Journal of Holistic and Scientific Studies

Article journey
Received
12/06/2026
Revised
13/07/2026
Accepted
20/07/2026
Published
27/07/2026

Artificial Intelligence-Assisted Personalized Nutrition A Holistic Framework Linking Dietary Behaviour, Metabolic Health and Lifestyle Patterns

Xi Wang
Brown School, Washington University in St. Louis, St. Louis, MO 63130, USA

sobha.rg@gmail.com

Abstract— **SAI-driven personalized nutrition is revolutionizing nutrition advice by merging individual biological, behavioural, metabolic and contextual factors into adaptive nutrition systems. This study discusses the conceptual basis, the technology, clinical applications and implementation barriers to a comprehensive approach linking dietary habits, metabolic health and lifestyle. Data have shown that there is considerable inter-individual variability in glycemic responses, lipid metabolism, body composition, gut microbiome profiles, and nutrient requirements, making a one-size-fits-all approach to nutrition not very effective. The potential application of machine learning, deep learning, natural language processing, computer vision, recommender systems, wearable sensors, and mobile health platforms could enhance dietary assessment, food recognition, portion estimation, behavioral monitoring, metabolic-risk prediction, and meal planning. Combining data from genomic, metabolomic, proteomic, microbiome, physical-activity, sleep, stress, sedentary-behavior, and socioeconomic data provide more personalized, context-specific nutritional advice. In obesity, diabetes prevention, cardiovascular-risk reduction, and preventive healthcare, such systems have the potential for interesting applications. The success of their use, however, requires representative datasets, accurate and validated measurements, clinical interpretability, user engagement, affordability, digital access and integration of professional judgement. Multimodal data integration, long-term clinical trials, and diverse longitudinal datasets and standardized validation procedures should be emphasized in future research. In conclusion, an AI-driven holistic framework used to facilitate personalized nutrition, enhance metabolic outcomes and dietary adherence among populations, and is a supportive tool for responsive, evidence-based nutrition.**

Keywords: Artificial intelligence; personalized nutrition; dietary behaviour; metabolic health; lifestyle patterns

1. INTRODUCTION

Personalized nutrition is a novel nutrition approach that uses nutritional recommendations tailored to biological and behavioral traits, metabolism and environment of each person. Personalised nutrition is different from the traditional nutrition recommendations which are usually formulated for large population groups, as it acknowledges the fact that people can react differently to food and nutrition patterns. These differences can be due to genetic, metabolic, gastrointestinal microflora, health, age, physical activity, sleep, food preference and cultural differences. Personalized nutrition thus aims to combine individual data with dietary advice that is more relevant, accurate and effective. It needs to be scientifically valid, as well as practically feasible, ethically responsible and measurable in terms of health and physical functioning (Adams et al., 2020). Personalised nutrition can also be defined as an evidence-based approach that involves using individual characteristics to develop individual nutrition recommendations, not just relying on generalised nutrition advice (Bush et al., 2020).

Although the traditional dietary guidelines are still vital in improving the health of the population in general, their generalised nature might not be sufficient to achieve the best results for people with different metabolic profiles and lifestyles. Generally, if dietary exposure is the same, the results will be the same in different populations. But various actions of glucose metabolism, insulin sensitivity, lipid regulation, food preferences, disease risk and dietary adherence can have a significant impact on individual responses. Precision nutrition has therefore been suggested as a way around the challenges of one-size-fits-all approaches to nutrition. However, its public health value hinges on the scientific validity, cost-effectiveness, availability, and ability not to exacerbate existing health disparities (Chatelan et al., 2019). Personal nutrition should therefore be used in addition to population-level food and nutrition policies, not as an alternative, as the latter are still essential to reduce social inequalities and enhance public health (Mathers, 2019).

With the ability to process large, complex and multidimensional data, AI technology has greatly increased the possibilities for personalized nutrition. Machine-learning algorithms can detect patterns through dietary information, clinical or biochemical markers, genetic data, gut microbiome information, physical activity, sleep and behavioral data. The analytical capabilities provide for predicting dietary response, identification of metabolic risks and development of adaptive food recommendations. Machine learning has significant potential to enhance the accuracy of dietary assessment, dietary recommendations, and nutrition-related decision making (Ferrario & Gedrich, 2024). Moreover, the combination of AI and multimodal biological and lifestyle data can enhance the potential of dynamic and context-sensitive nutritional systems, which may adapt recommendations over time based on evolving health profiles and behaviors (Fu et al., 2026).

To truly understand personalized nutrition, one needs to grasp the interactions between eating behavior, metabolic health and day-to-day patterns of lifestyle. While diet influences metabolic outcomes, the metabolic outcomes influence dietary choices, with both influenced by taste, affordability, culture, social context, emotional condition and daily routine, body composition, insulin sensitivity, genetic variation, gut microbiota and physical activity. There is inter-individual variation in glucose and lipid responses to the same food, suggesting that blanket recommendations based on nutrients may not be appropriate for all individuals (Berry et al., 2020). The interaction between genetic factors and nutrients, the composition of the gut microbiome, dietary habits, and lifestyle behaviours also play a role in obesity and associated metabolic diseases (Mansour et al., 2024; Ordovas et al., 2018). Thus, successful AI-supported nutrition systems must be based on both biological, behavioural, and contextual factors and not only on dietary intake.

This study aims to explore how AI can inform a comprehensive personalized nutrition model connecting dietary patterns, metabolism, and lifestyle modifications. It analyzes machine-learning techniques, food assessment technology, microbiome and metabolic markers, wearable devices and lifestyle-monitoring technologies. The personalized nutrition approach can enhance the effectiveness of nutrition intervention by incorporating individual biological and behavioural characteristics; it can also play a role in disease prevention and in contributing to long-term health improvements based on evidence-based interventions that are responsive to the individual.

2. Conceptual Foundations of Artificial Intelligence-Assisted Personalized Nutrition

2.1 Definition and Principles of Personalized Nutrition

Personalized nutrition is a nutrition concept that aims at nutrition recommendations shaped by the biological, metabolic, behavioural and environmental profiles. It is based on the idea that the need and response to nutrition differ significantly between people due to factors such as age, genetics, disease susceptibility, gut microbiota, lifestyle and health status. Personalized nutrition is therefore more than just a conventional approach to nutrition, as it includes multidimensional information in individualised nutrition recommendations. A comprehensive understanding of nutrient responses and metabolic pathways linked to diseases can be achieved by integrating data from genomics, transcriptomics, proteomics, metabolomics, and microbiome assessments (Ramos-Lopez et al., 2022). In addition, life-stage attributes are crucial as nutritional requirements and metabolic risks differ across childhood and adolescence, adulthood and older ages (Yoon et al., 2024).

