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Perspectives, challenges and future of artificial intelligence in personalised nutrition research

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Abstract

Personalised nutrition (PN) has emerged as an approach to optimise individual health outcomes through more targeted and tailored dietary recommendations based on unique genetic, phenotypic, medical, lifestyle and contextual factors. The application of artificial intelligence (AI) presents an opportunity to achieve personalised nutrition advice at a scale that has population impact. This review introduces a nutrition audience to different AI applications and offers insights into the concepts of AI that might be relevant to the field of nutrition research. The current and future uses of AI in PN are discussed, as well as the potential benefits and challenges to their application. AI-driven solutions have the potential to improve health and reduce the risk of disease because they can consider more information about an individual in making recommendations. However, challenges such as data interoperability, ethical considerations, and model interpretability remain an issue limiting widespread use at this point. This review will provide a foundational understanding of the application of AI within PN and help to identify opportunities to leverage the potential of AI in transforming dietary guidance and enhancing health outcomes through innovative solutions.

Population dietary advice is designed to provide guidance to improve the health and wellbeing of the general population. Therefore, it does not account for individual differences in genetics, metabolism, lifestyle and circumstance[(1)]. Personalised nutrition (PN) has emerged as an approach to optimise individual health outcomes through more targeted and tailored dietary recommendations based on unique genetic, phenotypic, medical, lifestyle and contextual factors[(2,3)]. This paradigm shift from generalised dietary guidelines to personalised nutritional advice reflects the growing understanding that individual responses to food intake, nutrients bioavailability and dietary patterns can vary significantly[(4,5)]. PN is a field that can leverage human individuality to drive nutrition strategies that prevent, manage, and treat disease and optimise health[(3)]. The significance of PN is its potential to improve health outcomes more effectively than generic, nutrition advice[(2,6)], but the challenge remains to achieve personalised results at a scale that has population impact.

The application of artificial intelligence (AI) has potential to provide preventive healthcare, ease the workloads and burden of healthcare professionals, and provide more accurate diagnosis faster and more easily, which will reduce healthcare costs and improve outcomes for patients[(7)]. As a result, AI is starting to receive significant attention in areas of nutrition and lifestyle behaviour change too[(8)]. AI and machine learning (ML), as subset of the broader category of AI, allow analysis of complex, high-dimensional data sets that are common in nutrition and health behaviour research. ML algorithms, such as support vector machines and tree-based ensembles, have been widely used for different applications to identify patterns and make predictions from large datasets[(9)]. Deep Learning (DL) has achieved state-of-the-art performance in tasks such as image classification, object detection, and segmentation across different imaging modalities[(10)]. They have significantly improved our ability to analyse complex genomic data[(11)] and enabled more comprehensive and accurate predictions in functional genomics. Thus, the importance of AI in addressing complex biological and lifestyle data cannot be overstated. AI techniques can process massive and complex datasets, including genetic, phenotypic, and behavioural data, to generate highly personalised dietary recommendations[(12)]. Its' application allows dietary intake and health behaviour patterns to be uncovered, and individualised nutritional requirements to be determined that may not be apparent through traditional analysis methods.

This review offers insights into the concepts of AI that might be relevant to the field of nutrition research for a non-technical audience to help better understand what kind of AI technology might be most appropriate for certain data and analysis problems. In this review, current and future uses of AI in PN are critically examined, and the potential strengths and challenges discussed, primarily through a technical lens. The challenges faced in research and implementation of AI-driven PN solutions, such as data interoperability, technical AI-related, ethical considerations, and model interpretability are also discussed. It is thought that this

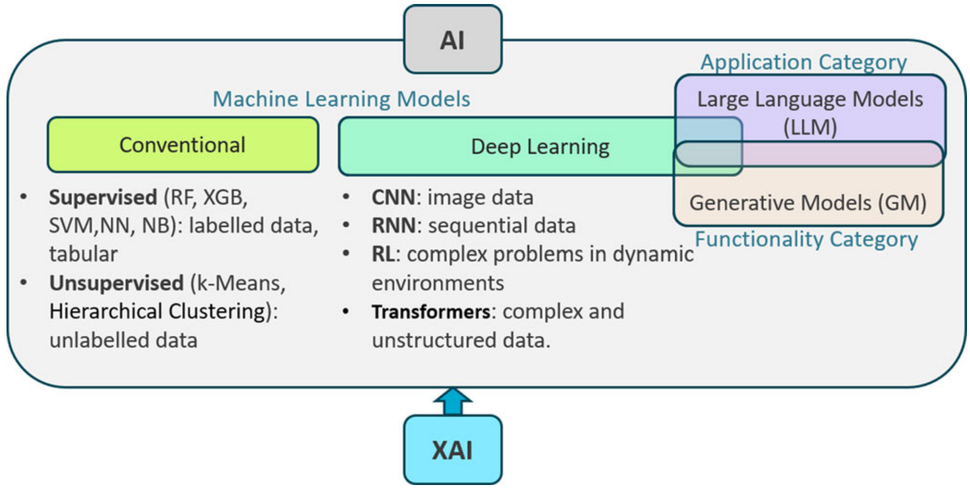

Figure 1. AI models and concepts applied to PN applications. Abbreviations provided in Table 1.

comprehensive review will enable the personalised nutrition (PN) academic community to understand the fundamental concepts and existing challenges to identify opportunities to leverage AI's full potential for transforming dietary guidance and enhancing health outcomes through innovative solutions.

This comprehensive review seeks to help those working in PN to understand the fundamental concepts and existing challenges of using AI in PN and with this foundational understanding, will identify opportunities to leverage AI's full potential for transforming dietary guidance and enhancing health outcomes through innovative solutions. For readers seeking a deeper dive into specific technical aspects such as advanced model architectures, high-dimensional data integration, or ethical frameworks for algorithmic bias there are other appropriate publications (see References[13–16]).

Fundamentals of AI and data for PN applications

Conventional machine learning (ML): supervised and unsupervised

ML is a cornerstone of AI applications in PN, offering well established techniques for analysing complex, well-structured data (see Figure 1).

