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REVIEW

Challenges, advances and future directions in nutritional epidemiology

Jijuan Zhang,[1,2,8] Tingting Geng,[1,2,8] Yuxiang Wang,[1,2] Hancheng Yu,[2,3] Pengfei Xia,[1,2] Changzheng Yuan,[4] Tao Huang,[5] Geng Zong,[6] Ju-Sheng Zheng,[7] Gang Liu,[2,3] and An Pan[1,2,*]

*Correspondence: panan@hust.edu.cn

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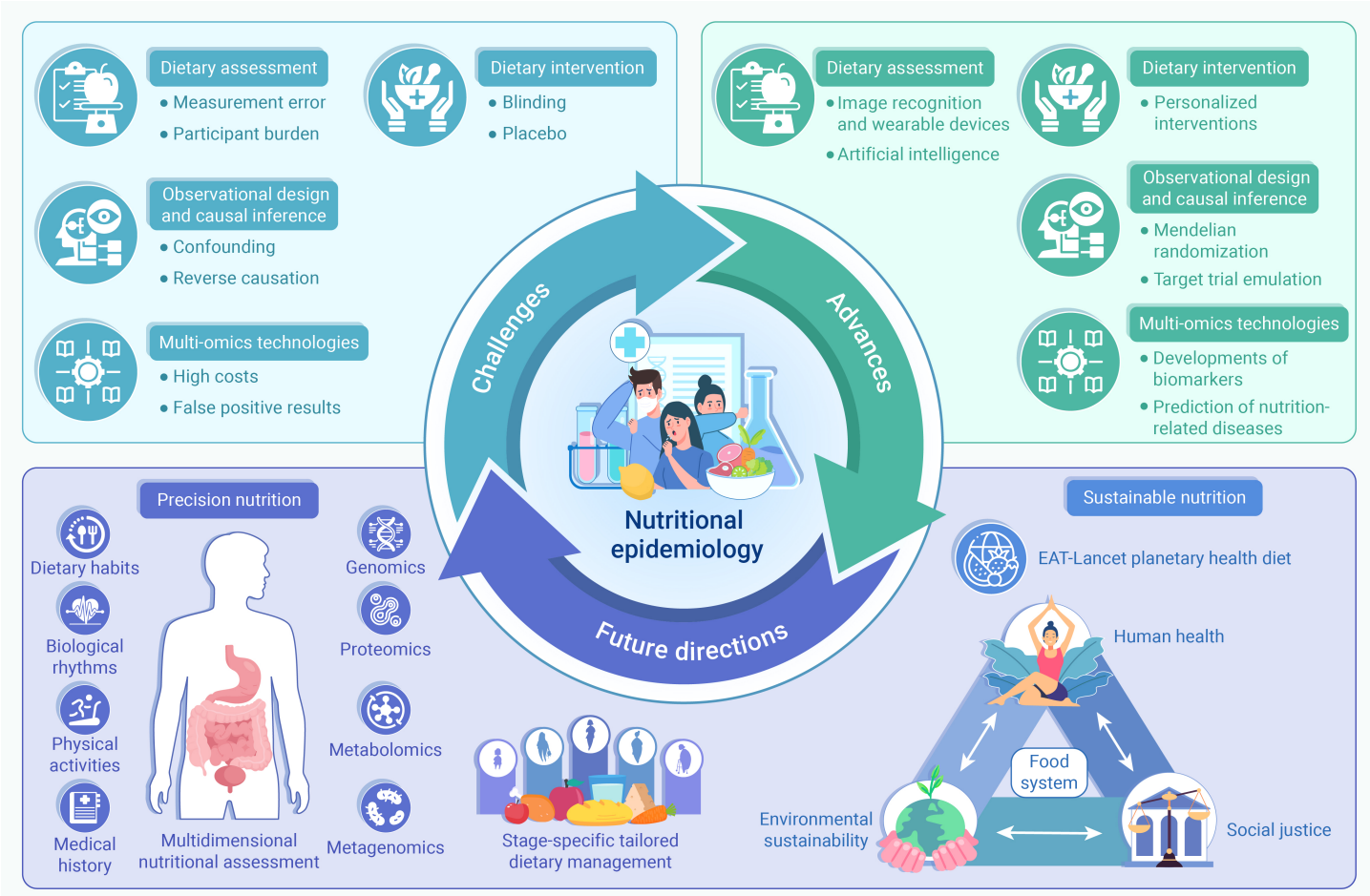
GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Key challenges in nutritional epidemiology include dietary assessment, intervention, and causal inference.
- Advances like multi-omics and artificial intelligence improve exposure assessment and mechanistic insight.
- Future directions integrate technology, nutrition, and environment on a broad scale.

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[1]Department of Epidemiology and Biostatistics, School of Public Health, Tongji Medical College, Huazhong University of Science and Technology, Wuhan 430000, China
[2]Centre for Obesity and Diabetes Research, School of Public Health, Tongji Medical College, Huazhong University of Science and Technology, Wuhan 430000, China
[3]Department of Nutrition and Food Hygiene, School of Public Health, Tongji Medical College, Huazhong University of Science and Technology, Wuhan 430000, China
[4]School of Public Health, the Second Affiliated Hospital, Zhejiang University School of Medicine, Hangzhou 310058, China
[5]Department of Epidemiology & Biostatistics, School of Public Health, Peking University, Beijing 100191, China
[6]Institute of Nutrition, Fudan University, Shanghai 200032, China
[7]Westlake Laboratory of Life Sciences and Biomedicine, School of Medicine and School of Future Biomedicine, Westlake University, Hangzhou 310060, China
[8]These authors contributed equally
*Correspondence: panan@hust.edu.cn

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Nutritional epidemiology is an interdisciplinary field that uses epidemiological methods to study diet-disease relationships in humans at the population level. It provides essential evidence to inform dietary guidelines, guide nutritional policies, and ultimately enhance human well-being. Over the years, nutritional epidemiology has achieved landmark contributions, including establishing the preventive role of folic acid in neural tube defects and revealing the harmful effects of trans fatty acids and sugar-sweetened beverages. Yet, the field faces persistent methodological and translational challenges, particularly in dietary assessment, dietary intervention implementation, and causal inference for complex diet-disease relationships. Recent technological advances are, however, catalyzing progress in exposure assessments and mechanistic insights. Simultaneously, emerging paradigms such as precision nutrition and sustainable nutrition are further expanding its scope. This review offers an integrated summary of these prevailing challenges, advancements, and emerging directions in nutritional epidemiology to shape future research efforts.

INTRODUCTION

Nutrition plays a particularly important role in the prevention and development of many diseases, especially chronic non-communicable diseases.[1] In 2017, suboptimal nutrition accounted for approximately 11 million deaths and 255 million disability-adjusted life-years globally.[2] Achieving optimal nutrition is therefore pivotal for reducing disease burden and promoting overall health across the life course.[3-4] Nutritional epidemiology is an interdisciplinary field that uses epidemiological methods to study diet-disease relationships in humans at the population level.[5] By providing high-quality evidence from populations, it informs public health initiatives, shapes dietary guidelines and policies, and ultimately enhance human well-being.

Over the years, achievements in nutritional epidemiology have profoundly shaped public health policies. For example, in the 1970s, researchers in western countries uncovered the critical role of folic acid in preventing neural tube defects.[6] This breakthrough, later reinforced by extensive studies including clinical trials, paved the way for a landmark decision in 1996, when the US Food and Drug Administration approved the fortification of grain products with folic acid. Within just five years, the incidence of neural tube defects declined by 19% in the US,[7] underscoring the power of evidence-based nutrition policy. Due to the detrimental effects of trans fatty acids,[8] the World Health Organization launched the "REPLACE" guidance in 2018, aiming at eliminating industrial trans fatty acids from the global food supply.[9] Likewise, accumulating evidence has linked sugar-sweetened beverages to higher risks of type 2 diabetes and coronary heart disease.[10-11] In response, many countries and regions, such as Mexico and the UK, adopted diverse taxation strategies on sugar-sweetened beverages to reduce consumption, encourage product reformulation, and generate revenue for health-related initiatives.[12] Recent years, ultra-processed food (UPF) has emerged as a major nutritional concern, with strong evidence linking its consumption to cardiometabolic disease, mental disorders, and mortality.[13] In recognition of these risks, the World Health Organization has initiated guideline development to address UPF intake,[14] while several countries (e.g., Argentina, Brazil, Norway, and Mexico) are exploring policy measures such as front-of-package labelling, marketing restrictions for children, and taxation to curb consumption.[15]

Despite the achievements in nutritional epidemiology, many controversial issues remain unresolved, such as debates surrounding the restriction on red meat consumption and the effectiveness of vitamin and mineral supplements.[16-17] In parallel, the field faces persistent challenges in accurate assessment of dietary exposures, the implementation of effective dietary interventions, and the establishment of causality in diet-disease relationships. Nevertheless, with the advancement of technologies like multi-omics, artificial intelligence, and wearable sensor devices, research breakthroughs are continuously emerging, enabling us to explore new directions such as precision nutrition and sustainable nutrition. This review aims to discuss major challenges, recent methodological and technological advances, and future directions in nutritional epidemiology.

CHALLENGES AND ADVANCES

Dietary exposure assessment

Assessing accurate dietary intake levels is a central challenge in nutritional epidemiology. Dietary exposures are inherently complex, multidimensional, and cumulative, with assessment further hindered by possible changes in dietary habits, reliance on subjective recall, and misreporting. Generally, diet records, 24-hour recalls, food frequency questionnaires (FFQs), and circulating biomarkers are common dietary assessment methods used in nutritional epidemiologic studies. The following is a brief overview of these methods and the challenges they encounter (Table 1).

Diet records provide accurate and open-ended information about participants' diets, encompassing both the types and quantities of foods consumed over an extended period (e.g., one or more weeks). Because participants record their dietary intakes in real time, this method relies less on memory and reduces the likelihood of omitting or misreporting foods. Nevertheless, the burden placed on participants to record their diets may lead to low compliance, and prolonged diet recording may influence participants' dietary habits. In addition, collecting and processing record data may be time-consuming and costly.[18] This method is generally considered high-quality and is commonly used to validate the effectiveness of other dietary assessment methods and monitor compliance in dietary intervention trials.[19-20] For example, in the European Prospective Investigation into Cancer (EPIC) - Norfolk study, a sub-study of the EPIC study, the 7-day diet diaries were used to assess participants' dietary intakes.[21]

The 24-hour recall method assesses both the types and quantities of foods consumed within the past 24 hours. Since this method requires participants to recall their dietary intakes over a short period, it is less dependent on memory, relatively less time-consuming and inexpensive, and associated with higher compliance. However, the 24-hour recall is still susceptible to short-term recall bias, subject to considerable within-person random error, and faces criticism of not representing long-term dietary habits.[18] Despite these limitations, it is widely used in nutritional surveys to evaluate the average dietary intake level of a specific population, such as the United States National Health and Nutrition Examination Survey.[22]

Table 1. Overview of common dietary assessment methods.

