Research Article

# Role Of Artificial Intelligence In Nutrition: Current Applications And Challenges

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**Abstract**

Artificial Intelligence (AI) is an emerging and rapidly expanding technology in nutrition that holds significant potential to revolutionise the field. AI and its algorithms, is capable of understanding complex interactions, analysing complex data and interpreting images. The key applications of AI in nutrition field are in personalized nutrition and diet planning, dietary intake assessment and monitoring, prevention of malnutrition, disease prevention and management, virtual nutritional guidance, food product development and nutrition research. AI is reshaping the field of nutrition in ways that were unimaginable in the previous era. Through their accuracy and efficiency, wearable devices, and chatbot applications are revolutionizing the nutrition field. However, AI applications are not well known in this field, especially in low- and middle-income countries. AI applications may be adapted and applied in nutrition, but they need to be investigated. Addressing data privacy and bias, ensuring the accuracy of AI algorithms and overcoming ethical concerns are major future challenges. Need of the hour is interdisciplinary collaboration between AI experts and nutritionists for more seamless, effortless and accurate results.

**Keywords:** Artificial Intelligence (AI), Nutrition, Diet planning, Dietary intake, Nutritional guidance.

## Introduction

Nutrition science is the multidisciplinary study of foods, nutrients, and other substances therein, investigating their biochemical and physiological effects on the human body in health, and disease.

Artificial Intelligence (AI) has gained enormous attention in recent years for its capability of analysing vast and complex datasets, recognizing patterns, identifying and interpreting images and generate tailored nutritional recommendations (1,2). AI- powered “digital dietitians” are being developed to provide continuous dietary support, especially when there is limited access to healthcare professionals. AI is also increasingly being used in foods and nutrition as it is being used in almost every field. Hence, it has become necessary to study its scope in this field, future challenges and ethical considerations. The aim of this review is to explore how AI is reshaping the field of nutrition by providing a comprehensive analysis of its various applications. The article also looks for the challenges or constraints in its use.

## Current Applications of AI in Nutrition

Artificial intelligence is increasingly being employed in the field of nutrition and has many applications particularly in personalized nutrition and diet planning, dietary intake assessment, prevention of malnutrition, disease prevention, virtual nutritional guidance, food product development and research. According to Sosa-Holwerda et al. (2024), AI’s role in nutrition is at a developmental stage, focussing mainly on dietary assessment and less on prediction of malnutrition, lifestyle interventions, and diet-related diseases comprehension (3).

## 1.Dietary Intake Assessment and Nutritional Monitoring:

Dietary assessment is one of the most important steps in the nutrition care and the most concerning issue in nutrition research. Multiple traditional dietary assessment tools are used by dietitians, but these methods (for example, 24 hours recall method and food frequency questionnaire) are mostly dependent on memory, where they are subjected to human errors and the process is very tedious. These methods also require a highly experienced and skilled interviewer to enable the collection of useful and reliable data and its analysis. Mahendran et al. (2024) have also pointed out that traditional methods of dietary evaluation mainly rely on self-reported data or structured interviews carried out under the guidance of dietitians and also require significant investment of time (4). On the basis of numerous studies, Mehta et al. (2025) reported that error in measurement, requirement of intensive training, resources, and time burden for personnel and participants were found to be important limitations in self-reported dietary intake using traditional methods (5). Food composition databases for estimating the macro- and micro-nutrient content of diets (calculated using traditional methods) may be limited or were last updated more than 10 years ago, limiting the data on foods such as ultra-processed foods (6). The use of AI in dietary assessment may reduce these problems and address the pressing demand for precise and minimal-effort dietary evaluation (7).

AI is used to assess nutritional intake based on food images, natural language input, or user interaction with digital platforms (8). AI automate tasks such as classification of food images, estimation of portion size, and prediction of nutrient content, enabling more efficient nutritional tracking (9). An example of AI-powered dietary assessment tool is goFOOD$^{TM}$ 2.0, that utilizes computer vision to identfy foods and estimate portion sizes from photographs (10). Snap-n-Eat is also a mobile food recognition system that identifies food items and estimates their nutritional content from smartphone images (11). In another face recognition method, where image analysis was done through an object recognition camera where an image was taken before and after eating and a unique number was given for each meal; after that, an estimation of energy and nutrient composition are accurately calculated through the system (12). EZNutriPal is an interactive diet monitoring system that processes unstructured mobile data, such as speech and free-text, for dietary recording and personalized nutrition tracking (11). There is one more app “Open Fit”, which can estimate and identify energy intake through short videos (13). A smart dining table capable of measuring food weight has been developed to monitor total calorie consumption. Other technologies, such as microphones, piezoelectric sensors, and accelerometers, have been shown to track biting, chewing patterns, and swallowing frequencies, along with arm and wrist motions, to evaluate calorie intake through physical activity (14). Several mobile apps were developed for dietary monitoring. One such app is goFOOD$^{LITE}$ (a new version of goFood $^{TM}$), which is suitable for studying the eating patterns of individuals (15). Natural Language Processing (NLP) plays an increasingly central role in capturing the behavioural dimensions of dietary assessment by analyzing text-based inputs such as food diaries, conversational logs with chatbots, and social media entries. AI is also been used to extract patterns in eating behaviour, detect anomalies (e.g., binge eating, late-night snacking), and assess emotional states which influence food choices (9).