Supervised learning involves training algorithms on labelled datasets to predict specific outcomes, such as linking dietary intake patterns to metabolic responses or disease risks. Tree-based methods such as XGB or Random Forest, Support Vector Machines, Naïve Bayes, and K-Nearest Neighbors belong to this class of models. This review does not mention linear and logistic regression as they are traditional statistical models used for data analysis and modelling. Tree-based methods proved to be effective in capturing complex patterns[17] yet being less complex and less computationally demanding than advanced Artificial Neural Network (ANN) models for plenty of applications. These models are particularly appealing when dealing with static tabular data to identify patterns between input variables and targeted outcomes, for example, nutrient intake[18], disease prediction[19], or health intervention engagement[20].

Unsupervised learning, in contrast, identifies hidden patterns in unlabelled data. To that end, the algorithm searches for patterns present in the data based on similarities, and groups data that share similar characteristics. This approach has been used in metabolic phenotyping[21], to identify profiles or biomarker signatures of health and disease risks[22], or clustering microbiome samples into groups that share similar microbial compositional patterns[23].

Deep learning

DL is a subset of ML that leverages Artificial Neural Networks (ANN) models – so called Deep Neural Networks (DNN) – to analyse and process data. With the ability to automatically extract and learn features from raw data, deal with complex, high-dimensional, or unstructured data, ANN have great capabilities to identify complex relationships and patterns between inputs data (e.g. genomic, microbiome, medical, lifestyle data, or any other) and targeted outcomes such as nutrient deficiencies, food intolerances, engagement interventions etc. Depending on the data format and application, some model types may be more appropriate than others. Unlike ML, it requires large datasets to train on and better computational resources. Thus, if data is limited traditional ML models are recommended over ANN.

Convolutional Neural Networks (CNN) is a type of DNN which are particularly effective for image analysis and as such have been extensively used for image-based dietary assessments such as identifying food items from photographs[17,20,21,24]. It performs convolution on input data using filters to produce feature maps and extract positional relationships in the image data. CNN can be used to automate food recognition tasks, enhancing the accuracy of dietary intake monitoring.

Recurrent Neural Networks (RNN) is a type of DNN specialised for sequence modelling. It is designed to capture historical information in time series data and is capable of learning order dependence in sequence prediction problems. For instance, to understand the impact of food intake in predicting BMI[25] or to predict the risk of chronic diseases based on dietary habits to inform early warnings for at-risk individuals. Long short-term memory (LSTM) is a type of advanced RNN designed to overcome the so-called *vanishing gradient problem,* the problem when the learning signals (called gradients) become very small as they move through the model. This problem makes it difficult for traditional RNN to learn and retain information from earlier steps in long sequences. LSTM networks use a specialised structure to preserve important information over longer time periods, improving their ability to handle long-term dependencies.

Reinforcement Learning (RL) is suitable for complex problems in dynamic environments for which an optimal solution is unknown, and labelled data is unavailable. In RL, 'learner' which

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Table 1. Table of common abbreviation used in the field of AI and within this review

Abbreviation	Explanation
AI	Artificial Intelligence
ML	Machine Learning
PN	Personalised Nutrition
PH	Precision Health
PH	Precision Health
XGB	Extreme Gradient Boosting
RF	Random Forest
SVM	Support Vector Machines
KNN	K-Nearest Neighbours
NB	Naïve Bayes
ANN	Artificial Neural Network
DNN	Deep Neural Networks
CNN	Convolutional Neural Networks
RNN	Recurrent Neural Networks
LSTM	Long short-term memory
RL	Reinforcement Learning
NLP	Natural Language Processing
LLM	Large Language Models
XAI	eXplainable AI

refers to the AI system or model can act autonomously to reach its goals without the need for constant human guidance, and as such it is called an *agent*. The agent makes choices and does things in the environment to see what works best. Each choice can earn a reward, or a penalty based on a user-defined set of rules. The algorithm then adjusts its future choices to get more rewards and fewer penalties. This allows it to master a task without being told exactly how to do every step.

RL is emerging in PN by enabling systems to adapt dietary recommendations over time based on feedback and evolving health data. These advanced DL techniques allow for dynamic and personalised dietary modelling as well as an opportunity to consider different data as an input – multi modal systems – to capture interactions between diet, genetics, and lifestyle. It is suitable for analysis of big data from different sources to generate adaptive models over time for personalised health recommendations[26–28].

Transformers are a specific type of DL model originally developed for text, that is, natural language processing (NLP) but has successfully expanded to other data and applications. It is based on *self-attention* mechanisms[29], which enable the model to consider the entire context of the input to better understand its meaning. Transformers are suitable for complex and unstructured data of any type - text, images, time series, tabular data or their combination) – so their application is widespread.

Natural language processing

NLP and Large Language Models (LLM), as the most advanced technology in NLP, are instrumental in extracting insights from textual data such as those related to dietary behaviours. NLP algorithms are useful to analyse food diaries, survey responses, and social media content to identify eating habits, preferences, and patterns in words. These insights can be used to customise dietary interventions and understand broader trends in dietary behaviour. NLP also supports sentiment analysis, helping to capture emotional responses to food and dietary changes, or interventions, which is crucial for designing user-friendly and sustainable nutrition programmes[13]. Advanced Large Language Models (LLMs) are mostly built on Transformer ANN architecture due to their ability to analyse the entire context at once. For example, ChatGPT is powered by an LLM in combination with transformers and RL from human feedback. It and similar technologies could be used for PN advice by creating meal plans[30].

Explainable AI (XAI)

Advanced DNN models are quite complex in structure, and therefore often referred to as a 'black box' because its internal decision-making processes are not interpretable or transparent to humans. As AI systems become more complex and influential in providing dietary recommendations, there is a growing need for more transparency and interpretability in their decision-making processes. Also, having limited input from nutritional experts to guide the system to generate safe and accurate recommendations has raised questions about the trustworthiness of the nutritional advice provided by such AI systems[30].