Methods	Definitions	Advantages	Disadvantages	Applications
Diet records	A method in which participants document all types and amounts of foods and beverages consumed over a defined period (e.g., a few days or weeks)	1. Providing accurate and detailed information on diets 2. Real-time recording reduces reliance on memory 3. Low risk of omitting or misreporting foods	1. High recording burden may reduce compliance 2. Prolonged recording can alter usual dietary behaviors 3. Data collection and processing are time-consuming and costly	1. Validating the effectiveness of other dietary assessment methods 2. Monitoring compliance in dietary intervention trials
24-hour recalls	A method that assesses both the types and quantities of foods consumed within the past 24 hours	1. Providing accurate and detailed information on diets 2. Less dependent on memory 3. Less time-consuming and inexpensive 4. Higher compliance	1. Recall bias 2. Within-person random error 3. Less representative of long-term dietary habits	Widely used in nutritional surveys to assess and monitor population dietary intake
Food frequency questionnaires	A method that assesses long-term habitual food intakes over a specified period, typically the past year, by recording the frequency and portion size of representative food items	1. Providing long-term habitual food intake information 2. Cost-effective 3. Efficient 4. Higher compliance	1. Recall bias 2. Risk of omitting certain food items 3. Less accurate estimates of energy and nutrient intakes 4. Time-consuming to develop study- or population-specific food frequency questionnaires	Commonly used in large-scale cohort studies to assess the long-term habitual food intake
Circulating biomarkers	Biological indicators that can assess the nutritional status of the human body	1. Objective assessment of dietary exposures 2. Internal dose after digestion, absorption, or metabolism	1. Short-term exposures rather than long-term cumulative intakes 2. Lack of biomarkers with sufficient sensitivity and specificity for many foods 3. Costly 4. Laboratory measurement error	1. Validating other dietary assessment methods 2. Monitoring compliance in dietary intervention trials 3. Assessing nutrient-disease relations

The FFQ assesses long-term habitual food intakes by inquiring about the average frequency and portion size of specific foods consumed over a designated period, typically the past year. The food items in the FFQ are selected based on the dietary characteristics of the specific population, and generally similar foods are grouped to reduce the number of items in an FFQ. The FFQ is in general a cost-effective and efficient tool, often achieving high compliance and demonstrating sufficient validity in large-scale epidemiologic studies.[23] Nevertheless, it may omit certain food items, provide less accurate estimates of absolute energy and nutrient intakes, and is inevitably affected by recall bias. Large-scale cohort studies, such as the Nurses' Health Study and the Health Professionals Follow-up Study,[24-25] commonly use FFQs to assess long-term dietary intakes.

Circulating biomarkers are biological indicators that can assess the internal nutrient level of the human body. Examples include genistein and daidzein as markers of legumes intake (Table 2).[26-27] Dietary biomarkers provide objective assessments of dietary exposures, reflecting the internal dose after digestion, absorption, or metabolism. However, because some biomarkers have short half-lives, they may capture only short-term exposures rather than long-term cumulative intakes. In addition, many foods still lack biomarkers with sufficient sensitivity and specificity. Even for well-established biomarkers, measurement procedures can be costly, and their validity may be influenced by laboratory measurement error.[18] At present, biomarkers remain widely used to validate other dietary assessment methods and to monitor compliance in dietary intervention trials.[19,28]

In recent years, new techniques have advanced the field of dietary exposure assessment. One representative example is the web-based Automated Self-Administered 24-Hour Dietary Recall (ASA24).[29] Compared with traditional 24-hour recalls, ASA24 substantially reduces costs while facilitating more efficient investigation of dietary intakes. Importantly, its validity has been shown to be comparable to that of traditional diet records and FFQs.[30] Additionally, image recognition technologies have been developed to advance dietary assessments.[31-33] These systems can automatically extract information on both the types and quantities of foods from photographs. Unlike traditional diet records, 24-hour recalls, or FFQs, which rely on subjective estimation of foods and are prone to inaccuracies, image recognition applies standardized criteria, enabling objective, accurate, rapid, and cost-effective evaluation of dietary intakes. In recent years, with the advancement of artificial intelligence (AI) and large language models (LLMs), the recognition of dietary images and the estimation of dietary intakes have become increasingly automated, intelligent, efficient, and user-friendly.[34-36] Nevertheless, the accuracy of food identification and portion size estimation can be affected by image quality, while mixed dishes often remain difficult to classify. Validated biomarkers specific to certain food groups have also emerged as objective indicators of dietary internal exposures, providing complementary evidence to self-reported data and enhancing the accuracy of dietary assessmensts.[26] Furthermore, wearable devices such as continuous glucose monitoring and electrochemical biosensors,[37-40] have advanced internal exposure measurement by continuously tracking nutrient or biomarker levels in the human body, thereby offering real-time and objective dietary internal exposure data. Despite their promise, many food group biomarkers remain undeveloped and existing biomarkers can be influenced by within-person variability, while wearable devices may suffer from calibration and accuracy issues, and both approaches may require costly assays.

Traditional dietary assessment methods remain widely applied, yet recent advances have substantially improved the efficiency and accuracy of dietary assessments. Each approach offers strengths but also carries limitations. Researchers are encouraged to integrate multiple dietary assessment methods and employ cross-validation to achieve a more comprehensive evaluation of dietary exposures.

Observational study design

Due to constraints related to feasibility, cost, and ethics, large-scale and long-term randomized controlled trials (RCTs) are often difficult to implement in practice. Consequently, most evidence in nutritional epidemiology is derived from observational studies, including cross-sectional surveys, case-control studies, cohort studies, and hybrid designs such as nested case-control studies. For instance, landmark observational studies such as the Nurses' Health Study and the Health Professionals Follow-up Study.[24-25] A concise comparison of observational and intervention studies is presented in Table 3.

The observational designs offer several advantages. They are generally more feasible, less costly, and capable of enrolling large sample size. Moreover, they capture dietary behaviors and disease occurrence in real-world settings, thereby enhancing the generalizability of findings.

Nevertheless, observational studies face notable challenges. Dietary exposures are complex, characterized by high correlations and potential interac-

Table 2. Validated candidate biomarkers of major food groups.[26-27]

Food group	Validated candidate biomarkers	Biospecimen	Correlation (r) with intake measured by 24-hour recalls or diet records	Correlation (r) with intake measured by food frequency questionnaires
Vegetable	Ergothioneine	Serum/plasma	0.26	0.19–0.28
	α-Carotene	Serum/plasma	0.04–0.52	0.17–0.50
	Lycopene	Plasma	0.25	Not available
	β-Carotene	Plasma	0.16	Not available
Fruit	Proline betaine	Serum/plasma	0.25–0.77	0.15–0.55
	Proline betaine	Urine	0.48–0.80	0.43–0.50
	β-Cryptoxanthin	Serum/plasma	0.04–0.49	0.11–0.57
	Lutein	Plasma	0.25	Not available
	Zeaxanthin	Plasma	0.26	Not available
Legumes	Genistein	Serum/plasma	0.51	0.33–0.62
	Genistein	Urine	0.53	Not available
	Daidzein	Serum/plasma	0.49	0.09-0.49
	Daidzein	Urine	0.44	Not available
Dairy	Pentadecanoic acid	Serum/plasma	0.17–0.54	0.03–0.36
	Pentadecanoic acid	Red blood cells	Not available	0.06–0.30
	Pentadecanoic acid	Adipose tissue	0.16–0.72	0.09–0.39
	trans-9-Hexadecenoic acid	Serum/plasma	Not available	0.06–0.39
	trans-9-Hexadecenoic acid	Red blood cells	Not available	0.07–0.32
Meat	Acetylcarnitine	Urine	Not available	0.26–0.32
	4-Hydroxyproline	Serum/plasma	Not available	0.075–0.36
Chicken	3-Methylhistidine	Serum/plasma	Not available	0.40–0.54
Fish/shellfish	3-carboxy-4-methyl-5-propyl-2-furanpropanoate	Serum/plasma	0.47	0.24–0.47
	3-carboxy-4-methyl-5-propyl-2-furanpropanoate	Urine	Not available	0.26–0.27
	Docosahexaenoic acid (22:6n-3)	Serum/plasma	Not available	0.26–0.37
	Docosahexaenoic acid (22:6n-3)	Adipose tissue	Not available	0.15
Whole-grain wheat and rye	Alkylresorcinols	Serum/plasma, adipose tissue	0.40–0.55	0.17–0.39
	Dihydroxybenzoic acid	Plasma/urine	0.35–0.57	0.10–0.43
	Dihydroxyphenyl propanoic acid	Plasma/urine	0.26–0.57	0.23–0.46
	Dihydroxyphenyl pentanoic acid	Plasma/urine	0.17–0.52	Not available
Tea	4-O-Methylgallic acid	Urine	0.14–0.62	0.41–0.50
	Theanine	Serum/plasma	0.28–0.51	0.23–0.50
Coffee	Trigonelline	Serum/plasma	Not available	0.12–0.66
	Quinic acid	Serum/plasma	0.74	0.16–0.77
Fats and oils	Eicosapentaenoic acid (cis-20:5n-3)	Serum/plasma	Not available	0.29–0.44
	Docosapentaenoic acid (cis-22:5n-3)	Serum/plasma	Not available	0.24–0.38
	DHA (cis-22:6n-3)	Serum/plasma	Not available	0.25–0.36
Alcohol	Phosphatidylethanol	Whole blood	Not available	0.26–0.79
	Ethyl glucuronide	Urine	Not available	0.20–0.60
Sugar	Sucrose	Urine	0.20–0.30	Not available
	$\delta^{13}C$	Blood	Not available	0.28–0.35

Table 3. Key differences between observational and intervention studies.

	Observational studies	Intervention studies
Research objectives	Associations between dietary factors and disease risks	Effects of dietary interventions on health outcomes
Common designs	Cross-sectional study, case-control study, cohort study, nested case-control study, case-cohort study	Randomized controlled trials, cluster-randomized trials, crossover trials, non-randomized trials
Strengths	Large sample sizes; long-term follow-up; less costly; more feasible; capture dietary behaviors and disease occurrence in real-world settings; useful for hypothesis generation	Stronger causal inference; controlled exposure; minimizes confounding when well-designed
Limitations	Confounding bias; reverse causation bias; selection bias; dietary exposures are complex and dietary assessment often relies on self-report; cannot prove causality	Expensive; ethical and feasibility constraints; compliance and attrition issues; small sample sizes; short-term follow-up; limited generalizability
Examples	Nurses' Health Study, European Prospective Investigation into Cancer Study	The Prevención con Dieta Mediterránea trial, The D-Health Trial

tions among food components, and individuals' eating patterns may change over time. Additionally, confounding and reverse causation bias often obscure the interpretation of associations, complicating efforts to draw causal inferences.

To improve the quality and reliability of evidence, advances have been made in nutritional epidemiology. Approaches such as matching, propensity score methods, stratified analyses, and multivariable adjustment help mitigate confounding bias. Mendelian randomization (MR), which uses genetic variants as instrumental variables, offers a means to address unmeasured confounding.[41] Target trial emulation further strengthens causal inference by structuring observational analyses to mimic RCTs, with clearer definitions of exposure onset, follow-up procedures, inclusion and eligibility criteria, and comparison groups.[42] From a study design perspective, long-term follow-up enables clear delineation of the temporal sequence between dietary exposures and disease outcomes, reducing the risk of reverse causation. Repeated dietary assessments help capture temporal variability in diet. Additionally, cross-cohort data harmonization enhances statistical power and facilitates replication of findings across diverse populations. At the same time, rapid advances in multi-omics technologies (such as metabolomics, proteomics, metagenomics) allow researchers to uncover novel biological pathways and mechanistic insights linking diet to health, especially when combined with experimental studies.