2.2 Precision Nutrition versus General Dietary Guidance

General dietary advice gives general guidelines to minimise the risk of nutrition deficiencies and chronic disease on a population level. This type of guidance is still useful, but it does not take into consideration the variation in physiological reactions, food selections, culture, and disease types between individuals. Precision nutrition works around this by tailoring a diet to a specific person based on personal information to create an optimal diet for them. Precision nutrition can support good nutritional decisions by building biological and contextual variations instead of making broad assumptions about the effects of nutrition on populations (Stover & King, 2020). A life stage approach also shows that the dietary requirements of different life stages can differ (Yoon et al., 2024). The major differences among general dietary guidance, personalized nutrition, precision nutrition, and AI-assisted holistic nutrition are summarised in Table 1.

Table 1. Comparison of General, Personalized, Precision, and AI-Assisted Nutrition Approaches

Primary basis	Principal data used	Main advantage	Key limitation	References
Population-level nutritional requirements	Age, sex, dietary standards, and public-health evidence	Provides accessible recommendations for broad populations	Does not fully address individual metabolic variability	(Stover & King, 2020)
Individual characteristics and preferences	Dietary behaviour, health status, lifestyle, and food preferences	Improves personal relevance and dietary adherence	May rely heavily on self-reported information	(Yoon et al., 2024)
Biological variability in dietary	Genomic, metabolomic, microbiome, and	Supports targeted interventions	Requires validated biomarkers and	(Ramos-Lopez et al., 2022)

response	clinical data	based on metabolic profiles	specialised data	
Continuous integration of biological, behavioural, and contextual data	Diet, biomarkers, wearable data, microbiome, sleep, and activity	Generates adaptive and continuously updated recommendations	Requires high-quality multidimensional datasets	(Mendes-Soares et al., 2019)

2.3 Role of Artificial Intelligence and Machine Learning

AI and ML are used in the field of personalized nutrition to uncover complex and nonlinear patterns in vast amounts of nutritional and clinical data. Algorithms, based on dietary data, glucose levels, exercise, microbiome composition, laboratory indicators, and demographic data, can predict individual responses. The postprandial glycaemic response of non-diabetics has been estimated using machine-learning models, and personalized dietary recommendations have been made, as an example of the potential of computational prediction in nutrition practice (Mendes-Soares et al., 2019). This is especially important in type 2 diabetes, where there is an inter-individual difference in glucose response to meals, insulin sensitivity and glycaemic control, which need more personalised prevention and management strategies (Wang & Hu, 2018).

2.4 Data-Driven Nutrition Assessment and Decision-Making

Data-driven nutrition assessment uses objective measures of metabolism and behaviour, as well as dietary information, to support decision making. Controlled feeding studies have shown that the processing of food and macronutrient content can affect energy intake and metabolic outcomes. Ultra-processed diets can lead to an excess calorie intake and weight gain even when meals are matched on some nutrition parameters (Hall et al., 2019). Furthermore, there are distinct differences between plant-based low-fat and animal-based ketogenic diets in their effect on spontaneous energy intake, suggesting that general macronutrient groups are not the only factors affecting energy intake responses (Hall et al., 2021).

2.5 Development of Holistic Personalized Nutrition Frameworks

A comprehensive personalized nutritional system should include diet and dietetic behavior, metabolic parameters, omics data, physical activity, sleep, psychological status and the environmental context. AI can integrate these data sources, provide real-time risk adjustments and make adaptive recommendations. These frameworks should also be clinically interpretable, ethically responsible, inclusive and population-level nutrition policy compatible (Ramos-Lopez et al., 2022). Biological accuracy together with behavioural and contextual information help in better prevention, management and dietary adherence in the long-term. The proposed holistic architecture puts together several individual-level data streams into a continuously adaptive personalized nutrition system as depicted in Figure 1.

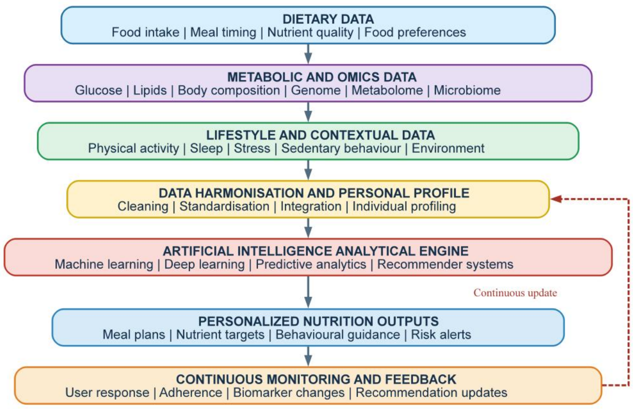

Figure 1. Holistic Architecture of AI-Assisted Personalized Nutrition

3. Dietary Behaviour Assessment and AI-Based Nutrition Profiling

3.1 Dietary Intake and Eating-Pattern Assessment

The timing, frequency, composition and quality of meals are known to affect metabolic outcomes therefore accurate assessment of dietary intake is essential for AI-assisted personalized nutrition. Assessments of eating patterns should therefore not only determine nutrient intakes, but also mealtime, length of the fasting period, snacking habits and intra-individual variability. Thus, early time-restricted feeding has been reported to be beneficial for insulin sensitivity, blood pressure, and oxidative stress without any weight loss, highlighting the metabolic significance of the timing of food intake (Sutton et al., 2018). Eating within ten hours has also been associated with weight loss, blood pressure and atherogenic lipids among the metabolic syndrome population (Wilkinson et al., 2020).

3.2 Food Preferences, Habits, and Cultural Influences

Taste, cost, culture, family habits, food availability and beliefs influence food preferences and habits. These influences should be considered for AI-based nutrition profiling, as recommendations that go against established behaviors will not be followed up. Although intermittent fasting and other eating patterns may offer some metabolic benefits, it is also important to consider the suitability of such practices for each person, depending on their health, lifestyle, and daily routine (De Cabo & Mattson, 2019). Further, calorie restriction might also aid with weight loss without the addition of time-restricted eating, suggesting that behavioural feasibility, as well as energy intake, should not be overlooked (Liu et al., 2022).

3.3 Digital Food Diaries and Image-Based Dietary Recognition

Digital food diaries and image-recognition systems can enhance dietary assessment and decrease reliance on self-reported memory. Smartphone apps can take pictures of meals, estimate portions, recognize the type of food, and categorize the nutrient quality of food. These may be especially helpful for tracking carbohydrate sources as better-quality carbohydrates and increased intake of dietary fiber have consistently been linked to better cardiometabolic and overall health outcomes (Reynolds et al., 2019). AI can thus assist in determining whether a food is a refined or minimally processed carbohydrate source in everyday foods. Table 2 shows the primary digital and AI-assisted techniques to measure dietary intake, eating patterns and nutrition-related behaviour.

