet and health. *Annual Review of Nutrition*, 44(1): 257–288, https://doi.org/10.1146/annurev-nutr-062322-030557

Menichetti, G., Ravandi, B., Mozaffarian, D., and Barabási, A.-L. (2023). Machine learning prediction of the degree of food processing. *Nature Communications*, 14: 2312, https://doi.org/10.1038/s41467-023-37457-1

Milani, G.P., Silano, M., Mazzocchi, A., Bettocchi, S., De Cosmi, V., and Agostoni, C. (2021). Personalized nutrition approach in pediatrics: a narrative review. *Pediatric Research*, 89(2): 384–388, https://doi.org/10.1038/s41390-020-01291-8

Miyazawa, T., Hiratsuka, Y., Toda, M., Hatakeyama, N., Ozawa, H., Abe, C., Cheng, T.-Y., Matsushima, Y., Miyawaki, Y., Ashida, K., Iimura, J., Tsuda, T., Bushita, H., Tomonobu, K., Ohta, S., Chung, H., Omae, Y., Yamamoto, T., Morinaga, M., Ochi, H., Nakada, H., Otsuka, K., and Miyazawa, T. (2022). Artificial intelligence in food science and nutrition: a narrative review. *Nutrition Reviews*, 80(12): 2288–2300, https://doi.org/10.1093/nutrit/nuac033

Monteiro, C.A., Cannon, G., Levy, R.B., Moubarac, J.-C., Louzada, M.L., Rauber, F., Khandpur, N., Cediel, G., Neri, D., Martinez-Steele, E., Baraldi, L.G., and Jaime, P.C. (2019). Ultra-processed foods: what they are and how to identify them. *Public Health Nutrition*, 22(5): 936–941, https://doi.org/10.1017/s1368980018003762

Mortazavi, B.J. and Gutierrez-Osuna, R. (2021). A review of digital innovations for diet monitoring and precision nutrition. *Journal of Diabetes Science and Technology*, 17(1): 217–223, https://doi.org/10.1177/19322968211041356

Mu, W., Kleter, G.A., Bouzembrak, Y., Dupouy, E., Frewer, L.J., Radwan Al Natour, F.N., and 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, https://doi.org/10.1111/1541-4337.13296

Namkhah, Z., Fatemi, S.F., Mansoori, A., Nosratabadi, S., Ghayour-Mobarhan, M., and Sobhani, S.R. (2023). Advancing sustainability in the food and nutrition system: a review of artificial intelligence applications. *Frontiers in Nutrition*, 10: 1295241, https://doi.org/10.3389/fnut.2023.1295241

Nikolola-Alexieva, V., Valeva, K., and Pashev, S. (2024). Artificial intelligence in the food industry. *BIO Web of Conferences*, 102: 04002, https://doi.org/10.1051/bioconf/202410204002

Ning, Y., Teixayavong, S., Shang, Y., Savulescu, J., Nagaraj, V., Miao, D., Mertens, M., Ting, D.S.W., Ong, J.C.L., Liu, M., Cao, J., Dunn, M., Vaughan, R., Ong, M.E.H., Sung, J.J.-Y., Topol, E.J., and Liu, N. (2024). Generative artificial intelligence and ethical considerations in health care: a scoping review and ethics checklist. *The Lancet Digital Health*, 6(11): e848–e856, https://doi.org/10.1016/S2589-7500(24)00143-2

Ojo, T.F., Akpor, O.A., Talabi, Y.J., and Afolalu, A.S. (2025). AI-powered platforms for interactive nutrition education based on WHO (World Health Organization) guidelines – an overview. *ABUAD Journal of Engineering Research and Development (AJERD)*, 8(1): 161–168, https://doi.org/10.53982/ajerd.2025.0801.17-j

Papastratis, I., Konstantinidis, D., Daras, P., and Dimitropoulos, K. (2024). AI nutrition recommendation using a deep generative model and ChatGPT. *Scientific Reports*, 14: 14620, https://doi.org/10.1038/s41598-024-65438-x