Overall, nutritional epidemiology is evolving from traditional observational approaches toward more rigorous, systematic, and mechanistically informed research paradigms. With continued methodological innovation, expansion of large-scale data resources, and integration of molecular and experimental studies, future research will be better equipped to identify true causal relationships between diet and health, ultimately strengthening the scientific foundation for public health policy and personalized nutrition interventions.

Dietary intervention

Dietary intervention studies yielded critical insights into the causal relationship between diet and health outcomes. For instance, RCTs have demonstrated that adherence to a Mediterranean diet can significantly reduce the incidence of major cardiovascular events and diabetes.[43-44] By contrast, large-scale trials of nutrient supplementation have shown limited benefits. Vitamin D supplementation, for example, has not consistently reduced the risk of diabetes, cancer, cardiovascular events, or mortality compared with placebo in the general population.[45-47]

Common challenges persist in the field of dietary intervention. A primary difficulty is blinding. Apart from certain trials focusing on nutrient supplements, blinding is often difficult to implement, and its absence may introduce potential selection or information bias.[18] Second, unlike pharmaceutical trials, it is difficult to design placebos in dietary intervention studies, except in studies of nutrient supplements. This limitation complicates the design of control groups and challenges the interpretation of results.[48] Third, recruiting suitable participants is a challenge. Individuals willing to commit to long-term trials often have stronger health consciousness and may not be representative of populations with nutritional deficiencies, thereby limiting generalizability. In addition, ensuring participant compliance is challenging. In cases where interventions are strict and prolonged, declining adherence may lead to participant withdrawal and loss to follow-up. For example, in an intervention study exploring the impact of the dairy food on cardiometabolic and cognitive health among overweight individuals, the attrition rate reached 49.3% at 12 months of the study. Among the attrition reasons, the inability to comply with the dietary requirements accounted for 27.0%, while time commitment was responsible for 10.8%.[49] Generally, long-term intervention studies with hard endpoints demand extensive resources and often suffer from high attrition. Consequently, many researchers opt for short-term intervention studies that emphasize intermediate endpoints. Finally, the translation of nutritional interventions into real-world practice presents considerable challenges. Some interventions are effective in trial settings but often fail to be translated into real-world practice, in part because of contextual barriers such as food availability, affordability, and accessibility. For instance, large-scale food fortification programs aimed at reducing micronutrient deficiencies have shown promising results in clinical trials, yet their implementation in low- and middle-income countries is frequently hindered by limited infrastructure, inconsistent food distribution systems, and socioeconomic disparities.[50]

Traditional dietary interventions have primarily focused on dietary patterns and nutrients. More recently, novel intervention approaches, such as those targeting meal timing and mindful eating, have gained increasing attention. The following sections provide an overview of these innovative approaches.

Dietary rhythm may influence the effects of diet and represents a promising target for intervention. Time restricted eating (TRE) has emerged as a novel strategy, requiring participants to confine food intake to a 4-12 hour window each day, with the remaining 12-20 hours dedicated to fasting or consuming only water or calorie-free beverages.[51-52] Researchers have observed that the TRE with a 6-hour feeding period per day can improve insulin sensitivity, β-cell responsiveness, blood pressure, oxidative stress, and appetite in individuals with prediabetes compared with a 12-hour feeding schedule.[53] Also, TRE with a 8-hour feeding period per day was effective for weight loss and lowering of glycosylated hemoglobin concentrations compared with daily calorie restriction in adults with type 2 diabetes.[54] However, another study has shown that the TRE was no more effective than daily calorie restriction in reducing body weight, body fat, or metabolic risk factors in participants with obesity.[55] Furthermore, researchers have combined meal timing with calorie restriction, giving rise to intermittent calorie restriction (ICR) strategies such as alternate-day fasting (ADF) and the 5:2 diet. ADF requires participants to alternate between eating and fasting every other day, while the 5:2 diet integrates five days of regular eating with two days (usually non-consecutive) of fasting within a week. Participants are free to eat on eating days, while should maintain daily energy intake between 0 to 500 kcal on fasting days.[56-57] A meta-analysis has demonstrated that the ICR can effectively reduce body weight, fat content, serum triacylglycerols and systolic blood pressure compared with usual diets.[58]

Mindful eating is a behavioral approach that applies principles of mindfulness to dietary practices. It emphasizes awareness, attention, and non-judgmental observation during eating, encouraging individuals to focus on the sensory experience of food, recognize internal cues of hunger and satiety, and reduce automatic or emotionally driven eating. Evidence suggested that mindful eating was associated with a healthier dietary pattern,[59] and may contribute to improved physical health and psychological well-being.[60]

Personalized dietary interventions, which tailor dietary recommendations to individual characteristics such as genetic background, lifestyles, and gut microbiota, have emerged as a promising direction in recent years. Evidence indicated that personalized dietary interventions could improve diet quality and support effective health management. For instance, the Food4Me study, which included 1,607 participants from seven European countries, demonstrated that the personalized dietary recommendations were more effective than the general dietary advice in promoting choices of healthy food. These recommendations were tailored by comparing nutrient intake with dietary guidelines and translating this into advice on food groups such as fruits and vegetables. Additional personalized advice was based on anthropometric measures, metabolic biomarkers, genetic variants in five nutrient-responsive genes, and physical activity data from accelerometers and the Baecke questionnaire, thereby integrating diet, body, genetic, and lifestyle information into individualized guidance.[61] Moreover, a personalized dietary program tailored to individual postprandial glucose and triglyceride responses, microbiome profiles, and health history led to significant reductions in triglyceride levels and improvements in body weight, waist circumference, glycated hemoglobin, diet quality, and microbiome composition, compared with standard dietary advice.[62] Additionally, in populations with prediabetes, personalized diets tailored to clinical and microbiome features significantly improved blood glucose levels compared to the Mediterranean diet.[63]

Implementing interventions in real-world settings is essential. Compared with RCTs, real-world intervention studies typically impose fewer inclusion restrictions on participants, resulting in larger and more diverse samples. Their flexible design enhances generalizability and practical relevance. Several real-world cluster RCTs in rural China have shown that salt substitutes reduced blood pressure and lowered the risks of hypertension, stroke, major cardiovascular events, and all-cause mortality compared with regular salt.[64-66] Nonetheless, real-world intervention studies face limitations, including suboptimal randomization and potential confounding.

Overall, dietary intervention studies have advanced understanding of the causal relationships between diet and health, though challenges in trial design, adherence, and real-world translation persist. Emerging dietary interventions such as time-restricted eating, mindful practices, and personalized dietary recommendations expand dietary strategies and hold promise for strengthening nutrition-based interventions and promoting health.

Causal inference

Most nutritional epidemiological studies are observational in nature and thus vulnerable to bias. For example, cross-sectional dietary surveys are particularly susceptible to reverse causation bias, while case-control studies often face recall and selection bias. Even prospective cohort studies, though generally considered more robust, remain susceptible to confounding bias from lifestyles, socioeconomic factors, and other factors that co-vary with diet. These limitations restrict causal inference, underscoring that observational study can establish associations but not causal relationships. Although dietary intervention studies can mitigate biases common in observational research (e.g., selection bias, reverse causation, confounding) and establish causality, they are hindered by challenges in blinding, compliance, resources, and ethics.

Reliable causal inferences are essential for decision-making and ideally stem from high-quality RCTs. However, when high-quality RCTs with hard endpoints are lacking, decisions may rely on well-conducted prospective cohort studies or small-scale, short-term RCTs with intermediate endpoints. For example, updates to the United States Dietary Guidelines have relied heavily on prospective cohort evidence.[67]

Early in the 1960s, Hill proposed criteria for causal inference, including strength, consistency, temporality, biological gradient (dose-response), plausibility, coherence, and experimental evidence.[68] In subsequent years, directed acyclic graphs (DAGs) were introduced as a visual tool to represent hypothesized causal relationships between exposures and health outcomes, aiding the identification of confounders, mediators, and instrumental variables.[69] For example, in nutritional epidemiology, socioeconomic status may confound the association between sugar-sweetened beverage intake and diabetes, while body mass index may act as a mediator, and genetic variants influencing taste preference can serve as instrumental variables. A DAG helps to make these assumptions explicit, visually clarifying the hypothesized causal pathways.

Building on the logic of instrumental variables, MR has become increasingly applied in nutritional epidemiology. By using genetic variants as instrumental variables to proxy dietary exposures, MR enables causal inference in diet-disease relationships, as demonstrated in studies of coffee and dairy intakes with health outcomes.[70-71] Because genetic variants are randomly assigned at meiosis and precede health outcomes in temporal order, MR can reduce bias from confounding and reverse causation.[41] Nonetheless, limitations remain, such as biased estimates from weak instruments[72] and violations of core assumptions due to linkage disequilibrium.[73] In nutritional epidemiology, challenges are amplified because dietary exposures are time-varying, compositional, and intercorrelated, which undermines instrument validity and increases the risk of MR assumption violations.[74] Consequently, MR studies in nutritional epidemiology should prioritize well-defined dietary exposures, robust genetic instruments, and clear causal hypotheses, while incorporating rigorous sensitivity analyses to strengthen causal inference.

Complementing MR, target trial emulation has provided a methodological framework to design observational studies as simulated randomized trials. By explicitly defining the study population, interventions, control groups, exposure onset, follow-up procedures, and outcomes, target trial emulation enhances transparency and interpretability, thereby strengthening causal inference.[42] In nutritional epidemiology, target trial emulation has been applied to evaluate the effects of dietary patterns and supplement use. For instance, prior studies have emulated trials to assess the impact of the Dietary Approaches to Stop Hypertension diet on all-cause and cardiovascular mortality among patients with myocardial infarction,[75] as well as the effectiveness of vitamin D supplementation on knee osteoarthritis.[76]

Synthesizing existing evidence is an essential step in causal inference. Traditionally, systematic reviews and meta-analyses have played a central role in the integration and evaluation of evidence. In recent years, researchers have introduced the "burden of proof" framework, an adaptation of meta-analysis that quantifies the average risk function between exposures and health outcomes after adjusting for known biases. This approach not only assesses whether associations exist and their magnitude, but also evaluates the strength of the supporting evidence.[77-80] Previous "burden of proof" studies have evaluated increased diabetes risk from processed meat and sugar-sweetened beverages,[78] and elevated risks of cardiovascular disease and diabetes from insufficient vegetable intake.[80] A concise comparison among MR, target trial emulation, and evidence synthesis is presented in Table 4.

In summary, various theories and methods continue to evolve, collectively enhancing our capacity to conduct causal inference in nutritional epidemiology. By rigorously examining the effects of diet on health based on the best available evidence, we can effectively conduct causal inference and formulate nutritional policies.

Multi-omics technologies

Conventional studies typically emphasize macro-level factors such as dietary patterns, lifestyle behaviors (e.g., physical activity, smoking, alcohol use), and disease outcomes. However, they often overlook micro-level mechanisms, including diet-related genes, nutrient metabolic pathways, and gut microbiota compositions.

In recent years, high-throughput omics technologies have enabled micro-level exploration of diet-health relationships. These include genomics, epigenetics, transcriptomics, proteomics, metabolomics, and microbiomics. Several of these technologies have already been applied in nutritional epidemiology (Figure 1). The following section introduces the omics approache commonly employed in this field.

