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Food Recommender System: A Review on Techniques, Datasets and Evaluation Metrics

Yi-Ying Chow [1], Su-Cheng Haw [1]*, Palanichamy Naveen [1], Elham Abdulwahab Anaam [1] ,

Hairulnizam Bin Mahdin [2]

[1] Faculty of Computing and Informatics, Multimedia University, 63100 Cyberjaya, Selangor, Malaysia

[2] Fakulti Sains Komputer dan Teknologi Maklumat, Universiti Tun Hussein Onn Malaysia, 86400, Johor, Malaysia.

sucheng@mmu.edu.my (Corresponding author)

Abstract. With the rise of digital platforms and the availability of large amounts of data, food recommender systems have become a powerful tool for helping people discover new and delicious meals. Today, these systems use algorithms and machine learning models to analyze ingredients and recommend meals based on factors such as cuisine, dietary restrictions, and ingredient compatibility. Hence, this paper aims to review the various recommendation techniques employed in the food recommender system. We also discuss the various algorithms that are used in meal recommender systems, including collaborative filtering, content-based filtering, and hybrid approaches. Overall, this paper provides a comprehensive overview of the current state-of-the-art meal recommender systems and to identify the opportunities for future enhancement and development in this field.

Keywords: food recommender, meal recommender, recommender system, collaborative filtering, content-based, hybrid approaches

1. Introduction

In today's digital age, the internet has become a vast network of interconnected computers that enables the easy sharing and manipulation of information. One of the most common uses for these systems is in e-commerce, where they assist users in finding products that align with their preferences or interests. These systems present users with a list of items likely to interest them based on their current selections and profile information. The goal of a recommendation system is to provide relevant recommendations to the user. Besides that, the abundance of online food-related content has made it challenging for users to sift through and select the options that best align with their preferences. The sheer volume of information from sources such as social media and recipe websites causes finding desired food items to be overwhelming. Obtaining cooking inspiration from digital sources is becoming increasingly popular because food recommender system (RS) will also recommend other types of food, such as restaurant meals or supermarket products. Thus, food recommendation is becoming increasingly important for assisting users in quickly discovering the food items that match their preferences.

RS is widely utilized in various domains, such as music and video streaming services, e-commerce websites, social media platforms, and online content providers (Elahi et al., 2023; Lim et al., 2023; Zaveri et al., 2023). These systems are designed to filter and select the most relevant information based on the user's preferences and interests, by determining the match between the user and the item and inferring the similarities between them to provide personalized recommendations. E-commerce such as Amazon, Alibaba, and eBay, is the first industry where RS was widely used. E-commerce RS can generate accurate suggestions for the customer from the huge amount of data on their online behavior, especially during this COVID-19 pandemic. RS can help customers find the items they prefer more easily and suggest they purchase the items they never bought before, which meet their needs (Oyebode & Orji, 2020).

Many people experience challenges in their daily life due to the variety of food and human lifestyles changing rapidly. The food recommender systems (FRS) have recently received increased attention due to their importance in maintaining a healthy lifestyle (Gao et al., 2020; Li et al., 2023). Other than suggesting meals based on users' preferences, recommender systems can help manage the large amount of information in the food and health industry, particularly in areas such as suggesting new recipes and promoting healthy eating habits. Food recommendation systems also can track dietary habits, identify health concerns, and motivate individuals to change their eating behaviors.

2. Phases In The Recommendation Process

Creating a recommendation system involves several steps: information collection, explicit feedback, implicit feedback, learning, and recommendation phases. Fig. 1 illustrates the phases in the recommendation process.

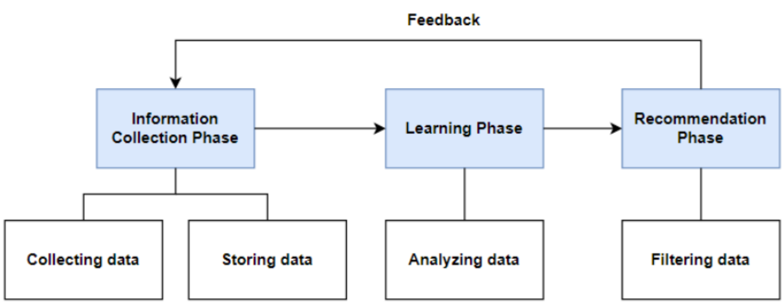


Fig. 1: Phases in the recommendation process.

During the information collection phase, the data that will be used as input for the recommendation is collected and stored. The first step in developing a recommender system is to gather the data. Users' input data can be collected in three ways: explicit, implicit, and hybrid. Obtaining explicit input data, such as ratings, feedback, and comments on a product, can be challenging as not all users may be willing to provide such information. However, when obtained, this type of data is considered more accurate and useful as it provides clear insights into the user's preferences and opinions (Kumar et al., 2019). Implicit input data refers to data that is automatically collected by the system, such as browsing history, clickstream data, and purchase history. This type of data is easy to obtain as it is already present within the system, but it may not be as accurate as explicit input data as it doesn't require user effort to provide feedback or ratings. The advantage of this input method is that it reduces the burden on the user and allows for easier data collection (Isinkaye et al., 2015). Hybrid feedback combines the benefits of both explicit and implicit input methods by using a combination of user-provided feedback and data readily available within the system to improve the performance and accuracy of the recommendation system. The system can better understand the user's preferences and behavior by utilising data from multiple sources, resulting in more accurate recommendations (Kumar et al., 2019).

During the learning phase, learning algorithms are employed on the user's data derived from the information collection phase feedback. The learning algorithms are useful in identifying the patterns that will be used in specific situations.

In the recommendation phase, however, a suggestion or prediction is generated for the user. Data from the information collection phase is filtered using various techniques to find the most suitable information for providing recommendations to the user. The available filtering techniques will be discussed in the next section [6].

In general, the recommendation technique can be broadly divided into three main techniques, which include content-based (CB), collaborative filtering (CF), and hybrid-based (HB). CB techniques influence recommendations based on what the user has previously browsed or is currently browsing.

