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Review

A Scoping Review of Artificial Intelligence for Precision Nutrition

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ABSTRACT

With the role of artificial intelligence (AI) in precision nutrition rapidly expanding, a scoping review on recent studies and potential future directions is needed. This scoping review examines: *1*) the current landscape, including publication venues, targeted diseases, AI applications, methods, evaluation metrics, and considerations of minority and cultural factors; *2*) common patterns in AI-driven precision nutrition studies; and *3*) gaps, challenges, and future research directions. Following the Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) process, we extracted 198 articles from major databases using search keywords in 3 categories: precision nutrition, AI, and natural language processing. The extracted literature reveals a surge in AI-driven precision nutrition research, with ~75% ($n = 148$) published since 2020. It also showcases a diverse publication landscape, with the majority of studies focusing on diet-related diseases, such as diabetes and cardiovascular conditions, while emphasizing health optimization, disease prevention, and management. We highlight diverse datasets used in the literature and summarize methodologies and evaluation metrics to guide future studies. We also emphasize the importance of minority and cultural perspectives in promoting equity for precision nutrition using AI. Future research should further integrate these factors to fully harness AI's potential in precision nutrition.

Keywords: artificial Intelligence, precision nutrition, machine learning, deep learning, literature review

Statement of Significance

This scoping review offers the most recent advancements in artificial intelligence (AI) for precision nutrition, expanding the scope to not only AI methodologies and their applications in precision nutrition but also evaluates publication venues, targeted diseases, datasets, and minority and cultural perspectives, which have been mostly overlooked in prior studies. Furthermore, with numerous gaps and challenges discussed in the article, this review significantly improves the understanding of AI's potential in precision nutrition and provides new directions for future research.

Abbreviations: AD, Alzheimer's disease; AI, artificial intelligence; ANOVA, analysis of variance; AUC, area under the curve; AUROC, area under the receiver operating characteristic; CGM, continuous glucose monitoring; CRC, colorectal cancer; DSS, decision support system; EHR, electronic health record; EN, enteral nutrition; FEL, food exchange list; FFQ, Food Frequency Questionnaire; HbA1c, hemoglobin A1c; HEI, Healthy Eating Index; ICU, intensive care unit; LLM, large language model; LSTM, long short-term memory; MIMIC-IV, Medical Information Mart for Intensive Care IV; NLP, natural language processing; PPGR, postprandial glycemic response.

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Introduction

Precision nutrition is an advanced approach [1] to dietary planning that tailors nutritional guidance to individual characteristics [1], including genetics [2], lifestyle [3], and environmental factors [4]. This approach is designed to enhance overall health and well-being, as well as to prevent and manage diseases. As a critical part of precision health, precision nutrition recognize the vital connection between diet and health, advocating for personalized dietary plans instead of generic guidelines [5–7]. These plans are developed using scientific data on how individual bodies respond to different foods, aiming to optimize health outcomes by addressing unique dietary needs.

The integration of artificial intelligence (AI) into precision nutrition opens up unprecedented opportunities to enhance the efficacy and personalization of nutritional recommendations. AI can analyze vast amounts of data from diverse sources, such as multiomic profiles [8], dietary habits [9], and medical histories [10], enabling the identification of nuanced dietary needs at the individual level [9]. The domain of AI is advancing at an unprecedented pace of development, evolving from classical methodologies– such as recommendation systems, regression analyses, and classification techniques– to cutting-edge innovations in generative AI (GenAI) and large language models (LLMs). This rapid progress is reflected in the growing number of researchers incorporating AI technologies to enhance personalized dietary recommendations [11–13] and to improve disease management [14,15]. Concurrently, there is a significant increase in both the volume and variety of data available. For example, it is projected that the United States will record 1 billion patient visits annually within electronic health record (EHR) systems [16], which include a variety of data such as structured data, clinical notes, medical images, laboratory results, genomic data, and patient-generated health information. Given these advancements, there is a critical need for a comprehensive literature review that synthesizes recent research and evaluates the potential of advanced AI tools and new datasets in advancing precision nutrition. Such a review is essential not only for understanding the current landscape but also for identifying future directions and opportunities in the field.

This literature review includes articles discussing the latest advancements in AI and their applications in precision nutrition. Section "Methods" outlines our search strategy and keywords, along with our selection of articles. Section "Results" presents our results and findings across various categories: publication venues, disease areas, precision nutrition applications using AI, dataset releases and normalized data types, AI methods, evaluation metrics, and minority and culture. Section "Discussion" discusses possible avenues for future research. The contribution of this review lies in our inclusion of more comprehensive sources of research, detailed information about research methods, and research materials, including detailed dataset links and descriptions in Supplemental Table 1.

Compared to previous literature review on AI for precision nutrition [5,17–19], we included a larger number of recent articles, driven by the substantial increase in relevant publications after 2022. We also broadened our search criteria by utilizing a more extensive set of keywords and incorporating a wider range of databases. Although earlier literature reviews focused primarily on AI's applications in health and nutrition, our review extends beyond this by examining publication venues, targeted diseases, applications, datasets used in research, AI methods, evaluation metrics, and considerations for minority and cultural factors to provide a comprehensive overview of AI applications in precision nutrition. We analyzed the publication venues of the reviewed articles to highlight the emerging nature of this field. Additionally, we examined the targeted diseases to identify the major focus areas within the research community. AI applications in the reviewed literature were categorized into three distinct groups, and we visualized their relationships to the targeted diseases. The datasets used in the reviewed articles are listed in section "Results" and detailed in the Supplemental Table 1 to assist future research in using the available data. Furthermore, our review systematically categorized AI methods into eight groups, with each method described alongside examples from precision nutrition research. Evaluation metrics used to assess AI models were also categorized and explained with relevant examples. Finally, we conducted an in-depth discussion on minority and cultural topics, exploring the impact and potential of various factors, such as socioeconomics, cultural sensitivity, technology accessibility and digital literacy, ethical and privacy concerns, personalized nutrition needs, community-based approaches, and policy and advocacy, on AI for precision nutrition. We believe these insights can provide our readers with a better understanding of the field of precision nutrition and AI, while inspiring future research in this domain.

Methods

To comprehensively capture of studies in the emerging field of AI for precision nutrition, we utilized a scoping review strategy following the Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) [20].

Eligibility criteria and search strategy

Inclusion criteria in our search strategy included articles *1*) ranging from 8 December, 2014 to 28 May, 2024 in English sourced from reputable academic databases, including ACL Anthology, ACM Digital Library, EMBASE, IEEE Xplore Library, PubMed, Scopus, and Web of Science; and *2*) with keywords in subject heading, title, abstract, and keyword sections. We used search keywords in three categories: precision nutrition keywords (for example, precision, nutrigenomics-based, eating, and nutritional genomics), AI keywords (for example, machine learning, unsupervised learning, ensemble learning, random forest, and expert system), and natural language processing keywords (for example, text mining, natural language processing, and foundation language models). The full list of search keywords in each category is provided in Supplemental Text 1. We used the following keyword logics across searches in all databases: (precision nutrition keywords) AND {[artificial intelligence keywords] OR [natural language processing keywords]}.

Exclusions criteria included *1*) editorials, errata, letters, notes, and comments; and *2*) animal studies.

Selection of articles

A total of 881 literature articles were retrieved after removing duplicates. Thirty reviewers screened all these retrieved articles in 3 rounds. A flowchart describing the review process is shown in Figure 1. In the first round, reviewers conducted abstract screening and excluded articles that were not relevant ($n = 449$) or without abstract ($n = 5$). In the second round, those that were related ($n = 358$) but did not have enough information ($n = 69$) were included for full-text screening. In the third round, the full text of these 427 articles was reviewed to determine their relevance to the literature review topic and articles not relevant ($n = 169$) or inaccessible ($n = 11$) were excluded. Additionally, animal studies ($n = 49$) were also excluded. This process resulted in 198 relevant articles included in this literature review. Given that this is a scoping review, no risk of bias assessment was performed. Moreover, elements from the extracted studies were synthesized into key themes, including findings, methodologies, evaluation metrics, AI applications, datasets used, populations studied, and minority information, and were further analyzed and presented in section "Results" of this review.