The integration of nutrition and genomics has engendered the interdisciplinary field of nutrigenomics.[81] This field enhances understanding of diet-related genetic variation, providing a basis for explaining individual differences in dietary responses and identifying high-risk populations susceptible to specific dietary factors.[82] For instance, circulating cholesterol, a crucial biomarker for cardiovascular health, is associated with a range of genes, such as *apolipoprotein E*, *apolipoprotein A-I*, and *ATP-binding cassette subfamily A1*. Individuals with different genotypes may exhibit distinct responses to dietary cholesterol intake, resulting in varying levels of circulat-

Table 4. Key difference among Mendelian randomization, target trial emulation, and evidence synthesis.

	Mendelian randomization	Target trial emulation	Evidence synthesis
Definition	Uses genetic variants as instrumental variables to proxy dietary exposures to infer potential causal relationships	Reconstructs real-world observational data to mimic the design of a randomized controlled trial	Synthesizes existing evidence across multiple studies to provide both qualitative and quantitative evaluation
Strengths	Minimizes confounding and reverse causation; leverages lifelong genetic exposure	Bridges gap between randomized controlled trials and observational studies	Summarizes large bodies of evidence; increases statistical power
Limitations	Weak instrument bias; genetic pleiotropy; linkage disequilibrium; limited dietary exposures with genetic proxies	Dependent on quality and completeness of observational data; residual confounding	Publication bias; heterogeneity; quality depends on included studies
Applications	Assessing potential causal relationships between dietary factors and diseases	Evaluating potential effects of dietary interventions on diseases	Pooling and quantifying risk estimates of dietary exposures

ing cholesterol, and consequently, distinct risks of cardiovascular diseases.[83] In addition, researchers found that the positive association between sugary beverage intakes and body mass index (BMI) was stronger in individuals with a higher polygenic risk for elevated BMI, compared with those with a lower polygenic risk. This finding suggested that populations genetically predisposed to higher BMI are more susceptible to sugary beverages.[84]

Proteins and metabolites, as downstream products of genes, are influenced by diets and are closely related to the onset and progression of diseases. Proteomics is commonly assessed by high-throughput mass spectrometry, antibody-based platforms (e.g., Olink), and aptamer-based platforms (e.g., SomaScan). In nutritional epidemiology, it has been used to capture molecular signatures of dietary intakes, elucidate molecular pathways and identify biomarkers or therapeutic targets for diet-related diseases. For example, proteomic studies have revealed signatures of healthy dietary patterns, highlighting proteins as mediators between healthy dietary patterns and major chronic diseases.[85] Metabolomics primarily relies on techniques such as nuclear magnetic resonance, gas chromatography-mass spectrometry, and liquid chromatography-mass spectrometry.[86] It facilitates the discovery of objective dietary biomarkers, helping refine dietary exposure assessment and reduce recall bias. For instance, plasma metabolomics has identified metabolites, such as quinic acid and its potential derivatives, associated with coffee intakes.[87] Moreover, metabolomics enables exploration of metabolic pathways underlying dietary effects.[88]

The gut microbiota, typically assessed using techniques like 16S rRNA gene sequencing and metagenomics, serves as a critical bridge in diet-health relationships.[89] Investigating the gut microbiota helps illustrate how diet influences nutrient absorption, metabolism, and disease risk, offering a potential target for interventions. For example, higher consumption of fish and plant-based foods has been linked to short-chain fatty acid producing commensals, which exert anti-inflammatory effects and protect the intestinal mucosa.[90] In addition, individuals with lactose intolerance exhibit distinct microbial signatures, characterized by reduced abundance of lactose-fermenting taxa such as *Bifidobacterium*, alongside enrichment of gas-producing bacteria that contribute to bloating and discomfort.[91-92] These observations underscore how intolerance-related microbial shifts can exacerbate gastrointestinal symptoms and highlight the potential of microbiota-targeted strategies in managing dietary sensitivities. Complex carbohydrates and plant-derived polysaccharides escape digestion by human enzymes but are metabolized by gut microbes into short-chain fatty acids, which support mucosal integrity, regulate immune responses, and lower inflammation. Prebiotic fibers such as inulin and fructooligosaccharides selectively stimulate beneficial taxa like *Bifidobacterium* and *Faecalibacterium*, reinforcing their role in maintaining gut homeostasis.[93] Together, these examples highlight the gut microbiota's central role in mediating diet-health relationships and point toward personalized nutrition strategies.

In recent years, the integration of multiple omics technologies has advanced the elucidation of multi-level mechanisms underlying diet and nutrition-related diseases. For instance, by integrating metabolomics and gut microbiota technologies, researchers have suggested that compared with nut supplementation alone, the Mediterranean diet reshaped gut microbiota, which subsequently drove improvements in participants' metabolomic profiles, including phosphatidylcholines, cholesterol esters, triglycerides, and insulin resistance markers.[94] Likewise, greater adherence to a plant-based diet was associated with reduced risks of colorectal and liver cancers, accompanied by reduced abundances of gut microbiota *Collinsella* and *Desulfovibrionaceae*, and blood metabolomic changes, including elevated caffeine-related metabolites and decreased branched-chain amino acid metabolites.[95] By integrating genomics and proteomics, researchers showed that higher intakes of omega-3 polyunsaturated fatty acids (PUFA), such as stearidonic acid (SDA), docosapentaenoic acid (DPA), and docosahexaenoic acid (DHA), were associated with reduced risks of rheumatoid arthritis (RA), with stronger protective associations in individuals at high genetic risk of RA. Proteomic analyses further identified key proteins, including TNFRSF4, LAMP-3, CD80, TNFRSF9, PDCD1, CD27, and TNFRSF1B, connecting these fatty acids to RA through immune and inflammatory pathways.[96] Through combined metabolomic, proteomic, and transcriptomic analyses, the study found that compared with controls on a higher-carbohydrate diet, participants following a short-term modified Atkins diet showed elevated plasma and cortex 3-hydroxybutyric acid levels. Brain proteomics and transcriptomics further suggested activation of oxidative phosphorylation and inhibition of sirtuin signaling, highlighting mitochondrial pathways as key mediators of diet-related metabolic changes in epilepsy.[97] Collectively, these studies highlight the clinical potential of multi-omics approaches in uncovering diet-driven pathways and advancing precise strategies for disease prevention.

It is essential to recognize the challenges posed by omics technologies. First, requirement for advanced equipment and potential high costs of measurement limit the broad application of multi-omics technologies. Second, handling high-dimensional omics data demands complex statistical approaches, and addressing false positive results is crucial for robust findings. Third, measurement errors from sample processing and detection may compromise accuracy. Finally, limited comparability across omics platforms, batch effects within the same platform, and the lack of standardized protocols in detection methods collectively hinder reproducibility of results. With effective strategies to address these hurdles in the future, multi-omics techniques hold great promise in enhancing our understanding of the interplay between diet and health.

FUTURE DIRECTIONS

Precision nutrition

Traditional nutritional epidemiology emphasizes population-level diet-health relationships, offering broad dietary recommendations but may not fully account for inter-individual variability. In fact, individual nutritional needs vary due to multiple factors, such as genetic background, metabolic characteristics, gut microbiota, lifestyles, circadian rhythms, disease status, and food environments. Thus, a "one-size-fits-all" approach may be insufficient for achieving optimal health.

Precision nutrition, also known as personalized nutrition, is a research direction rooted in assessing inter-individual differences in nutritional requirements and responses. It develops scientific and personalized nutritional regimens for individuals based on their unique characteristics such as genetic background, metabolic characteristics and lifestyles within the framework of dietary guidelines.[98] Moreover, nutritional exposures are cumulative across the life course and often exert strong effects during sensitive windows of

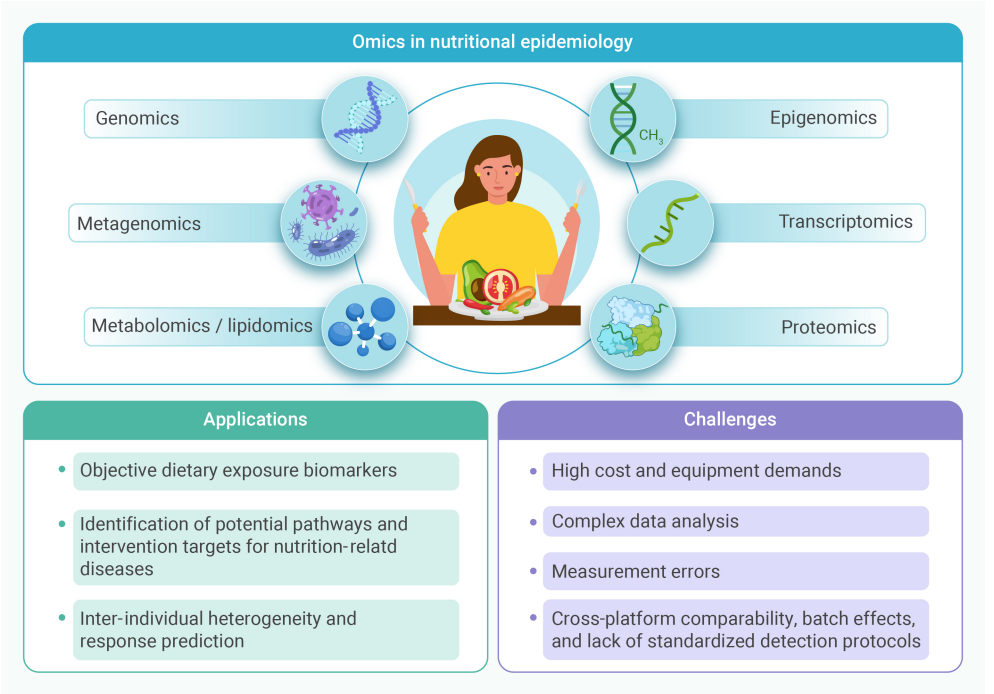

Figure 1. Omics in nutritional epidemiology

development. Precision nutrition therefore extends beyond managing nutrition for a specific life stage; it is a lifelong process continuously adapting to distinct dietary needs from infancy to old age.[99] Early-life nutrition is particularly critical, as inadequate or excessive exposures can have long-lasting consequences for disease risk. For example, early-life famine exposure has been associated with increased risks of infectious diseases, diabetes and cardiovascular disease in adulthood,[100-102] while sugar rationing in the first 1,000 days after conception in the UK was associated with lower risks of cardiovascular disease, metabolic dysfunction-associated steatotic liver disease and related liver outcomes, asthma and chronic obstructive pulmonary disease.[103-105] These findings underscore the importance of early-life nutritional interventions in determining lifelong health trajectories.

