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Food recommendation towards personalized wellbeing

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A R T I C L E I N F O

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A B S T R A C T

Background: The intersection of nutrition and technology gave birth to the research of food recommendation system (FRS), which marked the transformation of traditional diet to a more personalized and healthy direction. The FRS uses advanced data analysis and machine learning technology to provide customized dietary advice according to users' personal preferences, and nutritional needs, which plays a vital role in promoting public health and reducing disease risks.

Scope and approach: This review presents the architecture of FRS and deeply discusses various recommendation algorithms, including the content-based method, collaborative filtering method, knowledge graph-based method, and hybrid methods. The review further introduces existing data resources and evaluation metrics, and highlights key technologies in user profiling and food analysis. In addition, the wide application of personalized FRS is summarized, and the importance of these systems in satisfying users' dietary preferences and maintaining balanced nutrition is emphasized. Finally, the key challenges and development trends of FRS are deeply analyzed from data level, model level and user experience level.

Key findings and conclusions: Personalized FRS shows great potential in helping users make healthier dietary decisions. Although there are still many challenges, such as dealing with heterogeneous data and interpretability. But with the progress of technology, there will be broader development in the future. For example, the powerful data processing ability of deep learning will effectively improve the accuracy of the system. In addition, the application of interactive recommendation system and large language model will also provide strong support for satisfying user experience and improving acceptance.

1. Introduction

Nutrition is the cornerstone of maintaining human health and wellbeing. Appropriate nutrient intake is important for promoting growth, maintaining physiological function, and preventing diseases (Hilsabeck et al., 2024). However, the nutritional imbalance caused by serious shortages and excess of nutrition is becoming a universal threat to global nutritional security (Mannar et al., 2020). This imbalance increases the occurrence of cancers and chronic diseases such as cardiovascular disease, diabetes, obesity (Mozaffarian et al., 2022). Therefore, cultivating good eating habits and ensuring balanced nutrition intake have become important strategies for maintaining health. Nevertheless, how to combine food selection with individual's unique dietary needs is a complex challenge. This is because scientific dietary intake needs to comprehensively consider the multiple interactions among individual differences, health status, cultural background and nutritional knowledge (Kirk et al., 2021).

Food recommendation is an effective way to deal with this complex challenge. Traditional food recommendation mainly depends on expert knowledge and experience, which is usually difficult to adapt to individual differences and the ever-changing pace of life (Trivedi et al., 2024). Under the background of the rapid development of the Internet,

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the intelligent recommendation system uses artificial intelligence (AI) technology to provide personalized suggestions to users through data analysis, machine learning and algorithms (Da'u & Salim, 2020). Its utility has spanned various fields, from academic and news management to the customization of entertainment and shopping (Amir et al., 2023; Liu et al., 2024). In the field of food nutrition and health, with the progress of emerging sensor equipment and smart wearable technology, the combination of AI and diet management is closer, which eventually leads to the development of FRS (Forouzandeh et al., 2024). Compared with traditional food recommendation methods, FRS can provide more personalized, dynamic, and extensible solutions by automatically analyzing users' dietary preferences, health data, or living habits.

However, the complexity of diet and food brings great challenges to FRS. The essence of these challenges lies in the individuation of food recommendation. It must consider the complexity of food attributes, dietary preferences and nutritional and health needs wisely in order to provide balanced and appropriate dietary suggestions (Chen et al., 2021). First of all, the types, ingredients, cooking methods, and visual attributes of food are diverse and multimodal, which makes it complicated to accurately analyze and understand the types of food and its nutritional value (Liu et al., 2021). Therefore, it is necessary to conduct multi-modal and multi-scale analysis of food in order to gain a deep semantic understanding and provide accurate basis for recommendation. Secondly, dietary preference is influenced by many factors, including taste preference, cultural background, genetic characteristics and contextual information, which leads to significant differences in dietary needs among different users (Khan et al., 2021). Consequently, it is necessary to establish an accurate analysis model through user profiles to fully capture users' dietary preferences and needs. In addition, food recommendation can't be separated from multi-dimensional consideration of nutrition and health, which requires the recommendation system to take into account users' personal preferences and scientific health guidance to form a reasonable recommendation balance.

Some reviews related to FRS have been conducted. Min et al. (2019) provided a unified framework for food recommendation, and determined the importance of context information, domain knowledge, personal model, and food characteristics to FRS. We not only summarize the technical methods to analyze these key factors, but also introduce a variety of recommendation algorithms that can integrate these factors. Bondevik et al. (2023) investigated different algorithms, the data and how it is processed and evaluation methods for food recommendation through systematic literature review. However, the survey results only summarize the food recommendation as a whole, but lack the analysis and comparison at the detail level. In summary, different from their works, we not only discussed the framework, data resources, key algorithm technology, and evaluation index of FRS in detail, but also summarized the latest research on FRS based on user preferences and nutritional needs from the perspective of personalization. Finally, the main challenges and future trends are analyzed from multiple levels. Through these efforts, we aim to promote the development and application of FRS, bridge the computational gap in food science, and provide indispensable insights for scholars and practitioners to explore innovative methods and new applications.

2. Food recommendation system

FRS is an information filtering system that provides users with foods that meet their preferences or needs, according to their historical behaviors and preferences. The framework of FRS includes five modules as shown in Fig. 1: 1) data collection, 2) user profile module, 3) food analysis module, 4) recommendation algorithm, 5) evaluation modules. The data collection module collects users' attributes, behavior, and health information, as well as food images, ingredients, and recipes. The user profile module obtains its potential embedding vector by learning a comprehensive representation of the user. The food analysis module obtains a latent vector representation of the multimodal food information by using feature extraction technology. Finally, with the help of the recommendation algorithm and evaluation modules, the system provides users with a reasonable diet choice experience.

2.1. Data resources

The data resource is the cornerstone of building recommendation system. The rapid development of mobile Internet technology, electronic sensors and smart wearable devices provides convenience for data acquisition. In the field of food recommendation, three primary types of data are utilized: health data, food data, and knowledge graphs (refer to Fig. 2 and Table 1).

Food data sources: Food data mainly includes food pictures, food categories, recipes, ingredients, nutritional information, cooking instructions, food flavors, etc. It is the most basic data resource used in FRS. In the age of Internet, people upload and share large amounts of data related to diet on social networks, which can be easily collected with a web crawler (Norouzi et al., 2017). For example, crowdsourcing consumer comment websites such as Yummly[1] and Meishijie,[2] recipe-sharing websites and social media provide a wealth of user-diet interaction information. Through the posting of messages, purchases, likes, and other behaviors, the characteristics of users and the interaction between users and diet can be characterized explicitly or implicitly. In addition, researchers and authoritative organizations have published self-built data sets, such as Food101 (Bossard et al., 2014), foodRecSys (Gao et al., 2019), Recipe1M (Marın et al., 2021). These platforms and data sets together provide data on food attributes and user preferences needed by FRS.

Health data sources: Health data describes the user's basic health information, health index information and health behavior data (exercise, sleep quality) and other attributes. Unlike dietary data, the acquisition of health data is strict and limited. Because health data involves personal privacy and sensitive information, it is necessary to strictly abide by relevant laws and regulations when obtaining and sharing health data to protect user privacy and data security (Yera et al., 2023). Although medical institutions and insurance companies have large amounts of health data, only authorized research institutions or individuals can obtain access it, which limits the channels through which ordinary users can obtain health data (Dhiman et al., 2024). Currently, the health data used in FRS mainly comes from health guides issued by some authoritative organizations such as TWD (Wyld et al., 2010), DASH,[3] ADA (Association, 2019) and NHANES.[4] In addition, FRS mostly use clinical collections and self-build health datasets by mining literature, but most health datasets are private (Theodoridis et al., 2019).

Knowledge graphs (KG): KG can effectively organize data and express knowledge for effective and extensive exploration in traditional and advanced applications in many fields. In recent years, food-related knowledge graphs that provide a formal, unified, and shareable representation of food in the field of food nutrition. For example, FoodKG (Haussmann et al., 2019), AgriKG (Chen et al., 2019), FlavorGraph (Park et al., 2021) and other knowledge graphs bring together general information about food. Food knowledge graphs such as Foodbar KG (Zulaika et al., 2018) and RcpKG (Lei et al., 2021) not only include the relevant information of food, but also establish their interaction and contact with users, which can support personalized food recommendation. Healthy Diet KG (Huang et al., 2019), Food4healthKG (Fu et al., 2022), KG4NH (Fu et al., 2023) and other knowledge graphs organize food knowledge and health knowledge together, which can further give personalized healthy eating suggestions based on food knowledge graphs. It is worth mentioning that only a few knowledge graphs consider the joint use of

[1] Yummly. https://www.yummly.com.
[2] Meishijie. https://www.meishij.net.
[3] DASH. https://www.nhlbi.nih.gov/health-topics/dash-eating-plan.
[4] NHANES. https://wwwn.cdc.gov/nchs/nhanes/default.aspx.