Content-based: The CB filtering algorithm is a domain-specific method that examines item characteristics to make predictions. It is particularly efficient in suggesting documents like web pages, articles, and news. The CB technique generates recommendations based on user profiles and characteristics extracted from the content of items previously evaluated by the user (Isinkaye et al., 2015). A CB filtering system, such as PRES, selects items by comparing the content of the items to a user's preferences, rather than by comparing the preferences of similar users as in collaborative filtering. It generates recommendations by matching each document in the collection to a user profile. The more input and feedback a user provides, the more accurate the recommendations will be. It utilizes the user profile to make personalized recommendations to the user. The documents are ranked according to factors such as similarity, newness, closeness, and relevance, with the top-ranked documents displayed as hyperlinks on the current web page. CB utilizes different models to establish the similarity between documents in order to produce relevant suggestions. Different Vector Space Models, such as Term Frequency Inverse Document Frequency (TF/IDF) or Probabilistic models like Naive Bayes classifiers, Decision Trees, or Neural Networks, can be used to model the connections between different documents in a corpus. These methods make recommendations by learning from the underlying model through statistical analysis or machine learning. TF-IDF is a widely used method for converting text into numerical representations that can be utilized to train machine learning models for prediction (Zhang et al., 2020). The system primarily focuses on two aspects: a planned strategy from the user's selections and the previous data obtained from the user's interaction with the RS.

Collaborative Filtering: CF is a technique that forecasts the users' opinions depending on the opinions and evaluations of like-minded individuals (Zhang et al., 2020). A large volume of published studies states that utilising the public's collective knowledge to make decisions is the fundamental principle of CF. Initially, a consumer gives some of the provided objects a rating, either implicitly or explicitly. Next, the recommendation system detects the closest neighbors whose likes are identical to that of a certain consumer and suggests goods that the surrounding neighbors enjoyed (Tran et al., 2018).

In 2018, Tran et al. (2018), stated that Item-based, matrix factorization, model-based, and user-based techniques are typically used as the foundation for CF implementation. Firstly, to enhance the quality of the consumer suggestions and the scalability of the collaborative filtering algorithms, an item-based method is used to handle the recommender system problems novelly. A typical issue with traditional collaborative filtering methods is the challenge of finding suitable neighbors among a large number of potential neighbors. Item-based algorithms sidestep this constraint by focusing on the relationships between objects first, instead of the ties between consumers. Consumers' recommendations are calculated by looking for products comparable to those they have previously enjoyed. Item-based algorithms may be able to provide similar quality as user-based algorithms with less online computation, as the relationships between items are often unchanging (Andika et al., 2022). Next is the Matrix Factorization (MF) technique. It is used in recommendation systems to solve the problem of the size of the generated datasets and the rating matrix's sparseness, which indicates that for each consumer, only a limited amount of things is reviewed. Therefore, Matrix Factorization does a good job of handling these difficulties. MF approaches have gained more attention, primarily as an unsupervised learning technique for dimensionality decrease and implicit variable decomposition. Both text mining and spectral data analysis have effectively been used. The latent factor model is the foundation for the majority of MF models. A rating matrix is characterized by a latent factor model with the combination of an item factor matrix and a user factor matrix. MF is considered the most effective and precise method for addressing the sparsity problem in the recommendation system database (Bokde et al., 2015).

The model-based technique is one of the CF implementations. Different from the neighborhood-based methods, the space required is frequently relatively minimal. Furthermore, prediction speed training and speed were substantially quicker during the preprocessing stage of building the trained model. It can also avoid overfitting. Similar to supervised or unsupervised machine learning techniques, a summary structure of the data is constructed beforehand in model-based methods. As a result, the prediction phase and the training or model-building phase are obviously distinct. Some examples of traditional machine learning techniques are rule-based methods, decision trees, neural networks, support vector machines, regression models, and Bayes classifiers (Aggarwal, 2016). Lastly, the recommender system's scalability issue must be resolved using the algorithm for CF on the cloud computing infrastructure. A user-based CF algorithm using the Hadoop cloud computing platform could use to address the scalability issue with CF. The Hadoop platform is frequently used because it uses open-source cloud computing. Google.com has successfully analyzed the MapReduce framework on the Hadoop platform. The MapReduce framework enables the consumer to divide a large issue into several smaller issues, which can eventually be managed by the Hadoop platform, increasing processing performance. By utilizing the Hadoop platform, designers can simply enable the application to run in parallel. The user history profile, which may be seen as a rankings matrix for each entry representing the ranking a user has assigned to an item, is obtained as the initial phase of the collaborative filtering process. The resemblance between consumers is determined in the second stage, followed by the location of closest neighbors. There are several ways to assess similarity. The pearson correlation coefficient is the most popular and was adopted as a standard for CF (Zhao & Shang, 2010).

Hybrid-based: HB method blends collaborative and content-based filtering techniques while providing recommendations, taking the context of the item into consideration (Chew et al., 2022; Chew et al., 2021). User-to-item and user-to-user relationships also play a significant role in the recommendation process. The framework offers personalized recommendations based on the user's profile and addresses the issue of users overlooking relevant information. It gathers user profile data and considers the context of the film, including the user's viewing history and the movie's ratings. This approach not only leverages the benefits of CB but it also performs similarity matching filtering for all items, particularly when any user hasn't evaluated the items, it can filter out and recommend them to users, thus avoiding the cold-start problem. Additionally, this method also benefits from collaborative filtering (Li et al., 2021). This method employs the combination of similar calculations, which is known as the hybrid approach as both methods are utilized to generate the results. It is found to be more accurate than other methods as it addresses the issues of domain dependency and interest in a content-based system which are typically encountered in other approaches.