Advanced technologies underpin future development of precision nutrition. First, omics approaches can deepen insights into genetics, metabolism, and gut microbiota, which, combined with surveys and clinical examinations, provide essential data for assessing individual nutritional needs.[106] Second, wearable and mobile sensing devices enable real-time monitoring of nutritional biomarkers (e.g., serum biomarkers of nutrients), metabolic parameters (e.g., continuous 24-hour glucose profiles, energy expenditure, resting metabolic rate), vital signs (e.g., blood pressure and heart rate), and behavioral changes (e.g., physical activity patterns and sleep parameters), supporting timely adjustments to nutritional advice.[107-108] Furthermore, these wearable and mobile sensing devices have facilitated individual-resolution study designs such as nutritional n-of-1 clinical trials.[109-110] Third, advances in AI and LLMs enable rapid data processing, efficient integration and analysis of complex heterogeneous multimodal data, facilitating evidence-based and interpretable personalized nutritional recommendations. Nonetheless, limitations remain, such as data privacy concerns, potential bias in training datasets, and the need for rigorous clinical validation. Recently, practical applications are already emerging, including AI-driven dietary coaching apps that provide individualized meal planning, clinical decision support systems assisting healthcare professionals in tailoring nutrition therapy, and conversational agents that deliver real-time dietary feedback. Together, these innovations position AI/LLMs-driven nutrition tools as scalable solutions for individualized dietary guidance in both clinical and public health practice.[35,111-112] Fourth, digital twin technology offers a cutting-edge approach by creating dynamic virtual replicas of individuals that integrate omics, sensor, and clinical data. These personalized digital twins can simulate dietary interventions, predict long-term health outcomes, and optimize nutrition strategies before implementation.[113] For example, they may be applied to model metabolic responses to dietary exposures, forecast glycemic control, and evaluate the impact of personalized diets on health risks in patients with diabetes.[114] Overall, the integrated application of above-mentioned technologies plays a pivotal role in transforming precision nutrition into a proactive, predictive, and highly individualized practice.

However, precision nutrition still faces major challenges. First, the evidence base for precision nutrition is still underdeveloped. Although studies have shown that precision nutrition interventions can aid individuals in reducing the intake of discretionary foods, controlling blood glucose levels, and achieving weight loss more effectively than traditional dietary recommendations,[61-63,115-117] most existing studies are small and short-term trials with intermediate endpoints. Consequently, large and long-term trials with hard end points are needed. Second, data privacy and ethics remain pressing concerns, as handling large multi-dimensional data may lead to data misuse, privacy breaches, and ethical dilemmas. Strong data protection and regulatory policies are essential to safeguard personal information, enable responsible sharing, and ensure precision nutrition services meet ethical standards. Finally, precision nutrition often depends on costly technologies, restricting access and widening disparities. Lowering costs and implementing equity-focused policies are essential to ensure broader public benefit.

Overall, precision nutrition, as an emerging research direction, continues to broaden the scope of nutritional epidemiology. Simultaneously, it confronts many unresolved issues. Overcoming these issues is crucial for promoting personalized nutrition.

Sustainable nutrition

The food system exerts profound environmental impacts, with food production accounting for about 30% of global greenhouse gas emissions and 70% of freshwater use.[118-120] Concurrently, unhealthy diets have been identified as major drivers of adverse health outcomes, contributing to approximately 11 million deaths worldwide in 2017.[1] Thus, unsustainable and unhealthy diets accelerate environmental degradation and pose significant threats to human health.

In 2019, the EAT-Lancet Commission advocated for a global food system shift towards healthy and sustainable diets to promote both human and planetary health.[121] After the release of the 2019 EAT-Lancet report, a growing number of studies have assessed the associations of the planetary health diet with health outcomes and its environmental impacts in diverse populations.[122] Most studies indicated that adherence to the planetary health diet was associated with reduced risks of mortality and several chronic diseases,

including cardiovascular disease, diabetes, and cognitive decline.[122-126] Nevertheless, there was concerns that this plant-based dietary pattern may carry a risk of micronutrient inadequacy, particularly for micronutrient present in greater amounts and more bioavailable forms in animal-source foods (e.g., iron, calcium).[127-128] However, evidence suggests that with regional adaptations and inclusion of nutrient-dense foods, the planetary health diet can provide adequate micronutrient intakes.[129-130] From an environmental perspective, numerous modeling studies highlighted the sustainability of the planetary health diet, showing that its adoption could substantially reduce greenhouse gas emissions, land use, and total nitrogen and phosphorus use.[122,131-132]

The EAT-Lancet Commission 2.0 highlighted that the food system lies at the intersection of human health, environmental sustainability, and social justice. In recent years, the COVID-19 pandemic, climate change, and rising geopolitical instability have profoundly reshaped the food system, exacerbating entrenched inequities. Researchers emphasized that the food system transformation must safeguard both human and planetary health, while simultaneously ensuring justice and equity across societies.[133-135] Regarding the right to food, all stages of food production, processing, distribution, and consumption should be conducted fairly to ensure that healthy, sustainable, culturally diverse, convenient, and appealing diets are available, affordable, and accessible to individuals across different groups and social strata. Concerning the responsibility to the environment, current food systems exhibit stark inequalities in the distribution of both burdens and benefits. The diets of the wealthiest 30% of the global population account for more than 70% of the environmental pressures from food systems. Fairness demands a more equitable sharing of environmental responsibility among populations. For decent work, food system laborers must be guaranteed stable employment, fair wages, safe working conditions, social protection, avenues for collective voice, autonomy, and dignity.[136]

Nutrition epidemiology has played a pivotal role in developing and refining the planetary health diet, as well as in advancing the field of sustainable nutrition. At the population level, it provides evidence-based recommendations on food group intake, and quantifies the health effects of the planetary health diet, which serve as the foundation for constructing sustainable dietary patterns. Beyond the initial design of the planetary health diet, nutrition epidemiology continues to assess the diet's impacts across diverse populations, guiding necessary adjustments and improvements. Looking ahead, it is pivotal for nutritional epidemiology to engage in cross-disciplinary collaborations, and more integrated studies are needed to evaluate health, sustainability, and equity dimensions of the planetary health diet, thereby providing robust scientific evidence to inform policymaking.

In China, rapid but uneven urbanization has created a dual burden of malnutrition, with undernutrition remaining prevalent in rural areas while overnutrition increases in urban populations.[137] Concurrently, the Chinese food system has exerted a substantial environmental burden, being responsible for 19% of the national greenhouse gas emissions,[138] 95% of ammonia emissions, and 51% of nitrous oxide emissions.[139] Additionally, the dietary diversity reveals pronounced disparities across regions, social groups, and generations. With regard to health, previous studies have shown that adherence to the planetary health diet was associated with reduced risks of cardiovascular disease,[140-141] diabetes,[140-141] hypertension,[142] metabolic dysfunction-associated steatotic liver disease,[143] and cognitive impairment.[144] Looking ahead, sustainable nutrition solutions are essential for population health. For example, diversifying staple foods with grains and legumes such as millet, buckwheat, quinoa, lentil, and chickpea in "smart flour" formulations offers gluten-free protein and fiber alternatives to wheat products and may help reduce the burden of wheat-related metabolic diseases.[145] From an environmental perspective, alignment with the planetary health diet was associated with a decrease in greenhouse gas emissions,[140-141] while region-specific adaptations of this diet may enhance environmental sustainability in China.[146] From a social perspective, evidence remains limited, although one study suggested that adherence to the planetary health diet may result in a modest increase in diet costs.[141] Further research is needed to evaluate its broader social impacts and to develop social strategies for promoting the planetary health diet. For example, in the context of China's multi-ethnic society, ethnobotanical knowledge and diverse ethnic dietary traditions may provide useful insights into traditional foods, food preparation practices, and culturally embedded eating patterns. Such knowledge may help identify locally acceptable and potentially health-promoting dietary components, while also informing culturally tailored strategies for the adoption of sustainable diets. Overall, future efforts should focus on developing China-specific adaptations of the planetary health diet to advance the goals of a healthy China, beautiful China, and rural revitalization.

CONCLUSION

Nutritional epidemiology continues to face persistent challenges, including the accurate assessment of dietary exposures, the design and implementation of effective dietary interventions, and the establishment of causality in diet-disease relationships. Yet, cutting-edge technologies such as multi-omics combined with AI are reshaping nutritional epidemiology by enabling deeper insights into individual biology and scalable personalized guidance. Emerging frameworks such as digital twin technology further extend these prospects, offering predictive and proactive approaches to nutrition and health. In parallel, epidemiological research is driving global dietary transformation, highlighting the imperative of advancing human well-being while safeguarding planetary health. Collectively, these innovations and directions define the future agenda of nutritional epidemiology: leveraging technological innovation to deepen nutritional research, addressing the complex diet-health-environment nexus and promoting population well-being and planetary health on a broad scale.

REFERENCES

1. AGlobal burden and strength of evidence for 88 risk factors in 204 countries and 811 subnational locations, 1990-2021: A systematic analysis for the Global Burden of Disease Study 2021. (2024). *Lancet* **403**:2162-2203. DOI:10.1016/s0140-6736(24)00933-4
2. Health effects of dietary risks in 195 countries, 1990-2017: A systematic analysis for the Global Burden of Disease Study 2017. (2019). *Lancet* **393**:1958-1972. DOI:10.1016/s0140-6736(19)30041-8.
3. Mozaffarian D., Blanck H. M., Garfield K. M., et al. (2022). A Food is Medicine approach to achieve nutrition security and improve health. *Nat. Med.* **28**:2238–2240. DOI:10.1038/s41591-022-02027-3
4. Tessier A. J., Wang F., Korat A. A., et al. (2025). Optimal dietary patterns for healthy aging. *Nat. Med.* **31**:1644–1652. DOI:10.1038/s41591-025-03570-5
5. Willett W. (2012). Nutritional epidemiology (3rd edn). Willett W. (ed). Oxford University Press, pp:1–529. DOI:10.1093/acprof:oso/9780199754038.001.0001
6. Smithells R. W., Sheppard S., Schorah C. J., et al. (1980). Possible prevention of neural-tube defects by periconceptional vitamin supplementation. *Lancet* **1**:339–340. DOI:10.1016/s0140-6736(80)90886-7
7. Honein M. A., Paulozzi L. J., Mathews T. J., et al. (2001). Impact of folic acid fortification of the US food supply on the occurrence of neural tube defects. *JAMA* **285**:2981–2986. DOI:10.1001/jama.285.23.2981
8. Mozaffarian D., Katan M. B., Ascherio A., et al. (2006). Trans fatty acids and cardiovascular disease. *N. Engl. J. Med.* **354**:1601–1613. DOI:10.1056/NEJMra054035
9. World Health Organization. (2018). WHO plan to eliminate industrially-produced trans-fatty acids from global food supply. https://www.who.int/news/item/14-05-2018-who-plan-to-eliminate-industrially-produced-trans-fatty-acids-from-global-food-supply
10. Pacheco L. S., Tobias D. K., Haslam D. E., et al. (2025). Sugar-sweetened or artificially sweetened beverage consumption, physical activity and risk of type 2 diabetes in US adults. *Diabetologia* **68**:792–800. DOI:10.1007/s00125-024-06351-w
11. Pacheco L. S., Tobias D. K., Li Y., et al. (2024). Sugar-sweetened or artificially-sweetened beverage consumption, physical activity, and risk of cardiovascular disease in adults: a prospective cohort study. *Am. J. Clin. Nutr.* **119**:669–681. DOI:10.1016/j.ajcnut.2024.01.001
12. World Health Organization. (2023). Global report on the use of sugar-sweetened beverage taxes, 2023. https://www.who.int/publications/i/item/9789240084995
13. Lane M. M., Gamage E., Du S., et al. (2024). Ultra-processed food exposure and adverse health outcomes: Umbrella review of epidemiological meta-analyses. *BMJ* **384**:e077310. DOI:10.1136/bmj-2023-077310
14. World Health Organization. (2025). Call for experts to develop a WHO guideline on consumption of ultra-processed foods. https://www.who.int/news-room/articles-detail/call-for-experts-to-develop-a-who-guideline-on-consumption-of-ultra-processed-foods
15. Scrinis G., Popkin B. M., Corvalan C., et al. (2025). Policies to halt and reverse the rise in ultra-processed food production, marketing, and consumption. *Lancet* **406**:2685–2702. DOI:10.1016/S0140-6736(25)01566-1
16. Zhang F. F., Barr S. I., McNulty H., et al. (2020). Health effects of vitamin and mineral