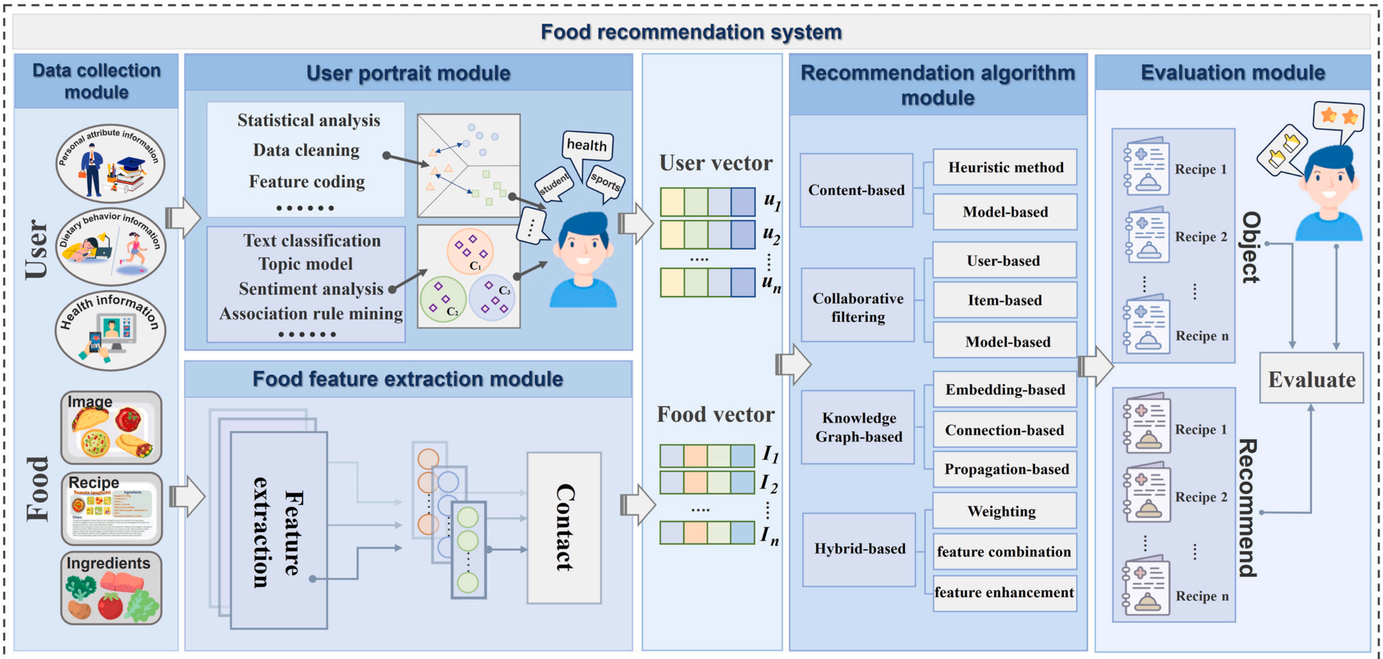

Fig. 1. Overall framework of food recommendation system. Parts of the graph were downloaded from https://www.freepik.com and http://www.iconfont.cn and modified accordingly.

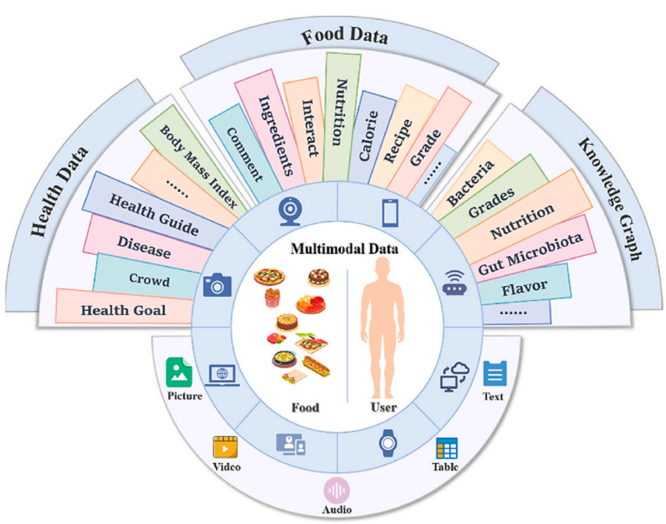

Fig. 2. Available data resources from the Internet, electronic sensors and smart wearable devices. They contain multimodal data including pictures, videos, audio, tables and texts. Parts of the graph were downloaded from https://www.freepik.com and http://www.iconfont.cn and modified accordingly.

multimodal data, such as AgriKG (Chen et al., 2019) and RcpKG (Lei et al., 2021). These multimodal diet knowledge graphs have the unique potential to further promote the development of food recommendations.

Facing these complex and diverse data sets, data standardization technology and pretreatment of heterogeneous data sets are the basis to ensure data availability and applicability. At present, the commonly used data standardization technologies of FRS include data cleaning, data conversion, feature extraction, normalization and standardization (Singh, Varma, et al., 2024). The preprocessing of heterogeneous data sets mainly focuses on feature extraction and fusion. It is an effective way to extract and select features by machine learning techniques such as principal component analysis (PCA) and linear discriminant analysis (LDA) (Chen et al., 2019). In contrast, feature fusion is a more complicated task, and the traditional weighted average method is often difficult to meet the task requirements. Therefore, multi-modal fusion technology based on deep learning is needed to improve it.

2.2. Food analysis module

Food analysis is a basic link of FRS, which provides a high-level understanding of food types (for example, food categories and ingredients), recipes and nutritional information for recommendation systems. Among them, text data is a common data type of food information. FRS uses natural language processing technology to analyze and process food text data, such as keyword extraction, named entity recognition and text classification. Keyword extraction technology mainly uses word frequency statistics to extract food keywords that frequently appear in texts. Common algorithms include Bag-of-Words model, Term frequency-inverse document frequency (TF-IDF), TextRank, LDA topic model, etc. (Alfarizi et al., 2022; Yu & Xiang, 2023). Named entity recognition technology is based on rules, statistics and deep learning methods to identify food names in texts, which provides convenience and accuracy for the identification of food information(Ju et al., 2022).

Food images are another important data type. The latest development of computer vision technology makes it possible to quickly analyze food images(Thames et al., 2021). Fine-grained analysis of food images is inseparable from key technologies such as food recognition, target detection, food segmentation and nutrition estimation. Among them, food image recognition belongs to the category of image classification. It extracts image features through convolutional neural network (CNN) or Transformer structure, and makes category prediction at the final fully connected layer. Food target detection aims at automatically identifying and locating food areas from food images. It is realized by marking bounding boxes in food images and assigning category labels to foods in each box. Common target detection algorithms include Fast R-CNN, YOLO and SSD. Food segmentation is a dense labeling task. It can separate the food part from the background in the image, which provides a basis for more accurate food analysis. Common algorithms include U-Net, DeepLab and Mask R-CNN. In addition to the types of food, the nutritional information of food can also be automatically extracted from the image(Shao et al., 2023). At present, researchers have explored solutions to mining nutritional information through monocular map recognition method, multi-view reconstruction method and fusion recognition method.

In addition, multimodal data such as video and voice provide rich contextual information and additional information sources for FRS, and making full use of this information is helpful to improve the performance of food information mining. Therefore, multimodal data fusion based on multimodal representation learning can obtain powerful multi-level abstract representation ability.

2.3. User profile

One of the core tasks of building a recommendation system is how to analyze the attributes and interests of users accurately, namely user profile. Generally speaking, user profile can be divided into two types: user basic profiles and user preference profile.

The user's basic profile involves the processing of the user's basic information (age, gender, etc.), contextual information (region, occupation, etc.) and health information (mental health, disease, etc.), which can help the recommendation system to better understand the user's background and characteristics (Dhiman et al., 2024). Common user-based profile methods primarily divide the attribute labels for users based on statistical analysis, data cleaning, and feature coding (Yera et al., 2023). In addition, supervised learning technology based on machine learning can realize the mining of unknown user attributes.