## 2. Personalised Nutrition and Diet Planning

AI is progressively playing an important role in dietary management, where it provides creative approaches for personalized nutrition. Traditionally, dietary recommendations have been generalized, focusing on the requirements of the overall population instead of the individuals’ unique differences in metabolic health, lifestyle, or genetic composition. This generalised approach of meal planning frequently fails to address the individual nutritional requirements and personal health goals where the individuals will face a challenge in adherence to healthy diets in a lifelong manner due to multiple personal and environmental factors that are not addressed in this one-size-fits-all approach (16). Therefore, the use of personalized approaches will enhance adherence to dietary recommendations and improve nutrition-health outcomes (17).

Recent reviews emphasize that a new science called Nutrigenomics forms a scientific foundation for Precision Nutrition by uncovering gene–nutrient interactions and enabling genotype-based dietary interventions. The integration of AI with nutrigenomics is providing more precise, individualized insights into dietary needs and health outcomes (18). Precision nutrition–using individual-level data to predict how a given person may respond to a nutritional intervention, and tailor the intervention for that individual (19). In addition to anthropometric, biochemical, clinical, and dietary data, and socioeconomic, psychosocial and environmental data, other factors that are now possible to measure on a larger scale, include genetic, metabolic, proteomic, or microbiome signatures, which may predict the response to specific nutritional interventions (19 -21). Waheed et al. (2025) discussed how diet–gene interactions are crucial in managing neurological disorders such as Alzheimer's disease and Parkinson's disease (22). Previously, this was not possible without the aid of AI.

The iDietScore meal recommender system provides personalized meal planning for athletes and active individuals through a rule-based expert system. The HeartMan decision support system (DSS) is a mobile-health-based app designed to assist congestive heart failure patients in self-managing their disease through personalized recommendations. (11). ZOE uses advanced ML algorithms together with comprehensive biological data such as gut microbiome composition, postprandial glycaemic responses, and blood lipid profiles to generate individualized dietary recommendations tailored to users' metabolic and physiological responses. It predicts individual responses to different foods in real time and adjusts dietary suggestions accordingly. This holistic and adaptive approach aims to optimize metabolic health and prevent diet-related chronic diseases (23).

## 3. Malnutrition Screening

Malnutrition—defined to include undernutrition and overnutrition, is complex in its aetiology and assessment. The coexistence of both undernutrition and overnutrition or the double-burden of malnutrition, adds further complexity to the development of intervention programs to meet the nutritional needs in these populations (24). According to Hinostroza et al. (2025), AI offers a scalable solution to improve early detection and intervention of malnutrition in regions burdened by undernutrition and limited access to trained healthcare professionals (25). Machine learning algorithms have been used for assessment of nutritional status using easily accessible

parameters such as anthropometric data, dietary intake surveys, and demographic information (14). AI enables early diagnosis and personalized care by integrating various health data (26). These models can process large datasets to identify patterns and risk factors that might be missed through conventional screening methods. One of the methods used for malnutrition screening is MUST-Plus model, which uses electronic health record (EHR) data and machine learning to accurately predict malnutrition risk by analyzing clinical assessments, physiological data, and lab results (27). The convolutional neural network (CNN) algorithm efficiently identifies children at risk of malnutrition and provides personalized intervention recommendations (28).
AI models have shown promising results in predicting malnutrition risks, enabling timely intervention, help bridge inequalities in access to care, reduce the burden on health systems in resource-constrained environments and improve food and nutrition security by supporting evidence-based decisions at national and international levels (29-30). AI tools are increasingly being used to enhance malnutrition screening, optimize resource allocation, and take policy decisions related to public health nutrition (3).