supplements. *BMJ* **369**: m2511. DOI:10.1136/bmj.m2511
17. Libera J., Iłowiecka K. and Stasiak D. (2021). Consumption of processed red meat and its impact on human health: A review. *Int. J. Food Sci. Technol.* **56**:6115–6123. DOI:10.1111/ijfs.15270
18. Satija A., Yu E., Willett W. C., et al. (2015). Understanding nutritional epidemiology and its role in policy. *Adv. Nutr.* **6**:5–18. DOI:10.3945/an.114.007492
19. Wadell A. T., Bärebring L., Hulander E., et al. (2023). Dietary biomarkers and food records indicate compliance to study diets in the ADIRA (Anti-inflammatory Diet In Rheumatoid Arthritis) trial. *Front. Nutr.* **10**:1209787. DOI:10.3389/fnut.2023.1209787
20. Murai U., Tajima R., Matsumoto M., et al. (2023). Validation of dietary intake estimated by web-based dietary assessment methods and usability using dietary records or 24-h dietary recalls: A scoping review. *Nutrients* **15**:1816. DOI:10.3390/nu15081816
21. Lentjes M. A., McTaggart A., Mulligan A. A., et al. (2014). Dietary intake measurement using 7 d diet diaries in British men and women in the European prospective investigation into cancer-norfolk study: A focus on methodological issues. *Br. J. Nutr.* **111**:516–526. DOI:10.1017/s0007114513002754
22. Zipf G., Chiappa M., Porter K. S., et al. (2013). National health and nutrition examination survey: Plan and operations, 1999-2010. *Vital. Health Stat.* **1**:1–37.
23. Cui Q., Xia Y., Wu Q., et al. (2023). Validity of the food frequency questionnaire for adults in nutritional epidemiological studies: A systematic review and meta-analysis. *Crit. Rev. Food Sci. Nutr.* **63**:1670–1688. DOI:10.1080/10408398.2021.1966737
24. Rimm E. B., Giovannucci E. L., Stampfer M. J., et al. (1992). Reproducibility and validity of an expanded self-administered semiquantitative food frequency questionnaire among male health professionals. *Am. J. Epidemiol.* **135**:1114-1126; discussion 1127-1136. DOI:10.1093/oxfordjournals.aje.a116211
25. Bao Y., Bertoia M. L., Lenart E. B., et al. (2016). Origin, methods, and evolution of the three nurses' health studies. *Am. J. Public Health* **106**:1573–1581. DOI:10.2105/ajph.2016.303338
26. Landberg R., Karra P., Hoobler R., et al. (2024). Dietary biomarkers-an update on their validity and applicability in epidemiological studies. *Nutr. Rev.* **82**:1260–1280. DOI:10.1093/nutrit/nuad119
27. Al-Delaimy W. K., Ferrari P., Slimani N., et al. (2005). Plasma carotenoids as biomarkers of intake of fruits and vegetables: Individual-level correlations in the European Prospective Investigation into Cancer and Nutrition (EPIC). *Eur. J. Clin. Nutr.* **59**:1387–1396. DOI:10.1038/sj.ejcn.1602252
28. Edmands W. M., Ferrari P., Rothwell J. A., et al. (2015). Polyphenol metabolome in human urine and its association with intake of polyphenol-rich foods across European countries. *Am. J. Clin. Nutr.* **102**:905–913. DOI:10.3945/ajcn.114.101881
29. Subar A. F., Kirkpatrick S. I., Mittl B., et al. (2012). The Automated Self-Administered 24-hour dietary recall (ASA24): A resource for researchers, clinicians, and educators from the National Cancer Institute. *J. Acad. Nutr. Diet* **112**:1134–1137. DOI:10.1016/j.jand.2012.04.016
30. Park Y., Dodd K. W., Kipnis V., et al. (2018). Comparison of self-reported dietary intakes from the Automated Self-Administered 24-h recall, 4-d food records, and food-frequency questionnaires against recovery biomarkers. *Am. J. Clin. Nutr.* **107**:80–93. DOI:10.1093/ajcn/nqx002
31. Dalakleidi K. V., Papadelli M., Kapolos I., et al. (2022). Applying image-based food-recognition systems on dietary assessment: A systematic review. *Adv. Nutr.* **13**:2590–2619. DOI:10.1093/advances/nmac078
32. Ma P., Lau C. P., Yu N., et al. (2021). Image-based nutrient estimation for Chinese dishes using deep learning. *Food Res. Int.* **147**:110437. DOI:10.1016/j.foodres.2021.110437
33. Chotwanvirat P., Prachansuwan A., Sridonpai P., et al. (2024). Advancements in using AI for dietary assessment based on food images: Scoping review. *J. Med. Internet Res.* **26**:e51432. DOI:10.2196/51432
34. Yan R., Luo H., Lu J., et al. (2025). DietAI24 as a framework for comprehensive nutrition estimation using multimodal large language models. *Commun. Med. (Lond)* **5**:458. DOI:10.1038/s43856-025-01159-0
35. Sharma R., Gaur S. S., Ajay A., et al. (2025). Artificial intelligence and precision nutrition: Tailoring diets with data-driven insights. *Nutrire* **50**:56. DOI:10.1186/s41110-025-00360-4
36. Cohen Y., Jansen T., Onwuka S., et al. (2026). Advances and opportunities in measuring dietary intake: From omics to AI. *Nat Metab.* **8**:413-432. DOI:10.1038/s42255-026-01494-z
37. Wang M., Yang Y., Min J., et al. (2022). A wearable electrochemical biosensor for the monitoring of metabolites and nutrients. *Nat. Biomed. Eng.* **6**:1225–1235. DOI:10.1038/s41551-022-00916-z
38. Lorestani F., Zhang X., Abdullah A. M., et al. (2023). A highly sensitive and long-term stable wearable patch for continuous analysis of biomarkers in sweat. *Adv. Funct. Mater.* **33**:2306117. DOI:10.1002/adfm.202306117
39. Bakhshandeh F., Zheng H., Barra N. G., et al. (2024). Wearable aptalyzer integrates microneedle and electrochemical sensing for in vivo monitoring of glucose and lactate in live animals. *Adv. Mater.* **36**:e2313743. DOI:10.1002/adma.202313743
40. Tong X., Jiang T., Yang J., et al. (2025). Continuous glucose monitoring (CGM) system based on protein hydrogel anti-biofouling coating for long-term accurate and point-of-care glucose monitoring. *Biosens. Bioelectron.* **277**:117307. DOI:10.1016/j.bios.2025.117307
41. Tin A. and Köttgen A. (2021). Mendelian randomization analysis as a tool to gain insights into causes of diseases: A primer. *J. Am. Soc. Nephrol.* **32**:2400–2407. DOI:10.1681/asn.2020121760
42. Hernán M. A., Dahabreh I. J., Dickerman B. A., et al. (2025). The target trial framework for causal inference from observational data: Why and when is it helpful. *Ann. Intern. Med.* **178**:402–407. DOI:10.7326/annals-24-01871
43. Delgado-Lista J., Alcala-Diaz J. F., Torres-Peña J. D., et al. (2022). Long-term secondary prevention of cardiovascular disease with a Mediterranean diet and a low-fat diet (CORDIOPREV): A randomised controlled trial. *Lancet* **399**:1876–1885. DOI:10.1016/s0140-6736(22)00122-2
44. Ruiz-Canela M., Corella D., Martínez-González M., et al. (2025). Comparison of an energy-reduced Mediterranean diet and physical activity versus an ad libitum Mediterranean diet in the prevention of type 2 diabetes : A secondary analysis of a randomized controlled trial. *Ann. Intern. Med.* **178**:1378–1389. DOI:10.7326/annals-25-00388
45. Tobias D. K., Pradhan A. D., Duran E. K., et al. (2025). Vitamin D supplementation vs. placebo and incident type 2 diabetes in an ancillary study of the randomized Vitamin D and Omega-3 Trial. *Nat. Commun.* **16**:3332. DOI:10.1038/s41467-025-58721-6
46. Neale R. E., Baxter C., Romero B. D., et al. (2022). The D-Health Trial: A randomised controlled trial of the effect of vitamin D on mortality. *Lancet Diabetes Endocrinol.* **10**:120–128. DOI:10.1016/s2213-8587(21)00345-4
47. Virtanen J. K., Nurmi T., Aro A., et al. (2022). Vitamin D supplementation and prevention of cardiovascular disease and cancer in the finnish Vitamin D trial: A randomized controlled trial. *Am. J. Clin. Nutr.* **115**:1300–1310. DOI:10.1093/ajcn/nqab419
48. Staudacher H. M., Irving P. M., Lomer M. C. E., et al. (2017). The challenges of control groups, placebos and blinding in clinical trials of dietary interventions. *Proc. Nutr. Soc.* **76**:628. DOI:10.1017/s0029665117002816
49. Crichton G. E., Howe P. R., Buckley J. D., et al. (2012). Long-term dietary intervention trials: critical issues and challenges. *Trials* **13**:111. DOI:10.1186/1745-6215-13-111
50. Lawrence M., Wingrove K., Naude C., et al. (2016). Evidence synthesis and translation for nutrition interventions to combat micronutrient deficiencies with particular focus on food fortification. *Nutrients* **8**:555. DOI:10.3390/nu8090555.
51. Petersen M. C., Gallop M. R., Flores Ramos S., et al. (2022). Complex physiology and clinical implications of time-restricted eating. *Physiol. Rev.* **102**:1991–2034. DOI:10.1152/physrev.00006.2022
52. Parrotta M. E., Colangeli L., Scipione V., et al. (2025). Time restricted eating: A valuable alternative to calorie restriction for addressing obesity. *Curr. Obes. Rep.* **14**:17. DOI:10.1007/s13679-025-00609-z
53. Sutton E. F., Beyl R., Early K. S., et al. (2018). Early time-restricted feeding improves insulin sensitivity, blood pressure, and oxidative stress even without weight loss in men with prediabetes. *Cell Metab.* **27**:1212–1221.e1213. DOI:10.1016/j.cmet.2018.04.010
54. Pavlou V., Cienfuegos S., Lin S., et al. (2023). Effect of time-restricted eating on weight loss in adults with type 2 diabetes: A randomized clinical trial. *JAMA Netw. Open* **6**:e2339337. DOI:10.1001/jamanetworkopen.2023.39337
55. Liu D., Huang Y., Huang C., et al. (2022). Calorie restriction with or without time-restricted eating in weight loss. *N. Engl. J. Med.* **386**:1495–1504. DOI:10.1056/NEJMoa2114833
56. Santos H. O., Genario R., Tinsley G. M., et al. (2022). A scoping review of intermittent fasting, chronobiology, and metabolism. *Am. J. Clin. Nutr.* **115**:991–1004. DOI:10.1093/ajcn/nqab433
57. Varady K. A., Cienfuegos S., Ezpeleta M., et al. (2022). Clinical application of intermittent fasting for weight loss: Progress and future directions. *Nat. Rev. Endocrinol.* **18**:309–321. DOI:10.1038/s41574-022-00638-x
58. Schwingshackl L., Zähringer J., Nitschke K., et al. (2021). Impact of intermittent energy restriction on anthropometric outcomes and intermediate disease markers in patients with overweight and obesity: Systematic review and meta-analyses. *Crit. Rev. Food Sci. Nutr.* **61**:1293–1304. DOI:10.1080/10408398.2020.1757616
59. Paolassini-Guesnier P., Van Beekum M., Kesse-Guyot E., et al. (2025). Mindful eating is associated with a better diet quality in the NutriNet-Santé study. *Appetite* **206**:107797. DOI:10.1016/j.appet.2024.107797
60. Zainol Hisham N. R. J. and Yulita (2025). The relationships between daily mindful eating behavior and physical and psychological outcomes among university students: the moderating role of eating attitudes. *Mindfulness* **16**:2270-2281. DOI:10.1007/s12671-025-02623-7
61. Livingstone K. M., Celis-Morales C., Navas-Carretero S., et al. (2021). Personalised nutrition advice reduces intake of discretionary foods and beverages: Findings from the Food4Me randomised controlled trial. *Int. J. Behav. Nutr. Phys. Act.* **18**:70. DOI:10.1186/s12966-021-01136-5
62. Bermingham K. M., Linenberg I., Polidori L., et al. (2024). Effects of a personalized nutrition program on cardiometabolic health: A randomized controlled trial. *Nat. Med.* **30**:1888–1897. DOI:10.1038/s41591-024-02951-6
63. Ben-Yacov O., Godneva A., Rein M., et al. (2021). Personalized postprandial glucose response-targeting diet versus mediterranean diet for glycemic control in prediabetes. *Diabetes Care* **44**:1980–1991. DOI:10.2337/dc21-0162
64. Neal B., Wu Y., Feng X., et al. (2021). Effect of salt substitution on cardiovascular events and death. *N. Engl. J. Med.* **385**:1067–1077. DOI:10.1056/NEJMoa2105675