Table 2. AI-Supported Methods for Dietary Behaviour Assessment and Nutrition Profiling

Assessment component	Digital or AI method	Information generated	Application in personalized nutrition	References
Food identification	Deep-learning image classification	Food category, ingredients, and meal composition	Automated dietary recording and nutrient estimation	(Mezgec & Seljak, 2021)
Portion-size assessment	Computer vision and volume estimation	Estimated food volume and serving size	Calculation of calorie and nutrient intake	(Tahir & Loo, 2021)
Meal documentation	Smartphone food diaries and photographs	Meal timing, frequency, and food combinations	Identification of habitual eating patterns	(Höchsmann & Martin, 2020)
Dietary behaviour monitoring	Mobile nutrition applications	Goal achievement, adherence, and behavioural changes	Delivery of feedback, reminders, and behavioural support	(Villinger et al., 2019)
Automated dietary analysis	Integrated AI dietary-assessment systems	Food recognition and nutritional composition	Rapid generation of individualized dietary profiles	(Lu et al., 2020)
Habit and context recognition	Food-computing and multimodal analytics	Dietary context, preferences, and consumption patterns	Prediction of food selection and personalized recommendations	(Min et al., 2020)

3.4 Wearable Devices and Mobile Nutrition Applications

Activity, sleep, heart rate, glucose and eating-time data can be gathered continually with wearable devices and mobile applications. These technologies, used together with food diaries, can provide insights into the connection between food consumption and physiological responses in real time. Mobile systems can also deliver reminders, feedback and adaptive guidance based on changes in behavior or metabolic indicators (De Zambotti et al., 2019).

3.5 Behavioural Prediction and Dietary-Adherence Monitoring

Machine-learning models can assess repeated behavioral data to anticipate dietary missteps, understand obstacles to sticking to a diet, and know when extra support is needed. Responses of gut microbiota should also be considered when monitoring, as dietary changes may affect immune regulation and gut-microbial function (Wastyk et al., 2021). The links between diet, microbiome composition and host metabolism are further proof of the importance of combining behavioural and biological data in nutrition profiling (Asnicar et al., 2021).

3.6 AI-Assisted Personalized Meal Planning and Recommendations

AI-powered meal planning systems consider nutrition needs, taste preferences, metabolic risks, microbiome analysis, and lifestyle factors to provide personalized meal plans. Information on the gut microbiome can help to fine-tune dietary recommendations due to the role of gut microbes in glucose regulation, lipid metabolism, inflammation, and metabolic disease (Fan & Pedersen, 2021). Therefore, effective systems should offer a flexible, culturally appropriate, nutritionally balanced and continually evolving meal plan to help improve metabolism and encourage adherence. The process of converting the general dietary guidance into personalized meal suggestions is shown in the AI-driven workflow in Figure 2.

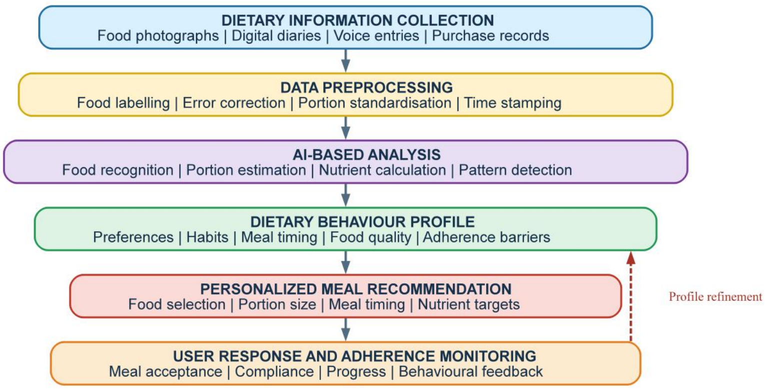

Figure 2. AI-Based Dietary Behaviour Assessment and Nutrition-Profiling Workflow

4. Integration of Metabolic Health Indicators

4.1 Metabolic Phenotypes and Individual Nutritional Responses

Metabolic phenotypes are observable variations in the way people metabolise nutrients, manage energy and respond to nutrition changes. These differences result from the interplay between age, body composition, genetics, gut microbiome, environmental exposure and lifestyle. Precision nutrition thus needs the recognition of different metabolic profiles and not a "one size fits all" approach to nutrition. Longitudinal metabolic assessment showed that people can have very personalised relationships between the food they eat and the change in their microbiome, as evidenced by repeated measurements over time (Johnson et al., 2019).

4.2 Glucose Regulation and Glycaemic Variability

Glucose regulation is a key parameter of metabolic health and a postprandial glucose surge is linked to insulin resistance and type 2 diabetes risk. AI-powered tools can combine glucose monitoring data with meal composition, activity, sleep patterns, and microbiome characteristics to forecast glucose responses. The differences in microbiome composition can be caused by host-related factors such as genetics, age, physiological state and exposure to medication, which may indirectly affect glucose regulation (Kurilshikov et al., 2021). This type of monitoring can then help to optimize carbohydrate choices, timing and portion sizes.

4.3 Lipid Metabolism, Obesity, and Body Composition

Lipid profile, adiposity, waist circumference and lean body mass are useful parameters to assess metabolic risk of obesity. Such indicators can be utilized in personalized nutrition systems to differentiate patients with different metabolic conditions despite the same body weight. It appears that the composition of gut microbes is as much influenced by environmental or lifestyle factors as by inherited genetic traits, and that modifiable behaviours could have a significant impact on lipid metabolism and obesity risk (Rothschild et al., 2018). Body-composition data integrated with dietary habits and biomarker analysis to identify patterns associated with weight gain, dyslipidaemia, and metabolic dysfunction through AI models.

4.4 Gut Microbiome and Nutrient–Microbiota Interactions

Gut microorganisms affect nutrient metabolism, immune function, intestinal integrity and production of bioactive metabolites. The adaptations of the microbiome to dietary supplements and probiotics are highly individual, however. Prolonged recovery after antibiotic exposure can be slow when using generic probiotic administration and may have different effects when using personalised microbial recovery (Suez et al., 2018). Individual host and microbial factors are also associated with resistance to probiotic colonisation, which suggests that universal recommendations for probiotics may not be effective (Zmora et al., 2018). It is thus possible that microbiome-based precision models could aid in predicting the dietary response (Hughes et al., 2019).

4.5 Genomic, Metabolomic, and Proteomic Data

The differences in nutrient metabolism may be determined by genetic information, whereas biochemical or physiological processes that are occurring in the body may be reflected in metabolomic and proteomic data. These data, when paired with microbiome data, provide a pathway between nutrients and inflammation, energy, and chronic disease. There is still hope for commercial translation, but several standardised analytical methods, validated biomarkers, and accessible technologies are needed (Mills et al., 2019). Beyond traditional markers of illness, microbial metabolites could also impact neurological activity, emotional state and quality of life (Valles-Colomer et al., 2019). Table 3 shows the metabolic indicators that can be incorporated into AI-assisted nutrition systems and their significance for dietary decision making.