It has been argued that XAI could build greater trust with the healthcare workforce by providing transparency into the AI decision-making process[31]. This would provide insight into contributors that drive an algorithm's decision-making process to generate an output, for example, dietary advice. A greater understanding of key contributing factors in an algorithm's decision process may boost trust in AI-generated outcomes. For instance, XAI can elucidate why a specific nutrient is recommended based on a user's genetic data or explain the relationship between microbiome composition and suggested dietary changes. However, recent studies report the dangers of overreliance and potentially being misled as a result of XAI[32,33], especially if variables are correlated and/or if deployed XAI does not capture casual relationships. Instead, using interpretable models, which are models that trace and comprehend the reasoning mechanisms behind the outcomes, has been recommended for high-stakes decisions[34]. However, interpretable models may be less accurate in handling complex, highly non-linear and/or high-dimensional data, which is a limitation of using these models. In multidisciplinary literature, explainable and interpretable are often used interchangeably. However, one should be aware they have completely different meanings as explained above and should be used appropriately.

The advantage and potential of XAI is its ability to help researchers and practitioners uncover potential biases or inaccuracies in AI models, ensuring that recommendations are both fair and scientifically reliable[27,29]. SHapley Additive exPlanations (SHAP)[35] and Local Interpretable Model-agnostic Explanations (LIME)[36] are the most popular explanation methods applicable to any ML model, and LLM. They show which parts of the input (like words in a sentence or features in data) has the biggest impact on the model's prediction. SHAP does this by fairly assigning credit to each factor that influences a prediction, similar to how rewards might be shared among team members based on their contributions. LIME, on the other hand, simplifies the model's decision just

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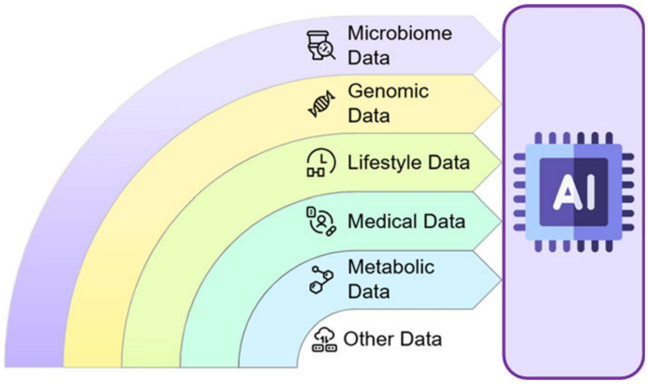

Figure 2. Data for AI-powered holistic PN.

around the example being examined, helping us understand why the model made that specific choice.

There is more literature using SHAP and in nutrition research it is used for explaining predictions and identifying relative importance of nutrition-related factors for different outcomes including mortalities[37,38], cardiovascular diseases[39,40], depression[41,42], feeding intolerances in preterm newborns[43], disengagement in online weight loss applications[20], overweight and obesity[44], glucose monitoring[45,46].

Unlike SHAP and LIME, which are model-agnostic, that is, methods that can be used with any kind of AI model, some XAI algorithms are specifically designed to explain only neural network-based models. Their taxonomy has been reviewed by Ibrahim et al.[47] and Samek et al.[48]. However, there is lack of evaluation of XAI methodologies[49].

Role of Data in AI Models

AI's potential to revolutionise PN lies in its ability to integrate diverse and complex datasets (Figure 2). In the following, the types of data that could be part of a PN framework[50] and the information they contain are described.

Medical Data allows nutrition recommendations to be tailored to an individual's unique health profile. Dietary recommendations could be aligned with an individual's health status, their risk factors and health needs to prevent or manage chronic diseases through more specific dietary strategies.

Genomic data provides insights into individual genetic predispositions, such as sensitivities and intolerances to specific nutrients or responses to treatment options.

Metabolomic data captures real-time snapshots of metabolic activity, offering a detailed understanding of an individual's physiological responses to dietary intake.

Microbiome data sheds light on the gut's role in health and nutrition, highlighting how gut bacteria interact with diet to influence overall well-being.

Lifestyle data, including physical activity, sleep habits, and stress patterns, meal timing and composition can be used to personalise recommendations within the context of their broader lifestyle routine.

Other data, including demographic information and other relevant health and wellbeing data that can be collected via variable devices, mobile and online application may also be informative in modelling complex process and interactions.

By synthesising these data, AI models generate holistic, data-driven insights that guide more precise and PN strategies. This integration is essential for understanding the dynamic interplay of factors influencing dietary behaviour and health, paving the way for innovative and effective interventions in PN.

Current AI applications in personalised nutrition

AI techniques have been applied to different PN applications, which can be broadly grouped into dietary assessment and monitoring, prediction of health outcomes, diet recommendations and microbiome analysis and nutritional genomics.

Dietary assessment and monitoring

Along with recommendation systems, this is the most mature application of AI in PN. Currently there are at least 11 AI-enabled food image recognition apps available from Australia's Apple App and Google Play[51]. They are transforming conventional dietary assessment and monitoring.

Traditional methods of dietary assessment are time consuming, requiring completion of food diaries or surveys. AI-driven solutions, integrated into mobile applications, offer more efficient, real-time alternatives for food recognition and tracking of food intake. The fundamental operating principles of AI-based food segmentation and classification systems for supporting nutrition monitoring are detailed in the work of Freitas et al.[52].

Segmentation performed with CNN is followed by estimation of energy and nutrient intake by combining CNN and NLP[53]. Tahir and Loo provide comprehensive summary of AI methodologies leveraged for automatic image-based food recognition and volume estimation methods for dietary assessment[24]. The authors identified several limitations, including the lack of comprehensive datasets for benchmarking and performance evaluation, which they regard as one of the biggest challenges. Additionally, they highlighted the issue of so-called *open-ended learning* - the inability of models to continuously learn and adapt to new information over time, without forgetting previously learned information. Furthermore, challenges remain in the accurate classification of ingredients in prepared and mixed food items.