Results

Publication venues

A total of 198 articles were disseminated across 142 venues, comprising 98 journals and 44 conferences. Specifically, the journals were manually classified into five distinct categories: *1)* Clinical Medicine (articles $n = 45$; venues $n = 33$), *2)* Food & Nutrition Science (articles $n = 35$; venues $n = 18$), *3)* Informatics (articles $n = 27$; venues $n = 19$), *4)* Computer Science (articles $n = 21$; venues $n = 18$), and *5)* Biology (articles $n = 16$; venues $n = 10$). This distribution reflects a high level of interest and activity in Clinical Medicine and Informatics, suggesting a strong focus on applying AI techniques in clinical settings for personalized nutrition interventions or medical applications. The significant presence of Food & Nutrition Science and Computer Science underscores the interdisciplinary efforts in applying AI to tackle precision nutrition challenges. Meanwhile, the comparatively smaller contributions from biology suggest a greater emphasis on basic research within the field.

We also observed a widespread distribution of articles on nutrition and AI across 142 journals and conferences, with the

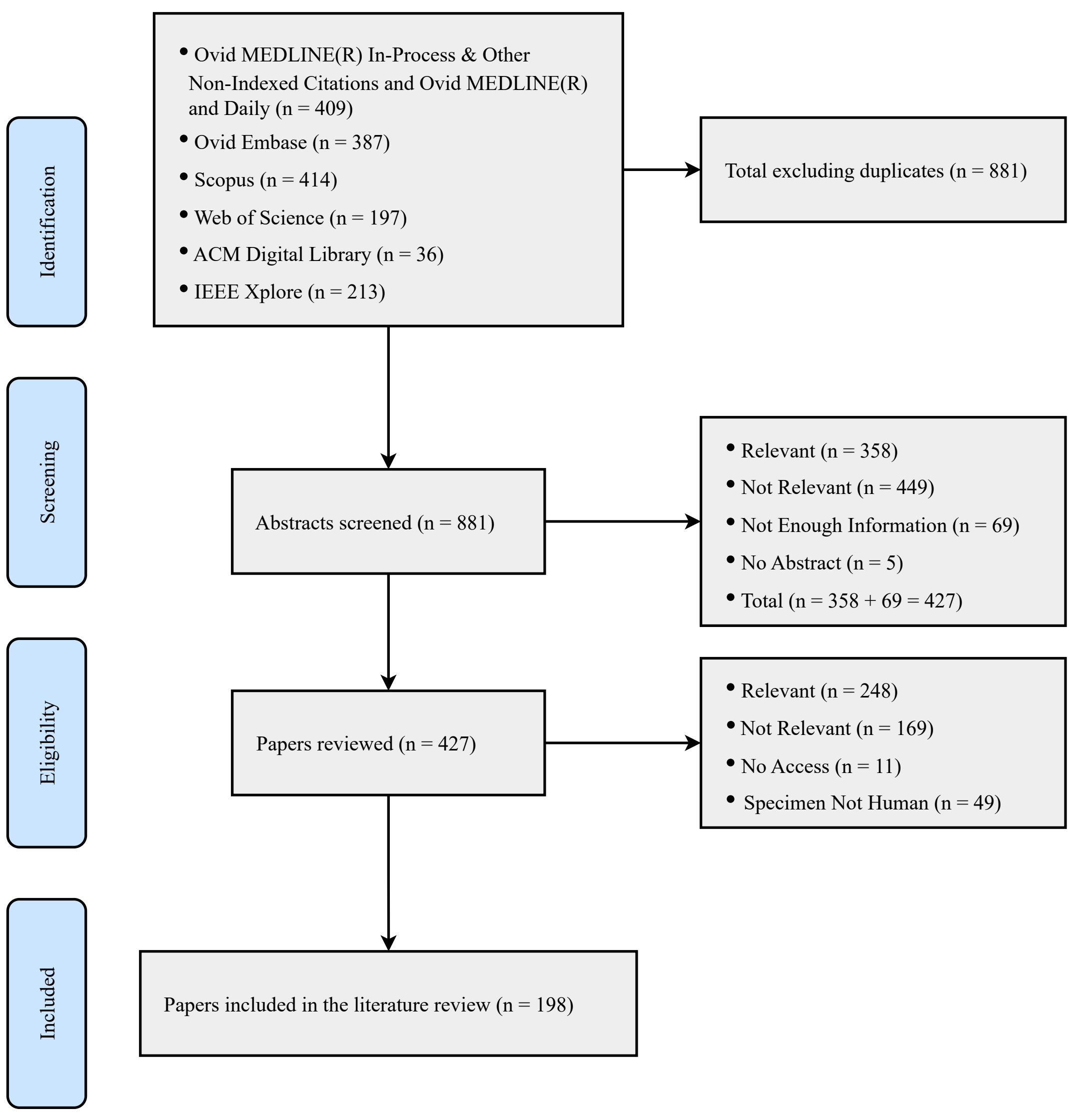

FIGURE 1. Flow diagrams for selecting articles.

majority of publications being limited to only one or two articles per venue. This distribution pattern reflects an interest from diverse communities in the intersection of nutrition and AI. With scholars from multiple fields collaborating on precision nutrition and AI topics leveraging their unique expertise, this suggests both the emerging nature of the field and its interdisciplinary character, as researchers from various disciplines contribute to exploring different aspects and implications. However, the scattered publication patterns also indicate fragmented knowledge, posing challenges for gathering comprehensive insights into precision nutrition and AI.

Disease areas

Among the 198 publications analyzed, 99 of them specifically studied one or more diseases. Overall, the top three most studied diseases among the 99 publications are: diabetes ($n = 67$), cardiovascular diseases ($n = 23$), and cancers ($n = 12$). Less studied diseases are: gastrointestinal disorders ($n = 6$), neurodegenerative diseases ($n = 5$), eating disorders ($n = 4$), mental health disorders ($n = 2$), obesity ($n = 1$), eye fatigue ($n = 1$), COVID-19 ($n = 1$), food allergies ($n = 1$), and skin disease ($n = 1$). Research on these less-studied diseases mostly emerged after 2020. Figure 2 shows the distribution of the number of articles for different disease areas over the years from 2014 to 2023. Beginning in 2018, there has been a significant rise in the number of articles exploring various diseases.

Diabetes, a pervasive metabolic disorder, has consistently attracted interest over the years. Among the reviewed articles on diabetes, 64 focused on type 2 diabetes, 11 focused on type 1 diabetes, 6 focused on prediabetes, and 3 focused on gestational diabetes. Many studies use AI technologies to assist diabetes self-management. For example, Bul et al. [21] evaluated a web-based AI-driven nutrition platform designed to assist people with diabetes and their caregivers in managing diet through personalized recipe recommendations, meal planning, and online shopping. Gyuk et al. [22] introduced a prediction algorithm aimed at improving the estimation of insulin needs for diabetics, addressing inefficiencies observed with current methods based on experience and conjecture. Other studies use machine learning techniques to develop predictive models for diabetes prevention. Ben-Yacov et al. [23] utilized a machine learning algorithm for predicting postprandial glucose responses to design diet for adults with prediabetes, highlighting the potential of precision nutrition to improve cardiometabolic health in prediabetes. Lee et al. [24] developed a predictive model for obesity risk by analyzing genetic, epigenetic, and dietary factors and their interactions. This suggests sustained attention toward understanding and addressing the complex challenges associated with diabetes self-management, prevention, and treatment using AI-driven approaches.

Cardiovascular diseases remain a recurring focus, with varying levels of attention over the years. Most studies leverage AI to identify the relationship between diet and metabolic patterns in relation to cardiovascular diseases [25]. For example, Shah et al. [25] explored how individual metabolic responses to diet contribute to cardiometabolic-cardiovascular disease risks, using machine learning to identify metabolic patterns from diet in adults. Ben-Yacov et al. [23] designed an experiment to investigate the interaction between dietary modifications, microbiome composition, and host metabolic responses within a dietary intervention. The study compared a machine-learning-generated personalized postprandial-targeting diet to a Mediterranean (MED) diet in individuals with prediabetes.