There are a total of seven approaches for building the hybrid RS. The first approach is a weighted hybrid. Weighted recommender systems use multiple models to interpret the dataset. These systems combine the output of each model into fixed weightings, which remain constant across the training and testing sets. For example, a combination of a CB model and an item-item CF model, each with a weight of 50% in the final prediction, can be used. Moreover, in a hybrid switching approach, the chosen recommendation system depends on the specific context or situation. The decision of which system to use is based on criteria such as the user profile or other features relevant to the dataset. This approach adds an additional layer to the recommendation model, allowing it to adapt and select the best model for the current situation, considering each system's strengths and weaknesses.

In short, each technique has its advantages and disadvantages, as depicted in Table 1.

Table 1. Advantages and disadvantages of each type of RS.

	Content-based filtering	Collaborative filtering	Hybrid recommendation
Advantages	1) CB uses a user's profile and item information to make recommendations separately. 2) CB will make a recommendation based on the item's features.	1) CF methods make recommendations based solely on the ratings given by users, without taking into account the user's profile or characteristics of the items being recommended. 2) CF methods rely on the ratings and preferences of other users to make recommendations. 3) CF is direct and intuitive to implement	1) The hybrid recommendation system merges the advantages of content-based and collaborative filtering methods to overcome their limitations.
Disadvantag es	1) In CB, if there is not enough data about the user and the item, the recommendations will not be accurate. 2) Cold start and overfitting.	1) A problem arises when a new user joins, and there are no previous records of the user, known as the cold start issue. 2) A large quantity of data is necessary to make accurate recommendations. 3) CF methods struggle to handle large amounts of data and may become slow in processing.	1) It is complex because a combination of two different methods is used to create a single system.

3. Food Recommendation System

Recommender systems are effective in handling large amounts of data in various industries. In the healthcare industry, they can help individuals discover new meal ideas or promote healthier eating habits to prevent health issues (Ribeiro et al., 2022).

Healthy eating habit is essential and critical to prevent the risk of many diseases, such as diabetes, high blood pressure, stroke, cancer, mental illnesses, heart attack, and other chronic diseases. A study by the World Health Organization (WHO) revealed that 60% of child deaths each year are related to malnutrition, and approximately 30% of the world's population is estimated to be affected by various diseases. In addition, inadequate and unbalanced food intake is to blame for 14% of gastrointestinal cancer deaths, 9% of deaths from heart attacks, and 11% of deaths from ischemic heart disease worldwide (Rehman et al., 2017). Much research in the field of food centers around providing personalized suggestions for what to eat, based on a person's likes or health concerns. These systems also include features for tracking nutritional intake and persuading users to change their eating habits positively (Yang et al., 2017).

3.1. Types of FRS

According to Tran et al. (2018), four types of FRS are based on different types of user data to provide suitable suggestions. The first type of FRS is considering users' preferences based on the previous foods they liked. For instance, the FRS on the mobile application, called "Fatchum", recommends various food recipes when the users input the ingredients they want (Cruz et al., 2017). Fig. 2 shows the interfaces of "Fatchum".

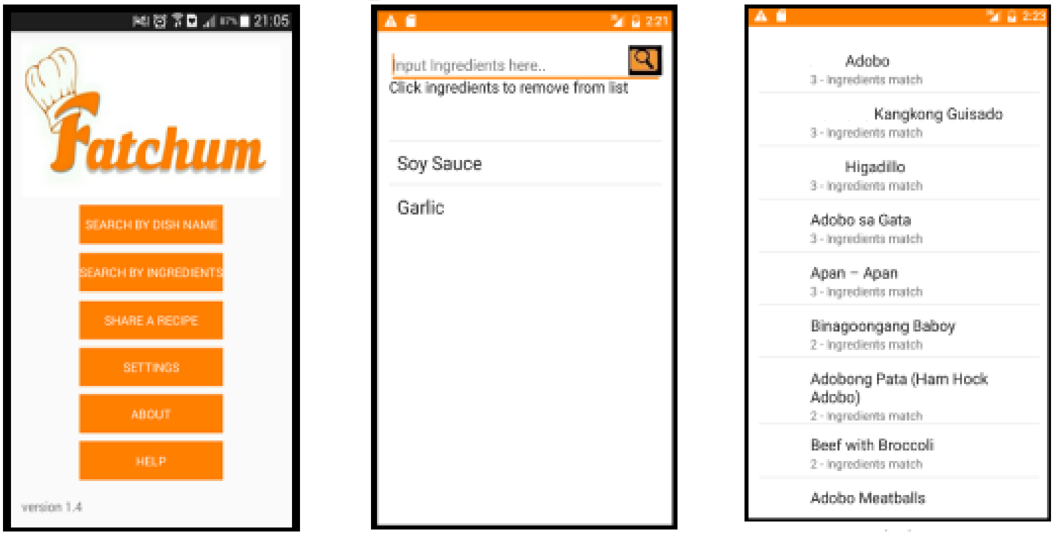
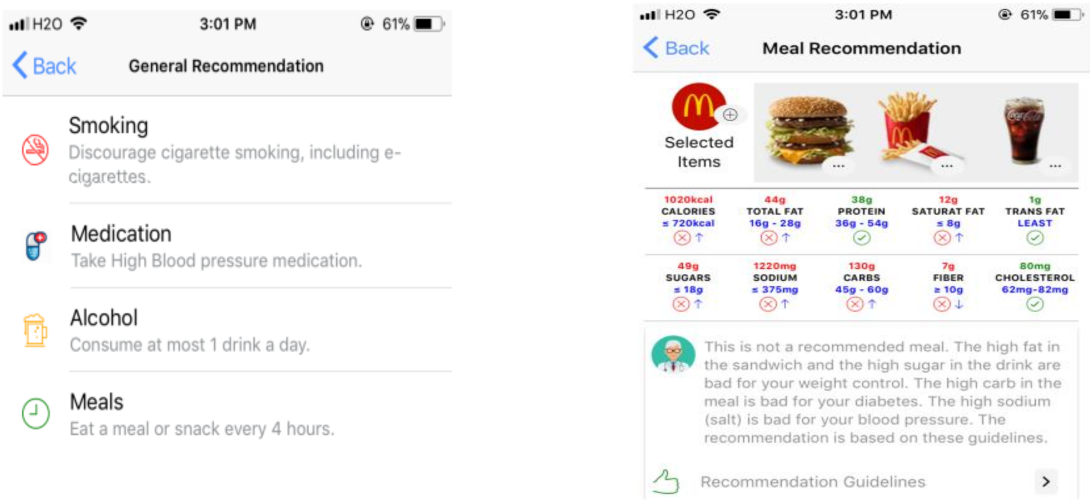