Phalle, A. and Gokhale, D. (2025). Navigating next-gen nutrition care using artificial intelligence-assisted dietary assessment tools – a scoping review of potential applications. *Frontiers in Nutrition*, 12: 1518466, https://doi.org/10.3389/fnut.2025.1518466

Rahmanti, A.R., Yang, H.-C., Bintoro, B.S., Nursetyo, A.A., Muhtar, M.S., Syed-Abdul, S., and Li, Y.-C.J. (2022). SlimMe, a chatbot with artificial empathy for personal weight management: system design and finding. *Frontiers in Nutrition*, 9: 870775, https://doi.org/10.3389/fnut.2022.870775

Raliya, R. (2024). Artificial intelligence for precision and sustainable agricultural. *ACS Agricultural Science & Technology*, 4(6): 628–630, https://doi.org/10.1021/acsagscitech.4c00290

Roy, R., Marakkar, S., Vayalil, M.P., Shahanaz, A., Anil, A.P., Kunnathpeedikayil, S., Rawal, I., Shetty, K., Shameer, Z., Sathees, S., Prasannakumar, A.P., Mathew, O.K., Subramanian, L., Shameer, K., and Yadav, K.K. (2022). Drug-food interactions in the era of molecular big data, machine intelligence, and personalized health. *Recent Advances in Food, Nutrition & Agriculture*, 13(1): 27–50, https://doi.org/10.2174/2212798412666220620104809

Russo, S. and Bonassi, S. (2022). Prospects and pitfalls of machine learning in nutritional epidemiology. *Nutrients*, 14(9): 1705, https://doi.org/10.3390/nu14091705

Saxena, R., Sharma, V., Saxena, A.R., and Patel, A. (2024). Harnessing AI and gut microbiome research for precision health. *Journal of Artificial Intelligence General Science*, 3(1): 74–88, https://doi.org/10.60087/jaigs.v3i1.68

Sharma, R., Nath, P.C., Lodh, B.K., Mukherjee, J., Mahata, N., Gopikrishna, K., Tiwari, O.N., and Bhunia, B. (2024). Rapid and sensitive approaches for detecting food fraud: a review on prospects and challenges. *Food Chemistry*, 454: 139817, https://doi.org/10.1016/j.foodchem.2024.139817

Sharma, S.K. and Gaur, S. (2024). Optimizing nutritional outcomes: the role of AI in personalized diet planning. *International Journal for Research Publication and Seminar*, 15(2): 107–116, https://doi.org/10.36676/jrps.v15.i2.15

Singer, P., Robinson, E., and Raphaeli, O. (2023). The future of artificial intelligence in clinical nutrition. *Current Opinion in Clinical Nutrition and Metabolic Care*, 27(2): 200–206, https://doi.org/10.1097/mco.0000000000000977

Singh, S., Sarma, D.K., Verma, V., Nagpal, R., and Kumar, M. (2023). Unveiling the future of metabolic medicine: omics technologies driving personalized solutions for precision treatment of metabolic disorders. *Biochemical and Biophysical Research Communications*, 682: 1–20, https://doi.org/10.1016/j.bbrc.2023.09.064

Singh, V.K., Hu, X.-H., Singh, A.K., Solanki, M.K., Vijayaraghavan, P., Srivastav, R., Joshi, N.K., Kumari, M., Singh, S.K., Wang, Z., and Kumar, A. (2024). Precision nutrition-based strategy for management of human diseases and healthy aging: current progress and challenges forward. *Frontiers in Nutrition*, 11: 1427608, https://doi.org/10.3389/fnut.2024.1427608

Sosa-Holwerda, A., Park, O.-H., Albracht-Schulte, K., Niraula, S., Thompson, L., and Oldewage-Theron, W. (2024). The role of artificial intelligence in nutrition research: a scoping review. *Nutrients*, 16(13): 2066, https://doi.org/10.3390/nu16132066