Profile of users' preferences involves the analysis of users' dietary interactions (dietary comments, purchase records, etc.), preference needs (dietary pattern preferences, health needs, etc.) and behavioral data (dietary logs, sports, etc.), which can explicitly or implicitly reflect users' interests and preferences (Dhiman et al., 2024). Among them, the most basic way is to use text classification, topic model, emotion analysis and other methods to extract and mine users' interest tags, which helps the recommendation system to better understand users' preferences and needs (Asani et al., 2020; Yera et al., 2023).

2.4. Recommendation algorithm

Recommendation algorithms play a vital role in FRS, which determines the recommendation effect and user experience of the system. These food recommendation algorithms can be roughly divided into four types: content-based approach, collaborative filtering approach, knowledge Graph-based approach and hybrid-based approach. Their principles and their respective advantages and disadvantages are shown in Fig. 3.

2.4.1. Content-based approach

The content-based recommendation method mainly recommends new foods according to the attributes of foods that users liked in the past, as shown in Fig. 3(a). From a technical point of view, content-based food

Table 1
Data sources in the field of food recommendation.

Type	Data source	Attribute	Multimodal	Reference
Food	Food-101	Categories	✓	Bossard et al. (2014)
	foodRecSys	Recipes, ratings, and ingredients	✓	Gao et al. (2019)
	Market2Dish	Recipes, ingredients, categories, ratings, and disease	✓	Wang et al. (2021)
	Recipe1M	Recipes and nutrition	✓	Marın et al. (2021)
	MenuRank	Menus, and nutrition	✓	Ju et al. (2022)
	MealRec	Ingredients, descriptions, categories, labels, and interactions	✓	Li et al. (2022)
	USDA[a]	Categories, and nutritional		-
	Food[1]	Recipes, categories, ingredients, user ratings, and comments	✓	-
	Yelp[b]	Restaurants, recipes, and interactions	✓	-
	Yummly[c]	Recipes, cuisines, ingredients, and interactions	✓	-
	Ta-da[d]	Recipes, ingredients, interactions, and tastes		-
	Meishijie[4]	Recipes, categories, ingredients, ratings, and comments	✓	-
	Cookpad[e]	Recipes, categories, ingredients, ratings, and comments	✓	-
	Allrecipes[1]	Recipes, categories, and comments	✓	-
	MyFitnessPal[f]	Recipes, categories, interactions, and comments	✓	-
Health	TWD	Weight control		Wyld et al. (2010)
	DASH[5]	Hypertensive diet plan		-
	ADA	Standards of medical care in diabetes		Association (2019)
	NHANES[6]	Demog, dietary, examination, and disease		
Knowledge graph	KG for the Food, Energy, and Water (FEW)[g]	Food, energy, and water		-
	Chinese Food KG	Ingredients, recipes, nutrients, symptoms, and crowd		Chi et al. (2018)
	Foodbar KG	Recipes, grades, comments, and user's interests		Zulaika et al. (2018)
	Healthy Diet KG	Food, symptoms, population, nutrients, and interactions		Huang et al. (2019)
	AgriKG	Agricultural products, plant, animal,nutrition, and origin	✓	Chen et al. (2019)
	FoodKG	Recipes, ingredients, and nutritional		Haussmann et al. (2019)
	Food KG with Cardiovascular Disease	Food nutrients and cardiovascular disease		Milanlouei et al. (2020)
	FKG	Ingredients, recipes, nutritional, and geographical		Rostami et al. (2021)
	RcpKG	Recipes, grades, comments, user's interests, culture, and social relations	✓	Lei et al. (2021)
	FlavorGraph	Recipes, ingredients, and flavor molecules		Park et al. (2021)
	Food4healthKG	Food, gut microbiota, and disease		Fu et al. (2022)
	KG4NH	Food, nutrition, bacteria, and disease		Fu et al. (2023)

[a] USDA. https://ndb.nal.usda.gov/ndb.
[b] Yelp. https://www.yelp.com/dataset.
[c] Yummly. https://www.yummly.com.
[d] Ta-da. https://github.com/Eimo-Bai/Ta-da-recipe-dataset.
[e] Cookpad. https://cookpad.com/tw/homepage.
[f] Myfitnesspal. https://www.myfitnesspal.com/.
[g] FEW. https://mospace.umsystem.edu/xmlui/handle/10355/62663.

recommendation can be divided into heuristic method and model-based method. Heuristic-based method is to recommend similar foods through specific calculation rules or simple feature matching according to users' favorite tastes, ingredients and other characteristics. Common algorithms are Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO) and Genetic Algorithm. Heuristic method is simple and intuitive, with high flexibility and efficiency. Model-based methods usually use vector space model, matrix decomposition and machine learning algorithms to represent users and food in vector form, and then recommend food by learning the similarity between the feature vectors of users and food. The model-based method uses a large amount of data for training, which can better capture users' personalized interests and behavior patterns and provide more accurate recommendation results.

2.4.2. Collaborative filtering approach

Collaborative filtering is a recommendation algorithm based on user behavior data (such as rating and purchase), which is mainly divided into three categories: user-based filtering, food item-based filtering and model-based method. As shown in Fig. 3(b), user-based filtering calculates the similarity between users by constructing a user relationship matrix. Then, food is recommended to the target user based on the preferences of neighboring users with similar interests to the target user (Thongsri et al., 2022). It is simple and intuitive, and is suitable for sparse data. Different from it, the filtering based on food items calculates the similarity between foods by constructing the relationship matrix of food items. When the number is huge, this method has obvious efficiency advantages. In contrast, the model-based method uses logistic regression, random forest and neural network to predict users' ratings or preferences for items, thus generating recommendations. It can provide more diversified and novel recommendations and improve the scalability of the algorithm.

2.4.3. KG-based approach

As shown in Fig. 3 (c), the recommendation method based on KG can make use of the rich semantic information and structural features in knowledge graph to improve the recommendation performance. The food recommendation methods based on knowledge graph are mainly divided into three categories: embedding-based method, connection-based method and propagation-based method. Among them, the embedding-based method uses knowledge graph embedding technology to represent entities and relationships as low-dimensional vectors, improving computational efficiency by calculating similarities. Chen et al. (2023) used the knowledge graph embedding technology based on TransD to learn the entity and relationship embedding of user-recipe graph, then used the message transmission mechanism of graph neural network (GNN) to capture the high-order relationship information of