Table 3. Metabolic Health Indicators for AI-Assisted Personalized Nutrition

Indicator category	Examples of measurements	Nutritional significance	Role in AI-based analysis	References
Glycaemic regulation	Fasting glucose, postprandial glucose, insulin sensitivity, and glucose variability	Identifies carbohydrate tolerance and diabetes risk	Predicts individual glycaemic responses to meals	(Mendes-Soares et al., 2019)
Lipid metabolism	Triglycerides, cholesterol fractions, and fatty-acid profiles	Indicates cardiovascular and metabolic risk	Supports dietary-fat and energy-intake recommendations	(Aron-Wisnewsky et al., 2020)
Body composition	Body-fat percentage, visceral fat, lean mass, and waist circumference	Distinguishes metabolically healthy and unhealthy obesity	Improves risk stratification and calorie targeting	(Hughes et al., 2019)
Gut microbiome	Microbial diversity, species abundance, and functional pathways	Reflects nutrient metabolism and diet–microbiota interactions	Predicts microbial responses to dietary interventions	(Johnson et al., 2019)
Genomic information	Nutrient-related variants and inherited metabolic traits	Identifies genetic differences in nutrient processing	Supports genetically informed recommendations	(Kurilshikov et al., 2021)
Metabolomic and proteomic profiles	Metabolites, proteins, enzymes, and inflammatory markers	Represents current metabolic and physiological activity	Enables early risk detection and response prediction	(Mills et al., 2019)

4.6 AI-Based Prediction of Metabolic Risk and Dietary Response

AI can combine glucose, lipid, body-composition, omics, microbiome and lifestyle data to assess and estimate metabolic risk and individual dietary response. These models help to identify signs of early disease, adapt meal planning and continually adjust nutritional recommendations (Chen et al., 2024). However, for reliable implementation, various datasets, external validation, clinical interpretability and proper protection of sensitive biological information are required. An example of the incorporation of metabolic markers and biological markers for risk classification and prediction of dietary response is shown in Figure 3.

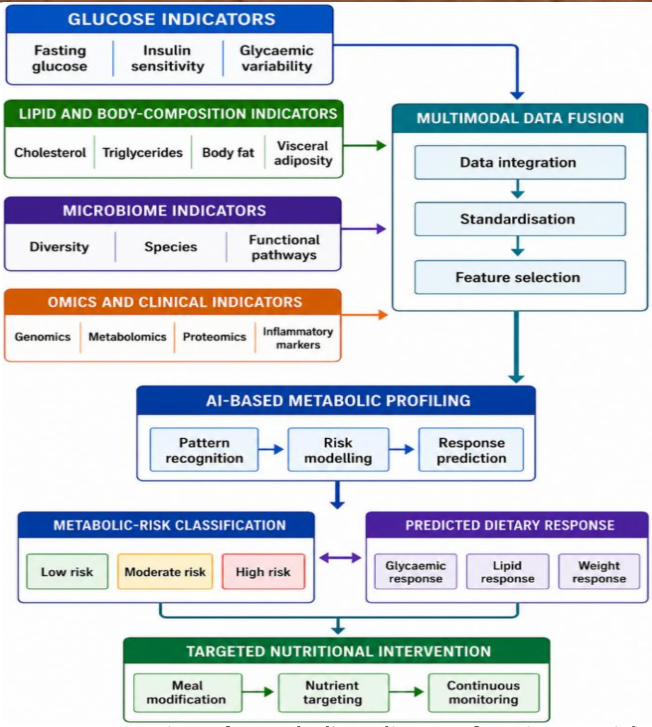

Figure 3. Integration of Metabolic Indicators for Dietary-Risk Prediction

5. Lifestyle Patterns in Personalized Nutrition Systems

5.1 Physical Activity and Energy Expenditure

Exercise has a significant impact on energy balance, glucose metabolism, fat metabolism, body composition and appetite regulation. When building systems for personalized nutrition, the activity intensity, activity duration, activity frequency and energy expenditure must be considered when developing diet recommendations. Data obtained through wearable technology and mobile apps can be utilized to modify calorie and macronutrient intakes and meal timing based on movement patterns throughout the day. Advanced nutritional evaluation tools more recently incorporate both physiological and behavioural data with food intake, to ensure more personalized and context-specific nutrition guidance (Cuparencu et al., 2026).

5.2 Sleep Quality, Duration, and Circadian Rhythms

The length of sleep, its quality, and the degree of alignment with the circadian rhythm affect the regulation of hormones, insulin sensitivity, hunger, food preferences and metabolic health. Poor and erratic sleep can lead to eating more of those high-energy foods and to irregular eating patterns. Therefore, personalized systems should take sleep habits and circadian rhythms into account in addition to the dietary information. This integration can be facilitated by image-assisted dietary assessment, which is able to assess the timing and content of food more accurately than traditional dietary recall, especially when eating habits vary during the day (Höchsmann & Martin, 2020).

5.3 Psychological Stress, Emotional Eating, and Mental Well-Being

Psychological stress can impact appetite, encourage emotional eating and decrease the likelihood of following scheduled eating behaviors. Microbiome metabolites, inflammatory pathways and changes in the microbiome due to diet also contribute to mental health. The gut microbiota is greatly influenced by diet over a lifetime and has important implications for both physical and mental well-being (Zmora et al., 2019). They should therefore be integrated into personalized nutrition platforms to predict dietary behaviour and offer dietary recommendations for reduction and/or improvement when considering stress indicators, mood patterns and eating triggers.

5.4 Sedentary Behaviour and Daily Routine

Even those achieving the recommended amount of physical activity could be at risk of metabolic dysfunction in the context of sedentary behaviours. The amount of time spent sitting, infrequent eating patterns, screen-based meals and inadequate daily activity levels can impact weight management and cardiometabolic risk. Automatic classification of foods using AI image assessment can enhance monitoring by identifying foods, measuring food sizes and detecting trends associated with sedentary behavior. Despite this, there is still a degree of accuracy variance between the current systems and those of the experts and objective ground truth measurements (Shonkoff et al., 2023).

5.5 Environmental and Socioeconomic Influences

Lifestyle patterns and metabolic outcomes are influenced by lifestyle factors and metabolic factors, both of which are determined by environmental factors, food availability, income, education, occupation and culture of the region. Extensive population studies have shown that the use of medicines, diet, smoking, the living environment, as well as other exposures, can substantially affect the composition of the gut microbiome (Gacesa et al., 2022). Failing to consider these population-specific factors creates the potential for population-specific microbiome reference ranges and disease-prediction models to be developed, emphasizing the need for population-specific data (He et al., 2018). Habitual diets can also induce the selection of distinct strains of microbes, with different genetic and functional traits, as observed for Prevotella copri (De Filippis et al., 2019).

5.6 Integration of Multidimensional Lifestyle Data

The activity, sleep, and stress data need to be combined with microbiome data, sedentary behaviour, socioeconomic context, and diet data to create holistic personalized nutrition systems. This integration is especially applicable to metabolic diseases like non-alcoholic fatty liver disease, where the microbial signatures are related to obesity, insulin resistance, drug use, and diet (Aron-Wisnewsky et al., 2020). AI can analyze these multi-dimensional inputs and detect risk patterns, better predict behaviour and deliver adaptive recommendations. The models should be culturally appropriate, clinically interpretable, and have a degree of flexibility to account for changes in health status and daily living conditions. The multi-dimensional process of lifestyle information leading to adaptive nutrition guidance is demonstrated in Figure 4.