Tahir, G.A. and Loo, C.K. (2021). A comprehensive survey of image-based food recognition and volume estimation methods for dietary assessment. *Healthcare*, 9(12): 1676, https://doi.org/10.3390/healthcare9121676

Theodore Armand, T.P., Nfor, K.A., Kim, J.-I., and Kim, H.-C. (2024). Applications of artificial intelligence, machine learning, and deep learning in nutrition: a systematic review. *Nutrients*, 16(7): 1073, https://doi.org/10.3390/nu16071073

Vasiloglou, M.F., Christodoulidis, S., Reber, E., Stathopoulou, T., Lu, Y., Stanga, Z., and Mougiakakou, S. (2020). What healthcare professionals think of "Nutrition & Diet" apps: an international survey. *Nutrients*, 12(8): 2214, https://doi.org/10.3390/nu12082214

Vilne, B., Ķibilds, J., Siksna, I., Lazda, I., Valciņa, O., and Krūmiņa, A. (2022). Could artificial intelligence/machine learning and inclusion of diet-gut microbiome interactions improve disease risk prediction? Case study: coronary artery disease. *Frontiers in Microbiology*, 13: 627892, https://doi.org/10.3389/fmicb.2022.627892

Waheed, A., Ghaffar, M., Mustafa, S., Abbas, A., Khan, S., Waheed, A., and Naz, H. (2024). Nutrigenomics and neurological disorders: exploring diet-brain interactions for cognitive health. *Neurogenetics*, 26(1): 10, https://doi.org/10.1007/s10048-024-00791-7

Wu, X., Oniani, D., Shao, Z., Arciero, P., Sivarajkumar, S., Hilsman, J., Mohr, A.E., Ibe, S., Moharir, M., Li, L.-J., Jain, R., Chen, J., and Wang, Y. (2025). A scoping review of artificial intelligence for precision nutrition. *Advances in Nutrition*, 16(4): 100398, https://doi.org/10.1016/j.advnut.2025.100398

Yang, X., Ho, C.-T., Gao, X., Chen, N., Chen, F., Zhu, Y., and Zhang, X. (2025a). Machine learning: an effective tool for monitoring and ensuring food safety, quality, and nutrition. *Food Chemistry*, 477: 143391, https://doi.org/10.1016/j.foodchem.2025.143391

Yang, Y., An, R., Fang, C., and Ferris, D. (2025b). Artificial intelligence in food bank and pantry services: a systematic review. *Nutrients*, 17(9): 1461.

Yeşilyurt, N., Yılmaz, B., Ağagündüz, D., and Capasso, R. (2022). Microbiome-based personalized nutrition as a result of the 4.0 technological revolution: a mini literature review. *Process Biochemistry*, 121: 257–262, https://doi.org/10.1016/j.procbio.2022.07.012

Zatsu, V., Shine, A.E., Tharakan, J.M., Peter, D., Ranganathan, T.V., Alotaibi, S.S., Mugabi, R., Muhsinah, A.B., Waseem, M., and Nayik, G.A. (2024). Revolutionizing the food industry: the transformative power of artificial intelligence – a review. *Food Chemistry: X*, 24: 101867, https://doi.org/10.1016/j.fochx.2024.101867

Zheng, J., Wang, J., Shen, J., and An, R. (2024). Artificial intelligence applications to measure food and nutrient intakes: scoping review. *Journal of Medical Internet Research*, 26: e54557, https://doi.org/10.2196/54557

Zou, Y., Zhao, L., Zhang, J., Wang, Y., Wu, Y., Ren, H., Wang, T., Zhang, R., Wang, J., Zhao, Y., Qin, C., Xu, H., Li, L., Chai, Z., Cooper, M.E., Tong, N., and Liu, F. (2022). Development and internal validation of machine learning algorithms for end-stage renal disease risk prediction model of people with type 2 diabetes mellitus and diabetic kidney disease. *Renal Failure*, 44(1): 562–570, https://doi.org/10.1080/0886022X.2022.2056053