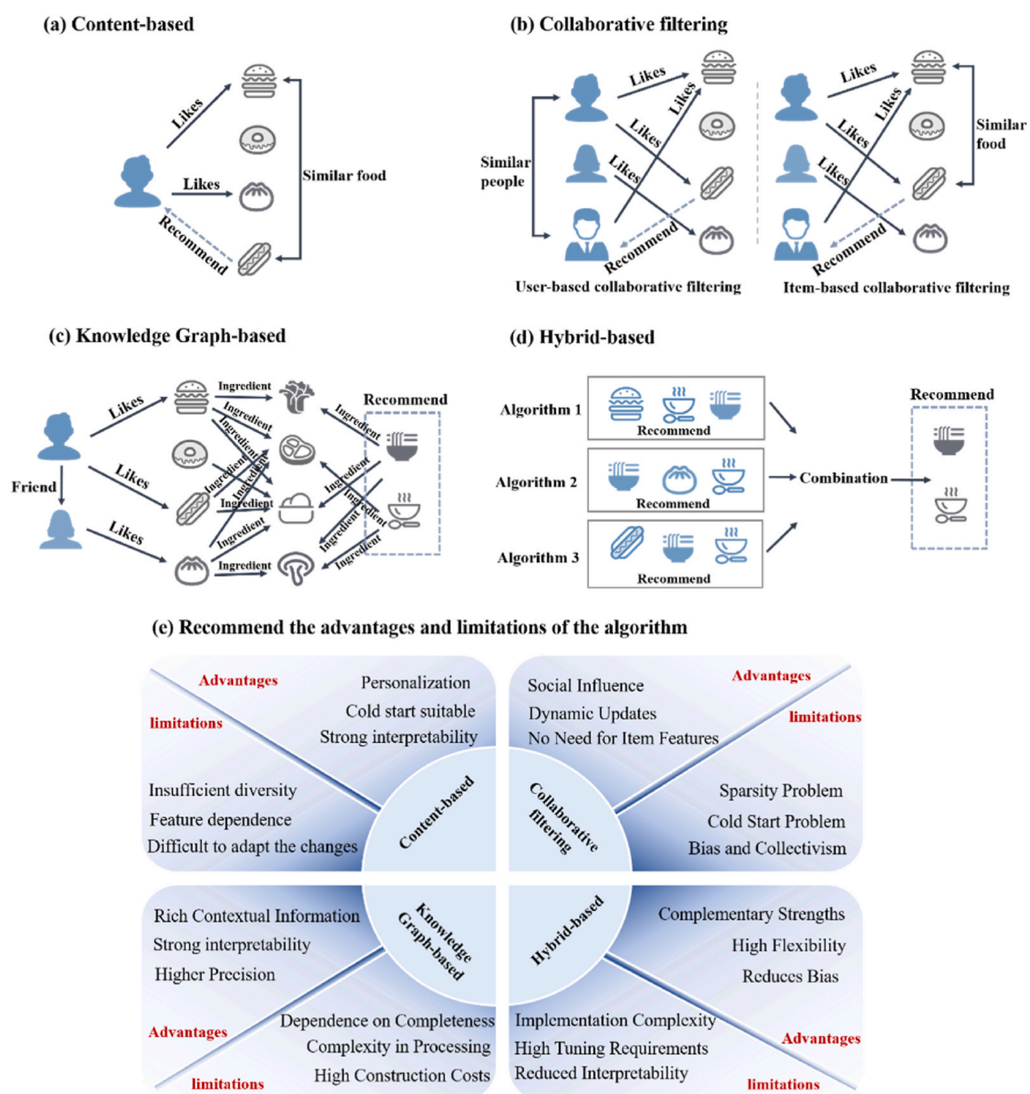

Fig. 3. Common food recommendation algorithms. Parts of the graph were downloaded from http://www.iconfont.cn and modified accordingly.

entities and update the entity representation, and finally realized the recommendation of healthy food under the multi-task learning strategy. However, it may miss complex relationships between entities. In contrast, the path-based method explores complex connections by traversing the graph to extract paths, scoring them based on length and relation weight. Zhang and Zhu (2021) used meta-path guidance strategy and weighted graph convolution network to obtain high-order structural information among users, dishes and ingredients, and predicted recipes that met users' preferences. While it uncovers important information, it can suffer from high computational complexity with lengthy paths. The propagation-based method combines semantic representation and path association, utilizing KG's rich knowledge to provide detailed, interpretable recommendations by aggregating high-level information from entities and relationships. For example, Zhang et al. (2023) proposed a collaborative knowledge dissemination graph attention network for recipe recommendation. This method designs a collaborative information dissemination strategy, which makes full use of user interaction and formula attribute information and can meet the needs of various influencing factors.

2.4.4. Hybrid-based approach

Hybrid method is a collection of two or more technologies to solve the limitations of single recommendation technology, as shown in Fig. 3 (d). The commonly used combination methods of mixing methods are: weighting, feature combination and layered mixing. Among them, the weighting method linearly combines the recommendation results of different recommendation methods according to a certain weight. The choice of its weight may need a lot of experiments to determine. For example, Rostami et al. (2023) designed a weighting mechanism to weigh the importance of time factors to different ratings, thus incorporating the dynamic nature of user preferences into the food recommendation process. Feature combination combines feature vectors generated by different recommendation methods, and then uses a single recommendation model to deal with these features. For example, Bai et al. (2022) mined the fine-grained representation requirements of users and recipes through multi-level views, and used a variety of knowledge-aware aggregation methods to fuse nodes, and finally proposed personalized food recommendations. This method can capture the features of different algorithms better, but it needs complex feature engineering and model training. Hierarchical mixing is the sequential superposition of multiple algorithms. One algorithm is used to narrow the recommendation range, and then another algorithm is used to make the final recommendation within the narrowed range. For example, Li et al. (2023) integrated nutritional factors into the task of recipe representation and recommendation. This method uses knowledge transfer scheme to transfer useful semantic information between preferences and health aspects, rather than simple integration.

2.5. Evaluation metrics

The purpose of evaluation is to measure the accuracy, efficiency and user satisfaction of FRS, so as to continuously optimize and improve the recommendation effect of the system. The evaluation methods of FRS mainly include offline evaluation and online evaluation. Offline evaluation uses non-real-time data sets to test the efficiency and reliability of recommendation methods, which can quickly evaluate the basic performance of recommendation systems. Online evaluation is mainly based on interactive questionnaires or interviews between users and the system to obtain online evaluation feedback. This evaluation method is closer to actual user behavior and can provide more realistic evaluation results.

2.5.1. Offline evaluation metrics

Offline evaluation methods are usually based on the leave-one-out method or k-fold cross validation to split the non-real-time data set, one part of the data set is used for training the system, and the other part is used for evaluation (Raza & Ding, 2022). Common evaluation indicators of offline evaluation methods can be divided into three types: Accuracy-based metrics, Ranking-based metrics and Error-based metrics (Bondevik et al., 2023).

Accuracy-based metrics focus on how well the recommendations match the user's true preferences. These metrics include: Accuracy, Precision, F-measure, Area Under the Roc Curve (AUC) and Hit Ratio (HR@K).

- Accuracy: The Accuracy metric shows how well the item recommended by the system matches what the user is actually interested in. That is, the ratio that the recommendation system predicts that the user's preference for an item is the same as the user's actual preference.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}} \tag{1}$$

Where, TP stands for true positive score, which means that the recommended positive sample conforms to the user's real preference. FP stands for false positive score, indicating that the recommended positive sample is not the item that users really prefer. TN stands for true negative score, which means that the recommended negative sample conforms to the items that user' don't like. FN stands for false negative score, indicating that the recommended negative sample is the user's preferred item.

- Precision: Precision indicates the ratio of the number of items that match the user's actual preferences to the total number of items recommended by the system in the recommendation result.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

- Recall: The recall rate is the proportion of the number of positive samples predicted correctly to the number of true positive samples. That is, the ratio between the number of items that the user is really interested in and the total number of items that the user is actually interested in among the items that the system recommends to the user.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

- F1-Score: F1-Score is the weighted harmonic average of Precision and Recall, aiming to comprehensively consider both accuracy and coverage.

$$\text{F1} - \text{Score} = 2*\frac{\text{Precision}*\text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}} \tag{4}$$

- AUC (Area Under the Roc Curve): The area under the ROC Curve (AUC) is used to measure the probability that the positive sample ranks higher than the negative sample in the recommendation result. ROC measures the performance of the system model under different thresholds. The value of AUC ranges from 0.5 to 1, with a value closer to 1 indicating better model performance.
- HR@K(Hit Ratio): HR@K indicates how many samples from the test set appear in the recommendation list. The number of samples in the recommendation list belonging to the test set is expressed as Hits@K, and the total number of samples in the recommendation list is n.

$$\text{HR@K} = \frac{\text{Hits@K}}{\text{n}} \tag{5}$$

Ranking-based metrics are used to incentivize the recommendation list to place the user's favorite recipe items at the top. Normalized discounted cumulative gain (NDCG@K), Mean reciprocal ranking (MRR), Mean Average Precision (mAP) and Mean Average Recall (mAR) are the most common evaluation indicators.

- NDCG@K (Normalized discounted cumulative gain): NDCG@K is a widely used metric to assess the quality of ranking lists. It assesses the quality of ranking recommendations by assigning higher scores to the top K recommendations.

$$NDCG@K = \frac{DCG@K}{IDCG@K} = \frac{\sum_{i=1}^{K} \frac{2^{rel_i}-1}{\log_2(i+1)}}{\sum_{i=1}^{|REL_K|} \frac{rel_i}{\log_2(i+1)}} \tag{6}$$

Where, DCG@K refers to the Discounted Cumulative Gain of the actual recommendation list; IDCG@K is the ideal situation where recommendations are listed in descending order of relevance. $|REL_K|$ represents the first K samples of the ideal list. rel_i indicates whether the i_{th} sample of the recommendation list is related to the test set, if so rel_i is 1, otherwise rel_i is 0.

- MRR (Mean reciprocal ranking): The MRR metric focuses on where the first relevant item appears on the recommended list.

$$MRR = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{P_i} \tag{7}$$

Where, N represents the total number of tested users, and P_i represents the position of the first food that meets the user's real preference in the recommended list.

- mAP (Mean Average Precision): mAP is used to evaluate the average accuracy of a recommendation system when returning multiple related items. It calculates the Average Precision for each user, and then averages the average precision for all users.
- mAR (Mean Average Recall): MAR is used to evaluate the average recall rate of recommendation system when it returns multiple related items.