Mobile apps integrated with AI algorithms enable users to scan food items, automatically recognise ingredients, and calculate nutritional values. Image analysis, another promising tool, utilises computer vision to identify food items from photographs, helping users track meals without manual input. Current accuracy is relatively high in identifying pre-categorised foods (87 % or more), however further improvements especially related to diversity of foods, mixed and culturally varied dishes[51] would support more widespread use of such tools in PN.

Initial steps towards fully automated food monitoring have been made by leveraging advanced AI models. LSTM-based system for food consumption identification to improve diabetes management, utilising dynamic temporal data representing full-day record of wrist movement, has demonstrated great performance[54]. This approach enables automatic meal detection and reduces reliance on patient's input, however, has constraints in relation to diabetes management due to the artificial pancreas systems – delayed insulin action and the need for pre-meal administration.

Lastly, engagement with digital tools is key to achieving successful behaviour change and improvements in digital health interventions. Although technology is increasingly utilised in health interventions, a notable challenge continues to be the decline in user engagement and non-use attrition[55]. ML-algorithms have been shown to be effective in predicting and

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explaining factors leading to disengagement, paving the way for improved and more supported delivery of personalised weight loss programmes or other personalised digital interventions reliant on engagement[20].

Personalised diet recommendations

Leveraging AI, in particular DNN models and large datasets, to generate tailored meal plans based on individual profiles has significantly increased[56]. Different data sources are exploited and combined with traditional surveys and questionnaires. These include data collected via wearable devices such as watches and activity trackers, demographics and personal data, preferences and motivation, health and clinical data (e.g. insulin levels), microbiota and genetic data. Physiological data is used most while use of genetics and microbiota data is less common. Data can be analysed with the range of AI technologies discussed in Section 2. However, an approach integrating all data relevant to generate personalised advice is still unavailable. Tsolakidis et al.[56] provided an overview of advancements in data-driven technologies for personalised nutrition, focusing on data collection methods employed in modern -ML technologies and their challenges.

Prediction models for health outcomes

AI predictive models, in particular those suitable for modelling time sequences, are promising for the prevention of chronic disease such as CVD, diabetes, and obesity due to their ability to analyse complex temporal data, capability to capture temporal relationships and identify correlations and patterns. AI-powered prediction models can estimate the likelihood of developing specific health conditions, enabling early intervention strategies and personalised dietary recommendations.

For instance, a person with pre-diabetes can receive AI-driven dietary recommendations obtained based on their health, dietary, lifestyle and genetic data which could help to avoid progression to Type 2 diabetes. Another example is leveraging AI models to predict how certain foods or nutrients may interact with a person's unique microbiome or identifying genetic predispositions to nutrient deficiencies or sensitivities that would allow for personalised dietary interventions to optimise gut health. Some initial steps have been made for the later example with two studies developing recommender system based on individuals' genetic data[57,58].

Few studies have deployed complex models or time series data in PN[21,59], and no studies have explored multimodal predictive models for chronic disease or other health outcomes directly related to PN. Combining diverse data sources, for example, clinical data, nutrition intake, health data, genetic or microbiome, has potential to improve the precision and effectiveness of health predictions with AI technologies but there is limited evidence of its application in PN at present.

Benefits and advantages of AI integration

AI integration in PN offers numerous benefits and advantages that significantly enhance the effectiveness and reach of dietary interventions. They can be broadly grouped into three main categories: (i) *scalability and accuracy*, (ii) *personalisation* and (iii) *dynamic and adaptiveness*.

(i) Scalability and accuracy

The era of 'big data' means that information can come from multiple sources such as wearable devices, mobile apps, websites, online journals, electronic medical reports, wearable devices. AI systems have capability to process vast amounts of complex data rapidly and precisely[60], enabling efficient analysis of large datasets and provision of real-time feedback. This capability allows for scalable nutrition solutions that can reach a wide population[61]. AI-driven tools, such as mobile applications and wearable devices equipped with conventional and DL algorithms, can provide dietary recommendations, enable real-time accurate nutrient estimation, monitor intake in real-time and personalised nutrition plans, making personalised nutrition accessible to users across different regions and socioeconomic backgrounds[62]. Leveraging ML enables predictive analytics for early intervention and better support[20]. A scoping review[63] has outlined the advantages of AI in improving accuracy of dietary assessment using a DL. ML and DL solutions are already part of various commercial programmes and apps for weight loss.

(ii) Personalisation

One of the benefits of integrating AI into PN research is its ability to enhance precision in identifying individual dietary needs. Unlike traditional methods that rely on generalised dietary guidelines[1], AI algorithms can analyse complex datasets to account for individual variation related to phenotype, genotype, lifestyle behaviour (diet, activity, etc.), goals, and preferences[64] to create tailored nutritional strategies. The ability of AI to harness large, multidimensional datasets provides an opportunity to improve the accuracy of identifying individual dietary needs and tailoring intervention accordingly.

ML models excel at recognising subtle patterns in these data, enabling the identification of specific dietary components that align with an individual's unique health requirements and goals. For instance, AI can predict how a person might be engaged during a weight loss programme[20], respond to certain foods based on their genetic predispositions or gut microbiome[8,65–67], reducing the trial-and-error approach often associated with dietary guidance. By leveraging this level of precision, AI ensures that dietary recommendations are more accurate and possibly also more effective in preventing disease, optimising health outcomes, and improving overall quality of life.

(iii) Dynamic and adaptiveness

Improved patient-provider communication can be made through the real-time monitoring and evaluation of patient progress via apps[68]. One of the key advantages of AI in PN is its ability to generate recommendations based on longitudinal data. Unlike traditional periodic dietary assessments that rely on self-reporting, AI models offer real-time monitoring capabilities[61], providing timely feedback and intervention. Adaptive nature allows for dynamic guidance[20], where recommendations are continuously refined as users log their behaviours such as their meals and snacks, exercise routines, and health metrics. Such real-time adjustment ensures that dietary advice remains relevant and effective, adapting to changes in the user's health status, activity levels, or even seasonal variations in food availability. By leveraging AI's capabilities in data analysis, real-time feedback, and adaptive learning, PN strategies can be more effectively implemented, potentially leading to better adherence to dietary guidelines and

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improved health outcomes. Longitudinal studies powered by AI provide an opportunity to reveal long-term effects of certain dietary patterns for instance the risk of chronic diseases based on dietary habits using RNN, unlike current approaches that consider only one time point[69].

