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A novel healthy and time-aware food recommender system using attributed community detection

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ABSTRACT

Food recommendation systems aim to provide recommendations according to a user's diet, recipes, and preferences. These systems are deemed useful for assisting users in changing their eating habits towards a healthy diet that aligns with their preferences. Most previous food recommendation systems do not consider the health and nutrition of foods, which restricts their ability to generate healthy recommendations. This paper develops a novel health-aware food recommendation system that explicitly accounts for food ingredients, food categories, and the factor of time, predicting the user's preference through time-aware collaborative filtering and a food ingredient content-based model. Based on the user's predicted preferences and the health factor of each food, our model provides final recommendations to the target user. The performance of our model was compared to several state-of-the-art recommender systems in terms of five distinct metrics: Precision, Recall, F1, AUC, and NDCG. Experimental analysis of datasets extracted from the websites Allrecipes.com and Food.com demonstrated that our proposed food recommender system performs well compared to previous food recommendation models.

1. Introduction

1.1. Background

Internet and mobile technologies allow people to access information anytime and anywhere (Karakaya & Aytekin, 2018; Park & Nam, 2019; M. Singh, 2020). Therefore, people's lifestyles have been intensively altered by online systems, including social media, e-commerce, and different lifestyle applications. When friends convene for dinner, they might share pictures on social media of the food they enjoy, and other people might turn to apps for recommendations when deciding what to eat. Today, diet preference is becoming increasingly important in meeting a variety of necessities, including basic nutrition, calories, taste, mental wellbeing, and sociocultural circumstances (J.-C. Kim & Chung, 2020; Premasundari & Yamini, 2019; Tran, Felfernig, Trattner, & Holzinger, 2021). Diet is a major contributor to the immense rise in the prevalence of obesity and diabetes (Bishop, et al., 2021; Mario, et al., 2022; Zhu, et al., 2022). According to the Global Burden of Disease Study, dietetic patterns are a significant component to thresholds of malnourishment, fatness, and adiposity, and unhealthy diets cause 11 million preventable early deaths annually (James, et al., 2018). Food recommendation systems are emerging as a new branch of science to resolve these concerns (Ali, et al., 2018; Chen & Toumazou, 2019; Vairale & Shukla, 2019). Food recommendation systems play a vital role across a wide range of online technology-based lifestyle applications, and they have become an essential component of many lifestyle services, which can, in turn, be used to influence people towards a healthy lifestyle. These systems seek appropriate food products that accommodate users' daily diet preferences while enabling these individuals to satisfy their basic biological and physiological needs and adequately perform their daily activities (H. I. Lee, Choi, Moon, & Kim, 2020; Norouzi, Nematy, Zabolinezhad, Sistani, & Etminani, 2017; Subramaniyaswamy, et al., 2019).

In the modern era, many online services and applications generate a large amount of information on the Internet. Amid such extensive information, Internet users are overwhelmed with trying to find the

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content they are looking for, leading to the well-known problem of information overload (Agapito, et al., 2017; H. Li, et al., 2019). Information overload is especially problematic in the case of Internet-based food services and food social networks, which provide users with excessive options, making it difficult for them to find their preferred foods. As a result, food recommendation has become a progressively important tool to meet potential customer requirements and assist consumers by effortlessly discovering appropriate food recommendations (Leipold, et al., 2018).

Considering the importance of nutrition and diet in individual and public health, the current study addresses the following research questions:

- **R1:** How can food recommendation systems simultaneously consider users' preferences and healthiness? To answer this question, our team incorporated users' preferences and health factors into the food recommendation model to guide them to a healthy diet.
- **R2:** How can a time-aware recommender system be used to identify and address changes in a user's diet and lifestyle? Our team addressed this research question by capturing the temporal information of ratings and using it to calculate user-similarity scores.
- **R3:** How does ingredients-aware food categorization affect the final performance of the recommender system? For this research question, we conducted experiments with and without various food group data. This research is discussed in Section 4 of this paper.

1.2. The current state-of-the-art research

Many food recommendation systems have been proposed in recent years to predict people's preferences and/or to guide their choices based on predetermined criteria (Gao, et al., 2019; Gao, et al., 2022; Meng, Feng, He, Gao, & Chua, 2020; Pecune, Callebert, & Marsella, 2020; Toledo, Alzahrani, & Martinez, 2019; Trattner & Elsweiler, 2017; Vivek, Manju, & Vijay, 2018). Despite the relative success of previous food recommender systems in learning individuals' preferences based on their historical interactions with food, these systems still suffer from several limitations:

- **Healthy recommendations:** Many previous food recommender systems (Gao, et al., 2019; Gao, et al., 2022; Mehrdad Rostami, et al., 2022; M. Rostami, Oussalah, & Farrahi, 2022; Toledo, et al., 2019) cannot guarantee that the recommended foods are a healthy choice for users since these systems do not incorporate nutritional information. In fact, most previous works have focused only on users' preferences.
- **Ingredients of foods:** Most previously published food recommendation models (Pecune, et al., 2020; Trattner & Elsweiler, 2017) have been based primarily on historical ratings; this approach uses a collaborative filtering method that ignores ingredients. Because individuals usually prefer foods that contain ingredients they enjoy, previous models may overlook some important parts of the recommendation. Some people may enjoy foods containing pork, while others may be allergic to certain spices used in preparing Food. As a result, traditional collaborative filtering models may not be able to consider all user preferences and tastes.
- **Time factor:** Traditional recommendation models (Gao, et al., 2019; Gao, et al., 2022; Meng, et al., 2020; Toledo, et al., 2019) assume that users who enjoyed similar foods in the past will enjoy them in the future. These models do not consider changes in users' food preferences, diets, or lifestyles over time, which can occur in real-life cases. As a result, they recommend inaccurate suggestions in real-life situations.
- **Data sparsity problem:** Most users have only rated a few foods, so standard recommendation models have problems identifying active user neighbors or similar items. Consequently, users can only receive food recommendations from standard food recommender systems if they have rated enough foods. Moreover, an item that has not yet received enough user ratings is called a "cold start food". As a result, this food item will also be ignored by such a standard recommendation model.
- **Food clusters:** Another issue often not considered by most previously published recommendation models is a given food's neighborhood or group aspect. This information allows similar foods to be identified and ratings for unknown foods to be predicted. Clustering-based models are typically used to group items in recommendation systems. However, this approach faces numerous difficulties, which are somehow intrinsic to traditional clustering algorithms. This includes, for instance, the need to specify the optimal number of clusters (as in k-means or fuzzy c-means clustering). Moreover, clustering algorithms calculate the similarity among foods by employing a specific user rating-based criterion. This limits the accuracy of clustering-based recommender systems in handling sparse datasets.
- **Controllability:** In previous healthy food recommender systems (Ahmadian, Rostami, Jalali, Oussalah, & Farrahi, 2022), end-users were not directly involved in the final recommendation process. As a result, these models did not allow users to influence the system by interacting with different kinds of inputs and parameters. An effective healthy food recommendation system should allow a user to specify the importance of their goals, their preferences, and their food's health factor.