Cancer research has received continuous focus since 2018. Most studies that mentioned cancers focus on studying diet intervention using machine learning for better health outcomes. Some focused on how cancer is directly related to the digestive system, such as colorectal cancer (CRC). Shiao [26] highlighted

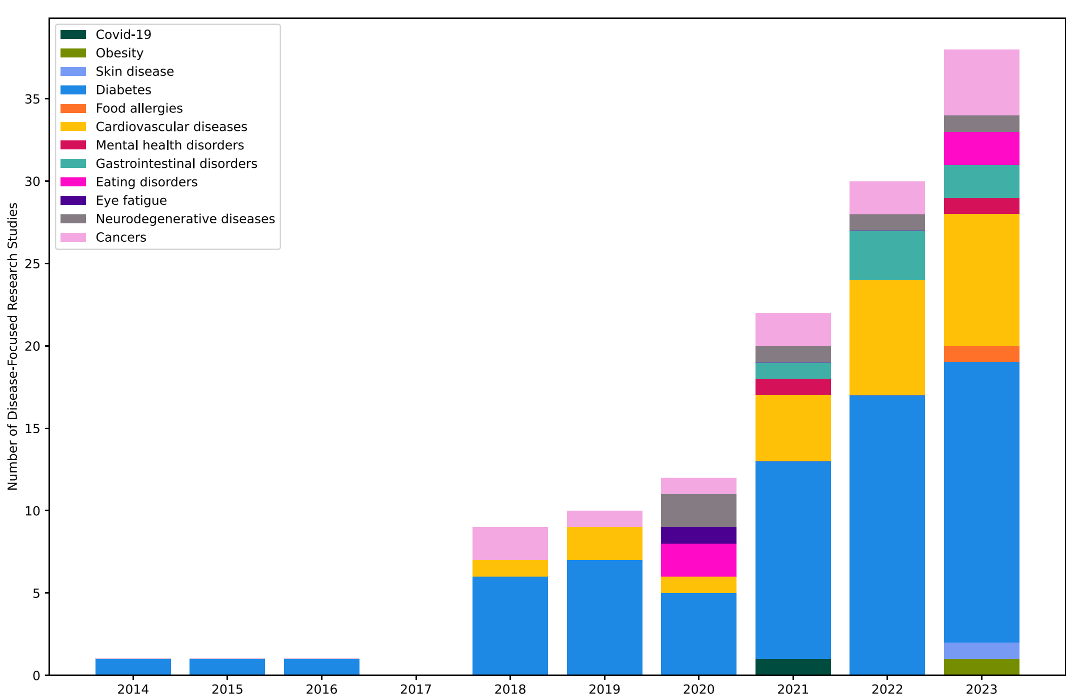

FIGURE 2. Trends in disease-focused research studies over the years.

the predictive power of dietary factors assessed through Healthy Eating Index (HEI) in influencing healthy eating behaviors, particularly relevant in the context of cancer prevention strategies tailored to multiethnic families affected by CRC. Other studies explores dietary intervention methods for general cancer rehabilitation, management, and prevention. For example, Raguvaran et al. [13] introduced an enhanced neural network model, called long short-term memory (LSTM) model, in an automated medical diet system tailored for cancer patients.

Diseases like gastrointestinal disorders, eating disorders, mental health disorders, neurodegenerative diseases, skin diseases, COVID-19 [27], eye fatigue [28], obesity [29], and food allergies [30] have emerged in later years, from 2020 to 2023, as shown in Figure 2. This trend highlights emerging or evolving health concerns that researchers are beginning to explore within the context of AI and precision nutrition. For example, Pigsborg et al. [29] utilized machine learning and metabolomics data to develop a predictive model that accurately predicted weight loss success in individuals, underscoring the potential of personalized nutrition strategies tailored to individual metabolic profiles to enhance weight loss outcomes.

Publications that do not mention any disease areas ($n = 99$) focus on general personalized nutrition recommendations using machine learning methods. This includes the use of recommender systems to tailor dietary recommendations [31] and healthcare recommendations [32], proposing meal detection algorithm using continuous glucose monitoring (CGM) [33], predicting metabolic responses to dietary intervention [34], predicting health outcomes based on individual physiological and microbial interactions [35], and explore gut microbiome and metabolomic signatures associated with weight loss and body composition responsiveness across different dietary regimens [36].

Precision nutrition applications using AI

From the included studies, the main applications of AI in precision nutrition are *1*) health optimization ($n = 106$), *2*) disease prevention ($n = 60$), and *3*) disease management ($n = 64$). Each reviewed article was manually categorized into one or more of these three categories.

Health optimization in the field of precision nutrition aims to enhance individuals' well-being through personalized nutrition (or dietary) interventions using various AI approaches. These interventions involve dietary strategies, including the use of predictive models to assess the success of diets and the application of machine learning to offer personalized diet recommendations, often leveraging personal health or genetic data. Health optimization involves conducting dietary intervention with various methods, such as developing machine learning models to offer personalized diets [29], designing AI applications based on users' specific health conditions and nutritional conditions [37], integrating genetic information and diet information into a personalized nutrition recommendation system [38], and utilizing AI to design tailored lifestyle intervention to achieve health optimization [39].

Disease prevention aims to reduce the incidence and impact of diseases through personalized nutrition (or dietary) interventions. Some disease prevention studies leverage machine learning algorithms to derive personalized nutritional plans that can prevent the onset of diseases such as reducing obesity levels in both adults [40] and children [41]. Other disease prevention research has applied machine learning models to predict disease risks, such as obesity [42] and depression [43], by analyzing clinical and nutritional variables. For recent diseases such as COVID-19, machine learning methods can be used to identify potential bioactive molecules in foods that target the SARS-CoV-2-host gene–gene (protein–protein) interactome [27]. The identified gene connection can inform the design of nutritional interventions against COVID-19 and other viral diseases.

Disease management encompasses a multifaceted approach aimed at improving the treatment, control, and overall well-being of patients diagnosed with various health conditions through personalized nutritional interventions and targeted strategies. Various approaches were used to implement effective disease management, such as building an AI-driven platform to support diabetes management through personalized recipe identification, meal planning, and online food shopping [21,44]. Another study utilized a machine learning model to predict enteral nutrition (EN) initiation for intensive care unit (ICU) patients aiding in EN management [15].

Figure 3 illustrates the relationship between three AI-powered precision nutrition applications and the specific disease areas they target. Studies utilizing AI and precision nutrition for diabetes patients outnumber those for other diseases. Most of these studies concentrate on diabetes management. Following diabetes, cardiovascular diseases and cancers rank second and third in the number of studies conducted. Unlike diabetes-focused studies, these studies emphasize disease prevention for cardiovascular diseases and cancers. For other disease areas, the main focus is health optimization. Overall, AI-based precision nutrition is understudied for other disease areas. However, Existing literature provides evidence that nutrition is linked to many health conditions, such as gastrointestinal disorders [45] and mental health disorders [46]. More research is needed to explore how AI-based precision nutrition could could aid in the prevention and management these conditions.

Dataset released and normalized data type

Among the 198 reviewed articles, 135 explicitly mentioned the use of $\geq$1 certain dataset, totaling 122 unique datasets. Except for ten datasets that are not publicly available, remaining datasets either have an open access link or can be requested from the authors. These datasets span across five data types: *1*) Dietary ($n = 62$), *2*) Evaluation and Survey ($n = 46$), *3*) Biochemical ($n = 44$), *4*) Clinical ($n = 39$), and *5*) Anthropometric ($n = 32$) [47]. We note that one dataset could belong to more than two types of data. Table 1 lists the seven most commonly used public datasets from reviewed articles, as well as the AI methods and Evaluation metrics used from all relevant research. The full list of datasets can be found in Supplemental Table 1 with four columns, including titles, dataset link or availability, dataset description, and dataset type [in terms of Anthropometric (A), Biochemical (B), Clinical (C), Dietary (D), and Evaluation and Survey (E)]. We believe that these descriptions can be helpful to current and future researchers.