## 4. Nutrition Education

Effective communication skills are essential for nutritionists and dietitians. They should focus on building rapport, demonstrating empathy, employing clinical reasoning, and practicing active listening. Improving these skills enhances patient satisfaction and clinical outcomes. Generative AI has also been explored as a pedagogical tool in nutrition education. Virtual simulated patients (VSPs) offer a new, more accessible approach to communication training in dietetics education (14). A recent study by Chen and Liou (2025) proposed integrating ChatGPT into communication training for dietetics students, demonstrating how AI-generated simulations could enhance students' confidence and reflective learning in counselling scenarios (31). The virtual dialogues offered by ChatGPT helped students practice empathic communication and improve feedback interpretation, with high engagement and positive reception from participants (32). The use of VSPs in health professionals' education is increasing, with evidence indicating that they can enhance both communication skills and clinical reasoning (14). ATLAS (authentic teaching and learning application simulation) is designed to improve communication skills in dietetics education by providing students with authentic learning experiences, multiple attempts, and instant personalized feedback (33).
AI chatbots, like ChatGPT, can provide instant, scientifically supported nutritional advice. These bots are trained on extensive datasets from texts, books, articles, and other online sources. As a result, they can clarify common myths, offer dietary recommendations, and explain complex nutrition topics in real time (34).
Nutrition professionals can use AI to analyze large datasets and provide customized educational content for various groups. This enhances the efficiency of nutrition education and promotes healthier dietary habits (35). According to Liu et al. (2023), AI prediction systems have great potential to create a personalized health education system, help shared decision making, and improve the effectiveness of diabetes nutrition counselling and health education (36).

## 5. AI for Sensory Science and Food Innovation

AI is emerging as a powerful tool in the field of sensory science and food innovation, especially in decoding and designing flavour profiles based on consumer preferences and nutritional needs (37). AI models are increasingly being applied to analyze complex chemical compositions of foods and correlate them with sensory characteristics such as taste, aroma, and texture (38). These systems use large databases of flavour molecules and sensory data to predict how combinations of ingredients will be perceived by consumers. This has direct applications in the development of healthier alternatives that retain desirable sensory characteristics (39).
By analyzing individual responses to different flavours and food textures, AI can support the creation of more appealing and nutritious products tailored to specific populations, such as infants, individuals with reduced taste sensitivity, or patients with dietary restrictions (39,40). These advancements mark a significant shift from traditional sensory analysis to a more data-driven, predictive, and personalized approach to new food products development.

## 6. Disease Prediction and Management

Modern eating habits and industrialization have increased the prevalence of non-communicable diseases like obesity, diabetes, cardiovascular disease, and cancer. At the individual level, traditional, population-based dietary recommendations often fail to reduce chronic diseases. Artificial intelligence is helpful in disease prediction and its prevention within nutrition science. Studies showcase the role of AI to identify patterns associated with disease risk. These machine learning models often incorporate dietary data, lifestyle factors, and health indicators to forecast the likelihood of specific health outcomes (41). According to a review by Sosa- Holwarda et al. (2024), the studies that used machine learning (ML) were mainly focused on prediction in different areas of nutrition, and body weight was one of them (3). A model was developed using 3-year health data record of 55,000 Japanese individuals which predicted body weight changes for the subsequent three years, by also identifying lifestyle behaviours; making it suitable in clinical practice (42). With a data set of 12,130 people in another study, dietary information and some other information like demographic and socioeconomic status, the AI model was able to predict nutritional variables linked to CVD. This CVD risk prediction model is equal or superior to other current tools used for the same purpose (43).

AI's ability to analyze complex information from genetics, the microbiome, and environmental factors enable a personalized, healthy diets that consider individual situations, accurately evaluating the effectiveness of interventions, overcoming data biases. These AI-driven methods include determining dietary risk factors, identifying bioactive compounds that help control sickness, and optimizing nutrition for longevity and well-being (44).

Diet-related metabolic disorders like liver cirrhosis (now known as MASLD previously known as NAFLD) are directly influenced by dietary habits. In the past, alcohol consumption and viral hepatitis were the most common causes of liver cirrhosis; however, a large percentage of cases are currently caused by metabolic dysfunction, which is frequently connected to poor dietary practices (45). Customized dietary therapies have been demonstrated to help reduce the progression of liver disorders and diseases with comparable metabolic foundations (14).

Salinari et al. (2023) showed the potential of AI to improve the treatment of diseases; predict the diseases, care and medication of patients; and monitor patients in real time (46). Several studies have demonstrated the significant potential of AI in optimizing malnutrition screening, body composition monitoring and personalized nutritional interventions for cancer patients (47-48). Kim et al. (2021) focused on the relationship between nutritional intake and the risk of developing overweight/obesity, dyslipidaemia, hypertension, and type 2 diabetes mellitus using AI (49). Bhat and Ansari (2021) were able to create machine learning techniques to predict diabetes and recommend proper diets for diabetic patients. They emphasized the importance of data analysis in healthcare, and were able to present a model for prediction of diabetes and dietary recommendation (50). Reddy et al. (2023) proposed an e-college nurse system focusing on BMI measurements and the early detection of Type-2 diabetes (51).