To address these drawbacks, this paper develops a novel time-aware and food ingredient-based recommendation model that simultaneously tackles all the aforesaid challenges. Our system particularly considers the health factor and the ingredient content of foods. The model is named the Healthy and Time-Aware Food Recommendation System (HTFRS). In short, HTFRS suggests desired and healthy foods to the active user. To predict user-based rates, we first consider the historical ratings of users. We use a novel attributed community-detection algorithm to categorize the initial foods into several groups, and we predict the ratings of unrated foods accordingly. As a result of these two types of rating predictions (i.e., user-based and food ingredient-based), we predict the final rating of unrated foods. We finally recommend the top-N healthy foods by considering a novel controllable multi-objective function that explicitly accounts for the health aspect of the food. Overall, the novelty of our developed food recommendation system can be summarized as below:

- **Healthy Recommendation:** In contrast with many previous food recommendation models, this paper incorporates health and nutrition factors into the food recommendation model so that the system guides users to a healthy eating style. In other words, the purpose of this study is to present the general framework for developing an efficient food recommendation model based on user preference and nutrition factors.
- **Ingredients-Aware:** Unlike classic food recommendation systems that ignore food contents in their recommendations, our model employs historical user ratings as well as food ingredients in the data-processing pipeline of our recommender system.
- **Time-Aware:** In contrast to previous works (Gao, et al., 2019; Gao, et al., 2022; Meng, et al., 2020; Toledo, et al., 2019) that have ignored the time factor, our model introduces a novel time-aware similarity function to capture the temporal information of ratings, which are then explicitly accounted for in calculating the user-similarity scores. In this model, we designed a weighting mechanism to weigh the importance of the time factor for different ratings, where old ratings have a lower importance than new ones. Armed with this time-aware function, we can incorporate the dynamic nature of users' preferences into the recommendation process.
- **Food Similarity-Based Recommendation:** To our knowledge, this is the first study where recipe information in the food

recommendation is represented with an attributed graph. This developed food content-based similarity matrix enabled us to efficiently overcome the cold-start foods problem of classic food recommendation systems. This matrix could also be used to predict the rating of unrated foods in the system since there could be a high correlation between a food's category and its ingredients.
- **Food Group-Aware:** Contrary to previous works that have ignored food categories, the developed system in this study explicitly accounts for this aspect. This new system systematically approaches the optimum number of food categories. To the best of our knowledge, this is the first work that accommodates sparse datasets by utilizing a graph-based representation where edge weights are calculated based on food ingredients-based similarities.
- **Controllable Recommendation:** This study develops, for the first time, a novel controllable food recommender system that enables users to participate actively in the recommendation process and to strike a balance between their own preferences and the health factor of the food.

In the remainder of this paper, the related works are highlighted in Section 2. Next, Section 3 represents the developed system is represented in detail. Experimental results and their discussions are detailed in Section 4. Finally, Section 5 concludes the paper briefly.

2. Related works

In recent years, recommender systems have emerged in various real applications with the aim of helping users easily find their favorite products among numerous available choices (Deldjoo, Bellogin, & Di Noia, 2021; Forouzandeh, Berahmand, Nasiri, & Rostami, xxxx; Hu, Shi, Li, & Hu, 2017; Shambour, 2021; Yao, Sheng, Wang, Zhang, & Qin, 2018; Q. Zhang, Lu, & Jin, 2021). Past users' preferences play a vital role in recommender systems since they can be utilized as a helpful input resource to predict the user's future preferences (Forouzandeh, Berahmand, & Rostami, 2020; Ruffo & Schifanella, 2009).

2.1. Time-aware recommender systems

In time-aware recommendation systems, users' preferences are modeled after temporal dynamics. A key idea in the time-aware recommender system and in temporal models is that a user's preferences can change over time along with their behavior. Since this concept plays a crucial role in the real recommendation, several time-aware models have been developed (Ahmadian, Joorabloo, Jalili, & Ahmadian, 2022). For instance, in (Zhao, Liang, & Wang, 2021), a context-aware recommendation method was introduced by improving the tensor factorization model through a consideration of changes in user preference over time as an additional bias factor. This method led to greater recommendation accuracy compared with that of other traditional recommendation approaches. In (Ahmadian, Joorabloo, et al., 2022), a time-aware recommendation method was developed based on temporal reliability and confidence criteria. The central idea of this method was to utilize the timestamps of assigned ratings to define the reliability and confidence factors that are customized to enhance the effectiveness of the recommendation process. This model used the temporal reliability measure to determine the reliability of the predicted rating. At the same time, the temporal confidence measure determined the effectiveness of the nearest neighbors for the target user. Bao (Bao & Zhang, 2021) showed that both a user's preferences and an item's popularity can significantly change over time, which suggests that these entities should be considered as temporal dynamic features in recommender systems. Bao proposed a neural network-based model to address these dynamic features and to account for the time factor in the recommendation process. In addition, a collective timeline methodology was developed to incorporate sessions with different timestamps into the recommendation process. A matrix factorization-based recommendation method was proposed in (J. Zhang & Lu, 2019). This method was shown to improve recommendation accuracy by capturing the temporal features of users and items through a time-based weighting strategy. To this end, the authors developed a personalized time-weight scheme to reduce the impact of older ratings when generating a recommendations list. In addition, the authors utilized a joint-objective function in the matrix factorization model to simultaneously learn the time-dependent latent factors of users and items. A community-detection approach was introduced in (Rezaeimehr, Moradi, Ahmadian, Qader, & Jalili, 2018) to identify overlapping communities according to the user-item interaction matrix. This approach also led to a decline in the negative effect of the data sparsity problem. In addition, the authors developed a model to consider the dynamic changes in users' preferences over time.