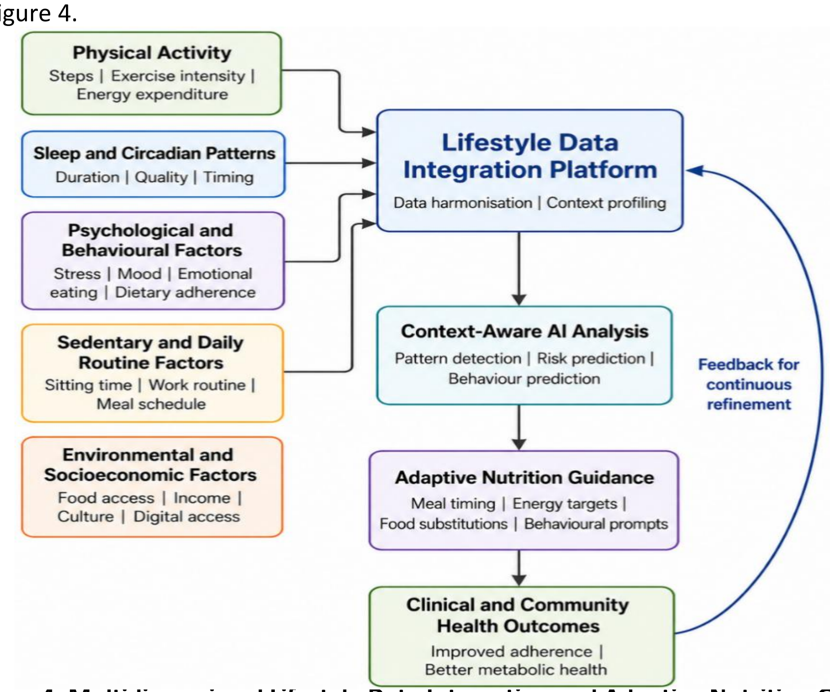

Figure 4. Multidimensional Lifestyle Data Integration and Adaptive Nutrition Guidance

6. Artificial Intelligence Methods and Digital Technologies

6.1 Machine Learning and Deep Learning Models

AI-driven personalized nutrition relies on machine learning and deep learning. These models can detect intricate relationships between food consumption, nutrient content, metabolic markers, lifestyle behaviours, and health outcomes. DNNs are especially capable of determining food regions, classification, and learning visual elements that might be challenging to be recorded by traditional dietary records (Mezgec & Seljak, 2021). The performance of the models, however, relies on the diversity of the data sets, accurate food labeling and cross-cultural and dietary validation.

6.2 Natural Language Processing for Dietary Data

All this unstructured dietary information contained in food diaries, clinical notes, survey responses, recipes, and conversational applications can be transformed into analysable information through natural language processing. Capable of recognising food names, ingredients, mealtimes, descriptions of portions and eating-related behaviours. A larger body of research in the field of food computing shows the potential of combining textual, visual, nutritional and contextual information to facilitate food recognition, recommendation and health-related decisions (Min et al., 2020).

This could also allow for a conversational dietary assistant that provides information and gives instant feedback.

6.3 Computer Vision for Food Recognition and Portion Estimation

Computer vision can be used to automatically identify food objects and estimate the number of food items from images. Go FOOD is one such system based on AI that can analyze images of meals and provide an estimation of what is being consumed, thereby minimizing the need to manually record meals (Lu et al., 2020). In image-based methods, object recognition, segmentation, depth estimation and volume calculation all take place, however mixed dishes and foods that are similar in appearance are still problematic (Tahir & Loo, 2021). Realistic images of the diet can be generated using shape-preserving techniques which could also further enhance the training of the model while preserving essential structural characteristics (Chen et al., 2024).

6.4 Recommender Systems for Personalized Nutrition

Nutrition recommender systems are systems that generate personalized meal recommendations based on the combination of dietary requirements, health problems, food preferences, allergies, cultural practices, and behavioural goals. These recommendations can be provided continuously through mobile applications and can aid in behavioral change by providing reminders, progress tracking and feedback. There is evidence that app-based nutrition interventions are effective at improving diet and selected nutrition-related health outcomes, though the effectiveness has been shown to differ by engagement and intervention design (Villinger et al., 2019).

6.5 Predictive Analytics and Digital-Twin Approaches

Predictive analytics can help to predict future metabolic risks, adherence to the diet and likely response to certain foods. Dynamic virtual representations of individuals based on constantly changing biological and behavioural data are added to this capability with digital-twin approaches. These models can simulate alternative meal plans before implementing recommendations (Fu et al., 2026).

6.6 Internet of Things, Wearable Sensors, and Mobile Health Platforms

Dietary records can be combined with data from physical activity, heart rate, sleep, glucose, and energy expenditure for devices connected to the internet. Technology-based assessment tools facilitate data collection but need to be assessed for usability, feasibility, validity, and participant burden (Eldridge et al., 2018). The coupling of mobile platforms with wearable sensors can aid in real-time monitoring and adaptive guidance. The general overview of the main AI techniques, inputs, outputs, and their applications in personalized nutrition systems is presented in Table 4.

Table 4. Artificial Intelligence Methods and Digital Technologies in Personalized Nutrition

AI or digital technology	Primary data input	Analytical output	Personalized nutrition application	References
Machine learning	Dietary, clinical, metabolic, and behavioural variables	Risk classification and response prediction	Identification of suitable dietary interventions	(Ferrario & Gedrich, 2024)
Deep learning	Food images and multidimensional datasets	Automated feature extraction and food classification	Dietary intake and meal-composition assessment	(Mezgec & Seljak, 2021)
Natural language processing	Food diaries, clinical notes, recipes, and user descriptions	Extraction of foods, ingredients, portions, and meal timing	Conversational assessment and automated record analysis	(Min et al., 2020)
Computer vision	Meal photographs and videos	Food recognition, segmentation, and volume estimation	Automated calorie and nutrient estimation	(Tahir & Loo, 2021)
Mobile recommender systems	Preferences, health goals, allergies, and dietary restrictions	Personalized meals and behavioural prompts	Meal planning and adherence support	(Villinger et al., 2019)

Wearable and IoT systems	Activity, sleep, heart rate, glucose, and energy expenditure	Continuous physiological and lifestyle monitoring	Real-time adaptation of recommendations	(Eldridge et al., 2018)
Validation and explainability tools	Model predictions and reference dietary measurements	Accuracy, transparency, and error assessment	Improvement of clinical confidence and interpretability	(Kirkpatrick et al., 2019)

6.7 Explainable and Responsible Artificial Intelligence

Transparency, data security, representative data sets, and the prevention and mitigation of algorithmic bias are essential for responsible AI. The dietary assessment tools should be compared to an appropriate reference method as there can be systematic errors between the self-reported and automated tools (Kirkpatrick et al., 2019). Explainable models are therefore critical for enabling those working with the practitioner and those using the model to understand why certain dietary recommendations are given.