Challenges and limitations

Data-related challenges

Data-related challenges play a key role in driving data-driven innovation within the field of PN[56]. To that end one of the main technical challenges in integrating AI into PN research is data heterogeneity and lack of interoperability among various data sources. PN relies on different and complementary data[50,64], each with its own format, structure, and collection methods. There is a lack of interoperable infrastructure and data standardisation that would enable data access and data harmonisation[70], which is a key challenge for developing effective multimodal AI systems. Moreover, differences in data standards, tools, and platforms across healthcare systems complicate the seamless exchange and analysis of information, limiting the potential for broader applications and scaling of PN interventions. Overcoming these challenges requires standardised protocols, improved data-sharing frameworks, and better tools for data integration.

AI-related challenges

Transparency and Trust: AI models, particularly DL algorithms, have the biggest potential in terms of their application in PN but at the same time are considered 'black boxes', meaning their decision-making processes are not interpretable by humans. The lack of transparency reduces their trustworthiness[71]. As a result, healthcare professionals may be hesitant to adopt AI technologies due to a lack of familiarity with AI tools, concerns about the reliability of AI-driven recommendations, or scepticism about the technology's clinical validity. This poses a significant challenge in PN, where understanding the rationale behind AI-generated decisions and recommendations is critical for uptake by healthcare professionals and patients. Different explainable AI (XAI) methods are introduced to mitigate this problem. Though explainability and interpretability are often used interchangeably, they refer to distinct concepts and should be used carefully. Interpretability refers to the intrinsic transparency of a model's internal structure, permitting direct inspection of how inputs mathematically or logically generate outputs. Explainability encompasses post hoc techniques, that is, methods applied after model training, applied to any model (including 'black boxes') to generate human-understandable rationales behind the model outputs. However, explanations obtained from different XAI methods are frequently non-identical and as such less trustworthy to guide clinical decision making[33]. They can be useful and provide insight into key factors that drive algorithms, but not the whole decision-making process. To be more trustworthy, explanations should be able to capture causality, context and match reality[33], however this still remains a challenge in the application of AI. These reasons are in support of the view that current XAI approaches will induce trust with the health-care workforce represent a false hope[31], though they may be very useful especially for system audit and troubleshooting[31,33]. As an alternative, redirecting focus from XAI to interpretable AI has been suggested[34].

Fairness: Lack of model opacity can complicate the identification of systematic errors or biases in the models. The *Fairlearn* package[72] and Fairness Indicators TensorFlow tool kit[72] can help in assessing models and mitigating unfairness.

Over-reliance: When it comes to AI use in applications, there is risk of over-reliance on AI[73]. Some studies have already reported how over-reliance on AI dialogue systems affects critical cognitive capabilities, including decision-making, critical thinking, and analytical reasoning of clinicians[74]. Educating on AI limitations, using AI only as an adjunct and domain expertise to judge and evaluate AI systems can prevent risks associated with over reliance while maximising the benefits of its application.

Generalisation: State-of-the-art models lack strong empirical evidence supporting model performance across diverse and heterogeneous datasets. This limitation raises concerns about the generalisability and reliability of AI-driven dietary advice, particularly for underrepresented populations. High-quality datasets and rigorous validation are essential for ensuring AI systems provide equitable, effective, and trustworthy personalised nutrition guidance.

Data privacy and security

AI models in PN may require access to sensitive health data, such as genetic information, personal health history, and real-time biometric measurements. This raises significant concerns about data privacy and security. Unauthorised access, breaches, or misuse of health data can lead to identity theft, discrimination, or other adverse consequences[75]. Moreover, ethical and legal risks due to gaps and inconsistencies in legal protection, remain a concern[76]. It is crucial to establish robust data protection measures, implement strong encryption methods, and ensure that AI models comply with privacy regulations such as the General Data Protection Regulation[77] and Health Insurance Portability and Accountability Act[78] to safeguard personal health information.

Future directions

Advancements in AI techniques

Future advancements in AI and the application of more sophisticated approaches show promise in advancing PN research.

Federated learning offers a way to train AI models across decentralised datasets, preserving individual privacy while leveraging diverse and extensive data sources. This approach is particularly relevant in healthcare, where sensitive data often cannot be centralised.

Explainable AI (XAI) is another critical development, aiming to make AI models more transparent and interpretable. By providing insights into how decisions are made, XAI will increase the level of trust healthcare professionals and individuals have in the technology, making personalised nutrition interventions more acceptable. Currently, they uptake in PN applications has been limited.

Additionally, *multimodal models* are gaining prominence for their ability to integrate various types of data – such as genomic, dietary, and lifestyle data – into a unified framework. These advancements will allow AI to generate more accurate, personalised, and actionable dietary recommendations.

Wholistic approach

A more holistic approach to AI in PN is essential to address the interconnected nature of human health. Integrating data from different sources can offer greater insights, supporting personalised dietary recommendations that promote overall health and wellbeing while also considering disease risk stratification and prevention. For instance, models that integrate data on stress, sleep, and physical activity alongside nutrition can provide a better picture of an individual's health and wellbeing. This information would enable interventions to address causes rather than symptoms.

Interdisciplinary collaboration

The future of AI-driven PN relies heavily on interdisciplinary collaboration. Nutritionists, AI researchers, and policymakers should work together to develop practical, ethical, and scalable solutions. Nutritionists provide domain expertise to guide AI model development and ensure recommendations are evidence-based and clinically relevant. AI researchers bring technical expertise to design robust and innovative models, and under the risk associated with the application of different approaches, while policymakers play a crucial role in setting regulations that protect data privacy and promote equitable access. Collaborative efforts between stakeholders will ensure that AI-driven personalised nutrition benefits a broader population while maintaining ethical integrity. On that note, future advancements in AI, particularly in DL, are expected to enhance PN research. These technologies may allow better data analysis of large volume multimodal data and hence lead to more accurate predictions and more effective personalised health recommendations[79] being delivered at scale.