2.2. Food recommender systems

Food recommender models can be viewed as intelligent algorithms that make personalized food recommendations from a wide range of choices. Using these models, researchers can efficiently address the well-known information overload problem. In recent years, food recommendation systems have gained increasing attention due to their applicability to healthy living (Mehrdad Rostami, et al., 2022). Most current studies in the food domain focus on providing users with recommendations for favorite food items based on their preferences and/or health problems (H. I. Lee, et al., 2020). A few of the latest food recommendation systems are reviewed in the remainder of this subsection. Some previous health and food recommendation systems have used content-based filtering. Healthy recipes were considered complex agglomerations of various traits derived from flavorings, food classifications, preparatory instructions, and nutritional information in (Lin, Kuo, & Lin, 2014), where the researchers introduced a content-driven composite factorization strategy (CTRMF engine) to address the innate aspects of the ingredients, the consumers, and the associated attributes. To improve recommendation outcomes, some approaches have suggested integrating content-based and demographic filtering methods using ontology- and knowledge-based technologies (Al-Nazer, Helmy, & Al-Mulhem, 2014; J. Kim & Chung, 2014). In this context, individual and social interests as well as health and religious limitations are modeled using a tailored ontology. CarePlan (Abidi & Chen, 2006) is a semantically representational paradigm that provides health coverage combining patients' health conditions with their individual opinions while ignoring other factors that could influence their food choice, such as their education, culture, and religion. The practicality and the short-term effectiveness of smartphone applications for diabetes prevention and management among obese individuals were investigated in (Fukuoka, Gay, Joiner, & Vittinghoff, 2015). Their mobile app software included a digital diary for self-monitoring their body weight, their activity level, and their caloric expenditure; it also included daily alerts to submit information and weight-reduction outcomes. As a result, texting and mobile applications have been recognized as viable strategies for administering weight-reduction programs and attaining significant clinical weight loss in obese communities. The authors introduced a web service for food recommendation termed PREFer (Prescription for Recommending Food) in (Bianchini, De Antonellis, De Franceschi, & Melchiori, 2017). Content-based retrieval selects suitable ingredients, a process carried out by comparing information applied to describe both the user's profile and the recipe. In addition, the recipes are graded based on clinical referencing prescribed systems (i.e., a well-balanced set of recipes suitable for a given group of individuals). The authors of (Ge, Ricci, & Massimo, 2015) have created a new method that enables consumers to harmonize their preferences with their wellbeing. Their recommender system is capable of not only providing food recommendations that fit the user's preferences but also of considering the user's health status. An Android platform was used to create the specified demonstration system.

Freyne and Berkovsky (Freyne & Berkovsky, 2010) explored how to

Table 1
Summary of the studied recommender systems.

Authors	Time-aware	Clustering	Health-aware	Food Ingredients
(Zhao, et al., 2021)	✔	–	–	–
(Ahmadian, Joorabloo, et al., 2022)	✔	–	–	–
(Bao & Zhang, 2021)	✔	–	–	–
(J. Zhang & Lu, 2019)	✔	–	–	–
(Rezaeimehr, et al., 2018)	✔	✔	–	–
(Lin, et al., 2014)	✔	–	–	✔
(Teng, et al., 2012)	–	✔	–	✔
(Bianchini, et al., 2017)	–	–	✔	✔
(Ge, Ricci, et al., 2015)	–	–	✔	–
(Freyne & Berkovsky, 2010)	–	–	✔	✔
(Ge, Elahi, et al., 2015)	–	–	–	✔
(Pecune, et al., 2020)	–	–	✔	–
(Gao, et al., 2022)	–	–	–	✔
Developed model	✔	✔	✔	✔

enhance content-based recommendations through recipe and ingredient ratings. By learning customers' dietary choices, the researchers intended to lessen the effort required to modify their diets from unhealthy to healthy. The researchers employed a list of ingredients from different recipes to apply the content-based method. This strategy, which employed the components in the recipes, fared the best according to their findings. While researching recipe recommendations through ingredient networks for a food preparation web service, Teng et al. (Teng, Lin, & Adamic, 2012) investigated the interaction among raw ingredients via network graphs as well as the significance of various components in producing the recipe. Teng's findings revealed probable ingredient substitutions proposed by users on the food preparation website. Furthermore, these outcomes stressed components that regularly co-occur. Moreover, the findings demonstrated that aspects of the ingredient lists, and nutritional information could be used to determine recipe evaluations. The authors of (Ge, Elahi, Fernaández-Tobías, Ricci, & Massimo, 2015) created a system that gathers users' preferences by asking them to review and tag the meals they frequently make at home. Afterwards, the algorithm ranks recipes and makes suggestions based on client interests. The authors discovered that their proposed enhanced matrix factorization technique performed exceedingly well compared with other content-based methods in the literature. In (Pecune, et al., 2020), a health-aware recipe recommender was developed to obtain a "healthy" tag for each recipe, quantifying the size of a healthy portion of food. The main advantage of this recommender system is to help people make better decisions when ordering healthy foods. The authors have investigated the performance of three different strategies: The first one relies only on users' preferences, the second one considers only health factors, while the third one combines both preferences and health factors. Gao (Gao, et al., 2019) proposed a food recommender based on three main data resources: the user's preferences, the food's ingredients, and the food's image. To this end, a neural-network model was applied to the input data resources to predict the preferences of the target user. The model evaluates user-to-user similarities¬ based on previous preferences, where the preference is inferred by exploring food ingredients and images of the foods.

Table 1 highlights the main characteristics of the studied recommender systems in this section. It is worth mentioning that all the above-mentioned food recommendation models ignore time factors and changes in users' lifestyles in their recommendation processes. Food recommendations, however, must consider timing factors, since people's preferences can change over time. As a result, in this paper, we propose a time-aware food recommendation model that simultaneously incorporates both health factors of foods and user preferences into the recommendation process.

3. Proposed method

In this section, our team proposes novel food recommender system, which incorporates a collaborative filtering model and a content-based model. The developed model, called the Healthy and Time-Aware Food Recommender System (HTFRS for short), is grouped as a hybrid recommender system that utilizes the advantages of both collaborative filtering and content-based models. HTFRS suggests a list of favorite foods by utilizing user similarities and food groups. Because the preferences, diets, lifestyles, and food habits of each user may change over time, HTFRS accounts for the time effects of historical ratings in the user-similarity calculation process.

The overview of the model is highlighted in Fig. 1. HTFRS has two main phases: (1) time-aware collaborative filtering and (2) the food ingredients-based prediction rating. In the first phase, the user-to-user similarity matrix is calculated while accounting for the timestamp of the rating. Finally, considering the users' similarities and historical ratings, the users' ratings are predicted using the collaborative filtering-based model. In the second phase, foods are first considered nodes in an attributed social network, where the ingredients of each food are indicated by node attributes. Next, based on this attributed social network representation, the food-to-food similarity matrix is calculated. By developing a novel attributed community-detection algorithm, the initial foods are grouped into several categories. Finally, the ratings of non-rated foods are predicted using the generated food clusters. After these two phases, the top-N healthy foods are recommended by combining collaborative filtering-based and food ingredients-based predicted rating and considering the nutrition facts of the foods. The remainder of this section details the various steps of the proposed food recommendation model. Moreover, for the clarity of the employed notations, the nomenclature used throughout the developed model is explained in Table 2.