Error-based metrics measure the difference between recommendation results and true ratings or preferences based on the prediction error of the recommendation system. Such indexes include Mean Absolute Error (MAE) and Root mean square error (RMSE), which focus on error control and optimization of recommendation systems.

- MAE (Mean Absolute Error): MAE measures the average absolute value of a recommendation system's prediction error for user interest. It is given in Eq. (9), where y_i is the actual value and $\hat{y}_i$ is the forecast value.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{8}$$

- RMSE (Root mean square error): RMSE defines the RMS error rate between the actual value and the predicted value.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|} \tag{9}$$

2.5.2. Online evaluation metrics

Online evaluation methods often conduct user experiments to test the effectiveness of recommender systems. however, due to factors such as high costs and time consumption, their application in FRS is not widespread. Two online evaluation methods that are main used are click rate (CTR) and A/B test.

- CTR (Click-through rate): CTR indicates that the proportion of the total number of recommended items that is clicked or selected. In the field of FRSs, some researchers tend to use the average values of metrics such as Recall or AUC to calculate and characterize CTR, aiming to achieve more robust evaluation.
- A/B testing: The A/B test compares the satisfaction score among the two groups by setting up a control test. It allows the change of recommendation system to be controlled and evaluated systematically.

So far, the research mainly focuses on the test of system accuracy. Accurate recommendation is an important factor to improve user satisfaction, because the accurate recommendation results verify that the system has the ability to meet the requirements of users in terms of dietary preferences and nutritional needs. However, with the increase of user demand, the consideration of usability, diversity and coverage needs further exploration. For example, some researchers are exploring innovative standards to measure user satisfaction or multidimensional evaluation of the health level of recommendation lists (Ahmadian et al., 2022; Metwally et al., 2021).

3. The latest application of personalized food recommendation system

Personalized FRS provides users with diet plans and food lists that meet their personal needs based on personalized information such as personal health status, dietary preferences, and dietary taboos, by using advanced data analyses and recommendation algorithms (Meng et al., 2020). As shown in Fig. 4, personalized FRS has been widely used to meet user preferences and nutritional and health needs.

3.1. Personalized food recommendations based on preferences

Preference-based personalized FRS employ users' personal information and taste preferences to recommend foods. The application goal of personalized FRS based on preference can be summarized as the following three aspects: satisfying food preferences, conforming to context constraints and obeying dietary behavior preferences. Table 2 summarizes the latest research on personalized food recommendation based on preference, and the detailed information of recommendation algorithm, key model technology data set and evaluation index they use.

3.1.1. Satisfy food preference

The fundamental reason for inducing human appetite lies in the food itself. People will first consider the ingredients, flavor and visual characteristics of food when choosing food. Therefore, satisfying these food attribute preferences is the primary task of personalized FRS.

Faced with ingredient preference, Jia et al. (2022) proposed a multi-view convolutional neural network with an attention mechanism for recipe recommendation. By applying attention mechanism to vectorized recipes, users' interest in recipes is transformed into their interest in ingredients, and then appropriate recipes are recommended to users by learning each user's preference weight for ingredients. In the research of Zhang et al (2019), the interaction between users and ingredients is captured by collaborative filtering method based on neural network, and the preferences of users for ingredients are analyzed by using generalized matrix decomposition (GMF), and finally recipes are recommended according to the preferences of ingredients.

The flavor of food directly determines whether people are willing to try or continue to eat a certain food. Nirmal et al. (2018) considered the importance of food flavor, defined a generalized flavor and nutrition optimization model, and recommended recipes that were more in line with users' preferences. Among them, the flavor optimization model uses a dish prediction model, recipe similarity measurement, normalized average support, and recipe authenticity measurement to determine the characteristics of dishes and flavors. Combined with a nutrition

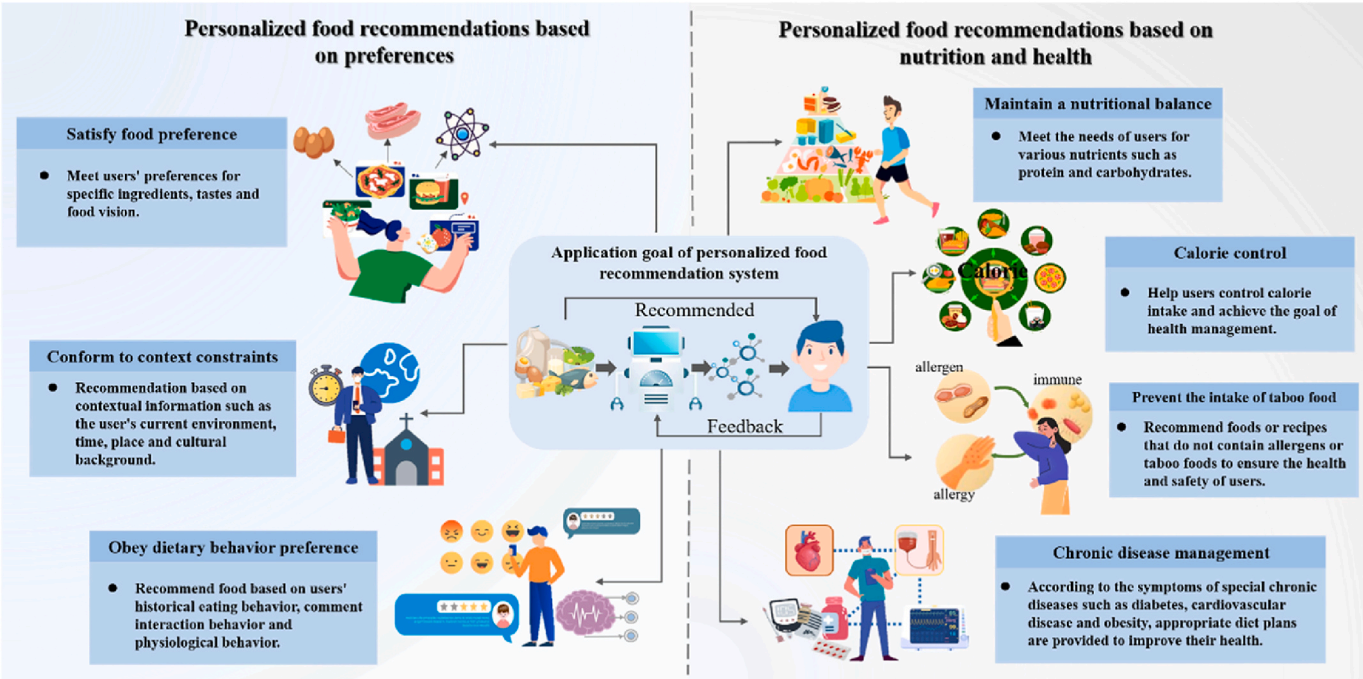

Fig. 4. Application target of personalized FRS. Parts of the graph were downloaded from https://www.freepik.com and http://www.iconfont.cn and modified accordingly.

Table 2
Application of personalized FRS based on nutrition and health.

Application target	Reference	Recommendation algorithm	Technology and model	Dataset	Evaluation metrics
Satisfy food preference	Zhang et al. (2019)	Collaborative filtering	Deep learning, generalized matrix factorization and spatial regularization network	Self-built dataset	mAP, HR@10, and NDCG@10
	Jia et al. (2022)	Content-based	Convolutional neural network and cluster analysis	Self-built dataset	HR@10 andNDCG@10
	Elsweiler et al. (2017)	Hybrid-based	Machine learning	Allrecipes	Accuracy
	Gao et al. (2019)	Collaborative filtering	Hierarchical attention mechanism, and convolutional neural network	Food-101, Yummly	Recall, AUC, and NDCG
	Nirmal et al. (2018)	Collaborative filtering	Three phase filtering, Random forests algorithm	AllRecipes and USDA	Accuracy
Conform to context constraints	Rostami et al. (2022)	Hybrid-based	Deep learning and graph clustering	Allrecipes	Precision, Recall, F1-Score, AUC and NDCG
	Jin et al. (2020)	Collaborative filtering	Deep neural network and multilayer perceptron	Self-built dataset	F1-Score andNDCG
	Gallo et al. (2022)	Hybrid-based	KNN and K-Means	Food	HR@10 and RMSE
	Khan et al. (2019)	Collaborative filtering	TF-IDF, topic modelling	Self-built dataset	Accuracy and coverage
	Hamdollahi Oskouei and Hashemzadeh (2023)	Collaborative filtering	Deep Learning	AllRecipes, Food	RMSE
Obey dietary behavior preference	Ling et al. (2022)	Hybrid-based	Hierarchical RNN and long short-term memories	Self-built dataset	Precision, Recalland NDCG
	Tsai et al. (2018)	Hybrid-based	Emotional analysis mechanism	Self-built dataset	User satisfaction
	Pritee et al. (2023)	Collaborative filtering	Emotional classification prediction	Self-built dataset	User satisfaction
	Islam et al. (2022)	Content-based	Fourier transform, discrete wavelet transform, and machine learning	Self-built dataset	Accuracy, AUC and F1-Score

optimization model, the system can recommend alternative foods with specific tastes and nutrients to users.