Dietary datasets consist of two main components: the dietary intake data of research participants and food nutrition composition databases. Dietary intake data are primarily collected from surveys, such as the INCA2 dataset [48]. The INCA2 dataset, derived from a survey conducted between 2006 and 2007,

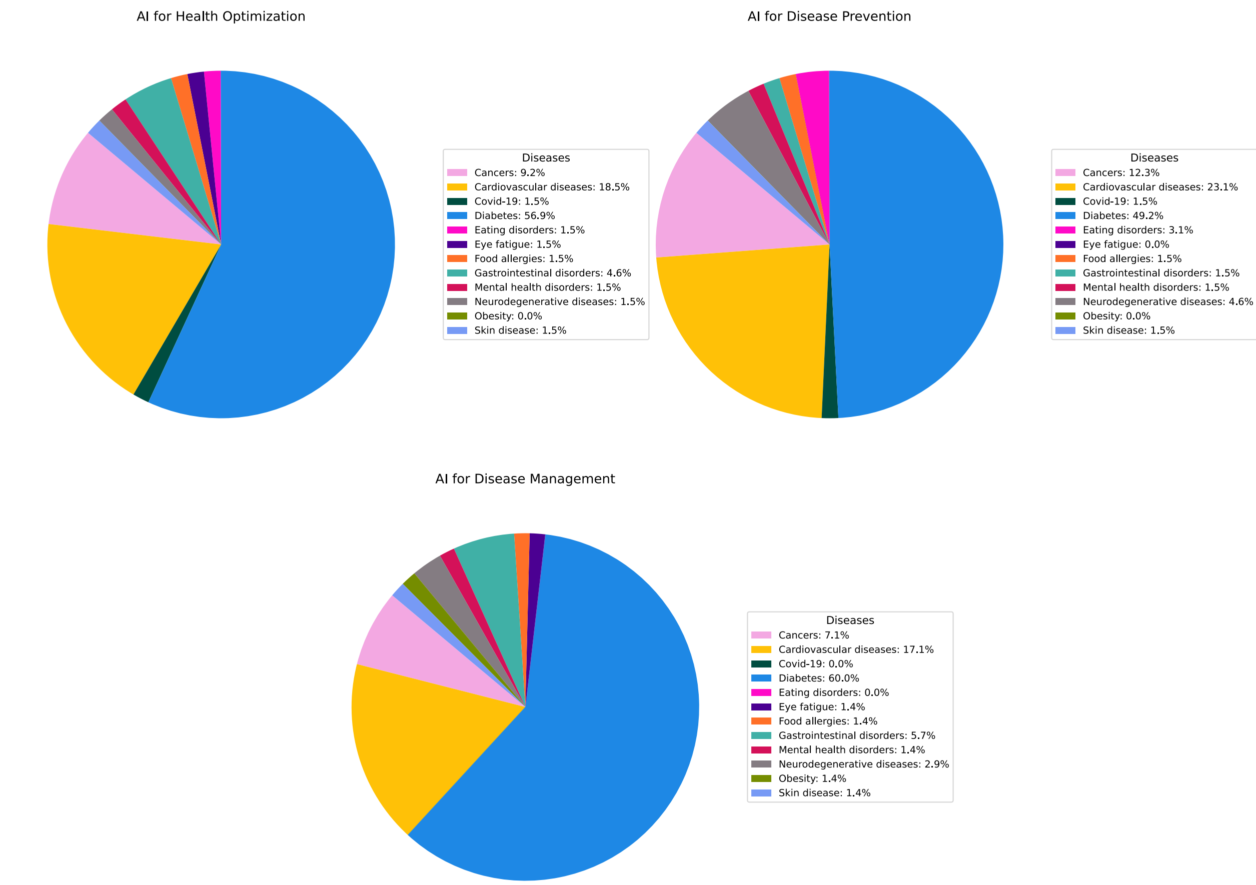

FIGURE 3. AI applications and disease targeted. AI, artificial intelligence.

includes individual food consumption records. It comprises seven-day food diaries for 2,624 adults and 1,455 children, recorded over several months to account for potential seasonality in eating habits. Food nutrition composition databases are publicly accessible and include examples such as the USDA National Nutrient Database [49], AI4FoodDB [50], and FooDB [51]. These databases are extensively used in research for recommending personalized diets [52], implementing personalized nutrition applications [53], and building recommender systems [54].

Evaluation and Survey datasets are mostly the data collected from researchers' proposed surveys or directly collected from social media platforms or prototypes, such as recruited participants' interviews, patients' conversations with chatbots, participants' browsing history, and posts and feedback from the Reddit subcommunities. For example, Bul et al. [21] used a web-based semi-structured survey to ask individuals with diabetes about the type of advice they expected from an application, as well as whether they already used applications to monitor or improve their physical activity, diet, or blood glucose levels. Apart from using survey questionnaires to create a dataset for research purposes, some researchers also generated data from research studies. Figueroa et al. [55] generated data consisting of conversations with a chatbot involving 18 women aged between 27 and 41 years. These conversations are mostly about nutrition and health information and can be valuable resources for future research. Participants' browsing history and posts and feedback from social media, such as the Reddit subcommunities, were also collected by researchers for predicting eating disorders [56] and studying emotional eating behavior [57].

Biochemical datasets include microbiome data, physiological data, and genetic/genomic data. Microbiome data are mostly gut microbiome data collected from fecal samples, and they are usually used for predicting metabolic responses [34], designing personalized diets for patients [58], and disease prevention [59]. Physiological data may include cholesterol concentration, blood glucose concentration or plasma glucose concentration, insulin concentrations level, and hemoglobin A1c (HbA1c) concentration. These data are used for offering personalized nutrition advice and disease management. Hillesheim et al. [60] used a k-means clustering model to classify participants into three metabotypes based on four biomarkers (triacylglycerol, total cholesterol, HDL cholesterol, and glucose) to offer personalized dietary advice. Shamanna et al. [61] used daily CGM and food intake data to provide guidelines that would enable individual patients to avoid foods that cause blood glucose spikes, thus benefiting patients with type 2 diabetes. Genetic/genomic datasets are mainly open-source public datasets. One such example is the ChEMBL database, a manually curated database of bioactive molecules with drug-like properties. It brings together chemical, bioactivity, and genomic data to aid the translation of genomic information into effective new drugs. Westerman et al. [62] utilized the ChEMBL database to create a machine-learning-based tool called PhyteByte. Given a protein target as input, the tool generates a list of food compounds with high confidence of eliciting relevant biological effects, along with their source foods and associated quantities.

Clinical datasets are usually derived from three key sources: clinical examination data, patient information data, and

TABLE 1
Seven most used public datasets from our reviewed literature.

Dataset	Link	Description	AI methods used	Evaluation metrics used
NHANES	https://www.cdc.gov/nchs/nhanes/	The National Health and Nutrition Examination Survey (NHANES) is designed to assess the health and nutritional status of adults and children in the United States. The survey is unique in that it combines interviews and physical examinations. NHANES collects data on the prevalence of chronic and infectious diseases and conditions (including undiagnosed conditions) and on risk factors such as obesity, elevated serum cholesterol levels, hypertension, diet and nutritional status, and numerous other measures. NHANES includes clinical examinations, selected medical and laboratory tests, and self-reported data.	Neural networks, conventional AI methods, ensemble learning,	R-squared, Chi-squared, *P* value, accuracy, precision, recall, F1 score, confusion matrix, AUC, AUROC, calibration plot, *t*-test, Mann–Whitney U test, sensitivity, specificity,
USDA National Nutrient Database for Standard Reference	https://agdatacommons.nal.usda.gov/articles/dataset/USDA_National_Nutrient_Database_for_Standard_Reference_Legacy_Release/24661818	USDA National Nutrient Database: The USDA National Nutrient Database for Standard Reference (SR) is the primary source of food composition data in the United States, forming the basis for most public and private food composition databases. This is the final release of the database in its current format. SR-Legacy will remain a leading stand-alone food composition resource and will be integrated into the new modernized system currently under development. SR-Legacy includes data on 7793 food items and ≤150 food components from SR28 (2015), with selected corrections and updates .	Conventional AI methods, neural networks, ensemble learning, expert system	*t*-test, ANOVA, accuracy
MIMIC-IV	https://physionet.org/content/mimiciv/1.0/	The Medical Information Mart for Intensive Care (MIMIC)-IV database consists of deidentified electronic health records for patients admitted to the Beth Israel Deaconess Medical Center. It contains 26 tables, including patient demographics, diagnosis notes, and free-text notes.	Conventional AI methods, representation learning, ensemble learning	AUC, SHapley Additive exPlanation (SHAP)
INCA2	https://www.data.gouv.fr/fr/datasets/donnees-de-consommations-et-habitudes-alimentaires-de-letude-inca-2-3/	The French dataset INCA2 was used to mine relevant substitutions. This dataset results from a survey conducted during 2006–2007 on individual food consumption. Seven-day food diaries were recorded for 2624 adults and 1455 children over several months, accounting for possible seasonality in eating habits.	Neural networks	-
AI4FoodDB	https://github.com/AI4Food/AI4FoodDB	The AI4Food database (AI4FoodDB) gathers data from a nutritional weight loss intervention involving 100 overweight and obese participants over the course of 1 mo. AI4FoodDB is the first public database to centralize food images, wearable sensor data, validated questionnaires, and biological samples collected from the same intervention.	-	-
FooDB	foodb.ca	FooDB (version 1.0) is a comprehensive resource on food constituents, chemistry, and biology, containing over 85,000 compounds. These data were accessed from foodb.ca on 9/27/2019.	Neural networks, reinforcement learning, ensemble learning	F1 score, AUC
avocado_SCFAs	https://github.com/wt1005203/McMLP	The data utilized in this study comprise synthetic data generated by the microbial consumer-resource model and real data sourced from 6 dietary intervention studies. These datasets represent interactions between food, gut microbes, and metabolic responses.	Neural networks	Spearman's rank correlation coefficient, predictive performance metrics