Integration with emerging technologies

The integration of AI with emerging technologies will enhance its effectiveness and accessibility in PN. Wearable sensors and Internet of Things devices are already transforming how health data is collected, offering real-time insights into physical activity, heart rate, and caloric expenditure. Modern continuous glucose monitors, which track blood sugar levels in real time[80] and wearable devices, provide invaluable data for dietary management, particularly for individuals with conditions like diabetes. But it is possible for their application to target the promotion of health and wellbeing as well as the prevention of disease progression. Already there are number of recommendation systems that combine data from wearable devices and AI to generate adaptive personalised dietary recommendations[56], but broadening the data sources available will support greater personalisation and tailoring to improve an individual's overall health.

Conclusion

This review has described different AI applications and offered insights into the concepts of AI that might be relevant to the field of nutrition research. The potential of AI to support large-scale, personalised and possibly more effective, dietary advice is significant. However, as with any emerging technology, it is critical to understand the science and consider the challenges associated with the application of such technology to a new area of research – such as personalised nutrition. AI-driven solutions consider more information about an individual in making recommendations, so they have the potential to improve health and reduce the risk of disease. However, challenges such as data access, data interoperability, ethical considerations, model reliability, generalisation and interpretability remain an issue limiting widespread use at this point. The application of AI in nutrition remains an emerging area of science, but there are great opportunities to leverage the potential of AI in transforming dietary guidance and enhancing health outcomes.

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References

1. Ge L, Sadeghirad B, Ball GDC, *et al.* (2020) Comparison of dietary macronutrient patterns of 14 popular named dietary programmes for weight and cardiovascular risk factor reduction in adults: systematic review and network meta-analysis of randomised trials. *BMJ* **369**, m696.
2. Cross V, Stanford J, Gómez-Martín M, *et al.* (2024) Do personalized nutrition interventions improve dietary intake and risk factors in adults with elevated cardiovascular disease risk factors? A systematic review and meta-analysis of randomized controlled trials. *Nutr Rev* **83**, e1709–e1721.
3. Bush CL, Blumberg JB, El-Sohemy A, *et al.* (2020) Toward the definition of personalized nutrition: a proposal by the American Nutrition Association. *J Am Coll Nutr* **39**, 5–15.
4. Verma M, Hontecillas R, Tubau-Juni N, *et al.* (2018) Challenges in personalized nutrition and health. *Front Nutr* **5**, 117.
5. de Hoogh IM, Reinders MJ, Doets EL, *et al.* (2023) Design issues in personalized nutrition advice systems. *J Med Int Res* **25**, e37667.
6. Celis-Morales C, Livingstone KM, Marsaux CF, *et al.* (2017) Effect of personalized nutrition on health-related behaviour change: evidence from the Food4Me European randomized controlled trial. *Int J Epidemiol* **46**, 578–588.
7. Väänänen A, Haataja K, Vehviläinen-Julkunen K, *et al.* (2021) AI in healthcare: a narrative review. *F1000Research* **10**, 6.
8. Miyazawa T, Hiratsuka Y, Toda M, *et al.* (2022) Artificial intelligence in food science and nutrition: a narrative review. *Nutr Rev* **80**, 2288–2300.
9. Jiang F, Jiang Y, Zhi H, *et al.* (2017) Artificial intelligence in healthcare: past, present and future. *Stroke Vasc Neurol* **2**, 230–243.
10. Zhou SK, Greenspan H, Davatzikos C, *et al.* (2021) A review of deep learning in medical imaging: imaging traits, technology trends, case studies with progress highlights, and future promises. *Proc IEE Inst Electr Electron Eng* **109**, 820–838.
11. Zhang YZ & Imoto S (2024) Genome analysis through image processing with deep learning models. *J Hum Genet* **69**, 519–525.
12. Ngugi Mwaura J (2024) The role of artificial intelligence in personalized nutrition. *Res Inven J Public Health Pharm* **3**, 22–25. https://doi.org/10.59298/RIJPP/2024/322225.
13. Hassanien AE & Soliman M (2023) *Artificial Intelligence: A Real Opportunity in the Food Industry*. Cham: Springer.
14. Russell SJ & Norvig P (2016) Artificial Intelligence: A Modern Approach, 3rd ed, Global edition. Harlow, UK: Pearson. p. 1. (Prentice Hall Series in Artificial Intelligence).
15. Mainzer K (2024) Limits of AI – Theoretical, Practical, Ethical, 1st ed. Berlin, Heidelberg: Springer. (Technik im Fokus).
16. Mukherjee A (2024) Ethics in Artificial Intelligence, 1st ed. Singapore: Springer Singapore Pte. Limited. (Studies in Computational Intelligence Series; v.1123).
17. Uddin S & Lu H (2024) Confirming the statistically significant superiority of tree-based machine learning algorithms over their counterparts for tabular data. *PLoS One* **19**, e0301541.
18. Kirk D, Catal C & Tekinerdogan B (2022) Predicting plasma vitamin C using machine learning. *Appl Artif Intell* **36**, 2042924.
19. Zou Q, Qu K, Luo Y, *et al.* (2018) Predicting diabetes mellitus with machine learning techniques. *Front Genet* **9**, 515.