In the face of visual preference, the existing methods usually take visual features as embedded items, and then recommend food by searching or collaborative filtering. For example, Elsweiler et al. (2017) predicted the preferred recipe by applying machine learning technology to extract food image features, and revealed the fact that combining low-level image features and recipe metadata as the input of the predictor can achieve good performance. Gao et al. (2019) regard food images as the key information of food to enhance the discrimination of recipes. This method encodes the user-menu interaction, obtains the embedded representation of menu images and menu components, and then dynamically aggregates the embedding into a more comprehensive menu representation by using the hierarchical attention module, so as to better infer the user's preference for recipes.

In a word, satisfying the preference for food is based on satisfying the preference for specific attribute information of food. Although this realizes the consideration of food preference constraints, it is difficult to achieve more fine-grained recommendations. Therefore, more researchers consider using deep learning methods to improve the accuracy of recommendations. They aim to achieve this by increasing the application weight of food information in the recommendation system. Additionally, they focus on modeling the direct interaction between users and attribute information more directly.

3.1.2. Conform to context constraints

Context information, such as environment, time, place and cultural background, is an important factor affecting users' diet choice. Therefore, personalized FRS should provide users with more reasonable food choices based on contextual information.

First of all, Dietary preference often changes with time, so personalized FRS should fully consider the time factor. Rostami et al. (2022) adopted a similar holistic approach to consider issues related to time and user community, thereby improving the quality of recommendations provided to users. This measure considers changes in food preferences over time so that the system can accommodate users with dynamic eating habits.

Similarly, Geographical and environmental factors also directly affect users' food choices. Jin et al. (2020) considered the information of the dishes in the restaurant, and used the powerful expressive force of neural network to capture users' personal dietary preferences, so as to recommend the dishes in the restaurant to users. In a preliminary study, Gallo et al. (2022) considered the use of water resources when recommending recipes. The main purpose of this study is to develop recipes that are less dependent on water. Khan et al. (2019) proposed a feature recognition technology based on integrated topic modeling, which fully considered users' tastes, demographics and costs, and was used for efficient user preference modeling and recipe recommendation.

In addition, cultural and religious norms greatly influence food choices. They define what foods are considered acceptable and influence people's attitudes towards certain foods. Hamdollahi Oskouei and Hashemzadeh (2023) proposed FRS based on deep learning, which created feature vectors of food and users from items such as food ingredients, cooking types, cultures, and religions through various deep learning frameworks, and then estimated preference scores based on this vector for food recommendation.

In the current research, a lot of work has begun to consider more constraints and rules in the process of food recommendation to improve the quality of recommendation. However, how to reasonably coordinate the relationships and restrictions among various constraints is still a problem worthy of attention.

3.1.3. Obey dietary behavior preference

Dietary behavior preference is usually hidden in diet history, emotional behavior and physiological behavior. Satisfying users' dietary preference is a challenging task for personalized FRS.

Diet history contains the user's eating habits and preferences. Ling et al. (2022) used hierarchical RNN to simulate the sequential behavior of users in a certain period of time, and trained the goal-oriented model from the historical food consumption data of similar groups of users, and then combined this goal-oriented recommendation model with the user model to realize food recommendation.

Comments and feedback are the direct embodiment of users' emotional behavior. Tsai et al. (2018) used emotion analysis mechanism to analyze users' eating emotions based on semantics, emoticons and image comments related to food and cooking, thus constructing the interactive relationship between food and personal emotions. By providing users with appropriate comfort food choices, they can help users alleviate negative emotions.

Physiological behaviors are the direct physiological responses and actions of users to external stimuli. Therefore, in order to satisfy the user's preference for physiological behavior, Pritee et al. (2023) considered the influence of hormone changes in specific emotions on food selection, and proposed a hybrid filtering recommendation system based on emotions. This system recommended appropriate foods according to the hormones secreted by users in specific emotions as well as the scores of the general age group and the general gender on specific diets. Considering the limitations of special patients in emotional expression, Islam et al. (2022) used emotion calculation module to analyze the brain signals captured by EEG, so as to predict people's emotional state of a certain food, and used TOPSIS (Technical for Order of Preference by Similarity to Ideal Solution) method to generate a food list that met users' preferences according to the predicted emotional state.

To sum up, in order to satisfy users' dietary preferences, personalized FRS needs to analyze users' behavior data. The analysis of these behavioral data involves the application of the key algorithm technology of user profile module, so it is the key to make accurate recommendations to choose the appropriate analysis method for specific behavioral data types and application scenarios.

3.2. Personalized food recommendations based on nutrition and health

Healthy food recommendation is based on users' health status, nutritional needs and dietary restrictions, aiming at recommending beneficial foods or recipes to improve users' health level and quality of life. The application objectives of personalized FRS based on nutrition and health can be summarized as follows: maintaining nutritional balance, calorie control, allergy prevention, dietary taboos and chronic disease management. Table 3 summarizes the latest research on personalized food recommendation based on nutrition and health, as well as the detailed information of recommendation algorithm, key model technology data set and evaluation index they use.

3.2.1. Maintain a nutritional balance

Currently, an increasing number of healthy recipes are recommended to promote the development of healthier habits. Gautam and Gulhane (2021) proposed a multi-constrained particle swarm optimization algorithm for dietary recommendations for the elderly in India. According to the basic health status of the elderly, this method formulates the nutritional requirements in different time periods, and then compares the specific nutrient content requirements in different time periods with the nutrient content recommended by the multi-constrained particle swarm optimization algorithm to improve the nutritional fitness of the recommended food. Perera et al. (2023) proposed a multi-objective FRS that comprehensively considered nutritional value, dietary diversity and preference. It encourages users to explore a wider range of food types and comprehensive nutritional supplements by quantifying their daily nutritional demand index.

To recommend healthier food, the common method is to infer the health-related characteristics from the ingredients of the formula and take this as the recommendation basis to provide users with health-oriented food choices. However, only healthy food ingredients cannot fully represent the health of the diet. This means that a finer-grained nutritional constraint is needed, which allows automatic generation of personalized diets that meet the requirements of the health gold standard.

3.2.2. Prevent the intake of taboo food

Personalized food recommendation needs to consider users' allergic reactions and dietary taboos, and recommend foods or recipes that do not contain allergens or taboos to ensure users' health and safety.

A personalized FRS can provide users with information on allergic foods, stimulate their attention to allergic problems, and help them make more rational food choices. For example, Samonte et al. (2022) developed a Web-based FRS, which provided food allergy information to

Table 3
Application of personalized FRS based on nutrition and health.

Application target	Reference	Recommendation algorithm	Technology and model	Dataset	Evaluation metrics
Maintain balanced nutrition	Gautam and Gulhane (2021)	Content-based	Multi constraint particle swarm optimization algorithm	Self-built dataset	Error and fitness
	Perera et al. (2023)	Content-based	Non-dominated sorting genetic algorithm	MealRec	Simpson index
Prevent the intake of taboo food	Samonte et al. (2022)	Content-based	Website development technology and decision support	Self-built dataset	User satisfaction
	Showafah and Sihwi (2021)	Content-based	Naïve bayes and similarity priority ranking	Self-built dataset	User satisfaction and usability
	Hasan et al. (2022)	Knowledge Graph-based	Optical character recognition (OCR) and TOPSIS	Self-built dataset	User satisfaction
	Yang et al. (2017)	Hybrid-based	k-means++ and convolutional neural network	Yummly and Food-101	Accuracy, mAP, MAE and RMSE
Chronic disease management recommendation	Sookrah et al. (2019)	Collaborative filtering	machine learning and multilayer perceptron	USDA	User satisfaction
	Chen et al. (2021)	Knowledge Graph-based	Attention mechanism and word embedding techniques	FoodKG and ADA	F1-Score, mAR, and mAP
	Mckensy-Sambola et al. (2021)	Hybrid-based	Knowledge reasoning technique	foodRecSys	Accuracy, precision, recall, and F1-Score
	Ramesh et al. (2021)	Content-based	Ripper algorithm, K-Means, and synthetic minority oversampling technique	Clinical dataset	User satisfaction
Calorie control	Lokuge and Ganegoda (2021)	Content-based	Latent dirichlet allocation model	Allrecipes	Topic coherence and perplexity measures
	Chavan et al. (2021)	Hybrid-based	Vector space modeling and term frequency-inverse document frequency	Allrecipes and USDA	Accuracy, Recall, Precision, mAP, and MAR
	Song et al. (2023)	Knowledge Graph-based	Attention mechanism, and graph neural network	Allrecipes	AUC, NDCG, and Recall

allergic people and recommended edible foods on restaurant menus to avoid allergic reactions. Showafah and Sihwi (2021) proposed a complementary food menu recommendation system for infants that considered not only the balance of important nutrients in food but also food allergy factors.