## 4. AI in Nutrition Practice

Artificial intelligence (AI) is rapidly advancing in healthcare and has the potential to transform practices used in clinical nutrition. It can improve patient outcomes and support healthcare professionals with personalized, evidence-based approaches (1). Patients can use AI techniques like wearable sensors to self-monitor variables (e.g. blood glucose level in diabetic patients), enabling personalized management of nutrition-related issues (30). AI enhances parenteral and enteral nutrition formulas by efficiently adjusting plans to meet individual patient needs and monitoring health to schedule follow-ups for abnormal results (1). AI can predict the likelihood and severity of adverse drug reactions based on factors like circulatory system diseases and parenteral nutrition in critically ill neonates (30).

AI-enabled devices improve dietary assessments by analyzing acoustic signals, jaw movements, and images of eating. Deep learning (DL) allows for rapid muscle mass evaluations through CT imaging, predicts early enteral nutrition needs for ICU patients, and verifies nasogastric tube (NGT) placement with chest X-rays. ML tools assess the risk of refeeding syndrome, while wearable devices monitor hydration and detect infections in patients on home parenteral support (1).

Recently, AI methods were used to guide and optimize total parenteral nutrition (TPN) formulas for infants in the neonatal intensive care unit (NICU) (52). Using information collected routinely in electronic medical records, the AI model "TPN 2.0" identified 15 specific formulas that improved safety, reduced cost, was rated higher by physicians compared to the current practice, and had fewer morbidities such as necrotizing enterocolitis (52).

Microbiota-directed complementary food (MDCF) has showed better results over traditional ready-to-use therapeutic food (RUTF), highlighting the utility of a precision nutrition approach using host gut microbiome as an input variable (53-54).

## 8. Nutrition Research

AI is revolutionizing every area of research by managing complex ideas and extensive information. Its role in research and academic writing is very much impactful (55). Nutrition research seeks to investigate the relationship between health and diet at individual and at the community level. In recent years, nutrition research is increasingly dependent on AI in terms of diagnoses, predictions and data explanation (56). Human cognitive functions are limited in terms of working memory capacity, speed in reading and calculation, and memory loss over time and the information that can be processed, whereas AI operates with minimal limitations (57). Machine learning (ML) utilizes algorithms to perform tasks by processing large datasets, recognizing complex patterns within the data and making predictions at a speed and scale beyond human capacity. AI can help us better understand more complex connections between food and health (58), including the effects of the lack of a healthy diet (46). According to Kassem et al. (2025), compared to traditional statistical methods, ML-based classification offers several benefits, such as reducing misclassification rates, improving generalizability and simplifying experimental procedures (14). AI can handle huge information & large data sets, can do dietary assessment, studying dietary patterns, predicting and evaluating nutrition intervention programmes, etc. AI applications can extract, structure and analyze large amounts of data from social media platforms also to better understand dietary behaviours and perceptions among the population. In summary, AI-based approaches have taken nutrition research to the new heights and are likely to further improve and advance this area.

## Ethical considerations and challenges

While some early chatbot-based experiments and generative language models like ChatGPT have demonstrated the ability to provide basic nutrition information and even personalized diet plans, studies consistently reveal limitations in the accuracy, safety, and contextual relevance of these systems when compared to human professionals (10).

### 1. Data privacy and security in AI-driven nutrition

Managing sensitive health and dietary data remains a big concern in AI-based nutrition systems (9). AI-driven systems rely on personal information like sensitive health information, including electronic health records (EHRs), genetic information, and dietary habits. Although this information is crucial for producing accurate dietary recommendations, it also creates risks related to data breaches and possible misuse. AI tools, such as dietary tracking applications, gather a variety of personal information, ranging from anthropometric measures to psychological health indicators, which raises privacy concerns. According to Detopoulou et al. (2023), about 1.6 million personal records were obtained by Google for AI development without having patient consent (59). Although these systems provide advantages in terms of efficiency, cost savings, and convenience, their reliance on sensitive information necessitates strict ethical oversight (14). To mitigate the risk of misuse and foster user confidence, sophisticated anonymization methods and secure data-sharing practices must be supported by robust accountability mechanisms. As the data is deeply personal in nature, ensuring strong safeguards against data breaches and misuse is very necessary (9).