Fig. 2: Interfaces of "Fatchum"

The second type of FRS provides suggestions that consider the nutritional needs of users based on their health conditions specified by them. To prevent the risk of diseases that have been discussed in the previous paragraph, this type of FRS is vital to be used as a specialized nutrition consulting system. For example, there is a personalized meal recommender system proposed by (Alian et al., 2018), this RS requires users to input various details, like their age, height, weight, meal preferences, estimated energy needs, body mass index, and blood pressure, to give general advice on healthcare, daily meals, and nutritional needs.This system will also recommend suitable meals to the users when they eat at some popular restaurants such as McDonald. Fig. 3(a) depicts the general recommendation for the user's health, while Fig. 3(b) shows a meal recommendation.

Furthermore, the third type of FRS focuses on balancing the preference and nutritional needs of the users. It is always appropriate to include both considerations on FRS so that it will not lead to some problems such as bad eating habits of users or food suggested may not always appeal to users. Thus, this type of FRS will attract more users and also improve their interest in using the system (Tran et al., 2018). Fig. 4 illustrates the meal planner and information about each meal, while Fig. 5 shows the total calories of the meal and nutrient information (Ribeiro et al., 2022).



(a) (b)

Fig. 3: (a) Recommendation for user's health, and (b) Meal recommendation

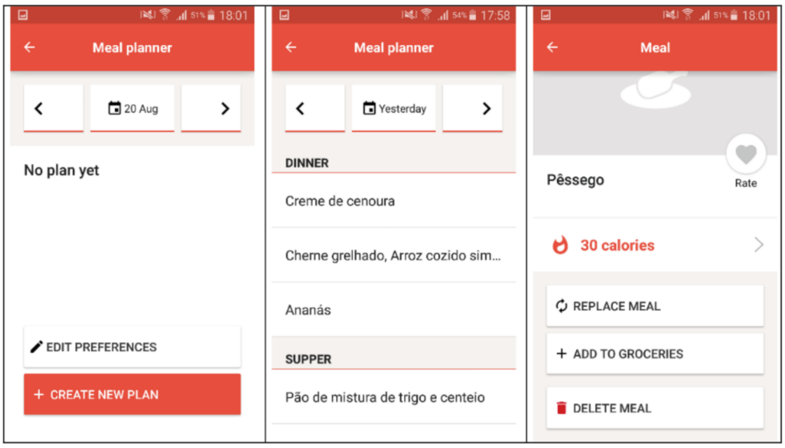


Fig. 4: Meal planner and information about each meal

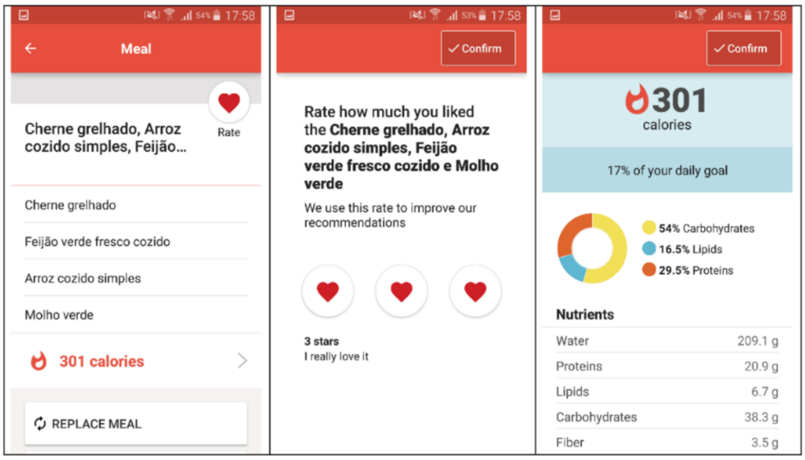


Fig. 5: Total calories of the meal and nutarient information

The last type of FRS will recommend foods for groups of users. A group recommendation system is suitable for suggesting the recipe or food during a group activity such as a family gathering dinner, birthday party, or some important festival. Many FRS apply the CF technique, which is also one of the popular techniques of other RS (Tran et al., 2018).

3.2. Related Work

In this section, related works on various techniques will be reviewed. Forbes and Zhu (2011) focused on RS, which uses a collaborative filtering method to combine ingredient content information. The foodRecSys-V1 dataset is used, which is obtained from allrecipes.com. A simple content-boosted matrix factorization algorithm is applied to work with the large dataset. Then, this study uses the RMSE to evaluate the algorithms' performances. The experimental evaluation measured the RMSE difference between the content-boosted and original algorithms. Cosine similarity or Pearson's correlation coefficient between two ingredients is calculated to determine the similarity based on the correlation.

Ntalaperas et al. (2015) suggested DISYS as an intelligent program that helps customers choose a healthy and suitable dish or meal when dining out based on their preferences, dietary goals, and health conditions. It is managed by restaurant managers who input their establishment's meals and dishes and nutritional information. Furthermore, dietitians can assist their clients by tracking their use of the DISYS application, which can provide insights into their food consumption habits. This study uses the USDA4 database v.26 for food ingredients and nutritional data, which has been supplemented with additional information required by our platform.

Jung and Chung (2016) proposed knowledge-based dietary nutritional recommendations for the management of obesity. To suggest personalized nutrition plans, the proposed method employs basic information from overweight young people and forms clusters of highly similar ones. It uses the weight of user-menu and runs collaborative filtering, which allows the production of a personalized menu plan within the cluster of similar overweight young people, which helps to manage obesity effectively. The study also assessed the effectiveness of the recommendation system that suggests dietary menus for overweight young people. The performance was evaluated using the SeeMe5 nutritional dataset, including user health data and contextual information. The collaborative filtering and user-menu merge matrix were created for individualized menu recommendation using the knowledge-based context-aware model. The sparse problem of CF was successfully addressed to improve menu recommendation accuracy.