Abbreviations: AI, artificial intelligence; ANOVA, analysis of variance; AUC, area under the curve; AUROC, area under the receiver operating characteristic.

molecular data. Clinical examination data include results from medical examinations and selected laboratory tests, which are instrumental in identifying disease risk factors [63], preventing diseases [64], and developing personalized nutrition applications [65]. One notable example is the NHANES dataset [66], frequently utilized in research. It comprises clinical examinations, medical and laboratory tests, and self-reported data, focusing on the prevalence of chronic and infectious diseases (including undiagnosed conditions) and risk factors such as obesity, high serum cholesterol, hypertension, diet, nutritional status, and other health indicators. In addition to clinical examination data, patient information data form another critical component of clinical datasets. Patient information data are usually collected in EHRs in healthcare systems, for example, patient demographics, diagnosis notes, and free-text notes. An example is the Medical Information Mart for Intensive Care (MIMIC)-IV database [67], containing deidentified EHRs of patients admitted to the Beth Israel Deaconess Medical Center. Wang et al. [15] utilized the MIMIC database to construct a model assisting in early evaluation of EN for patients in ICUs. The final type of clinical dataset is molecular data, typically obtained from blood or fecal samples, which supports the development of precision nutrition applications. These data provide molecular-level information from biological samples. For instance, Karakan et al. [58] used fecal samples from a cohort of 25 patients diagnosed with mixed irritable bowel syndrome to develop personalized diets for each patient.

Anthropometric datasets are usually the information about body composition, body mass index (BMI), weight measurements, and height. These data are typically combined with other biomedical data and clinical data to serve as features for machine learning algorithms. Kan et al. [28] developed a machine-learning-based model to predict the optimal dose of botanical combination for treating eye fatigue using 504 features collected from 303 subjects. These features include anthropometric features such as the body fat rate and eye-related indexes, demographic features such as gender and ethnicity, and clinical features such as diastolic blood pressure. Other studies also utilized a combination of anthropometric data with other data types to address challenges in type 2 diabetes prevention [68], and studying the correlation of psychological mechanisms and weight gain [69].

We found that researchers frequently created their own datasets for precision nutrition and AI research. Out of 135 articles utilizing ≥1 dataset, only 18 employed publicly available datasets. Of the 117 articles that generated their own datasets, only eight have made their datasets publicly accessible. The remaining datasets are either available upon request or remain private. This scarcity of easily accessible datasets presents significant challenges for researchers to study precision nutrition and AI.

AI methods and evaluation metrics

AI methods

Various AI methods have significantly advanced precision nutrition research, playing a crucial role in uncovering new health patterns from patient data, developing personalized nutritional recommendation systems, and creating healthcare management systems. Out of the 198 reviewed articles, 172 have utilized more than one AI method in their research. The remaining 26 articles are either literature reviews or do not explicitly specify the machine learning methods used. Instead, they only mention the type of task they aim to accomplish with machine learning models, such as modeling high-dimensional data as scores [70]. The AI methods employed in the 172 articles are categorized into 8 distinct categories: *1*) conventional AI methods ($n = 129$), *2*) ensemble learning ($n = 87$), *3*) neural networks ($n = 61$), *4*) representation learning ($n = 14$), *5*) GenAI ($n = 13$), *6*) expert systems ($n = 12$), *7*) logic methods ($n = 8$), and *8*) reinforcement learning ($n = 4$).

Apart from these AI methods, several studies have utilized or evaluated smart tools ($n = 7$) related to precision nutrition and AI research. The Viome AI Recommendation Engine [71] leverages domain knowledge and machine-learning-based models to optimize food and supplement recommendations for maintaining functional homeostasis. The MyBehavior app [72] utilizes a multiarmed bandit machine-learning-based model to provide automated, personalized feedback for physical activity and dietary behavior changes. The Food4Me FFQ [73] is a validated web-based Food Frequency Questionnaire designed for dietary intake data collection. Snap-n-Eat [74] is a mobile food recognition system that identifies food items and estimates their nutritional content from smartphone images. EZNutriPal [75] is an interactive diet monitoring system that processes unstructured mobile data, such as speech and free-text, for dietary recording and personalized nutrition tracking. The iDietScore meal recommender system [76] provides personalized meal planning for athletes and active individuals through a rule-based expert system. Finally, the HeartMan decision support system (DSS) [77] is a mobile-health-based clinical DSS designed to assist congestive heart failure patients in self-managing their disease through personalized recommendations.

Conventional AI methods are the most commonly used AI methods overall. Conventional AI methods include rule-based AI methods that operate on predefined rules and logic. In our reviewed literature, conventional AI methods include regression methods such as support vector machine (SVM) ($n = 17$), linear regression ($n = 8$), and generalized linear model ($n = 3$); clustering methods such as k-means ($n = 10$), k-nearest neighbors ($n = 6$), hierarchical ($n = 4$), and Gaussian mixture model ($n = 2$); feature extraction and selection methods such as elastic net ($n = 7$), attributable components analysis ($n = 3$), least absolute shrinkage and selection operator (LASSO) ($n = 3$), principal component analysis (PCA) ($n = 3$), linear discriminant analysis (LDA) ($n = 2$), Pearson correlation ($n = 1$), canonical correlation analysis ($n = 1$), and inverse document frequency ($n = 1$), and other classical methods such as decision tree ($n = 21$) and logistic regression ($n = 20$).

Regression is a conventional statistical method used to examine the relationship between a dependent variable (target) and one or more independent variables (predictors) [78]. In our reviewed literature, regression is primarily used to predict numeric values among various applications, such as weight loss [29,79] and weight gain [80].

Clustering is an unsupervised machine learning technique that groups a set of objects into clusters, where objects within the same cluster share greater similarity with each other than with those in different clusters [78]. K-means algorithm is mostly used as a clustering method to identify patient subgroups. For example, Hillesheim et al. [60] utilized k-means to categorize research participants into three distinct metabotypes based on four biomarkers, aiming to provide more targeted dietary advice. Vervoort et al. [69] applied k-means to identify subtypes among young individuals with obesity, based on psychological mechanisms that explain weight gain.

Feature extraction involves transforming the original data into a new, more informative and concise set of features. Conversely, feature selection focuses on choosing a subset of the most relevant features from the original data,helping to reduce the dimensionality of the feature space, enhance the model's generalization ability, and reduce computational requirements [81]. Feature extraction and selection methods are primarily used in research on diabetes, cardiovascular diseases, and cancer, with applications in disease prevention, health optimization, and disease management. These methods are typically employed as a dimensionality reduction tool [25,82], feature transformation tool [83,84], and tools for constructing sparse models [85,86].

In addition to the converntional AI methods, the second most commonly used method in the reviewed articles is ensemble learning, which combines multiple models to create a more robust and accurate model than any single constituent model [87]. For example, Tily et al. [88] used gradient boosting to predict postprandial glycemic response (PPGR) using gut microbiome activity, anthropometric factors, and food macronutrients as features. This work can aid in disease prevention, as managing PPGR is a key strategy in reducing risk of chronic metabolic diseases. To optimize health, Hernández-Hernández et al. [89] used random forest and XGBoost to generate food exchange lists (FEL). A high-quality FEL can enhance a healthy diet and lower risk of developing diabetes. In terms of machine learning tasks, most ensemble learning methods are utilized to construct either classification or regression models. Regression models are typically used for predicting continuous biochemical metrics such as glycemic responses and postprandial responses [88, 90]. In contrast, classification models are commonly employed for biomarker discovery, identifying elderly patients with malnutrition, and predicting the occurrence of potential diseases or disorders such as obesity [24], depression [43], and diabetes [91,92].