3.1. Time-aware collaborative filtering

Collaborative filtering-based recommender systems are based on the premise that similar users have similar preferences and favorites. Our collaborative filtering-based model uses the ratings of similar users to recommend favorite foods to active users. This phase of our proposed model employs the user–food rating matrix to estimate the user-to-user similarity matrix. Our approach presents a new time-aware similarity measure that combines the time factor with the users' ratings as below:

$$SimU(u,v) = \frac{\sum_{i\in A_{u,v}}\left((r_i(u)-\overline{r}(u))\times(r_i(v)-\overline{r}(v))\times TW_{(u,v,i)}\right)}{\sqrt{\sum_{i\in A_{u,v}}\left((r_i(u)-\overline{r}(u))^2\times TW_{(u,v,i)}\right)}\sqrt{\sum_{i\in A_{u,v}}\left((r_i(v)-\overline{r}(v))^2\times TW_{(u,v,i)}\right)}} \tag{1}$$

where $r_i(u)$ is the rating given to food f_i by user u, and $\overline{r}(u)$ is the average rating given by user u, and $A_{u,v}$ is the set of foods which are rated by both users u and v. Moreover, $TW_{(u,v,i)}$ denotes the Time Weight of the

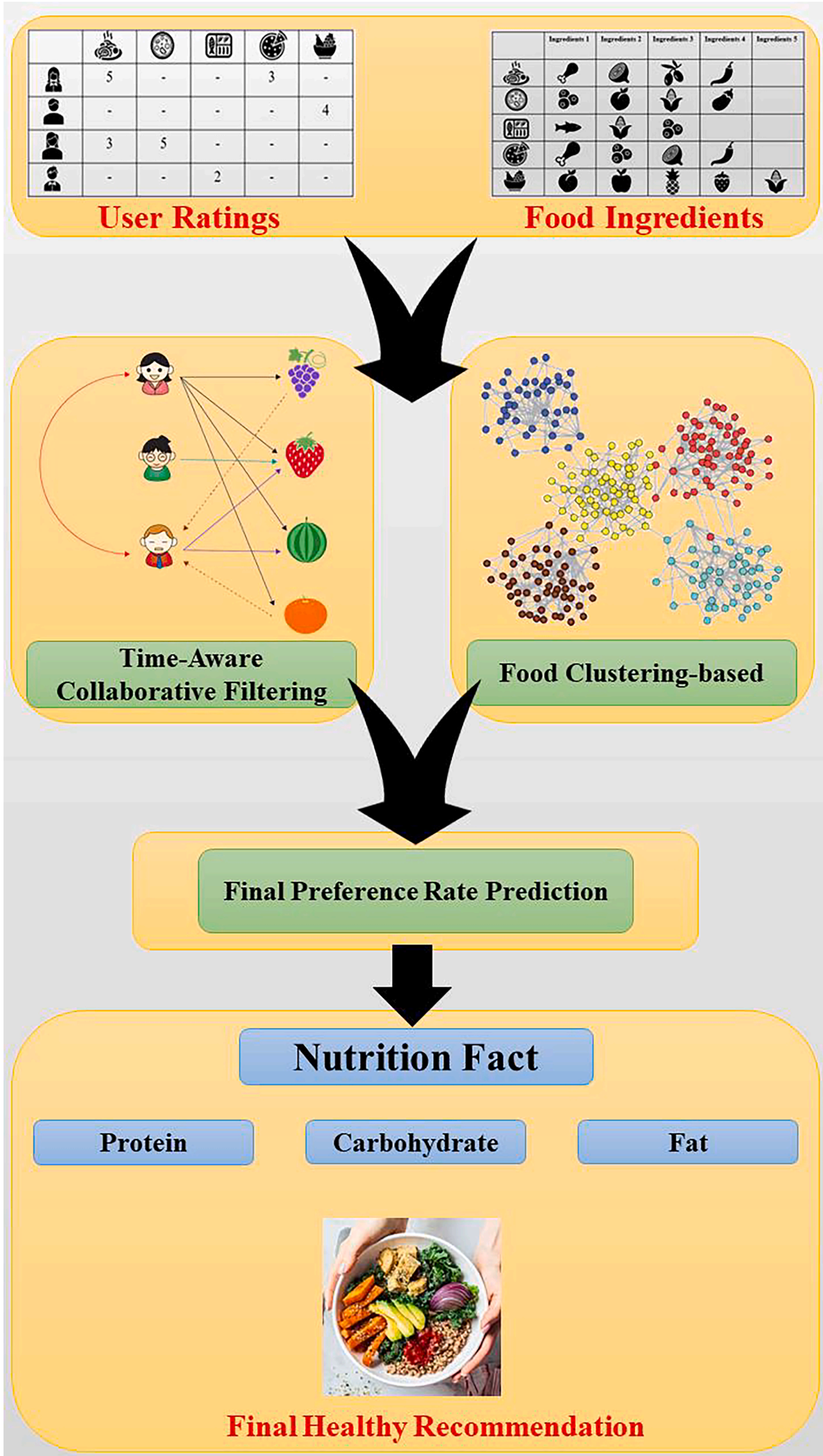


Fig. 1. Conceptual framework of the developed model.

Table 2
Nomenclature and parameters of proposed model.

Symbol	Description
Number of users	N
Number of foods	M
Number of Ingredients of Food i	k_i
User set	$U = \{u_1, u_2, u_3, \cdots, u_N\}$
Food set	$F = \{f_1, f_2, f_3, \cdots, f_M\}$
Ingredients of food i	$I_i = \{Ing_{\sigma(1)}, Ing_{\sigma(2)}, \ldots, Ing_{\sigma(k_i)}\}$where σ is some permutation of integers $\{1, 2, \cdots, M\}$
Number of all ingredients	K
Set of all ingredients	$\{I_1 \cup I_2 \cup I_3, \cdots, \cup I_M\} = \{Ing_1, Ing_2, \cdots, Ing_K\}$
User-Food rating matrix	$R = \{1, 2, 3, 4, 5\}^{N\times M}$
Similarity between user u and v	$SimU(u, v)$
Similarity between food f_i and f_j	$SimF(f_i, f_j)$
Rate given to food f_i by user u	$r_i(u)$
CF-based predicted rate for food f_i by user u	$p_i^{cf-based}(u)$
Time Factor Parameter	λ
Food-based predicted rate for food f_i by user u	$p_i^{food-based}(u)$
Balance parameter between CF-based and food-based ratings	β
Preference rate for food f_i by user u	$p_i^{Preference}(u)$
Healthy Factor of the food f_i	$HF(f_i)$
Healthy factor parameter	γ
Predicted rate for food f_i by user u	$p_i(u)$

ratings of users' rates u and v to food f_i that calculated as follows:

$$TW_{(u,v,i)} = \sqrt{e^{-\lambda(TP-t(u,i))} \times e^{-\lambda(TP-t(v,i))}} \quad (2)$$

where $t(u,i)$ indicates the time period of the recorded rate of user u to food f_i, TP denotes the maximum Time Period, and λ specifies a user control parameter that adjusts the impact of time factor. A high (resp. low) value of λ denotes a greater (resp. smaller) impact of time factor in calculating similarity values. To create the time periods, the user ratings are divided into different time periods according to their time intervals. In our experiments, the user ratings are split into monthly time.