### 2. Bias and fairness in AI nutrition models

Inherent bias within training data poses a significant challenge to the use of AI, as this bias is frequently transferred to the trained models. Issues like racial and gender biases, along with issues like imbalanced samples or incomplete data, can substantially reduce the effectiveness of AI applications in nutrition (11). According to Agrawal et al. (2025), bias within training datasets and algorithmic design may lead to unequal access and skewed health recommendations, especially for underserved or culturally diverse populations (9). Existing datasets often lack adequate demographic representation, causing biased AI outputs that disproportionately affect marginalized or underrepresented groups (14). Most nutrition-related AI studies originate from high- and upper-middle-income countries, with very few are from lower-middle-income nations (3). As Saraswat et al. (2022) point out, models trained on homogenous or Western-centric data may fail to generalize across diverse socio-economic or ethnic groups (60). Such biases not only undermine the credibility of AI systems but also worsen existing health disparities by neglecting the unique nutritional needs of different populations (14). Integrating culturally varied datasets is crucial for mitigation, ensuring algorithms provide equitable and inclusive recommendations for all populations. The quality and diversity of datasets used to train AI models are critical for ensuring fairness, precision, and reliability of personalized nutritional recommendations (14).

### 3. Reproducibility and Reliability

Reproducibility remains a challenge in using AI. AI models often produce varying results across different platforms or versions due to variations in algorithms, training datasets, or natural language prompts. Standardizing input/output formats and clinical testing frameworks is essential for reliable deployment (61-62).

Ensuring the reliability and precision of AI-generated nutritional advice is a complex task influenced by data integrity, model structure, and the dynamic nature of human health (14). Many AI systems rely on self-reported dietary information, which is prone to inaccuracies such as recall bias, deliberate underreporting, and cultural differences in food classification and consumption. These inaccuracies can undermine the quality of AI-generated recommendations, often leading to less-than-ideal or even inappropriate dietary advice (3, 59). A study evaluating the goFOOD$^{TM}$ system found moderate agreement between image-based dietary estimates & dietitian assessments and the performance was dependent on food type and lighting (63). In their study, Chen et al. (2021) revealed that AI could not identify more than one food item on the plate, which usually does not happen in real-life (64). Another study done to assess the accuracy and safety of dietary advice for users with food allergies through ChatGPT revealed that 4 out of 56 diets provided diets with allergens, no supplementation was suggested with a low vitamin D level diet, provided wrong calculations for portion sizes and followed recommendations from different dietary guidelines (65). A study compareing the results of nutritional guidance provided by different chatbots (including ChatGPT, Bing Chat, and Google Bard) showed inconsistencies in accuracy and reproducibility highlighting their limitations in clinical reliability (66).

## Conclusions

Artificial intelligence (AI) is rapidly transforming the field of nutrition, introducing novel capabilities that were previously unimaginable. Currently, AI is widely utilized for automated dietary assessment and nutritional monitoring, a transition that significantly accelerates data processing. Beyond broad tracking, AI increasingly drives personalized nutrition by factoring in an individual's metabolic health, lifestyle, and unique genetic composition. This technology excels at identifying individuals at risk of malnutrition, providing timely personalized intervention recommendations, optimizing public healthcare resource allocation, and informing policy decisions.

In education, Virtual Simulated Patients (VSPs) assist dietetics students by enhancing their communication and clinical reasoning skills during simulated counselling sessions. Furthermore, AI has emerged as a powerful tool in sensory science and food innovation, decoding consumer preferences to design custom flavour profiles that meet specific nutritional needs. By integrating dietary data, lifestyle factors, and health indicators, AI systems can effectively predict and manage chronic diseases while advancing preventative care. Consequently, its integration into nutrition practice enhances dietetic efficiency, while its application in nutrition research allows scientists to process massive datasets, recognize complex patterns, and make high-speed, large-scale predictions far beyond human capacity. AI is set to make healthcare not only more effective and personalized but also more accessible for everyone.

Despite the vast potential of AI in the field of nutrition, its integration is accompanied by significant challenges. First and foremost is the critical issue of managing the privacy of sensitive personal health information. Second, systemic bias within training datasets frequently transfers directly into the trained models, potentially skewing recommendations. Third, the field faces substantial challenges regarding reproducibility and reliability across different platforms or software versions, driven by variations in underlying algorithms, training datasets, and prompts. Addressing these limitations is essential to safely and effectively harness the power of AI in nutritional science. For the progress of AI in the field of nutrition, interdisciplinary collaboration between AI experts and nutritionists for more seamless, effortless and accurate results is very much required.

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