65. Yuan Y., Jin A., Neal B., et al. (2023). Salt substitution and salt-supply restriction for lowering blood pressure in elderly care facilities: A cluster-randomized trial. *Nat. Med.* **29**:973–981. DOI:10.1038/s41591-023-02286-8
66. Zhang X., Yuan Y., Li C., et al. (2024). Effect of a salt substitute on incidence of hypertension and hypotension among normotensive adults. *J. Am. Coll. Cardiol.* **83**:711–722. DOI:10.1016/j.jacc.2023.12.013
67. U.S. Department of Health and Human Services, U.S. Department of Agriculture. (2026). Dietary guidelines for Americans (10th ed.). https://cdn.realfood.gov/DGA.pdf
68. Hill A. B. (1965). The environment and disease: Association or causation. *Proc. R. Soc. Med.* **58**:295–300. DOI:10.1177/003591576505800503
69. Pearl J. (1995). Causal diagrams for empirical research. *Biometrika* **82**:669–688. DOI:10.2307/2337329
70. Li X., Cheng S., Cheng J., et al. (2022). Habitual coffee consumption increases risk of primary open-angle glaucoma: A Mendelian randomization study. *Ophthalmology* **129**:1014–1021. DOI:10.1016/j.ophtha.2022.04.027
71. Domenighetti C., Sugier P. E., Ashok Kumar Sreelatha A., et al. (2022). Dairy intake and Parkinson's disease: A Mendelian randomization study. *Mov. Disord.* **37**:857–864. DOI:10.1002/mds.28902
72. Shi R., Wang L., Burgess S., et al. (2024). MR-SPLIT: A novel method to address selection and weak instrument bias in one-sample Mendelian randomization studies. *PLoS Genet.* **20**:e1011391. DOI:10.1371/journal.pgen.1011391
73. Wang Y., Li T., Fu L., et al. (2021). A novel method for Mendelian randomization analyses with pleiotropy and linkage disequilibrium in genetic variants from individual data. *Front. Genet.* **12**: 634394. DOI:10.3389/fgene.2021.634394
74. Merino J. and Tobias D. K. (2022). The unique challenges of studying the genetics of diet and nutrition. *Nat. Med.* **28**:221–222. DOI:10.1038/s41591-021-01626-w
75. Bonekamp N. E., Cruijsen E., Visseren F. L., et al. (2023). Compliance with the DASH diet and risk of all-cause and cardiovascular mortality in patients with myocardial infarction. *Clin. Nutr.* **42**:1418–1426. DOI:10.1016/j.clnu.2023.06.033
76. Jin X., Ding C., Hunter D. J., et al. (2022). Effectiveness of vitamin D supplementation on knee osteoarthritis - a target trial emulation study using data from the Osteoarthritis Initiative cohort. *Osteoarthr. Cartil.* **30**:1495–1505. DOI:10.1016/j.joca.2022.06.005
77. Zheng P., Afshin A., Biryukov S., et al. (2022). The Burden of Proof studies: Assessing the evidence of risk. *Nat. Med.* **28**:2038–2044. DOI:10.1038/s41591-022-01973-2
78. Haile D., Harding K. L., McLaughlin S. A., et al. (2025). Health effects associated with consumption of processed meat, sugar-sweetened beverages and trans fatty acids: A Burden of Proof study. *Nat. Med.* **31**:2244–2254. DOI:10.1038/s41591-025-03775-8
79. Lescinsky H., Afshin A., Ashbaugh C., et al. (2022). Health effects associated with consumption of unprocessed red meat: A Burden of Proof study. *Nat. Med.* **28**:2075–2082. DOI:10.1038/s41591-022-01968-z
80. Stanaway J. D., Afshin A., Ashbaugh C., et al. (2022). Health effects associated with vegetable consumption: A Burden of Proof study. *Nat. Med.* **28**:2066–2074. DOI:10.1038/s41591-022-01970-5
81. Singar S., Nagpal R., Arjmandi B. H., et al. (2024). Personalized nutrition: Tailoring dietary recommendations through genetic insights. *Nutrients* **16**:2673. DOI:10.3390/nu16162673
82. Lal M. K., Sharma E., Tiwari R. K., et al. (2022). Nutrient-mediated perception and signalling in human metabolism: A perspective of nutrigenomics. *Int. J. Mol. Sci.* **23**:11305. DOI:10.3390/ijms231911305
83. Abdullah M. M., Jones P. J. and Eck P. K. (2015). Nutrigenetics of cholesterol metabolism: Observational and dietary intervention studies in the postgenomic era. *Nutr. Rev.* **73**:523–543. DOI:10.1093/nutrit/nuv016
84. Qi Q., Chu A. Y., Kang J. H., et al. (2012). Sugar-sweetened beverages and genetic risk of obesity. *N. Engl. J. Med.* **367**:1387–1396. DOI:10.1056/NEJMoa1203039
85. Zhu K., Li R., Yao P., et al. (2025). Proteomic signatures of healthy dietary patterns are associated with lower risks of major chronic diseases and mortality. *Nat. Food* **6**:47–57. DOI:10.1038/s43016-024-01059-x
86. Liu J., Zhao H., Yin Z., et al. (2023). Application and prospect of metabolomics-related technologies in food inspection. *Food Res. Int.* **171**:113071. DOI:10.1016/j.foodres.2023.113071
87. Manghi P., Bhosle A., Wang K., et al. (2024). Coffee consumption is associated with intestinal Lawsonibacter asaccharolyticus abundance and prevalence across multiple cohorts. *Nat. Microbiol.* **9**:3120–3134. DOI:10.1038/s41564-024-01858-9
88. Noerman S. and Landberg R. (2023). Blood metabolite profiles linking dietary patterns with health-Toward precision nutrition. *J. Intern. Med.* **293**:408–432. DOI:10.1111/joim.13596
89. Kujawska M. and Hall L. J. (2025). Microbe-diet interactions and personalized nutrition. *Annu. Rev. Food Sci. Technol.***16**:1-22. DOI:10.1146/annurev-food-111523-121845
90. Bolte L. A., Vich Vila A., Imhann F., et al. (2021). Long-term dietary patterns are associated with pro-inflammatory and anti-inflammatory features of the gut microbiome. *Gut* **70**:1287–1298. DOI:10.1136/gutjnl-2020-322670
91. Brandao Gois M. F., Sinha T., Spreckels J. E., et al. (2022). Role of the gut microbiome in mediating lactose intolerance symptoms. *Gut* **71**:215–217. DOI:10.1136/gutjnl-2020-323911
92. Angima G., Qu Y., Park S. H., et al. (2024). Prebiotic strategies to manage lactose intolerance symptoms. *Nutrients* **16**:1002. DOI:10.3390/nu16071002
93. Fu J., Zheng Y., Gao Y., et al. (2022). Dietary fiber intake and gut microbiota in human health. *Microorganisms* **10**:2507. DOI:10.3390/microorganisms10122507
94. Galié S., García-Gavilán J., Papandreou C., et al. (2021). Effects of Mediterranean diet on plasma metabolites and their relationship with insulin resistance and gut microbiota composition in a crossover randomized clinical trial. *Clin. Nutr.* **40**:3798–3806. DOI:10.1016/j.clnu.2021.04.028
95. Yuan F., Wang L., Nguyen S. M., et al. (2025). Plant-based diets, gut microbiota, blood metabolome, and risk of colorectal, liver, and pancreatic cancers: Results from a large prospective cohort study of predominantly low-income Americans. *Am. J. Clin. Nutr.* **12**:101135. DOI:10.1016/j.ajcnut.2025.101135
96. Chen L., Tan T., Chen Y., et al. (2025). Dietary polyunsaturated fatty acid and the risk of rheumatoid arthritis: Insights from genetic predisposition and proteomics. *Arthritis Rheumatol.* **77**:1475–1487. DOI:10.1002/art.43229
97. Leitner D. F., Siu Y., Korman A., et al. (2023). Metabolomic, proteomic, and transcriptomic changes in adults with epilepsy on modified Atkins diet. *Epilepsia* **64**:1046–1060. DOI:10.1111/epi.17540
98. Fu Y., Zhang K., Miao Z., et al. (2026). Advancing precision nutrition through multimodal data and artificial intelligence. *Adv. Sci. (Weinh)***12**:e21111. DOI:10.1002/advs.202521111
99. Chong M. F. (2022). Dietary trajectories through the life course: Opportunities and challenges. *Br. J. Nutr.* **128**:154–159. DOI:10.1017/s0007114522001295
100. Li Q., Collender P. A., Yu H., et al. (2025). Elevated risk of infectious diseases in adulthood after prenatal or early postnatal exposure to the Great Chinese Famine. *Proc. Natl. Acad. Sci. U.S.A.* **122**:e2513421122. DOI:10.1073/pnas.2513421122
101. Chen C., Nie Z., Wang J., et al. (2022). Prenatal exposure to the Chinese famine of 1959-62 and risk of cardiovascular diseases in adulthood: Findings from the China PEACE million persons project. *Eur. J. Prev. Cardiol.* **29**:2111–2119. DOI:10.1093/eurjpc/zwac210
102. Li C., C Ó. G. and Lumey L. H. (2024). Famine mortality and contributions to later-life type 2 diabetes at the population level: A synthesis of findings from Ukrainian, Dutch and Chinese famines. *BMJ Glob. Health* **9**:e015355. DOI:10.1136/bmjgh-2024-015355
103. Zheng J., Zhou Z., Huang J., et al. (2025). Exposure to sugar rationing in first 1000 days after conception and long term cardiovascular outcomes: Natural experiment study. *BMJ* **391**:e083890. DOI:10.1136/bmj-2024-083890
104. Zheng J., Zhou Z., Huang J., et al. (2025). Sugar rationing in the first 1000 days after conception and long-term risk of metabolic dysfunction-associated steatotic liver disease and major adverse liver outcomes: A natural experiment study. *Clin. Gastroenterol. Hepatol.* DOI:10.1016/j.cgh.2025.10.015
105. Zheng J., Yang C., Zhou Z., et al. (2025). Sugar restriction in the first 1000 days after conception, and long-term respiratory health: A quasi-experiment study. *Am. J. Clin. Nutr.* **122**:1759–1768. DOI:10.1016/j.ajcnut.2025.09.045
106. Ramos-Lopez O., Martinez J. A. and Milagro F. I. (2022). Holistic integration of omics tools for precision nutrition in health and disease. *Nutrients* **14**:4074. DOI:10.3390/nu14194074
107. Arshad M. T., Ali M. K. M., Maqsood S., et al. (2025). Personalized nutrition in the era of digital health: A new frontier for managing diabetes and obesity. *Food Sci. Nutr.* **13**:e71006. DOI:10.1002/fsn3.71006
108. Mortazavi B. J. and Gutierrez-Osuna R. (2023). A review of digital innovations for diet monitoring and precision nutrition. *J. Diabetes Sci. Technol.* **17**:217–223. DOI:10.1177/19322968211041356
109. Zhang K., Fu Y., Gou W., et al. (2025). Quantification of personalized glycemic sensitivity to food and its potential for precision nutrition in a series of n-of-1 trials. *Am. J. Clin. Nutr.* **122**:502–512. DOI:10.1016/j.ajcnut.2025.04.015
110. Ma Y., Fu Y., Tian Y., et al. (2021). Individual postprandial glycemic responses to diet in n-of-1 trials: Westlake N-of-1 trials for macronutrient intake (WE-MACNUTR). *J. Nutr.* **151**:3158–3167. DOI:10.1093/jn/nxab227
111. Kirk D., Kok E., Tufano M., et al. (2022). Machine learning in nutrition research. *Adv. Nutr.* **13**:2573–2589. DOI:10.1093/advances/nmac103
112. Wu X., Oniani D., Shao Z., et al. (2025). A scoping review of artificial intelligence for precision nutrition. *Adv. Nutr.* **16**:100398. DOI:10.1016/j.advnut.2025.100398
113. Monlezun D. J. and MacKay K. (2024). Artificial intelligence and health inequities in dietary interventions on atherosclerosis: A narrative review. *Nutrients* **16**. DOI:10.3390/nu16162601
114. Olawade D. B., Owhonda R. C., Alabi J. O., et al. (2026). Digital twin paradigm in diabetes prediction and management. *Diabetes Res. Clin. Pract.* **231**:113075. DOI:10.1016/j.diabres.2025.113075
115. Celis-Morales C., Livingstone K. M., Marsaux C. F., et al. (2015). Design and baseline characteristics of the Food4Me study: A web-based randomised controlled trial of personalised nutrition in seven European countries. *Genes Nutr.* **10**:450. DOI:10.1007/s12263-014-0450-2
116. Arkadianos I., Valdes A. M., Marinos E., et al. (2007). Improved weight management using genetic information to personalize a calorie controlled diet. *Nutr. J.* **6**:29. DOI:10.1186/1475-2891-6-29
117. Zeevi D., Korem T., Zmora N., et al. (2015). Personalized nutrition by prediction of glycemic responses. *Cell* **163**:1079–1094. DOI:10.1016/j.cell.2015.11.001