Rathi et al. (2017) proposed a system that could potentially increase Eatery hotspot sales, resulting in monetary benefits for both the developers and the eatery hotspot owner. Currently, the system only shows a directory of restaurants, but it has the potential to be expanded to include online reservations and food delivery services. Using the collected data, they applied a collaborative filtering method and ranking algorithm to recommend popular restaurants based on reviews and likes. This study used various APIs to mine data from various social networking sites such as Facebook and Twitter, using "Graph API" and "Tweepy," and then applied recommendation system techniques to the extracted data, recommending the eatery based on its ranking. The developed system can potentially boost sales for popular restaurants, providing financial benefits for developers and owners. For the evaluation part, cosine similarity between the rating from all the users was calculated to determine the similarity based on the correlation.

Vivek et al. (2018) focused on memory-based CF and propose two approaches, which include an item-based and a user-based approach. The item-based CF approach generates recommendations by determining similar recipes, rather than considering the user's preferences. The similarity between recipes is determined by whether or not the user has rated them, and not by the ratings' values. A ranked list of recommended recipes is generated using the similarity values. They used two similarity measures to calculate the similarity: Tanimoto Coefficient similarity and LogLikelihood similarity. Next, the system utilizes a user-based approach to recommend recipes, taking into account the preferences of the user and the similarity of other users with similar preferences. Two methods, the Pearson Correlation

Coefficient similarity, and Euclidean Distance similarity, were used to calculate the similarity between users. The system can use a fixed-size or threshold-based neighborhood. This study's dataset is foodRecSys-V1, which is collected from the Allrecipes website. The data of about 940 users and 1600 recipes with 9800 user preferences are obtained. The performance of the user-based approach is measured over a fivefold evaluation using Average Absolute difference (AAD) and Root Mean Squared Error (RMSE) is estimated. The user-based approach was more appropriate and performed better than the item-based collaborative filtering approach.

Li et al. (2018) conducted an exploratory study on an intelligent food choice method that recommends dishes based on individual dietary preferences, such as ingredients, spice types, and price. They proposed a method called "multi-attribute relation matrix tri-factorization" (MARMTF) to be used in a food recommendation system that considers different attributes and relationships. To assess the performance of our recommendation systems, they used the root mean squared error (RMSE) and mean absolute error (MAE). The MARMTF model outperformed existing recommendation methods in experiments using real-world data. The proposed system aims to make choosing food easier by using advanced algorithms and can potentially serve as a substitute for human waiters in restaurants in the future.

Besides that, Nouh et al. (2019) proposed an intelligent recommendation system that utilizes a hybrid learning method for personal well-being services called the Smart Recommender System of Hybrid Learning (SRHL). The study found that the hybrid method improves the accuracy of the recommendation system by 14.61% compared to traditional collaborative methods which primarily focus on finding similar entities. For the CF, The researchers describe an algorithm for determining user similarity using the user FM matrix. For the CB approach, they explore various models to calculate the similarity between the user and the FM with the highest similarity score being recommended to the user. They chose to use a weighted Euclidean distance measure for this system. MSE, MAE, and MAPE are used to assess the accuracy reach of errors. The study's findings show that the correlation of error was lower with the SRHL method than with other models.

Gao et al. (2020) developed a hierarchical attention-based food recommendation (HAFR) to recommend food based on the user's preference. This study used the foodRecSys-V1 obtained from AllRecipes.com to evaluate the proposed method. The evaluation metrics for recommendation such as Area Under the Roc Curve (AUC), Normalized Discounted Cumulative Gain (NDCG), and recall are adopted to evaluate the performance. The results indicated that HAFR has an average improvement of 12% compared to other recommendation methods, such as Factorization Machine (FM) and Visual Bayesian Personalized Ranking (VBPR).

Chavan et al. (2021) focused on developing the RS for healthy food choices with a hybrid model. This study shows the design, implementation, and evaluation process of three nutrition-based RS that apply CB, CF, and HF techniques. The Kaggle dataset, foodRecSys-V1, which contains food recipes and user reviews is used for further analysis. The researchers develop a weighted hybrid model with CB and CF techniques using SVD techniques to improve the limitations of both CB and CF techniques. Recall, precision, and accuracy are used to evaluate the performance of each model. The results show that the hybrid model performs best among the three models.

More recently, Thongsri et al. (2022) proposed a personalized food recommender system by using the combination of memory-based CF and the knapsack method. User-based CF, which is part of memory-based CF, is applied for calculating two users' similarity between new users and old users to know the new users' preferences. In order to carry out the process of prediction and recommendation when using this FRS, users' data are collected and used as a database. Two steps need to complete when applying this CF technique as follows. The first step is calculating to find out the similarity between the two users. Cosine similarity or Pearson's correlation coefficient between the rating from all the users is calculated to determine the similarity based on the correlation. For the second step, the prediction value is determined and computed using the previous step's results. Then, the system will list out the menu items from the most to the least preference to the new users as a recommendation. Based on the results, the researchers have discussed some problems that can be enhanced in the future. In the early stage, there are still few interactions while gathering users' data. Thus, the process of collecting sufficient data is time-consuming. The other issue found is the insufficient information on initial data for training the model. On the other hand, some contributions are using CF and the knapsack method for this study. The system can provide a suitable food recommendation based on the consumers' preferences and nutrition needs. The study's findings can be used as references for other countries, especially developing ones.