Additionally, the intake of taboo foods is a problem that is worthy of attention. People with diseases are usually asked to avoid the intake of certain types of food, which is usually owing to nutrition and health considerations. Yang et al. (2017) proposed a recipe recommendation system based on nutrition with reference to user data and visual food image characteristics, in order to meet individual's specific dietary restrictions and nutritional expectations. Hasan et al. (2022) proposed a personalized menu decoder recommendation system, which can help users understand menu items and screen foods containing prohibited ingredients.

The existing FRS for preventing dietary taboos is mainly realized by food label prompt, ingredient substitution suggestion and intelligent diet management. Among them, the user's health data and food composition information are the main factors to be considered. Using pre-defined rules and specific health guideline standards to recommend food can achieve satisfactory results, such as avoiding the appearance of certain ingredients or following specific dietary patterns. However, the diversity of recommendation results needs further study. The existing research solves the dilemma between accuracy and diversity in recommendation results by introducing multi-objective optimization algorithms such as genetic algorithm and particle swarm optimization. However, the method based on deep learning shows better advantages. For example, FRS combined with attention mechanism can adapt the weight of constraints and show obvious advantages.

3.2.3. *Chronic disease management*

Health management through proper diet planning is the key to the successful operation of the health system (Majnarić et al., 2021). Personalized FRS can recommend foods or recipes suitable for chronic disease management according to the symptoms or needs of users, as well as help users manage diseases and improve their health.

As a metabolic disease, diabetes is characterized by increased blood sugar levels. Therefore, in order to control and prevent the occurrence of diabetes, personalized FRS usually consider the user's blood sugar level as a measure of health status. For example, Ramesh et al. (2021) proposed a new rule model for food recommendations for elderly people with diabetes in India based on the food glycemic index (GI). The model uses the ripper algorithm to extract rules from real clinical data sets, which are used by rule-based classifiers to provide appropriate recommendations to users. Finally, the proposed system was evaluated by medical professionals and doctors, and achieved good recommendation results. Chen et al. (2021) referred to the nutritional diet requirements of the American Diabetes Association's guidelines for healthy living, and modeled the food recommendation task as a constrained question-and-answer problem on a large-scale food knowledge Graph.

Cardiovascular diseases such as hypertension and coronary heart disease are closely related to eating habits. Therefore, it is of great significance to intervene and manage dietary behavior. Therefore, Sookrah et al. (2019) proposed a FRS for patients with hypertension to help them develop healthy dietary plans. The system uses content-based filtering and a machine learning algorithm to predict the user's sodium intake standard according to factors such as the user's age, allergy, blood pressure level, lifestyle, and dietary intake to recommend personalized healthy diet plans for hypertensive patients.

In addition, obesity caused by excessive body fat accumulation is also a common chronic disease. Mckensy-Sambola et al. (2021) proposed a diet ontology related to healthy self-management of chronic multifactorial diseases (such as obesity and different levels of overweight), and proposed a diet recommendation system based on this knowledge ontology to help obese users control their diets. Among them, the body mass index (BMI) is used as the main index by which to evaluate a user's obesity level, and the recommendation system infers the most suitable diet according to that user's obesity data and returns a list of recipes that meet the details of that diet.

3.2.4. *Calorie control*

FRS can recommend foods or recipes that meet the user's calorie control needs according to the user's personal management goals, such as losing weight or gaining muscle, so as to achieve the goal of health management. For example, Lokuge and Ganegoda (2021) calculated the basal metabolic rate (BMR) based on the physical activity level parameters of users, and estimated their daily calorie allowance of users according to the fitness goals of various nutritional health measures. In order to further improve the accuracy and effectiveness of recommendation, Chavan et al. (2021) constructed a prediction function based on the factors of the user's age, activity level, height, and weight to infer the user's calorie demand. The content and preferences of personal recipes were considered as constraints. This hybrid model achieved better recommendation performance than did content-based and collaborative filtering algorithms. Song et al. (2023) proposed a self-monitoring calorie-aware heterogeneous graph network (SCHGN) to model the relationship between food components, and learn the calorie content in food through hierarchical messaging strategy. Finally, based on calorie constraints, we recommend recipes that satisfy users' preferences.

3.3. *Intelligent application service tool of FRS*

The development of new technologies such as artificial intelligence, big data and cloud computing has promoted the transformation from theoretical research to intelligent application service tools. Although the recommendation algorithm itself is very important, it is an important trend of FRS development to transform the algorithm into practical application and give them life and practicality. In recent years, intelligent healthy diet management platform and application program with practical application value have been developed. For example, Stahl et al. (2024) developed an application named LIFANA to provide personalized meal planning. The first round of short-term field trials in the Netherlands and other places show that the application can help users prevent malnutrition or overweight, and follow WHO's recommendations on calorie intake based on height, weight, gender and age and measured physical activity. In addition to the development of general dietary management tools, there has been a growing focus on creating applications tailored to the needs of special populations. For example, Chao and Hass (2020) put forward an interface of healthy food recommendation system for the elderly. In the 2 × 2 total factor experiment, the effectiveness of key UI design variables, search result layout and nutrition information format was systematically verified through further user testing research. Mustafa et al. (2020) put forward a menu planning application program (iDietScore™) for athletes, which provides personalized meal plans for athletes and active individuals according to their personal data, including energy and macro nutrient requirements, sports category, age group, training cycle, training time and personal food preference.

In recent years, with the development of intelligent medical care, the intelligent catering service platform for special disease management has provided assistance in promoting the transformation of medical service model. For example, Agapito et al. (2018) put forward an online service platform for dietary recommendation for chronic disease monitoring and management (DIETOS). By recruiting 20 patients with chronic kidney disease (CKD) and 20 age-matched healthy controls in the Department of Nephrology and Dialysis of Catanzaro (Italy) University Hospital, DIETOS has been verified as a patient and expert, and the correctness of analysis and recommendation has been evaluated. Norouzi et al. (2018) developed a knowledge-based mobile application system for recommending snacks for diabetics. Through three stages: knowledge-based engine design, system interface design and system output evaluation, the application program provides a more convenient way for diabetic patients to screen their diets.

Generally, these intelligent service platforms epitomize the practical application of theoretical research and are pivotal in enhancing the real-world applicability of Food Recommendation Systems (FRS). Looking ahead, the development of practical and user-friendly mobile tools is expected to play a more extensive and far-reaching role in the field of healthy diet management.

4. Existing challenges and future trends

FRS play an important role in encouraging users to make dietary choices according to their personal preferences and health status. However, the research of personalized FRS is still in the primary stage. In this section, we analyze the key challenges for the further development of personalized FRS and the key directions that should be followed in the future from three aspects: data, model, and user experience.

4.1. *Data level*

A broader representation of preferences. Currently, the number of attributes used in FRS and the acquisition methods are generally small, and the future research direction should be devoted to acquiring more abundant attributes. It is worth noting that the fine-grained characterization of preferences can be supplemented by detecting users' biological reactions to food through professional instruments. For example, Islam et al. (2022) calculated people's emotional state of food based on brain signals captured by EEG, which provided an effective way to record preferences. However, for the sake of portability and real-time, we think that miniature biosensors and integrated wearable devices will be a more promising choice. For example, flexible sensor (Kil et al., 2022) or smart watch devices (Sempionatto et al., 2021) can monitor physiological reactions such as skin electrical response and heart rate variability in real time, thus reflecting users' preferences for different foods more comprehensively. In addition, the current popular definition of health attributes often emphasizes macro standards, which leads to insufficient attention to the concept of precision nutrition. In the future, studying the relationship between metabolism and diet based on omics data will bring more accurate nutritional advice and intervention, which will mark a great progress in this field (Posma et al., 2020). At the same time, it is very important to detect the conflicts between various constraint attributes or rules. Most personalized FRS do not consider the weight of constraints, which leads to the fact that constraints with different attributes are regarded as equally important, but this may not be the case. Therefore, adaptive personalized recommendation based on individual users will be an important field to be considered in the future.