Neural networks are the third most popular method in the precision nutrition studies we reviewed. A neural network is an AI technique that enables computers to process data in a manner inspired by the human brain [93]. Neural networks have been primarily applied in diabetes and cancer studies focusing on disease prevention and health optimization. In terms of machine learning tasks, neural networks have been predominantly used for constructing classification models. These classification models are used for food classification and recognition [94], diabetes prevention [64,95], cancer prevention [96], and predicting metabolic responses [34].

Representation learning is a deep learning process where algorithms identify and extract meaningful patterns from raw data, creating representations that are easier to interpret and utilize [97]. For example, Abuhassan et al. [98] proposed an attention-based deep learning classification model to identify Twitter users at risk of getting eating disorders. They used Bidirectional Encoder Representations from Transformers (BERT) to extract sentence and word embeddings as inputs to their proposed model. In another study [38], the continuous skip-gram model is employed to generate word embeddings for unknown grocery products, which are then fed into an LSTM-based model for product categorization. Finally, these categorization results were incorporated into a decision recommendation system based on genetic algorithms.

GenAI are most recent approaches that use neural networks to identify the patterns and structures within existing data to generate new and original contents [99]. Generative AI are typically used for providing dietary and lifestyle recommendations [55,100,101]. Some researchers construct specialized chatbots while others utilize existing chatbots. For example, Niszczota, P. & Rybicka [30] utilized ChatGPT to offer nutritional advice and then evaluated the advice in terms of safety, accuracy and attractiveness.

Expert Systems are AI softwares designed to utilize the knowledge of human experts to develop a system capable of solving specific problems [102]. In our reviewed literature, expert systems are used for constructing mobile applications and DSSs aimed at promoting health optimization through personalized nutritional advice designed by nutritionists [68,75, 103–105] and promoting disease management for diabetes patient by providing actionable suggestion to support self-management of chronic conditions [82].

The logic method refers to the use of formal logical methods and principles to design and implement algorithms and models [106]. Logic methods from our reviewed articles are primarily applied in health optimization and disease management across various different applications. Such as implementing a mobile app for personalized meal planning [37], providing personalized dietary recommendation [107], building a drug and food recommendation system for type 2 diabetes patient [108], implementing applications for healthcare recommendation [32, 109], building a DSS for patients with multiple chronic conditions [44], and developing a learning-based system for diagnosis and personalized management of diabetes mellitus [110].

Reinforcement learning is a type of machine learning in which an agent learns to make decisions by interacting with an environment [111]. In our precision nutrition review, reinforcement learning has been applied to provide dietary suggestions by receiving rewards from nutritionist feedback on food recommendations [112] or from user feedback to offer personalized dietary and lifestyle recommendations [72].

The top three most popular AI methods, along with their subcategories, are illustrated in the Sankey diagram in Figure 4. Conventional AI methods, ensemble learning, and neural networks stand out significantly compared to other methods. Conventional AI methods are the most frequently used approach for studying diseases and applications. Figure 4 also depicts the relationship between the top three most researched diseases, AI methods, and AI applications. This suggests that in the field of precision nutrition and AI, researchers favor classical methods due to their well-defined procedures and evaluation standards. Very few researchers employed novel methods such as reinforcement learning and GenAI.

Besides the top three most researched diseases and the AI methods used to study them, there are other notable diseases that did not make it into Figure 4 but are worth mentioning, such as gastrointestinal disorders, neurodegenerative diseases, eating disorders, and mental health disorders. Gastrointestinal disorders were primarily studied using ensemble learning methods for

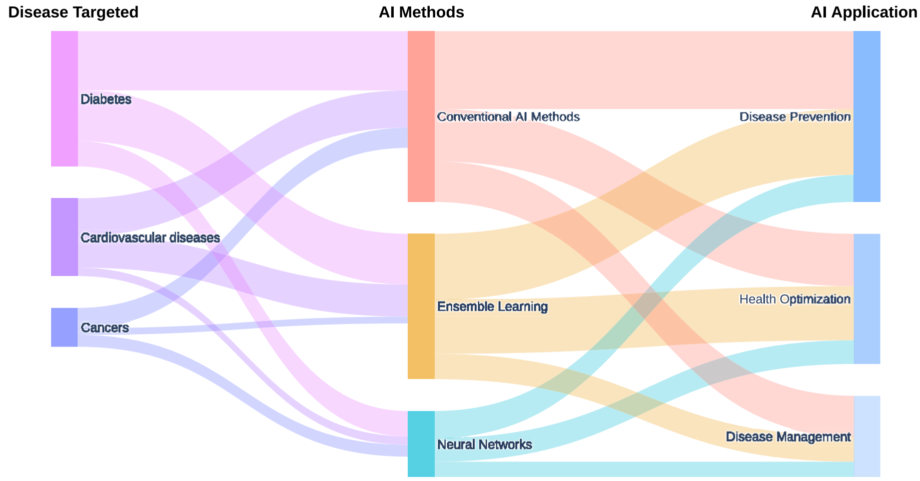

FIGURE 4. Disease, AI methods, and AI applications in the reviewed articles. AI, artificial intelligence.

health optimization and disease management. Examples include recommending personalized diets based on analyses of participants' stool and blood samples [71], as well as predicting the stages of chronic kidney disease to help slow its progression [113]. Neurodegenerative diseases, such as Alzheimer's disease (AD), were studied using ensemble learning methods for health optimization. Alashwal et al. [114] used a random forest classifier to identify the best features for differentiate AD patients and healthy patients. These features included nutritional measures, genes, and cognitive performance. Eating disorders were primarily studied for disease prevention using conventional AI methods and representation learning methods. Eating disorders, such as Binge-eating disorder, are predicted with correlation methods based on ecological momentary assessment data [115]. Another example is from Abuhassan et al. [98], who developed a multimodal deep learning model called EDNet to predict potential eating disorder patients. Mental health disorders such as depression used neural networks, ensemble learning methods, and conventional AI methods for disease prevention. For example, Hosseinzadeh Kasani et al. [43] used nutrition-related markers, such as energy, water, protein, fat, carbohydrates, and fiber, for early diagnosis of depression.

Evaluation

In the reviewed articles, we categorize different types of evaluation into statistical and machine learning metrics, health indicators and dietary assessment metrics, usability and performance metrics, and surveys and questionnaires.

Statistical and machine learning metrics evaluate the performance of AI models in precision nutrition.

The top ten evaluation metrics relate to AI model performance in precision nutrition are accuracy ($n = 39$), precision ($n = 29$), recall ($n = 25$), F1 score ($n = 22$), area under the receiver operating characteristic curve (AUROC) ($n = 12$) ($n = 10$), P value ($n = 7$), sensitivity and specificity ($n = 6$), and mean squared error (MSE) ($n = 5$) and are illustrated in Figure 5. Accuracy is the most commonly used metric in the reviewed studies and measures the proportion of correct predictions among all predictions [116]. Precision measures how accurately the model identifies positive cases out of all the cases it predicts as positive, and a high precision indicates that the model makes fewer false positive errors and performs reliably in its positive predictions [116]. Recall measures the proportion of true positive instances identified by the model among all the true positive instances, and a high recall indicates the model's strength in identifying true positives and minimizing missed positive instances [116]. F1 score is the harmonic mean of precision and recall, which ensures a balanced measure of a model's accuracy [116]. The AUROC evaluates the model's ability to distinguish between classes by plotting the true positive rate against the false positive rate [117]. The P value ($n = 7$) assesses the statistical significance of the predictions [118]. Similar to precision and recall, sensitivity and specificity measure the model's ability to accurately identify true positives and true negatives [119]. MSE measures the mean squared difference between actual and predicted values, evaluating regression models that predict continuous outcomes such as BMI and blood glucose levels [120].

In addition to Figure 5, Figure 6 illustrates the distribution of evaluation metrics across different data types. The evaluation metrics are distributed relatively evenly across different data types, indicating no clear preference or tendency for a specific metric to be used more frequently with any particular data type. However, precision and recall are used less frequently in biochemical data types. This is likely because biochemical data are more commonly evaluated using health indicators and dietary assessment metrics, such as glycemic control metrics [14], rather than the top ten evaluation metrics for AI outcomes shown in Figure 5.