7. Holistic Framework, Applications, Challenges, and Future Directions

7.1 Proposed Holistic AI-Assisted Personalized Nutrition Framework

An integrated and personalised artificial intelligence-driven nutrition system should be linked to consumption of food, monitoring of metabolic markers, physical activity, sleep and monitoring of behavior and environmental factors, and be continually integrated into a decision-making process. Using mobile apps, wearable technology, clinical data and food intake questionnaires, personalized suggestions can be derived from the data and sent to the individual.With the data gathered via mobile applications, wearable technology, clinical records, and food intake questionnaires, individual recommendations can be made and sent to the individual. The ease of use, perceived usefulness, digital literacy, quality of personalization, and user engagement of nutrition applications are all key factors that impact the successful implementation of these apps (De Zambotti et al., 2019; König et al., 2021).

7.2 Integration of Dietary, Metabolic, and Lifestyle Data

Food intake and energy expenditure should be included in the list of components of an integrated model, along with sleep, glucose regulation, body composition and dietary adherence. Activity trackers have the potential to drive higher levels of physical activity and create objective behavioural information for tailored nutrition profiling (Brickwood et al., 2019). Additionally, evidence suggests that when used as part of structured health interventions, wearable technologies can enhance physical activity and target health outcomes (Ferguson et al., 2022).

7.3 Applications in Obesity, Diabetes, Cardiovascular Disease, and Preventive Healthcare

AI systems could be used to help manage weight, prevent diabetes, reduce cardiovascular risk, and detect unhealthy lifestyle habits. Ongoing data on activity, heart rate, energy expenditure, meal consumption and sleep aid in tailoring calorie goals and recommendations for lifestyle. Commercial wearable devices, however, have different levels of accuracy in measuring steps, energy expenditure and heart rate and should be carefully selected and validated before use in clinical practice (Chinoy et al., 2021; Fuller et al., 2020).

7.4 Clinical and Community-Based Implementation

Clinical implementation necessitates the incorporation of health care workflows, professional supervision, validated algorithms and recommendations that are easily understood by health care workers and patients. Mobile platforms and cheap fitness trackers can be incorporated into community programmes to encourage healthy diet and activity. Wearable devices can also be worn by consumers and can deliver important research data, but the characteristics of the sensor, the algorithm used to process the data, the availability of data, and the design of the devices could affect the quality of the measurements (Henriksen et al., 2018).

7.5 Accessibility, Affordability, and Digital Inequality

While AI-driven personalized nutrition can offer many advantages, this may not be the case for people who are not tech-savvy, do not have a smartphone, Internet connection or the financial means to support these and other nutrition services, or do not receive professional guidance. Limited technological infrastructure, language barriers and subscription fees, as well as the cost of the devices, may limit adoption among disadvantaged groups. Such systems should therefore be easy to access and culturally appropriate and be affordable.

7.6 Research Gaps and Future Directions

Future research is needed to create a variety of tools for longitudinal data and to establish a set of uniform validation protocols, and to explore if the recommendations generated by AI lead to lasting clinical benefits. Consumer sleep monitoring data should be evaluated with extra care as there is some variation in the level of agreement between consumer and polysomnography. Sleep technologies, when embedded in a wearable format, also need to be better validated and understood before being widely integrated into nutrition and health care practices.

8. Conclusion

Artificial intelligence (AI)-supported personalized nutrition is a significant leap beyond basic nutrition advice and towards dynamic, personalized and evidence-based nutrition care. Combining dietary behavior, metabolic markers, physical activity levels, sleep patterns, psychological factors, environment, and other lifestyle factors, AI systems can offer a holistic view of each person's nutritional needs. Combined with other areas, such as machine learning, deep learning, natural language processing, computer vision, recommender systems, wearable sensors, and mobile health platforms, these technologies contribute to robust dietary assessment, metabolic-risk prediction, behavioural monitoring, and personalized meal planning. Technology could help to prevent or manage obesity, diabetes, cardiovascular disease and other nutrition-related metabolic diseases. However, the accuracy, variety and trustworthiness of the data to be used in predictive models are the foundations for their successful implementation. To build personalized nutrition systems, one should consider the differences in food culture, socioeconomic status, digital literacy, phenotypes, and access to technology. Automated recommendations must be in support of the person's nutrition and clinical judgment and not be used as a replacement for nutrition and clinical expertise. There is also a need for increased standardisation of dietary data, wearable measurements, metabolic biomarkers and validation procedures. In sum, a comprehensive AI-supported system can interrelate all dietary, metabolic, and lifestyle aspects within an adaptive decision-making system. Interdisciplinary research and clinical follow-up will be critical to bringing these technologies to fruition in the form of easy-to-use, reliable, and effective personalized nutrition interventions.

REFERENCES

1. Adams, S. H., Anthony, J. C., Carvajal, R., Chae, L., Khoo, C. S. H., Latulippe, M. E., Matusheski, N. V., McClung, H. L., Rozga, M., & Schmid, C. H. (2020). Perspective: Guiding principles for the implementation of personalized nutrition approaches that benefit health and function. Advances in Nutrition, 11(1), 25–34.
2. Aron-Wisnewsky, J., Vigliotti, C., Witjes, J., Le, P., Holleboom, A. G., Verheij, J., Nieuwdorp, M., & Clément, K. (2020). Gut microbiota and human NAFLD: Disentangling microbial signatures from metabolic disorders. Nature Reviews Gastroenterology & Hepatology, 17(5), 279–297.
3. Asnicar, F., Berry, S. E., Valdes, A. M., Nguyen, L. H., Piccinno, G., Drew, D. A., Leeming, E., Gibson, R., Le Roy, C., & Khatib, H. A. (2021). Microbiome connections with host metabolism and habitual diet from 1,098 deeply phenotyped individuals. Nature Medicine, 27(2), 321–332.
4. Berry, S. E., Valdes, A. M., Drew, D. A., Asnicar, F., Mazidi, M., Wolf, J., Capdevila, J., Hadjigeorgiou, G., Davies, R., & Al Khatib, H. (2020). Human postprandial responses to food and potential for precision nutrition. Nature Medicine, 26(6), 964–973.
5. Brickwood, K.-J., Watson, G., O'Brien, J., & Williams, A. D. (2019). Consumer-based wearable activity trackers increase physical activity participation: Systematic review and meta-analysis. JMIR mHealth and uHealth, 7(4), e11819.
6. Bush, C. L., Blumberg, J. B., El-Sohemy, A., Minich, D. M., Ordovás, J. M., Reed, D. G., & Behm, V. A. Y. (2020). Toward the Definition of Personalized Nutrition: A Proposal by The American Nutrition Association. Journal of the American College of Nutrition, 39(1), 5–15. https://doi.org/10.1080/07315724.2019.1685332
7. Chatelan, A., Bochud, M., & Frohlich, K. L. (2019). Precision nutrition: Hype or hope for public health interventions to reduce obesity? International Journal of Epidemiology, 48(2), 332–342.
8. Chen, G., Mao, Z.-H., Sun, M., Liu, K., & Jia, W. (2024). Shape-preserving generation of food images for automatic dietary assessment. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 3721–3731. https://openaccess.thecvf.com/content/CVPR2024W/MTF/html/Chen_Shape-Preserving_Generation_of_Food_Images_for_Automatic_Dietary_Assessment_CVPRW_2024_paper.html
9. Chinoy, E. D., Cuellar, J. A., Huwa, K. E., Jameson, J. T., Watson, C. H., Bessman, S. C., Hirsch, D. A., Cooper, A. D., Drummond, S. P., & Markwald, R. R. (2021). Performance of seven consumer sleep-tracking devices compared with polysomnography. Sleep, 44(5), zsaa291.
10. Cuparencu, C., Diener, C., Wilson, T., Gibbons, S. M., & Lucassen, D. A. (2026). Integration of modern technologies to advance dietary assessment. Nature Food, 7(1), 17–26.
11. De Cabo, R., & Mattson, M. P. (2019). Effects of Intermittent Fasting on Health, Aging, and Disease. New England Journal of Medicine, 381(26), 2541–2551. https://doi.org/10.1056/NEJMra1905136