Application of multimodal data in diet and health. The data related to health status and dietary preference not only come from a wide range of sources, but also present various forms such as text, images, charts and videos. However, the common data format in the current FRS is still text, and this single-modality based system is prone to problems such as repeated recommendations and lack of novelty. Therefore, it is an inevitable trend to explore and utilize the heterogeneous relationships in multimodal data for personalized food recommendation. However, it is challenging to integrate these data effectively, especially in combining multimodal information to improve recommendation performance. We believe that deep learning can be used as an effective solution. First of all, deep learning models such as CNN and Transformer with good expressive ability can provide a solid foundation for capturing information of different modes, which has been fully verified in the research of Shao et al (2023). At the same time, using transfer learning technology and attention mechanism to integrate the features of different modes can further enhance the robustness and adaptability of the model. In addition, GNN plays an important role in recommendation system by explicitly modeling the interactive information between users and items. Lei et al. (2021) constructed a multimodal FRS based on knowledge graph by integrating multimodal neural network and GNN. This provides us with a feasible way of thinking. In the future, using neural networks such as probabilistic graphical model (Yoon et al., 2019) and heterogeneous graph neural network (Yang et al., 2023) to capture the correlation between heterogeneous data will be more helpful to obtain a unified structured representation of multimodal data and improve recommendation performance. Therefore, making full use of multimodal data to explore multimodal FRS will require great attention in the future.

Ethical Principles and Data Privacy Protection. Personalized diet recommendation systems involve the use of sensitive information such as users' health data and eating habits. If ethical principles and privacy protection issues are not properly solved, it will affect users' trust in the system, reduce the usage rate and user stickiness of the system, and then affect the innovation and development of the FRS. With the popularization and application of FRS, ethical principles have been paid attention to first. For example, Karpati et al. (2020) listed 11 broad ethical principles, including transparency, justice and fairness, interests, responsibilities and privacy. At the same time, they also put forward an ethical framework based on the concept of Internet of Food (IoF) for ethical evaluation of the existing FRS. In the future, with the development of technology and the change of social concepts, ethical principles need to be constantly updated and adapted to the new situation.

It is worth noting that data privacy protection is also a key challenge. A common solution is to desensitize data to eliminate private data. Specific practices include encryption technology (Badsha et al., 2016), anonymization (Saleem et al., 2021) and privacy deletion (Slokom et al., 2021). For example, Qiao et al. (2022) removed the user's private data, redundant data and incomplete data in the data preprocessing stage, and realized the recommendation of healthy meals while protecting the user's privacy. However, the privacy and security of data in the process of transmission and storage have not been paid attention to. Edge computing (Ni et al., 2018) and federated learning technology are effective ways to solve this problem, and have achieved remarkable results in other fields. Taking the news field as an example, Yi et al. (2021) introduced the federated learning framework to design user model training locally, and realized the user privacy protection function that other centralized news recommendation methods did not have. These technologies enhance the protection of privacy by decentralizing data processing. Therefore, it can be transferred to the field of food recommendation to solve the data privacy and security problems in this field.

4.2. Model level

Interpretability of FRS. As AI has become more widely used in the field of food recommendations, interpretability has become particularly important (Vikram et al., 2024). The degree of trust and understanding that users place in FRS depends on the system's ability to provide clear and personalized explanations. Existing FRS often use black-box AI models to analyze recipe content, or dietary preferences to generate recommendations, thereby resulting in a lack of interpretability or transparency. This limits the degree to which users can trust and adopt the system's recommendations. In the future research, it is a feasible way to introduce interpretable artificial intelligence technology. For example, by analyzing the output of black-box AI models using techniques such as local feature importance (Saarela & Jauhiainen, 2021), proxy models (Afrabandpey et al., 2020), and counterfactual interpretation(Del Ser et al., 2024), a comprehensive interpretation of the decision process or recommendation outcomes can be generated. Roy et al. (2023)'s research provides a feasible scheme, which uses local interpretable model-agnostic explanations (LIME) and Shapley additional explanations (SHAP) to analyze the global and local explanatory results respectively. However, how to integrate the interpretable AI idea into FRS within a unified framework still needs further exploration.

4.3. User experience level

Interactive FRS. Human-centered interactive design is very important to improve the flexibility and applicability of intelligent systems (Holzinger et al., 2022). Therefore, Interactive question-and-answer recommendation system combined with conversational AI technology is a promising research direction in personalized food recommendation. Compared with traditional FRS, interactive question-and-answer FRS can combine natural language processing (NLP) and machine learning (ML) techniques to analyze users' intentions. Through multiple rounds of interactive question and answer, users' attributes, preferences and health needs can be deeply understood. For example, Chen et al. (2021) constructed a question-and-answer FRS based on a large-scale knowledge map. User query is regarded as a clear demand item, which realizes more personalized recommendation. However, it is a challenging task to analyze complex user questions and generate accurate answers. In the future, advanced deep learning algorithms such as GAN, VAE or BERT will help to improve the understanding and generation ability of the system and provide more accurate food recommendation services (Gao et al., 2021). In addition, the integration of recommendation system and wearable devices is also an effective way of interaction. Real-time and continuous physiological and activity data provided by wearable devices is an instant way to generate health opinions. Gaikwad et al. (2024) developed FRS named NutriWear by integrating wearable devices, web applications and data storage technology. By harnessing smartwatch data and pathological insights, it can provide tailor-made guidance and insights for diet planning. Therefore, developing interactive FRS with dynamic learning and updating functions will be the key to the next research.

Combing FRS with large language models. In recent years, the emergence of large language models (LLM) such as ChatGPT has subverted the research paradigm in the field of natural language processing, and also promoted the progress in many interdisciplinary research fields such as bioinformatics (Srivastava et al., 2024) and computational materials science (Singh, Shelar, et al., 2024). A large number of studies have proved that LLM's zero sample learning ability and open domain knowledge can effectively improve the common cold start and data sparsity challenges in recommendation systems. However, the research on LLM in FRS field is still very limited. We believe that the introduction of LLM will hopefully bring many benefits to the FRS field in the future. Firstly, based on extensive knowledge base and powerful reasoning ability, LLM can show accurate context awareness and strong adaptability to unknown data. Therefore, by using large language model to reshape personalized FRS, nuanced understanding of preferences and restrictions can be realized. At the same time, LLM combined with multi-objective optimization technology will show significant advantages in dealing with the complex constraints of FRS. For example, Zhang et al. (2024) proposed a multi-objective personalized interpretable health-aware food recommendation system (MOPI-HFRS) based on LLM, which effectively integrated users' dietary preferences, restrictions and nutritional diversity goals, thus achieving more personalized recommendation results. On the other hand, LLM's powerful text understanding and generation ability can not only provide valuable insight for recommendation results, but also show users the transparent decision-making process based on preferences and restrictions. For example, the food-oriented big language model (FoodSky) proposed by Zhou et al (2024) can provide clearer and more accurate food recommendation results by fine-tuning the big language model by integrating multiple data sources. In the future, the combination of reinforcement learning based on user feedback will help to promote the dynamic iterative improvement of system performance. In addition, the innovation and application of intelligent food information assistant assisted by LLM is expected to bring about a fundamental paradigm shift in the field of personalized food recommendation and create more novel and exciting new functions. For example, the chat robot CookPal built by Safitri et al (2023) based on the LLM can provide many suggestions on food selection or cooking methods, and provide valuable insights in promoting nutritious diet and healthy life.

5. Conclusions

The rapid development of FRS helps to strengthen the monitoring and customization of diets, thereby promoting the development of healthier eating habits. Although the potential of FRS is obvious, the complex interaction among individual differences, diversity of food choices and the necessity of nutritional balance still brings severe challenges to FRS. Future research should focus on improving these systems to better adapt to the changing dietary patterns and health aspirations of different groups of people. This includes developing more powerful methods to extract meaningful insights from complex multimodal data, enhancing privacy protection and interpretability of recommendation algorithms, and ensuring that technological innovations such as deep learning and interactive large language models are accessible and beneficial to all sectors of society. Through such efforts, we can foresee that personalized food recommendation will become the cornerstone of promoting healthier and more sustainable eating habits around the world in the future.

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Data availability

No data was used for the research described in the article.

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