Zitouni et al. (2022) proposed a two Dimensions Contextual Collaborative Recommender System (2DCCRS), a context-based collaborative recommendation system that considers internal context, external context, stakeholders, and stakeholders aggregation. The system aims to address the challenges posed by multidimensional contextual models, new items and new user problems. This study proposes the Healthy and Tasty (H&T) application, which uses the 2DCCRS framework to recommend the healthiest and most desirable meals that align with the user's needs. The middle layer of the system is based on a collaborative filtering algorithm that considers the user's preferences, interests, and priorities. This study applied Cosine similarity to compute the similarity values between two users. The effectiveness and robustness of the approach are evaluated using MAE and RMSE. The MAE is calculated as the average difference between predicted and actual values. On the other hand, RMSE is the square root of the average of the squared differences between the predicted and original values. The system achieved a precision rate of 83% and a recall rate of 86% with a community of 500 users.

Majjodi et al. (2022) examined the merits of nutrition labels and personalization in a recipe RS. The foodRecSys-V1 dataset is consulted by the researchers for algorithm training and further study. This dataset is divided into four recipe categories. Offline evaluation is conducted through RMSE and MAE to compare different recommender algorithms such as Non-negative factorization (NMF), Singular Value Decomposition (SVD), KNNWithMeans, etc. The results show that SVD provides the best performance than other algorithms which is 0.18 for RMSE and 0.12 for MAE. Therefore, for the online evaluation, SVD is integrated into the recommender interface to match the recipes to elicit the preferences of the user.

4. Discussion and Open Issue

Table 2 summarizes the related works reviewed. This table shows that CF and HB techniques are mostly applied in the related works. By combining the strengths of both CF and CB techniques, the HB technique outperformed other filtering techniques and improved the accuracy of the result in most of the research. HB can potentially overcome data sparsity issues by incorporating both user-item interactions and item features. This approach is also more flexible which can be adapted to different types of recommendation systems and can handle different types of data, such as text, images, and ratings. Besides, compared with other evaluation metrics, most of the studies use MAE and RMSE metrics to evaluate the accuracy and performance of the RS. Many researchers consulted the foodRecSys-V1 data set for algorithm training and further study.

Table 2 Summary of Related Work

Related Work	Findings	Dataset	Evaluation Matrix
Forbes & Zhu (2011) Content-boosted matrix factorization for recommender systems: experiments with recipe recommendation.	This paper focuses on RS which uses a collaborative filtering method to combine ingredient content information. A simple content-boosted matrix factorization algorithm is applied to work with the large dataset.	foodRecSys-V1	RMSE
Ntalaperas et al. (2015) DISYS: An intelligent system for personalized nutritional recommendations in restaurants.	This study describes DISYS as an intelligent program that helps customers choose a healthy and suitable dish or meal when dining out, based on their preferences, dietary goals, and health conditions. It is managed by restaurant managers who input the meals and dishes offered at their establishment and their nutritional information.	USDA4	Not available
Jung and Chung (2016) Knowledge-based dietary nutrition recommendation for obese management	This study focuses on proposing knowledge-based dietary nutritional recommendations for the management of obesity. To suggest personalized nutrition plans, the proposed method employs basic information from overweight young people and forms clusters of those with high similarity.	SeeMe5	Not available
Rathi et al. (2017) Eatery directory using recommendation system and data mining.	The system only shows a directory of restaurants, but it has the potential to be expanded to include online reservations and food delivery services. Using the data collected, the researchers are applying a collaborative filtering method and ranking algorithm to recommend popular restaurants based on reviews and likes.	Not available	Cosine similarity
Vivek et al. (2018) Machine learning-based food recipe recommendation system.	The item-based Collaborative Filtering approach generates recommendations by determining how similar different recipes are to each other, rather than considering the preferences of the user. The similarity between recipes is determined by whether or not the user has rated them, and not by the ratings' values.	foodRecSys-V1	Average Absolute difference (AAD), RMSE, precision, and recall
Li et al. (2018)	The MARMTF model outperformed existing recommendation methods in experiments using real-world data. The	Not available	RMSE and MAE

Application of intelligent recommendation techniques for consumers' food choices in restaurants.	proposed system aims to make choosing food easier by using advanced algorithms and can potentially serve as a substitute for human waiters in restaurants in the future.		
Nouh et al. (2019) A smart recommender based on hybrid learning methods for personal well-being services.	The study found that the hybrid method improves the accuracy of the recommendation system by 14.61% compared to traditional collaborative methods which primarily focus on finding similar entities. For the CF, The researchers describe an algorithm for determining user similarity using the user FM matrix. For the CB approach, they explore various models to calculate the similarity between the user and the FM with the highest similarity score being recommended to the user.	USDA Branded Food Products Database	MSE, MAE, and MAPE
Gao et al. (2020) Hierarchical attention network for visually-aware food recommendation.	A hierarchical attention-based food recommendation (HAFR) is developed to recommend food based on the user's preference. The results show that HAFR has an average improvement of 12% compared to other recommendation methods such as Factorization Machine (FM) and Visual Bayesian Personalized Ranking (VBPR).	foodRecSys-V1	Area Under the Roc Curve (AUC), Normalized Discounted Cumulative Gain (NDCG), and recall
Chavan et al. (2021) A recommender system for healthy food choices: Building a hybrid model for recipe recommendations using Big Data sets.	This study focuses on developing the RS for healthy food choices with a hybrid model. It shows the design, implementation, and evaluation process of three nutrition-based RS that apply CB, CF, and HF techniques.	foodRecSys-V1	Recall, precision, and accuracy.
Thongsri et al. (2022) Implementation of a personalized food recommendation system based on collaborative filtering and the knapsack method.	This study proposed a personalized food recommender system by using the combination of memory-based CF and the knapsack method. User base CF, which is part of memory-based CF, is applied for calculating two users' similarity between new users and old users to know what are the preferences of the new users.	Not available	Cosine similarity or Pearson's correlation
Zitouni et al. (2022)	This study describes a two Dimensions Contextual Collaborative Recommender System (2DCCRS), a	Not available	RMSE and MAE