20. Brankovic A, Hendrie GA, Baird DL, *et al.* (2023) Predicting disengagement to better support outcomes in a web-based weight loss program using machine learning models: cross-sectional study. *J Med Internet Res* **25**, e43633.
21. Kirk D, Catal C & Tekinerdogan B (2021) Precision nutrition: a systematic literature review. *Comput Biol Med* **133**, 104365.
22. Shomorony I, Cirulli ET, Huang L, *et al.* (2020) An unsupervised learning approach to identify novel signatures of health and disease from multimodal data. *Genome Med* **12**, 7.
23. Subedi S, Neish D, Bak S, *et al.* (2020) Cluster analysis of microbiome data by using mixtures of Dirichlet–multinomial regression models. *J Royal Stat Soc Ser C: Appl Stat* **69**, 1163–1187.
24. Tahir GA & Loo CK (2021) A comprehensive survey of image-based food recognition and volume estimation methods for dietary assessment. *Healthcare* **9**, 1676.
25. Cunha C, Duarte P & Oliveira R (2023) Nutrition control system based on short-term personal demands. *Proc Comput Sci* **224**, 565–571.
26. Mulani J, Heda S, Tumdi K, *et al.* (2020) Deep reinforcement learning based personalized health recommendations. In *Deep Learning Techniques for Biomedical and Health Informatics*, pp. 231–255 [B Agarwal, BR Acharya, M Mittal, A Abraham, Á Kelemen, editors]. Cham, Switzerland: Springer International Publishing.
27. Straková S (2023) User-Based Tailoring with Reinforcement Learning for an mHealth, COPD-focused Intervention for Increasing Physical Activity. University of Twente, Enschede.
28. Forman EM, Kerrigan SG, Butryn ML, *et al.* (2019) Can the artificial intelligence technique of reinforcement learning use continuously-monitored digital data to optimize treatment for weight loss? *J Behav Med* **42**, 276–290.
29. Vaswani A, Shazeer N, Parmar N, *et al.* (2017) Attention is all you need. *Adv Neural Inf Process Syst* **30**, 5998–6008.
30. Papastratis I, Konstantinidis D, Daras P, *et al.* (2024) AI nutrition recommendation using a deep generative model and ChatGPT. *Sci Rep* **14**, 14620.
31. Ghassemi M, Oakden-Rayner L & Beam AL (2021) The false hope of current approaches to explainable artificial intelligence in health care. *Lancet Digital Health* **3**, e745–50.
32. Cabitza F, Fregosi C, Campagner A, *et al.* (2024) Explanations considered harmful: the impact of misleading explanations on accuracy in hybrid human-AI decision making. In *Explainable Artificial Intelligence*, pp. 255–269 [L Longo, S Lapuschkin, C Seifert, editors]. Cham: Springer Nature Switzerland.
33. Brankovic A, Cook D, Rahman J, *et al.* (2024) Benchmarking the most popular XAI used for explaining clinical predictive models: untrustworthy but could be useful. *Health Inf J* **30**, 14604582241304730.
34. Rudin C (2019) Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nat Mach Intell* **1**, 206–215.
35. Lundberg SM & Lee SI (2017) A unified approach to interpreting model predictions. *Adv Neural Inf Process Syst* **30**, 4765–4774.
36. Caruana R, Lou Y, Gehrke J, *et al.* (2015) Intelligible models for healthcare: Predicting pneumonia risk, hospital 30-day readmission. In Proceedings of the 21th ACM SIGKDD international conference on knowledge discovery, data mining 10 August 2015 (pp. 1721–1730).
37. Park DJ, Baik SM, Lee H, *et al.* (2024) Impact of nutrition-related laboratory tests on mortality of patients who are critically ill using artificial intelligence: a focus on trace elements, vitamins, and cholesterol. *Nutr Clin Pract* **6**, 1423759.
38. Martin-Morales A, Yamamoto M, Inoue M, *et al.* (2023) Predicting cardiovascular disease mortality: leveraging machine learning for comprehensive assessment of health and nutrition variables. *Nutrients* **15**, 3937.
39. Turnbull N, Nghiep LK, Butsorn A, *et al.* (2024) Machine learning models identify micronutrient intake as predictors of undiagnosed hypertension among rural community-dwelling older adults in Thailand: a cross-sectional study. *Front Nutr* **11**, 1411363.
40. Wang YX, Kang JQ, Chen ZG, *et al.* (2025) Machine learning analysis of nutrient associations with peripheral arterial disease: insights from NHANES 1999–2004. *Ann Vasc Surg* **114**, 154–162.
41. Hosseinzadeh Kasani P, Lee JE, Park C, *et al.* (2023) Evaluation of nutritional status and clinical depression classification using an explainable machine learning method. *Front Nutr* **10**, 1165854.
42. Huang AA & Huang SY (2023) Exploring depression and nutritional covariates amongst US adults using shapely additive explanations. *Health Sci Rep* **6**, e1635.
43. Xu H, Peng X, Peng Z, *et al.* (2024) Construction and SHAP interpretability analysis of a risk prediction model for feeding intolerance in preterm newborns based on machine learning. *BMC Med Inf Decis Making* **24**, 342.
44. Sun Z, Yuan Y, Farrahi V, *et al.* (2024) Using interpretable machine learning methods to identify the relative importance of lifestyle factors for overweight and obesity in adults: pooled evidence from CHNS and NHANES. *BMC Public Health* **24**, 3034.
45. Zignoli A, Skroce K, Lipman DJ, *et al.* (2024) Personalized nutrition and machine-learning: exploring the scope of continuous glucose monitoring in healthy individuals in uncontrolled settings. *Biomed Signal Process Control* **90**, 105809.
46. Cao S & Hu Y (2024) Interpretable machine learning framework to predict gout associated with dietary fiber and triglyceride-glucose index. *Nutr Metab* **21**, 25.
47. Ibrahim R & Shafiq MO (2023) Explainable convolutional neural networks: a taxonomy, review, and future directions. *ACM Comput Surv* **55**, 206: 1–206:37.
48. Samek W, Montavon G, Lapuschkin S, *et al.* (2021) Explaining deep neural networks and beyond: a review of methods and applications. *Proc Inst Electr Electron Eng (IEEE)* **109**, 247–278.
49. Caterson J, Lewin A & Williamson E (2024) The application of explainable artificial intelligence (XAI) in electronic health record research: a scoping review. *Digital Health* **10**, 20552076241272657.
50. Özdemir V & Kolker E (2016) Precision Nutrition 4.0: a Big Data and Ethics Foresight Analysis—convergence of agrigenomics, nutrigenomics, nutriproteomics, and nutrimetabolomics. *OMICS: J Integr Biol* **20**, 69–75.
51. Li X, Yin A, Choi HY, *et al.* (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**, 2573.
52. Freitas CNC, Cordeiro FR & Macario V (2020) MyFood: A Food Segmentation and Classification System to Aid Nutritional Monitoring. In IEEE Computer Society. pp. 234–239. https://www.computer.org/csdl/proceedings-article/sibgrapi/2020/927400a234/1p2VAgQOsmc (accessed 21 January 2025).
53. Ruede R, Heusser V, Frank L, *et al.* (2021) Multi-task learning for calorie prediction on a novel large-scale recipe dataset enriched with nutritional information. In 2020 25th International Conference on Pattern Recognition (ICPR) 10 January 2021 (pp. 4001–4008). IEEE.
54. Dénes-Fazakas L, Simon B, Hartvég Á, *et al.* (2024) Personalized food consumption detection with deep learning and Inertial Measurement Unit sensor. *Computers Biology Med* **182**, 109167.
55. Eysenbach G (2005) The law of attrition. *J Med Internet Res* **7**, e402.
56. Tsolakidis D, Gymnopoulos LP & Dimitropoulos K (2024) Artificial intelligence and machine learning technologies for personalized nutrition: a review. *Informatics* **11**, 62.
57. Chen CH & Toumazou C (2019) Chapter 12 – Personalized expert recommendation systems for optimized nutrition. In *Trends in Personalized Nutrition* [Internet], pp. 309–338. [CM Galanakis, editor]. London: Academic Press.
58. Chen CH, Karvela M, Sohbati M, *et al.* (2018) PERSON—Personalized Expert Recommendation System for Optimized Nutrition. *IEE Trans Biomed Circuits Syst* **12**, 151–160.
59. Theodore Armand TP, Nfor KA, Kim JI, *et al.* (2024) Applications of artificial intelligence, machine learning, and deep learning in nutrition: a systematic review. *Nutrients* **16**, 1073.
60. Bajaj P & Lata K (2024) Artificial Intelligence and Chrononutrition: A Review Study on Role of AI in Revolutionizing Dietary Recommendations. In: 2024 11th International Conference on Computing for Sustainable Global Development (INDIACom) [Internet]. p. 548–552. https://ieeexplore.ieee.org/abstract/document/10498718 (accessed 9 January 2025).