12. De Filippis, F., Pasolli, E., Tett, A., Tarallo, S., Naccarati, A., De Angelis, M., Neviani, E., Cocolin, L., Gobbetti, M., & Segata, N. (2019). Distinct genetic and functional traits of human intestinal Prevotella copri strains are associated with different habitual diets. Cell Host & Microbe, 25(3), 444–453.
13. De Zambotti, M., Cellini, N., Goldstone, A., Colrain, I. M., & Baker, F. C. (2019). Wearable sleep technology in clinical and research settings. Medicine and Science in Sports and Exercise, 51(7), 1538.
14. Eldridge, A. L., Piernas, C., Illner, A.-K., Gibney, M. J., Gurinović, M. A., De Vries, J. H., & Cade, J. E. (2018). Evaluation of new technology-based tools for dietary intake assessment—An ILSI Europe Dietary Intake and Exposure Task Force evaluation. Nutrients, 11(1), 55.
15. Fan, Y., & Pedersen, O. (2021). Gut microbiota in human metabolic health and disease. Nature Reviews Microbiology, 19(1), 55–71.
16. Ferguson, T., Olds, T., Curtis, R., Blake, H., Crozier, A. J., Dankiw, K., Dumuid, D., Kasai, D., O'Connor, E., & Virgara, R. (2022). Effectiveness of wearable activity trackers to increase physical activity and improve health: A systematic review of systematic reviews and meta-analyses. The Lancet Digital Health, 4(8), e615–e626.
17. Ferrario, P. G., & Gedrich, K. (2024). Machine learning and personalized nutrition: A promising liaison? European Journal of Clinical Nutrition, 78(1), 74–76.
18. Fu, Y., Zhang, K., Miao, Z., Yang, G., Huang, Y., & Zheng, J. (2026). Advancing Precision Nutrition Through Multimodal Data and Artificial Intelligence. Advanced Science, 13(17), e21111. https://doi.org/10.1002/advs.202521111
19. Fuller, D., Colwell, E., Low, J., Orychock, K., Tobin, M. A., Simango, B., Buote, R., Van Heerden, D., Luan, H., & Cullen, K. (2020). Reliability and validity of commercially available wearable devices for measuring steps, energy expenditure, and heart rate: Systematic review. JMIR mHealth and uHealth, 8(9), e18694.
20. Gacesa, R., Kurilshikov, A., Vich Vila, A., Sinha, T., Klaassen, M. A., Bolte, L. A., Andreu-Sánchez, S., Chen, L., Collij, V., & Hu, S. (2022). Environmental factors shaping the gut microbiome in a Dutch population. Nature, 604(7907), 732–739.
21. Hall, K. D., Ayuketah, A., Brychta, R., Cai, H., Cassimatis, T., Chen, K. Y., Chung, S. T., Costa, E., Courville, A., & Darcey, V. (2019). Ultra-processed diets cause excess calorie intake and weight gain: An inpatient randomized controlled trial of ad libitum food intake. Cell Metabolism, 30(1), 67–77.
22. Hall, K. D., Guo, J., Courville, A. B., Boring, J., Brychta, R., Chen, K. Y., Darcey, V., Forde, C. G., Gharib, A. M., & Gallagher, I. (2021). Effect of a plant-based, low-fat diet versus an animal-based, ketogenic diet on ad libitum energy intake. Nature Medicine, 27(2), 344–353.
23. He, Y., Wu, W., Zheng, H.-M., Li, P., McDonald, D., Sheng, H.-F., Chen, M.-X., Chen, Z.-H., Ji, G.-Y., & Zheng, Z.-D.-X. (2018). Regional variation limits applications of healthy gut microbiome reference ranges and disease models. Nature Medicine, 24(10), 1532–1535.
24. Henriksen, A., Haugen Mikalsen, M., Woldaregay, A. Z., Muzny, M., Hartvigsen, G., Hopstock, L. A., & Grimsgaard, S. (2018). Using fitness trackers and smartwatches to measure physical activity in research: Analysis of consumer wrist-worn wearables. Journal of Medical Internet Research, 20(3), e110.
25. Höchsmann, C., & Martin, C. K. (2020). Review of the validity and feasibility of image-assisted methods for dietary assessment. International Journal of Obesity, 44(12), 2358–2371.
26. Hughes, R. L., Kable, M. E., Marco, M., & Keim, N. L. (2019). The role of the gut microbiome in predicting response to diet and the development of precision nutrition models. Part II: Results. Advances in Nutrition, 10(6), 979–998.
27. Johnson, A. J., Vangay, P., Al-Ghalith, G. A., Hillmann, B. M., Ward, T. L., Shields-Cutler, R. R., Kim, A. D., Shmagel, A. K., Syed, A. N., & Walter, J. (2019). Daily sampling reveals personalized diet-microbiome associations in humans. Cell Host & Microbe, 25(6), 789–802.
28. Kirkpatrick, S. I., Baranowski, T., Subar, A. F., Tooze, J. A., & Frongillo, E. A. (2019). Best practices for conducting and interpreting studies to validate self-report dietary assessment methods. Journal of the Academy of Nutrition and Dietetics, 119(11), 1801–1816.
29. König, L. M., Attig, C., Franke, T., & Renner, B. (2021). Barriers to and facilitators for using nutrition apps: Systematic review and conceptual framework. JMIR mHealth and uHealth, 9(6), e20037.
30. Kurilshikov, A., Medina-Gomez, C., Bacigalupe, R., Radjabzadeh, D., Wang, J., Demirkan, A., Le Roy, C. I., Raygoza Garay, J. A., Finnicum, C. T., & Liu, X. (2021). Large-scale association analyses identify host factors influencing human gut microbiome composition. Nature Genetics, 53(2), 156–165.
31. Liu, D., Huang, Y., Huang, C., Yang, S., Wei, X., Zhang, P., Guo, D., Lin, J., Xu, B., Li, C., He, H., He, J., Liu, S., Shi, L., Xue, Y., & Zhang, H. (2022). Calorie Restriction with or without Time-Restricted Eating in Weight Loss. New England Journal of Medicine, 386(16), 1495–1504. https://doi.org/10.1056/NEJMoa2114833
32. Lu, Y., Stathopoulou, T., Vasiloglou, M. F., Pinault, L. F., Kiley, C., Spanakis, E. K., & Mougiakakou, S. (2020). goFOODTM: An artificial intelligence system for dietary assessment. Sensors, 20(15), 4283.
33. Mansour, S., Alkhaaldi, S. M., Sammanasunathan, A. F., Ibrahim, S., Farhat, J., & Al-Omari, B. (2024). Precision