New contextual collaborative filtering system with application to personalized healthy nutrition education.	context-based collaborative recommendation system, which takes into account internal context, external context, stakeholders, and aggregation. The system aims to address the challenges posed by multidimensional contextual models, as well as new items and new user problems.		
Majjodi et al. (2022) Nudging towards health? Examining the merits of nutrition labels and personalization in a recipe recommender system.	A study that aims to examine the merits of nutrition labels and personalization in a recipe RS. Offline evaluation is conducted to compare different recommender algorithms such as Non-negative factorization (NMF), Singular Value Decomposition (SVD), KNNWithMeans, etc. The results show that SVD provides the best performance than other algorithms which is 0.18 for RMSE and 0.12 for MAE.	foodRecSys-V1	RMSE and MAE

From the related works, we noticed that towards recently, most RS do linked up with receipe, dietary and health concern, which is the third type of FRS. This type of FRS uses recipes to suggest meals that best suit the user's tastes and preferences. As such, it provide a better and improvised version of a typical recipe book by suggesting user-oriented recipes for improved meal planning. Moving forward, another group of researchers is looking into using the ingredient to suggest a substitute recipe. For instance, Gallo et al. (2022) offered an ingredient-based approach that suggested recipes using components that use the least amount of water during preparation. The proposed system is able to recognize user behavior and suggest recipes that use less water to prepare a meal.

We likewise saw towards recently, most researchers proposed hybrid based approaches (Murillo et al., 2022). Miranda et al. (2019) developed a platform for intelligent meal planning based on user personal characteristics. Metwally et al. (2021) presented a technique for learning food preferences from meal logs based on users' dietary patterns. On the other hand, Rostami et al. (2022) used user feedback and the composition of the food to create a meal suggestion FRS. Graph clustering is used to group users and food items together, and a deep learning-based method is also used in the recommendation engine. In a separate study, Rostami et al. (2023) further proposed a novel health-conscious food recommendation system that uses time-aware collaborative filtering and a food ingredient content-based model to predict the user's preference and explicitly account for food ingredients, food categories, and the factor of time.

From the review, we observed that it is difficult to develop a system that suggests both entities because food products and ingredients are typically combined in recipes rather than consumed separately (Ashraf et al., 2022). As a result, this feature should be addressed in the future in order to create a fully functional FRS.

5. Conclusion and Future Work

A recommendation system served as an information filter to narrow the amount of information so that only the most interesting and relevant content is presented. In this paper, we have reviewed the important of recommender system in the food domain. From our review, the HB approach offers several advantages. However, the specific implementation of an HB approach will depend on the particular data and associated method.

Further research is needed to optimize the combination of CB and CF in the HB approach, as well as to explore the potential of incorporating other recommendation techniques, such as knowledge-based or context-aware filtering. Additionally, evaluating the performance of HB in real-world RS would be valuable to assess its effectiveness.

References

Aggarwal, C.C. (2016). Model-based collaborative filtering. *Recommender Systems, Springer International Publishing,* 71–138.

Alian, S., Li, J., Pandey, V. (2018). A Personalized Recommendation System to Support Diabetes Self-Management for American Indians. *IEEE Access*, vol. 6, -73051.

Andika, H.G., Hadinata, M.T., Huang, W., Anderies, Iswanto, I. A. (2022). Systematic Literature Review: Comparison on Collaborative Filtering Algorithms for Recommendation Systems. *IEEE International Conference on Communication, Networks and Satellite*, 56-61.

Ashraf, M., Sohail, S.S., Chaudhry, B.M. (2022). Issues, Challenges, and Opportunities in Food Recommender Systems. *International Conference on Data Analytics for Business and Industry*, 570-574.

Bokde, D., Girase, S., Mukhopadhyay, D. (2015). Matrix factorization model in collaborative filtering algorithms: A survey. *Procedia Computer Science*, vol. 49, 136–146.

Chavan, P., Thoms, B., Isaacs, J. (2021). A recommender system for healthy food choices: building a hybrid model for recipe recommendations using big data sets. *Hawaii International Conference on System Sciences*, 3774-3783.

Chew, L.J., Haw, S.C., Subramaniam, S. (2021). A hybrid recommender system based on data enrichment on the ontology modelling. *F1000Research*, vol. 10, 937.

Chew, L.J., Haw, S.C., Subramaniam, S., Ng, K.W. (2022). A Hybrid Ontology-based Recommender System Utilizing Data Enrichment and SVD Approaches. *Journal of System and Management Sciences*, vol. 12(5), 139-154.

Chung, K., Boutaba, R., Hariri, S. (2016). Knowledge based decision support system. *Information Technology and Management*, vol. 17, 1–3.

Cruz, Z.M.C., Alpay, J.J.R., Depeno, J.D.D., Altabirano, M.J.C., Bringula, R. (2017). Usability of "Fatchum": A Mobile Application Recipe Recommender System. *6th Annual Conference on Research in Information Technology*, 11-17.

Elahi, M., Kholgh, D.K., Kiarostami, M.S., Oussalah, M., Saghari, S. (2023). Hybrid recommendation by incorporating the sentiment of product reviews. *Information Sciences*, vol. 625, 738-756.

Forbes, P., Zhu, M. (2011). Content-boosted matrix factorization for recommender systems: experiments with recipe recommendation. *ACM Conference on Recommender systems*, 261-264.

Gallo, I., Landro, N., La Grassa, R., Turconi, A. (2022). Food Recommendations for Reducing Water Footprint. *Sustainability*, vol. 14(7),3833.

Gao, X., Feng, F., He, X., Huang, H., Guan, X., Feng, C. (2020). Hierarchical Attention Network for Visually-Aware Food Recommendation. *IEEE Transactions on Multimedia*, vol. 22(6), 1647-1659.

Gao, X., Feng, F., Huang, H., Mao, X.L., Lan, T., Chi, Z. (2022). Food recommendation with graph convolutional network. *Information Sciences*, vol. 584, 170-183.

Isinkaye, F.O., Folajimi, Y.O., Ojokoh, B.A. (2015). Recommendation systems: Principles, methods and evaluation. *Egyptian Informatics Journal*, vol. 16(3), 261–273.