After the user similarity calculation phase, the rate of food f_i for user u will be predicted as below:

$$p_i^{cf-based}(u) = \overline{r}(u) + \frac{\sum_{v\in C_u} SimU(u, v).(r_i(v) - \overline{r}(v))}{\sum_{v\in C_u} |SimU(u, v)|} \quad (3)$$

where $SimU(u, v)$ indicates the similarity between user u and v and C_u is a set of neighbors of user u that have rated food f_i.

3.2. Food ingredients-based prediction rating

A challenge with classic recommender systems is the cold-start and data-sparsity problem, where prior ratings are not recorded for certain items. Because of the cold-start problem, a new food that has recently been added to the system may never have a chance to be recommended and may remain "cold" all the time. By combining content-based models and collaborative filtering models, hybrid recommendations provide insights to solve the item's cold-start and data-sparsity problem. Furthermore, item clustering-based techniques are used in content recommendation systems to provide more precise recommendations and to address this issue. In this study, we proposed a food clustering technique to improve the final recommendation performance. For this purpose, we proposed a new attributed community-detection algorithm for food clustering based on ingredients. Specifically, the proposed attributed community-detection algorithm partitions the food set into different disjoint subsets so that (1) some clusters contain densely connected foods while other clusters contain sparsely connected foods and (2) foods within the same clusters have more diverse ingredients, while foods belonging to different clusters may have less diverse ingredients.

Fig. 2 shows a scheme of the developed attributed community-detection algorithm for food clustering on a simple food set with seven foods. Because the developed community-detection algorithm uses food ingredients for food clustering, the initial input data consists of the ingredients of all foods. Next, a matrix of food attributes is created using the input data from the food ingredients. The rows in this matrix represent foods, while each column indicates a specific ingredient. If a food contains the corresponding ingredient, a value of 1 is assigned to the corresponding cell of the matrix; otherwise, a value of 0 is assigned. The food attribute matrix is then used to calculate the weight of each ingredient. Next, the food similarity matrix is calculated using the food-attributes matrix and the weight of the ingredients. Finally, food groups are identified based on food similarities. The remainder of this subsection details each of these steps.

First, to apply the attributed community detection algorithm for food clustering, the food set should be represented as an attributed social network. To this end, let $G(F, E, I)$ be a graph, where F is the set of all foods, E is the set of edges representing the existing similarity between the foods, and I shows the set of attribute vectors (i.e., set of all ingredients in all foods, $I = \{Ing_1, Ing_2, \cdots, Ing_K\}$). In the latter, Ing_i indicates the presence of i^{th} substance ingredient in that food. Moreover, K sets the dimension of node vector attributes (i.e., number of all ingredients).

Because of the large number of ingredients in the food recommender system, many attributes typically describe each node. Several attributes may be irrelevant to the food-clustering process. When the attributed graph contains many irrelevant and redundant attributes, this negatively impacts the performance of the graph analysis and increases the computational complexity of the food-clustering method. Therefore, reducing the dimensions of the node attributes (i.e., the food ingredients) is fundamental to the application of social network analysis. This simplification will also likely improve the performance of subsequent community-detection algorithms for food clustering.

In the first step of this phase, the weight of an individual ingredient is calculated using a term-weighting approach. The most popular term-weighting technique in the information-processing community is the term frequency-inverse sentence frequency (tf-isf) scheme. This scheme builds the insufficient term frequency (tf) factor to ensure an acceptable performance in text-retrieval tasks. This performance is then complemented by the inverse-sentence frequency (isf) factor, which varies inversely with the number of sentences in which it appears.

In our approach, each food is considered as a sentence where tokens correspond to its ingredients. Term weighting is the first step in calculating sentence similarity. For this purpose, an improved version of $tf-isf$ term weighting measure is employed for ingredients weighting. The weight of Ing_j in food f_i is set to zero if food f_i does not contain the ingredients Ing_j. Otherwise, the tf-isf-based weight of ingredient Ing_j in food f_i is calculated as follows:

$$w_{ij} = \log\left(\frac{M}{n_j}\right) \quad (4)$$

where M is the number of foods contained in the Food Set F and n_j counts the number of foods that contain ingredient Ing_j.

After calculating the weight of each ingredient Ing_j in each food, the final weight of ingredient set is calculated as follows:

$$w_j = \frac{\sum_{i=1}^{M} w_{ij}}{M} \quad (5)$$

After computing the importance score for each ingredient, the

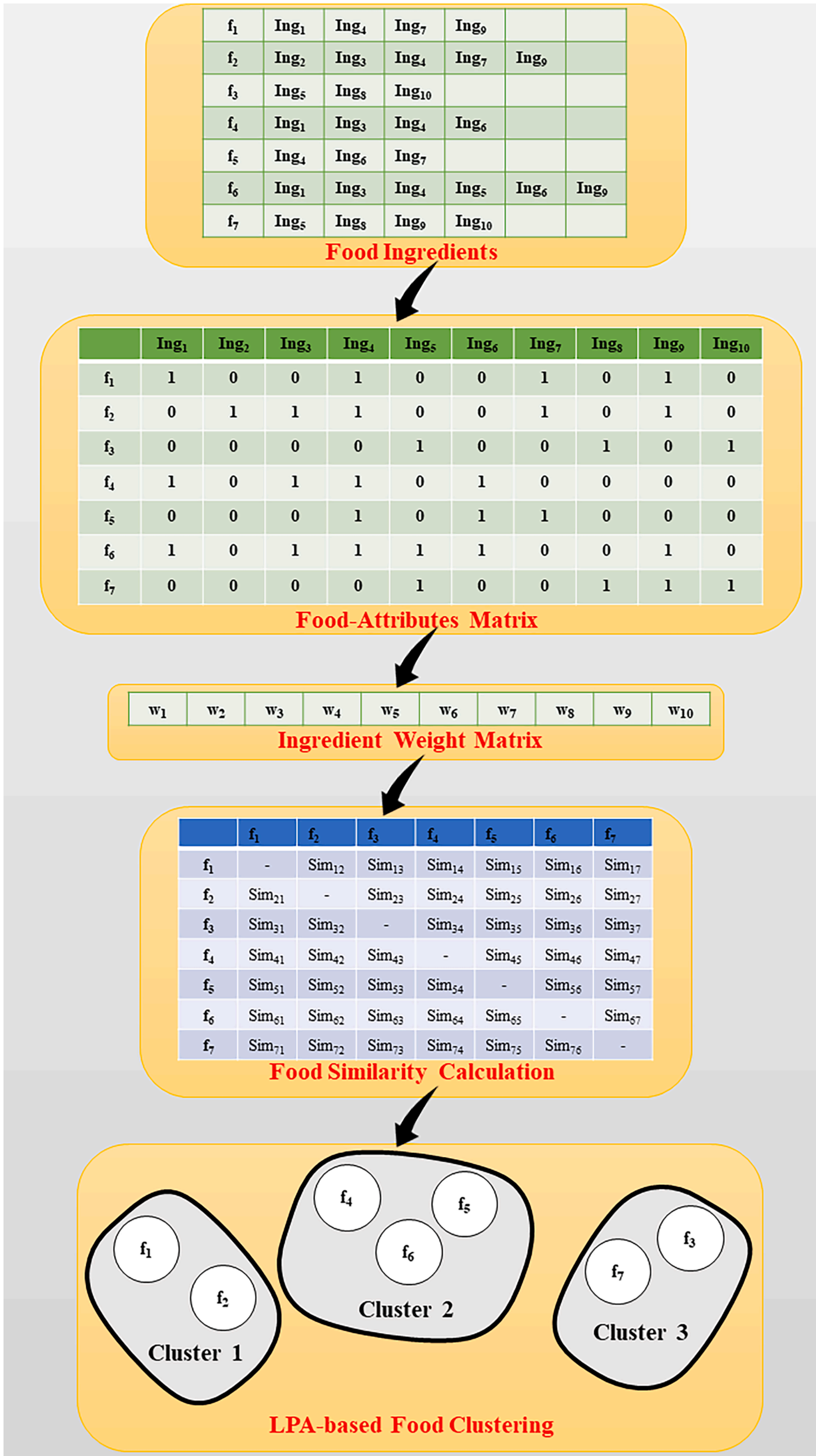


Fig. 2. The overall scheme of the developed food clustering method for a simple food set.

Table 3
The dietary recommendations based on the percent of the energy contribution.

Macronutrients	Percent of energy contribution
Protein	Min:10 - Max:15 - Average:12.5
Fat	Min:15 - Max:30 - Average:20
Carbohydrate	Min:55 - Max:75 - Average:65

similarity between foods f_i and f_j is determined according to their food ingredients as follows:

$$SimF(f_i, f_j) = \sum_{l=1}^{K} w_l \times \left(Sim_l(f_i, f_j)\right) \tag{6}$$

where w_l indicates the weight of ingredient Ing_l, $Sim_l\left(f_i, f_j\right)$ measures the similarity between foods f_i and f_j based on the presence of ingredient Ing_l only. This is calculated as follows:

$$Sim_l(f_i, f_j) = \begin{cases} 1, if Ing_l \in f_i \cap f_j \\ 0, Otherwise \end{cases} \tag{7}$$

After calculating food similarity, one can advance to the main step of the food-clustering method, where our team proposes a novel label propagation-based community-detection algorithm. The standard label propagation algorithm (LPA), which only utilizes the structural similarity of nodes for community detection, initially assigns a unique label to each node and subsequently chooses the node with the highest frequency in several updated steps. All nodes under the dense subgraph that reached the same label can be clustered as a community graph if the algorithm reaches an iteration with a maximum number of adjacent tags.

Due to the assumption of equal node importance and its subsequent effect on the updating phase and tiebreaker mode, the standard LPA faces instability and low performance. Intuitively, in each community, there are important nodes that contribute significantly to community construction (e.g., nodes located in the center of community). Typically, the higher the influence of a given node in the graph as compared with its adjacent nodes, the higher the significance of that node in the corresponding community construction. Nodes with high centrality or with a high influence score play the role of the dominator, and nodes with lower importance play the role of subordinator (Kumar & Panda, 2020; Mehrdad Rostami & Oussalah, 2022). Centrality measures assess the position of nodes in a social network by assigning them numbers or scores in accordance with their popularity (Kumar, Lohia, Pratap, Krishna, & Panda, 2022).

As mentioned, in the first phase, the initial food set F was converted into a graph $G(F, E, I)$ using ingredients-based similarity. In this phase, the popularity of each food in social network was calculated using a node centrality measure. The nodes with higher popularity in the weighted social network will be penetrable on their neighbor in terms of structure and attributes. We expect the nodes with a central position to contribute greatly to the control, guidance, and establishment of their communities. In contrast, nodes on the boundary level may be able to serve as intermediaries between communities. For this study, we used Laplacian centrality to measure node centrality.

After measuring the Laplacian Centrality, each node's Label Influence (LI) is calculated as below:

$$LI(i, l) = NC\_L(v_i, G) \tag{8}$$

where, $LI(i, l)$ denotes the influence of the l on the node i, that $NC\_L(v_i, G)$ is Laplacian Centrality (Qi, Fuller, Wu, Wu, & Zhang, 2012) of node i. Standard LPA assume that all neighbors propagate labels equally. To choose the best label for propagation, we used the label influence of neighbors in our attributed and improved LPA. Label Acceptance is measured as follows:

$$LA(m) = \left[argmaxLI_{p\in\Gamma(m)}(p, l)\right] \tag{9}$$

where $\Gamma(m)$ represents the first-order neighborhood of node $p \in F$. Each node will receive a node label with considerable influence among its first-degree adjacent nodes during the labels update phase.

After Food Clustering phase, the rate of food f_i for user u is predicted as below:

$$p_i^{food-based}(u) = \bar{r}_i + \frac{\sum_{j\in C_i} sim(f_i, f_j).(r_j(u) - \bar{r}_j)}{\sum_{j\in C_i} |sim(i, j)|} \tag{10}$$

where $r_j(u)$ is the rate of food f_j given by user u, $\bar{r}_j$ is the average rate of food f_i, $sim\left(f_i, f_j\right)$ is a similarity measure between foods f_i and f_j which can be calculated by Eq (6), and C_i shows the set of foods belonging to the group that food f_i is also belongs to.