Including the top metrics listed above, we summarize all the model-performance-related metrics in our reviewed articles. Statistical and hypothesis testing metrics include cosine distance, P value [35], R, R-squared [88], chi-squared [63], Spearman's rank correlation coefficient [34], Pearson correlation coefficient [28], t-test, analysis of variance, [75], and Mann–Whitney U test [121]. General model performance metrics include standard errors, out-of-bag error [110], bias, variance, training loss, validation loss [13], and error rate [84]. Task-related machine learning metrics evaluate the performance of models in either classification or regression tasks. Classification metrics assess a model's ability to classify data into categories and include: area under the curve (AUC), AUROC, M-AUC [122], precision, recall, F1 score [123], accuracy, misclassification rate [26], and classification rate [124]. Regression metrics evaluate a model's performance when predicting continuous outcomes, such as

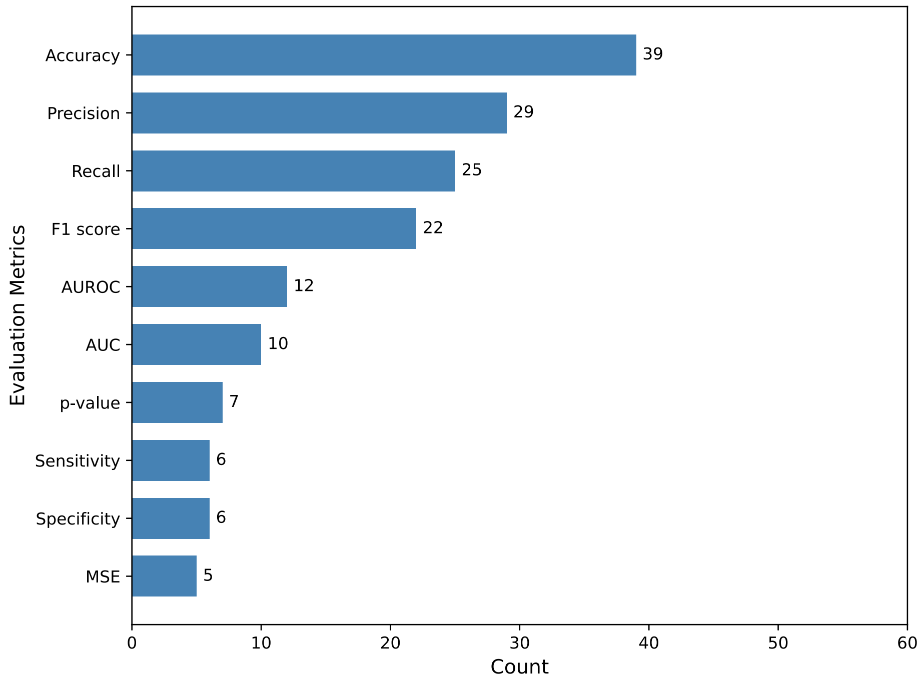

FIGURE 5. Top 10 statistical and machine learning evaluation metrics.

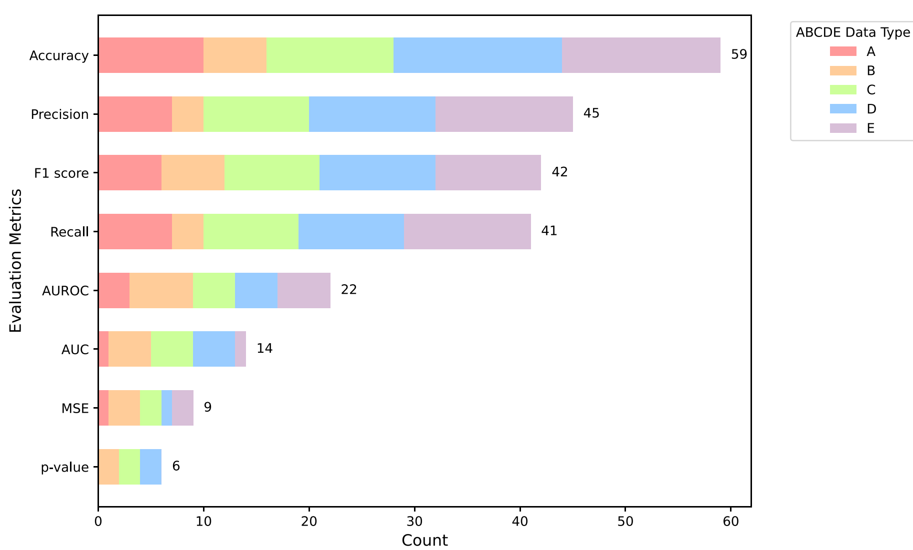

FIGURE 6. Top 10 evaluation metrics and their numbers when applied to ABCDE data.

blood glucose levels, and include: MSE [125], pseudo-R-squared [79], root-mean-squared error, and odds ratios [126].

Health indicators and dietary assessment metrics are quantifiable measures used to assess an individual's health status and adherence to certain nutritional recommendations. Health indicators, which reflect changes in clinical outcome before and after AI-assisted precision nutrition interventions, play a significant role in the overall assessment process. These indicators can be categorized into 3 main groups: metabolic, cardiovascular, and cancer-related metrics. In our reviewed articles, all 3 indicators are mainly utilized to assess the effectiveness of personalized nutrition intervention. Metabolic indicators, such as BMI, body fat percentage, waist circumference [127], HbA1c levels, fasting blood glucose, insulin sensitivity [61], etc., serve as measures of weight control among individuals with overweight conditions caused by illness such as type 2 diabetes. Cardiovascular indicators encompass blood pressure and blood lipids [128], focusing on managing hypertension and improving cardiovascular health. Cancer-related indicators involve genetic scores. Dietary assessment metrics evaluate dietary patterns and adherence to certain nutritional recommendations, which include dietary intake data and MED diet adherence, evaluating the similarity of an individual's diet to the standard MED dietary pattern based on an Australian survey that contains 14 relevant questions [100], HEI [129], frequency of dietary lapses [130], and qualitative healthy food assessment [131].

Usability and performance metrics, such as latency [132], computational efficiency, coupling, and cohesion metrics [133], assess the performance and user-friendliness of the AI systems.

Surveys and questionnaires, such as nutrition questionnaires [77], were used to gather user feedback and evaluate the impact of the AI system on users' quality of life.

Minority and culture

Historically, many racial/ethnic minority groups and people with lower socioeconomic status have seen a higher prevalence of illnesses and death from chronic diseases in the United States. Despite advancements in improving overall health in the United States, racial and ethnic disparities still persist [134]. Understanding and addressing the unique nutritional needs of minorities is key to developing effective and personalized nutritional strategies for at-risk populations.

Among the 198 reviewed articles, 12 articles were identified to include minority information. These articles were further reviewed and individually analyzed for factors commonly observed to affect health outcomes in minority groups, such as: *1*) socioeconomic factors, *2*) cultural sensitivity, *3*) technology accessibility/digital literacy, *4*) personalized nutrition needs, *5*) ethical and privacy concerns, *6*) community-based approaches, and *7*) policy and advocacy. This section synthesizes findings from these 12 selected articles and identifies the targeted key factors, practical applications, and recommendations for future research in AI and precision nutrition.

Socioeconomic factors, such as income level, education, and access to resources, can significantly impact health outcomes. Of the 12 articles referencing minority groups, 8 included information related to the influence of socioeconomic factors on minority populations [21,55,64,68,92,135–137]. Several studies examined the impact of socioeconomic status on health outcomes. Articles in this category highlighted the increased risks of certain health conditions, such as maternal mortality [135], hypertension [136], and type 2 diabetes mellitus [21,68,137], in low socioeconomic minority populations. Lifestyle factors, including limited abilities to maintain healthy lifestyles, health literacy, and access to healthcare and quality nutrition, were observed to contribute to disparities in health outcomes among minority populations. To meet the needs of low socioeconomic minority communities, many of these articles highlighted the importance and need for more targeted health interventions, such as the inclusion of budget-friendly recipes and budget supermarket chains [21] and display of recipe cost for individual budgeting [68]. In addition, a better understanding of low socioeconomic populations can be achieved through the targeted recruitment of participants from structured health programs intended for low-income individuals such as Supplemental Nutrition Assistance Program Education [55], and the representation for socioeconomic diversity through the selection of socioeconomic-related demographics such as education level and poverty ratio [64] and the inclusion of diverse socioeconomic classes in studies [92].