Kumar, M.V., Kumar, P.N.V.S.P. (2019). A Study on Different Phases and Various Recommendation System Techniques. *International Journal of Recent Technology and Engineering*, vol. 7(5C), 38-41.

Li, D., Zaki, M.J., Chen, C. (2023). Health-guided recipe recommendation over knowledge graphs. *Journal of Web Semantics*, vol. 75, 100743.

Li, L., Zhang, Z., Zhang, S. (2021). Hybrid Algorithm Based on Content and Collaborative Filtering in Recommendation System Optimization and Simulation. *Scientific Programming*, vol. 2021, 7427409, 2021.

Li, X., Jia, W., Yang, Z., Li, Y, Yuan, D., Zhang, H., Sun, M. (2018). Application of intelligent recommendation techniques for consumers' food choices in restaurants. *Frontiers in psychiatry*, vol. 9, 415.

Lim, Y.F., Haw, S.C., Ng, K.W., Anaam, E.A. (2023). Hybrid-based Recommender System for Online Shopping: A Review. *Journal of Engineering Technology and Applied Physics*, vol. 5 (1), 12-34.

Lin, W.C., Tsai, C.F., Chen, H. (2022). Factors affecting text mining based stock prediction: Text feature representations, machine learning models, and news platforms. *Applied Soft Computing*, vol. 130, 109673.

Majjodi, A.E., Starke, A.D., Trattner, C. (2022). Nudging towards health? examining the merits of nutrition labels and personalization in a recipe recommender system. *ACM Conference on User Modeling, Adaptation and Personalization*, 48-56.

Metwally, A.A., Leong, A.K., Desai, A., Nagarjuna, A., Perelman, D., Snyder, M. (2021). Learning Personal Food Preferences via Food Logs Embedding. *IEEE International Conference on Bioinformatics and Biomedicine*, 2281-2286.

Miranda, R., Ferreira, D., Abelha, A., Machado, J. (2019). Intelligent nutrition in healthcare and continuous care. *IEEE, International Conference in Engineering Applications*, 1-6.

Murillo, V.G.M., Avendano, D.E.P., Lopez, F.R., Calleros. J.M.G. (2022). A Systematic Literature Review on the Hybrid Approaches for Recommender Systems. *Computación y Sistemas*, vol. 26(1), 357–372.

Nouh, R.M., Lee, H.H., Lee, W.J., Lee, J.D. (2019). A smart recommender based on hybrid learning methods for personal well-being services. *Sensors*, vol. 19(2), 431.

Ntalaperas, D., Bothos, E., Perakis, K., Magoutas, B., Mentzas, G. (2015). DISYS: an intelligent system for personalized nutritional recommendations in restaurants. *Panhellenic Conference on Informatics*, 382-387.

Oyebode, O., Orji, R. (2020). A hybrid recommender system for product sales in a banking environment. *Journal of Banking and Financial Technology*, vol. 4, 15–25.

Rathi, S., Rander, R., Sanghvi, P., Shah, S. (2017). Eatery Directory Using Recommendation System and Data Mining, *Journal of Computer Engineering*, vol. 1, 39-42.

Rehman, F., Khalid, O., Haq, N.U., Khan, A.U.R., Bilal, K., Madani, S. A. (2017). Diet-Right: A Smart Food Recommendation System. *KSII Transactions on Internet and Information Systems*, vol. 11(6), 2910-2925.

Ribeiro, D., Barbosa, T., Ribeiro, J., Sousa, F., Vieira, E.F., M. Silva, A. Silva. (2022). SousChef System for Personalized Meal Recommendations: A Validation Study", Applied Sciences vol. 12(2), 702.

Rostami, M., Farrahi, V., Ahmadian, S., Jalali, S.M.J., Oussalah, M. (2023). A novel healthy and time-aware food recommender system using attributed community detection. *Expert Systems with Applications*, vol. 221, 119719.

Rostami, M., Mourad, O., Vahid, F. (2022). A Novel Time-aware Food recommender-system based on Deep Learning and Graph Clustering. *IEEE Access,* vol. 10, 52508 – 52524.

Thongsri, N., Warintarawej, P., Chotkaew, S., Saetang, W. (2022). Implementation of a personalized food recommendation system based on collaborative filtering and knapsack method. *International Journal of Electrical & Computer Engineering*, vol. 12(1), 2088-8708.

Tran, T.T.N., Atas, M., Felfernig, A. Stettinger, M. (2018). An overview of recommender systems in the healthy food domain", Journal of Intelligent Information Systems, vol. 50(3), 501–526.

Vivek, M.B., Manju, N., Vijay, M.B. (2018). Machine learning based food recipe recommendation system, *International Conference on Cognition and Recognition*, 11-19.

Zitouni, H., Meshoul, S., Mezioud, C. (2022). New contextual collaborative filtering system with application to personalized healthy nutrition education. *Journal of King Saud University-Computer and Information Sciences,* vol. 34(4), 1124-1137.

Yang, L., Hsieh, C.K., Yang, H., Pollak, J.P., Dell, N., Belongie, S., Cole, C., Estrin, D. (2017). Yum-me: A personalized nutrient-based meal recommender system: A personalized nutrient-based meal recommender system. *ACM Transactions on Information Systems,* vol. 36(1), 1–31.

Zaveri, A.A., Mashood, R., Shehmir, S., Parveen, M., Sami, M. Nazar, N. (2023). AIRA: An Intelligent Recommendation Agent Application for Movies. *Journal of Informatics and Web Engineering*, vol. 2(2), 72-89.

Zhang, X., Luo, H., Chen, B., Guo (2020). Multi-view visual Bayesian personalized ranking for restaurant recommendation", *Applied Intelligence,* vol. 50(9), pp. 2901–2915, 2020.

Zhao, Z.D., Shang, M.S. (2010). User-based collaborative-filtering recommendation algorithms on Hadoop. *Third International Conference on Knowledge Discovery and Data Mining*, 478–481.