3.3. Preference rating prediction

After the collaborative filtering-based rating prediction and the food ingredients-based rating prediction, the final prediction of food f_i for the user u is defined as a convex combination of collaborative filtering-based and food-based predictions as below:

$$p_i^{Preference}(u) = \beta.p_i^{cf-based}(u) + (1-\beta).p_i^{food-based}(u) \tag{11}$$

where $p_i^{cf-based}(u)$ and $p_i^{food-based}(u)$ are the collaborative filtering-based prediction and food ingredients-based prediction of food f_i for the user u, respectively and the parameter β controls the weight of the cf-based and the food-based predictions.

3.4. Food health factor calculation

Among preventable noncommunicable diseases, nutrition plays a major role. The World Health Organization (WHO) states that "non-communicable diseases (NCDs) tend to be chronic and are a combination of genetic, physiological, environmental, and behavioral factors." In line with the WHO's classification, cardiovascular diseases, diabetes, chronic respiratory diseases, and malignancy are the main types of NCDs. There are two types of risk factors for NCD development, consisting of modifiable behaviors (tobacco, excessive sodium consumption, alcohol use, and physical inactivity) and metabolic factors (raised blood pressure, overweight, obesity, etc.) (A. Singh, et al., 2017). Diet is related to a variety of modifiable behavioral and metabolic risk factors. For instance, diet plays a crucial role in preventing and treating chronic diseases throughout one's lifetime. Moreover, the importance of diet in the etiology of major NCDs has been recognized by several expert groups, who have emphasized the importance of changing food environments that contribute to these risks (Beaglehole, et al., 2011; Organization, 2014; Swinburn, et al., 2013).

Developing systems for nutritional profiling to facilitate healthier choices is one way in which the World Health Organization could promote healthy eating and reduce the burden of preventable non-communicable diseases. In addition, such systems should be flexible enough to accommodate individual conditions and circumstances. For example, when providing healthy food recommendations to people with specific health situations, it is crucial that these systems consider food ingredients alongside the users' preferences. The distinguishing feature of our developed recommendation model is the simultaneous consideration of food ingredients and nutrition facts.

Our model uses the amount of macronutrients to evaluate the health factor of a given food. Fat, protein, and carbohydrates are examples of macronutrients that provide energy and essential components to sustain life. One's diet must contain a combination of these macronutrients to maintain health and longevity. There is no universal combination of macronutrients that can provide optimal health as per the WHO's

Table 4
Statistics of Allrecipes.com and Food.com datasets.

Characteristics	Allrecipes.com	Food.com
#Users	68,768	25,076
#Foods	45,630	178,265
#Ratings	1,093,845	749,053
#Ingrdiants	5,073	33,147

recommendation. Diets containing different amounts of these macronutrients have historically survived in human populations.

Overall health authorities' guidance given by the WHO in this matter is summarized in Table 3. In view of this health dietary recommendations, and the percent of the energy contribution available in the macronutrients of the foods (Protein, Fat and Carbohydrate), the Healthy Factor (HF) of food f_i is calculated as below:

$$HF(f_i) = \left(1 - \frac{ProDistance(f_i) + FatDistance(f_i) + CarbDistance(f_i)}{100}\right)*5 \tag{12}$$

where, $ProDistance(f_i)$, $FatDistance(f_i)$ and $CarbDistance(f_i)$ indicate the distance between the dietary recommendations range and the Protein, Fat and Carbohydrate of the food f_i, respectively. Considering the ideal range food macronutrients of dietary recommendations (Table 3), $ProDistance(f_i)$, $FatDistance(f_i)$ and $CarbDistance(f_i)$ will be equal to zero if the Protein, Fat and Carbohydrate of the food f_i was between the Min and Max value of that Macronutrients. Otherwise they will be equal to the distance between the Macronutrients of the food f_i and the average value and of that Macronutrients. It is obvious that foods which are completely within the range of dietary recommendations will have a Healthy Factor (HI) equal to 5. On the other hand, foods which are completely unhealthy will have a value close to 0.For example, in the case of one food with a Percent of energy contribution of 30, 20, 50 for Protein, Fat, and Carbohydrate, respectively, and considering the dietary recommendation in Table 3, $ProDistance(f_i)$, $FatDistance(f_i)$ and $CarbDistance(f_i)$ will be 17.5, 0 and 15, respectively. Therefore, the final HF of this food will be 3.375.

3.5. Final healthy recommendation

After calculating the final preference rating based on previous users' ratings and Healthy Factor of a given food according to the percent of its energy content, the final rating of food f_i for user u is calculated by integrating Preference Rating and Healthy Factor recommendation as:

$p_i(u) = (1-\gamma).p_i^{Preference}(u) + \gamma.HF(f_i)$(13).where $p_i^{Preference}(u)$ is the Preference Rating Prediction of food f_i for user u calculated using Eq (11), $HF(f_i)$ indicates Healthy Factor of food f_i measured using Eq (12). Moreover, the parameter γ provides a trade-off between user preference and health factor content. This parameter can be set in the range of 0 to 1. As this parameter increases, the food health factor component is deemed more important in the final recommendation. Our controllable recommender system allows users to directly influence the final recommendations; they can adjust the recommendations based on their preferences and the health factor of the foods. In this controllable parameter, users can choose which of these two goals (i.e., preference and health) is most important to them in the final food recommender system. By setting this parameter to 0, only the user's preferences will be considered, and the health of the foods will be fully ignored in the recommendation process. In contrast, if this parameter is set to 1, the recommendations only account for the health factor of the foods, and no consideration is given to the user's ratings and preferences. There is no constant value for this parameter since the importance of healthy food in one's diet differs from one user to another. Indeed, through the creation of this user parameter (i.e., by adjusting the health factor parameter), our controllable food recommender system enables end-users to participate in the food recommendation process.

Lastly, in the Top-N recommendations stage, the developed model predicts the ratings of non-rated foods for the target user and then chooses top N non-rated foods to recommend.

The overall pseudo-code of developed health food recommendation mode is summarized in Algorithm 1.