nutrition unveiled: Gene–nutrient interactions, microbiota dynamics, and lifestyle factors in obesity management. Nutrients, 16(5), 581.
34. Mathers, J. C. (2019). Paving the way to better population health through personalised nutrition. EFSA Journal, 17(Proceedings of the Third EFSA Scientific Conference: Science, Food and Society Guest Editors: Devos Y, Elliott KC and Hardy A). https://doi.org/10.2903/j.efsa.2019.e170713
35. Mendes-Soares, H., Raveh-Sadka, T., Azulay, S., Edens, K., Ben-Shlomo, Y., Cohen, Y., Ofek, T., Bachrach, D., Stevens, J., & Colibaseanu, D. (2019). Assessment of a personalized approach to predicting postprandial glycemic responses to food among individuals without diabetes. JAMA Network Open, 2(2), e188102–e188102.
36. Mezgec, S., & Seljak, B. K. (2021). Deep neural networks for image-based dietary assessment. Journal of Visualized Experiments (JoVE), (169), e61906.
37. Mills, S., Lane, J. A., Smith, G. J., Grimaldi, K. A., Ross, R. P., & Stanton, C. (2019). Precision nutrition and the microbiome part II: Potential opportunities and pathways to commercialisation. Nutrients, 11(7), 1468.
38. Min, W., Jiang, S., Liu, L., Rui, Y., & Jain, R. (2020). A Survey on Food Computing. ACM Computing Surveys, 52(5), 1–36. https://doi.org/10.1145/3329168
39. Ordovas, J. M., Ferguson, L. R., Tai, E. S., & Mathers, J. C. (2018). Personalised nutrition and health. Bmj, 361. https://www.bmj.com/content/361/bmj.k2173.abstract
40. Ramos-Lopez, O., Martinez, J. A., & Milagro, F. I. (2022). Holistic integration of omics tools for precision nutrition in health and disease. Nutrients, 14(19), 4074.
41. Reynolds, A., Mann, J., Cummings, J., Winter, N., Mete, E., & Te Morenga, L. (2019). Carbohydrate quality and human health: A series of systematic reviews and meta-analyses. The Lancet, 393(10170), 434–445.
42. Rothschild, D., Weissbrod, O., Barkan, E., Kurilshikov, A., Korem, T., Zeevi, D., Costea, P. I., Godneva, A., Kalka, I. N., & Bar, N. (2018). Environment dominates over host genetics in shaping human gut microbiota. Nature, 555(7695), 210–215.
43. Shonkoff, E., Cara, K. C., Pei, X. (Anna), Chung, M., Kamath, S., Panetta, K., & Hennessy, E. (2023). AI-based digital image dietary assessment methods compared to humans and ground truth: A systematic review. Annals of Medicine, 55(2), 2273497. https://doi.org/10.1080/07853890.2023.2273497
44. Stover, P. J., & King, J. C. (2020). More nutrition precision, better decisions for the health of our nation. The Journal of Nutrition, 150(12), 3058–3060.
45. Suez, J., Zmora, N., Zilberman-Schapira, G., Mor, U., Dori-Bachash, M., Bashiardes, S., Zur, M., Regev-Lehavi, D., Brik, R. B.-Z., & Federici, S. (2018). Post-antibiotic gut mucosal microbiome reconstitution is impaired by probiotics and improved by autologous FMT. Cell, 174(6), 1406–1423.
46. Sutton, E. F., Beyl, R., Early, K. S., Cefalu, W. T., Ravussin, E., & Peterson, C. M. (2018). Early time-restricted feeding improves insulin sensitivity, blood pressure, and oxidative stress even without weight loss in men with prediabetes. Cell Metabolism, 27(6), 1212–1221.
47. Tahir, G. A., & Loo, C. K. (2021). A comprehensive survey of image-based food recognition and volume estimation methods for dietary assessment. Healthcare, 9(12), 1676. https://www.mdpi.com/2227-9032/9/12/1676
48. Valles-Colomer, M., Falony, G., Darzi, Y., Tigchelaar, E. F., Wang, J., Tito, R. Y., Schiweck, C., Kurilshikov, A., Joossens, M., & Wijmenga, C. (2019). The neuroactive potential of the human gut microbiota in quality of life and depression. Nature Microbiology, 4(4), 623–632.
49. Villinger, K., Wahl, D. R., Boeing, H., Schupp, H. T., & Renner, B. (2019). The effectiveness of app-based mobile interventions on nutrition behaviours and nutrition-related health outcomes: A systematic review and meta-analysis. Obesity Reviews, 20(10), 1465–1484. https://doi.org/10.1111/obr.12903
50. Wang, D. D., & Hu, F. B. (2018). Precision nutrition for prevention and management of type 2 diabetes. The Lancet Diabetes & Endocrinology, 6(5), 416–426.
51. Wastyk, H. C., Fragiadakis, G. K., Perelman, D., Dahan, D., Merrill, B. D., Yu, F. B., Topf, M., Gonzalez, C. G., Van Treuren, W., & Han, S. (2021). Gut-microbiota-targeted diets modulate human immune status. Cell, 184(16), 4137–4153.
52. Wilkinson, M. J., Manoogian, E. N., Zadourian, A., Lo, H., Fakhouri, S., Shoghi, A., Wang, X., Fleischer, J. G., Navlakha, S., & Panda, S. (2020). Ten-hour time-restricted eating reduces weight, blood pressure, and atherogenic lipids in patients with metabolic syndrome. Cell Metabolism, 31(1), 92–104.
53. Yoon, Y. S., Lee, H. I., Oh, S. W., & Lee, H. (2024). A Life-Stage Approach to Precision Nutrition: A Narrative Review. Cureus, 16(8). https://www.cureus.com/articles/280260-a-life-stage-approach-to-precision-nutrition-a-narrative-review.pdf
54. Zmora, N., Suez, J., & Elinav, E. (2019). You are what you eat: Diet, health and the gut microbiota. Nature Reviews Gastroenterology & Hepatology, 16(1), 35–56.
55. Zmora, N., Zilberman-Schapira, G., Suez, J., Mor, U., Dori-Bachash, M., Bashiardes, S., Kotler, E., Zur, M., Regev-Lehavi, D., & Brik, R. B.-Z. (2018). Personalized gut mucosal colonization resistance to empiric probiotics is

associated with unique host and microbiome features. Cell, 174(6), 1388–1405.