https://doi.org/10.1017/S0029665125100657 Published online by Cambridge University Press

61. Zheng J, Wang J, Shen J, *et al.* (2024) Artificial intelligence applications to measure food and nutrient intakes: scoping review. *J Med Internet Res* **26**, e54557.
62. Abdallah S, Godwins OP & Ijiga AC (2024) AI-powered nutritional strategies: analyzing the impact of deep learning on dietary improvements in South Africa, India, and the United States. *Magna Sci Adv Res Rev* **11**, 320–345.
63. Zheng J, Wang J, Shen J, *et al.* (2024) Artificial intelligence applications to measure food and nutrient intakes: scoping review. *J Med Internet Res* **26**, e54557.
64. Adams SH, Anthony JC, Carvajal R, *et al.* (2020) Perspective: guiding principles for the implementation of personalized nutrition approaches that benefit health and function. *Adv Nutr* **11**, 25–34.
65. Zeevi D, Korem T, Zmora N, *et al.* (2015) Personalized nutrition by prediction of glycemic responses. *Cell* **163**, 1079–1094.
66. Shima H, Masuda S, Date Y, *et al.* (2017) Exploring the impact of food on the gut ecosystem based on the combination of machine learning and network visualization. *Nutrients* **9**, 1307.
67. Carpio LE, Sanz Y, Gozalbes R, *et al.* (2021) Computational strategies for the discovery of biological functions of health foods, nutraceuticals and cosmeceuticals: a review. *Mol Divers* **25**, 1425–1423s8.
68. Chen J, Gemming L, Hanning R, *et al.* (2018) Smartphone apps and the nutrition care process: current perspectives and future considerations. *Patient Educ Couns* **101**, 750–757.
69. Maurya A, Wable R, Shinde R, *et al.* (2019) Chronic kidney disease prediction, recommendation of suitable diet plan by using machine learning. In 2019 International Conference on Nascent Technologies in Engineering (ICNTE) 04 January 2019 (pp. 1–4). IEEE.
70. Cabitza F & Campagner A (2021) The need to separate the wheat from the chaff in medical informatics: introducing a comprehensive checklist for the (self)-assessment of medical AI studies. *Int J Med Inf* **153**, 104510.
71. Vayena E, Blasimme A & Cohen IG (2018) Machine learning in medicine: addressing ethical challenges. *PLoS Med* **15**, e1002689.
72. Weerts H, Dudík M, Edgar R, *et al.* (2023) Fairlearn: assessing and improving fairness of AI systems. *J Mach Learn Res* **24**, 1–8.l.
73. Kostick-Quenet KM & Gerke S (2022) AI in the hands of imperfect users. *NPJ Digit Med* **5**, 197.
74. Zhai C, Wibowo S & Li LD (2024) The effects of over-reliance on AI dialogue systems on students' cognitive abilities: a systematic review. *Smart Learn Environ* **11**, 28.
75. Choi SJ, Johnson ME & Lehmann CU (2019) Data breach remediation efforts and their implications for hospital quality. *Health Serv Res* **54**, 971–980.
76. Gostin LO, Halabi SF & Wilson K (2018) Health data and privacy in the digital era. *JAMA* **320**, 233–234.
77. Regulation P (2018) General data protection regulation. *Intouch* **25**, 1–5.
78. Act A (1996) Health insurance portability and accountability act of 1996. *Public Law* **104**, 191.
79. Mustapha A, Mustapha M, Mustapha S Harnessing Artificial Intelligence in Personalised Nutrition and Microbial Health: Optimising Public Health Outcomes. http://capdr.org/wp-content/uploads/2024/12/49.-Aishatu-Mustapha-et-al.pdf
80. Reddy N, Verma N & Dungan K (2023) Monitoring technologies-continuous glucose monitoring, mobile technology, biomarkers of glycemic control. In *Endotext* [Internet], [KR Feingold, MR Blackman, editors]. South Dartmouth, MA: MDText.com, Inc.

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