Cultural sensitivity in precision nutrition involves the recognition and integration of diverse cultural dietary practices, preferences, and traditions into personalized nutritional guidance and interventions. Of the 12 articles in this data set, four included references to cultural sensitivity, such as having more international representation in cuisine options for recipe platforms [21] and recommender systems [136], consideration of cultural lifestyles and values program designs [68], and Native American representation [137]. These studies emphasized the need to include a diverse range of cultural dietary practices, preferences, and traditions in nutritional guidance. Studies in this category suggested including a broad range of recipes for diverse ethnic groups particularly for Asian subgroups [21], African populations [21], and Native Americans [137] to provide more culturally specific resources for individuals. Tailoring educational materials to cultural and linguistic needs of minority groups, such as providing translations for non-English speakers [68], was also discussed as a way to improve accessibility for individuals. These methods demonstrated an improvement in adherence and effectiveness of health interventions in diverse populations.

Technology Accessibility/Digital Literacy refers to the design and implementation of digital tools and platforms to ensure that they can be used and understood effectively by everyone. Six articles referenced technology accessibility and digital literacy, particularly for minority groups who may face unique challenges due to the intersectionality of other limiting factors [21,55,68,136–138]. One study emphasized the need to improve accessibility for individuals with visual impairments [21], which is common among individuals with diabetes, through the inclusion of screen reader compatibility and larger text options. Few of these studies also noted the importance of offering training and/or guidance for users with lower digital literacy [68] and incorporating culturally familiar tools, such as YouTube and WhatsApp [55], and other culturally appropriate AI-powered assistants and smart speakers [137] to make digital tools more accessible for minority communities. Another study highlighted the socioeconomic considerations of technology accessibility by ensuring that all participants have access to study resources (for example, smartphones and Internet data plans) as a prerequisite for participating in the study [138].

Ethical and privacy concerns are critical when designing and implementing health interventions, especially those involving digital technology. Four articles in this dataset highlighted minority participants' privacy concerns [55] and the importance of adhering to ethical data collection practices [68,138], such as Institutional Review Board (IRB) guidelines, and Health Insurance Portability and Accountability Act (HIPAA) to maintain trust and encourage participation in minority populations [137]. Through participant interviews, 1 study highlighted minority participants' privacy concerns with health chatbots, particularly regarding location data. Researchers in this study discussed how providing participants with transparency about how data are used can help mitigate these concerns, build trust, and improve participation rates [55].

Personalized nutrition needs involve tailoring dietary recommendations to individual needs and considering unique risks and preferences, which can significantly enhance the effectiveness of health interventions, particularly for minority populations with diverse dietary habits and health challenges. Three articles in this dataset discussed methods that included unique personalization features based on user backgrounds and highlighted the importance of tailoring nutrition advice [68,136,137]. For example, 1 article utilized interviews and surveys to tailor nutrition education and lifestyle programs to the unique risks faced by underserved farmworkers, acknowledging their specific environmental and biological factors [68]. Additionally, 2 articles discussed the use of recommender systems [136] and virtual assistant technology such as Amazon's Alexa [137] to make dietary advice more relevant and to enhance user engagement and adherence to dietary plans. These findings support the tailored approach that personalized nutrition and AI can achieve in supporting diverse populations more effectively and improving outcomes in minority communities.

For community-based approaches, four articles in our dataset described the use of interviews, surveys, and built in community platforms to highlight the effectiveness of community-driven interventions in minority populations [21,55,68,135]. One study described the use of interviews and surveys of vulnerable and underserved farmworkers in California, including racial/ethnic minorities and low-income individuals, to guide software development tailored to the needs of the target users [68]. In this study, user feedback was used throughout the development process in determining desirable aspects such as user language, more formal specification of features and functionality of the app, and evaluation criteria. Through community involvement, researchers described the value in addressing the unique needs of various target groups in making informed health decisions in a personalized and adaptable manner. Other examples included providing community-driven platforms to determine recipe popularity and partnering with local organizations and programs to recruit participants. These articles demonstrated the effectiveness of aligning interventions with local needs and preferences through improving engagement, and ultimately lead to better health outcomes for target populations

Policy and advocacy underscore the need for systemic changes and policy support to improve health outcomes. Two articles in this section focused on the role of policy and advocacy in enhancing health interventions, particularly for minority populations. One study briefly discussed the need for supportive policies to facilitate the dissemination of effective weight loss programs widely through innovative health technologies [139]. Another study called on intensifying efforts to reduce maternal mortality in low-income countries through global standards, technical support, and accountability measures [135]. These studies showed that policy and advocacy can play a pivotal role in improving health outcomes and ensuring that health interventions are effective and inclusive for all populations.

Discussion

In this review, we systematically examined the AI for precision nutrition literature on publication venues, disease targeted, precision nutrition applications using AI, datasets, AI methods and evaluation metrics, and minority and culture. The reviewed literature highlights a rapidly growing and expanding field. By summarizing disease areas, available datasets, applicable AI methods, and many more future topics, we believe that this literature review summarized available materials and possible directions for future research in precision nutrition and AI.

Several gaps have been identified in precision nutrition studies. First, the use of novel AI methods in precision nutrition remains limited. AI, especially GenAI, has become a groundbreaking tool across various fields, including data generation, drug discovery [140], and healthcare [141]. Among the studies we reviewed, there are 13 studies employing GenAI to give dietary and lifestyle recommendations [55,100,101] and generate nutritional advice [30]. Apart from the limited use of GenAI, our results indicate that deep representation learning and deep neural networks are also not widely adopted in precision nutrition studies. Deep representation learning and deep neural networks could be a very useful tool in precision nutrition studies. Abuhassan et al. [98] developed a multimodal deep learning model called EDNet, using historical tweets, user biographies, and online behaviors from Twitter to classify user engagement with eating disorder content, achieving ≤94.32% accuracy and 93.91% F1 score, significantly outperforming baseline methods. This is one of the few studies to employ deep neural networks, demonstrating their high effectiveness in identifying nutrition-related diseases.

The second gap in precision nutrition research is the lack of high-quality, publicly available labeled datasets. According to our findings in the dataset section, most researchers in this field create their own datasets. The availability of more publicly accessible dietary, evaluation and survey, biochemical, clinical, and anthropometric datasets would significantly facilitate the application of advanced AI methods in precision nutrition studies. To fully harness the potential of integrating diverse data types—including patient information, dietary intake, gut microbiome profiles, and genetic data—we propose the development of a digital twin of an individual using a foundational model. This digital twin could offer a dynamic, personalized representation of an individual's health, providing deeper insights into nutritional needs and enabling more effective disease prevention strategies. This approach has the potential to revolutionize precision nutrition by integrating multimodal data for more accurate and effective health interventions.

Furthermore, there are numerous challenges in applying AI to precision nutrition. A major challenge is bias within the training data, which is often carried over to the trained model. For instance, racial [142] and gender biases [143], along with issues like imbalanced samples or incomplete data, can substantially affect the effectiveness of AI applications in precision nutrition. To identify articles addressing bias, we searched for those that included demographic and cultural variables in their dataset descriptions, as such variables may introduce potential biases. Two studies have addressed cultural biases [55,137]. For example, Figueroa et al. [55] design chatbots in Spanish and address the linguistic bias present in most health chatbots, which predominantly operate in English. Other articles [64,68,92,135,136,138,139] do not address bias but include variables like gender, ethnicity, or education in their datasets as predictive features in machine learning models. Another challenge is hallucinations from GenAI models, which can mislead nonexperts users. According to a survey conducted by Ji et al. [144], these hallucinations can be categorized into hallucinations from data, hallucinations from training and inference, and metrics measuring hallucinations. To identify articles that discussed hallucinations, we looked for those utilizing LLMs. In our reviewed literature, only one article mentions hallucinations [30]. Last but not least, one major challenge in using AI for precision nutrition are ethical issues and concerns about user privacy. Ethical challenges require that AI systems be designed and implemented to upholds human rights, fairness, and transparency. To examine ethical considerations, we searched for articles with ethical data use statements. In our reviewed literature, Thomas et al. [145] created a tutorial with guiding principles and a checklist to help nutrition researchers address ethical issues in AI and machine learning. Other researchers addressed this issue by obtaining ethical approval from authorities [22,146]. In summary, addressing biases, mitigating hallucinations, and upholding ethical principles are essential for the reliable and equitable application of AI in precision nutrition.

Author contributions

The authors' responsibilities were as follows – XW, DO, ZS, YW: designed the study, conducted the data analysis, and wrote and revised the manuscript; PA, SS, JH, AEM, SI, MM, L-JL, RJ, JC: reviewed, wrote, and revised the manuscript; and all authors: revised, read, and approved the final manuscript.

Conflict of interest

The authors report no conflicts of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.advnut.2025.100398.

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