118. Vermeulen S. J., Campbell B. M. and Ingram J. S. I. (2012). Climate change and food systems. *Annu. Rev. Environ. Resour.* **37**:195–222. DOI:10.1146/annurev-environ-020411-130608
119. Steffen W., Richardson K., Rockström J., et al. (2015). Sustainability. *Planetary boundaries: Guiding human development on a changing planet. Science* **347**:1259855. DOI:10.1126/science.1259855
120. Molden D. (2007). Water for food, water for life: A comprehensive assessment of water management in agriculture. Molden D. (ed). Earthscan; International Water Management Institute, pp: 1-645. DOI:10.4324/978184977379
121. Willett W., Rockström J., Loken B., et al. (2019). Food in the anthropocene: the EAT-Lancet Commission on healthy diets from sustainable food systems. *Lancet* **393**:447–492. DOI:10.1016/s0140-6736(18)31788-4
122. Tulloch A. I. T., Borthwick F., Bogueva D., et al. (2023). How the EAT-Lancet Commission on food in the anthropocene influenced discourse and research on food systems: A systematic review covering the first 2 years post-publication. *Lancet Glob. Health* **11**:e1125–e1136. DOI:10.1016/s2214-109x(23)00212-7
123. Wang Y., Pan D., Zhang C., et al. (2025). Planetary health diet and risk of mortality and chronic diseases: Results from US NHANES, UK Biobank, and a meta-analysis. *Sci. Adv.* **11**:eadq5147. DOI:10.1126/sciadv.adq5147
124. Stubbendorff A., Janzi S., Jukkola J., et al. (2025). Mini-review of the EAT-Lancet planetary health diet and its role in cardiometabolic disease prevention. *Metabolism* **172**:156373. DOI:10.1016/j.metabol.2025.156373
125. Dalile B., Kim C., Challinor A., et al. (2022). The EAT-Lancet reference diet and cognitive function across the life course. *Lancet Planet. Health* **6**:e749–e759. DOI:10.1016/s2542-5196(22)00123-1
126. Gomes Gonçalves N., Cacau L. T., Ferreira N. V., et al. (2024). Adherence to the planetary health diet and cognitive decline: Findings from the ELSA-Brasil study. *Nat. Aging* **4**:1465–1476. DOI:10.1038/s43587-024-00666-4
127. Beal T., Ortenzi F. and Fanzo J. (2023). Estimated micronutrient shortfalls of the EAT-Lancet planetary health diet. *Lancet Planet. Health* **7**:e233–e237. DOI:10.1016/s2542-5196(23)00006-2
128. Mishra A., Sulser T. B., Gabriel S., et al. (2025). Affordability and nutritional challenges for the future of EAT diets: An economic modelling analysis. *Lancet Planet. Health* **9**:101325. DOI:10.1016/j.lanplh.2025.101325
129. Fabios E., Zazpe I., Santiago S., et al. (2025). EAT-Lancet reference diet and nutritional adequacy in children: Examining the planetary health diet index for children (PHDI-C). *Eur J Nutr* **65**:16. DOI:10.1007/s00394-025-03858-9
130. Hanley-Cook G. T., Argaw A. A., de Kok B. P., et al. (2021). EAT-Lancet diet score requires minimum intake values to predict higher micronutrient adequacy of diets in rural women of reproductive age from five low- and middle-income countries. *Br. J. Nutr.* **126**:92–100. DOI:10.1017/s0007114520003864
131. van Zanten H. H. E., Bekkers V., Beier F., et al. (2025). Integrating circularity into the 2025 EAT-Lancet framework: A global modelling analysis. *Lancet Planet. Health* **9**:101337. DOI:10.1016/j.lanplh.2025.101337
132. Michailidis V., Lugato E., Panagos P., et al. (2025). Impact of healthy diet shifts on soil greenhouse gas emissions across Europe. *Glob. Chang. Biol.* **31**:e70624. DOI:10.1111/gcb.70624
133. Biesbroek S., Kok F. J., Tufford A. R., et al. (2023). Toward healthy and sustainable diets for the 21st century: Importance of sociocultural and economic considerations. *Proc. Natl. Acad. Sci. U.S.A.* **120**:e2219272120. DOI:10.1073/pnas.2219272120
134. EAT-Lancet Commission 2.0: Securing a just transition to healthy, environmentally sustainable diets for all. (2023). *Lancet* **402**:352-354. DOI:10.1016/s0140-6736(23)01290-4
135. Marrero A., Nicoson C., Kelahan H., et al. (2024). Equity as a priority in EAT-Lancet-aligned food system transformations. *Nat. Food* **5**:811–817. DOI:10.1038/s43016-024-01047-1
136. Rockström J., Thilsted S. H., Willett W. C., et al. (2025). The EAT-Lancet Commission on healthy, sustainable, and just food systems. *Lancet* **406**:1625–1700. DOI:10.1016/s0140-6736(25)01201-2
137. Wang X., Bodirsky B. L., Müller C., et al. (2022). The triple benefits of slimming and greening the Chinese food system. *Nat. Food* **3**:686–693. DOI:10.1038/s43016-022-00580-1
138. Crippa M., Solazzo E., Guizzardi D., et al. (2021). Food systems are responsible for a third of global anthropogenic GHG emissions. *Nat. Food* **2**:198–209. DOI:10.1038/s43016-021-00225-9
139. Gu B., Ge Y., Ren Y., et al. (2012). Atmospheric reactive nitrogen in China: Sources, recent trends, and damage costs. *Environ. Sci. Technol.* **46**:9420–9427. DOI:10.1021/es301446g
140. Wu M., Lv Y., Liu W., et al. (2025). Exploring environmental and cardiometabolic impacts associated with adherence to the sustainable EAT-Lancet reference diet: Findings from the China health and nutrition survey. *Environ. Health Perspect.* **133**:57028. DOI:10.1289/ehp15006
141. Cai H., Talsma E. F., Chang Z., et al. (2024). Health outcomes, environmental impacts, and diet costs of adherence to the EAT-Lancet diet in China in 1997-2015: A health and nutrition survey. *Lancet Planet. Health* **8**:e1030–e1042. DOI:10.1016/s2542-5196(24)00285-7
142. Lei L., Qin H., Chen Y., et al. (2025). Association between adherence to EAT-Lancet diet and risk of hypertension: An 18-year national cohort study in China. *J. Am. Nutr. Assoc.* **44**:40–49. DOI:10.1080/27697061.2024.2399826
143. Zhang S., Yan Y., Zeng X. F., et al. (2025). Associations of the EAT-Lancet reference diet with metabolic dysfunction-associated steatotic liver disease and its severity: A multicohort study. *Hepatology* **81**:1583–1594. DOI:10.1097/hep.0000000000001039
144. Li Z., Ye K. X., Yang M., et al. (2025). Planetary health diet and cognitive decline in Chinese older adults: Balancing health benefits and environmental sustainability. *Food Res. Int.* **219**:116977. DOI:10.1016/j.foodres.2025.116977
145. Aweya J. J., Sharma D., Bajwa R. K., et al. (2025). Ancient grains as functional foods: Integrating traditional knowledge with contemporary nutritional science. *Foods* **14**:2529. DOI:10.3390/foods14142529
146. Ye B., Xiong Q., Yang J., et al. (2024). Adoption of region-specific diets in China can help achieve gains in health and environmental sustainability. *Nat. Food* **5**:764–774. DOI:10.1038/s43016-024-01038-2

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AUTHOR CONTRIBUTIONS

All authors contributed to the literature search and interpretation of the available evidence. Jijuan Zhang drafted the manuscript, and all authors critically revised the manuscript.

DECLARATION OF INTERESTS

An Pan is an Editorial Board member of the Innovation Nutrition and was blinded from reviewing or making final decisions on the manuscript. Peer review was handled independently of this member and their research group. The other authors declare no conflicts of interest.

DATA AND CODE AVAILABILITY

No new data were created or analyzed in this study.