Algorithm 1 Healthy and Time-aware Food Recommender System (HTFRS)

Input: Rating matrix R, Food Ingredients set $I = \{Ing_1, Ing_2, ..., Ing_M\}$, and the trade-off parameters λ, β and γ.
Time-aware Collaborative Filtering Phase:
User Similarity Calculation Using Eq (1)
CF-based rate prediction Using Eq (2)
Food Ingredients-based Phase:
Ingredients Weighing Using Eq (5)
Food Similarity Calculation Using Eq (6)
Food Graph Generation Considering the Food Similarities
Food Centrality Calculation
Assign a Unique Label to Each Food in the Food Graph
Label Influence Calculation Using Eq (8)
while Food Labels Change
Food Sorting based on their Centralities Values
For Each Food Update its Labels Using Eq (9)
Select the Label has a Higher Food's Centrality
end **while**
Generate Food Clusters
Food Cluster-based rate prediction Using Eq (10)
Preference Rate Prediction:
User Preference Rate Prediction Using Eq (11)
Final Healthy Food Recommendation
Food Health Factor Calculation Using Eq (12)
Final Rate Prediction Using Eq (13)
Output: Top-N Healthy Food Recommendation

4. Experimental results

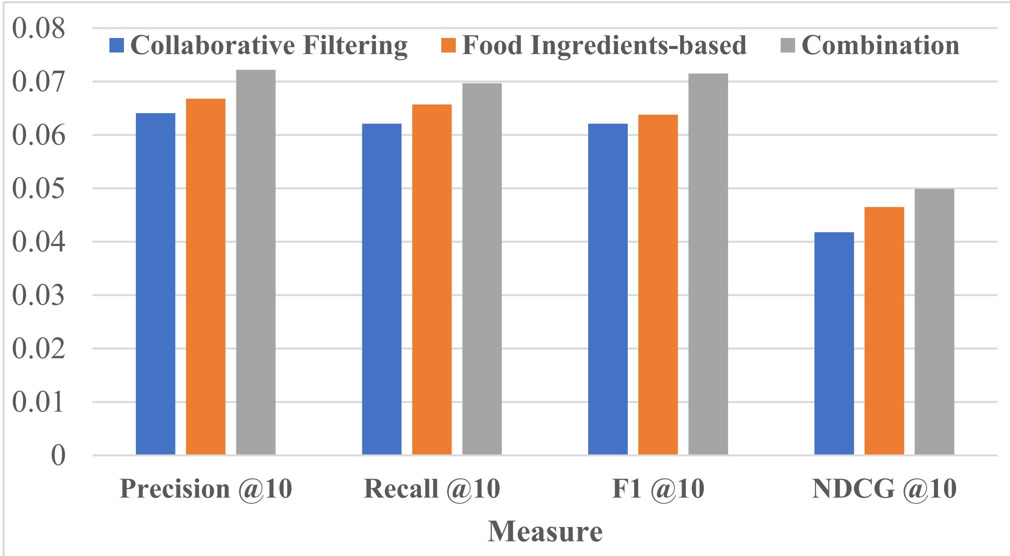
We aim to evaluate the effectiveness of the developed food recommender system (i.e., HTFRS) in this section through several experiments. Additionally, we compare HTFRS to other state-of-the-art food recommender systems. Details on the dataset, evaluation measures, obtained results, parameter sensitivity analysis, statistical analysis, and discussion can be found in the corresponding subsections.

4.1. Datasets

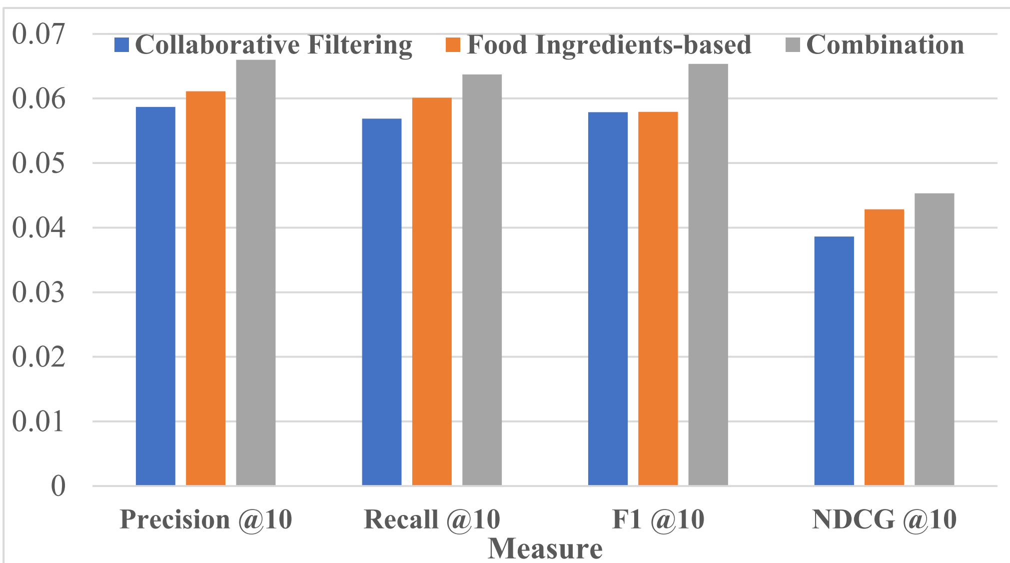
We have conducted a comparison of two recommendation models utilizing two datasets collected from https://www.allrecipes.com and https://www.food.com. In Allrecipes food social network, foods' ingredients and nutrition, users' ratings, and timestamps are crawled for each food. The ratings assigned to foods by users are in the range of [1, 5], where a rating score of 1 for a food denotes that the user has no interest in this food, while a rating score of 5 indicates the highest interest. The rating of a variety of foods is utilized to generate implicit feedback, indicating whether the users interacted with foods. After preprocessing the crawled dataset, we obtained 68,768 users; 45,630 foods; and 1,093,845 ratings in total.

Moreover, data collected for Food.com from 2000 to 2018 includes 25,076 users, 178,265 foods, and 749,053 ratings. As with the allrecipes.com dataset, users rated foods from 1 to 5 in the Food.com dataset. Moreover, for both datasets, we collected the following information for each food in addition to user ratings: ingredients, total energy (kcal), protein (g), carbohydrate (g), fat (g) and the percentage of energy contribution for each macronutrient. Table 4 provides detailed descriptions of these datasets.

The food clustering process required natural language processing (NLP) techniques to specify food ingredients from the crawled text related to the food ingredients. This was accomplished by distinguishing the ingredients from a predefined list using a string-matching methodology implemented in NLTK (natural language processing toolkit). During the main phases of the developed system, input foods were formalized and preprocessed. Several preprocessing steps were included



(a) Allrecipes.com dataset



(b) Food.com dataset

Fig. 3. Evaluation of the User-based prediction and Food-based prediction phases.

Table 5
Characteristics of compered food recommender systems.

Name	Method	Year
HAFR	**Hierarchical Attention Food Recommendation:** The goal of this study is to formulate the problem of food recommendation as predicting user preference for recipes based on three factors: user ratings, food ingredients, and food images.	2020
CFRR	**Collaborative Filtering Recipe Recommendations:** This study aims to design and develop a food recommender system based on a user's preferences expressed through feedback, ratings, and other interactions.	2021
FGCN	**Food recommendation with Graph Convolutional Network:** The purpose of this paper is to develop a new food recommendation system using Graph Convolutional Networks, which will take advantage of the complex relations between ingredient-ingredient, ingredient-recipe, and recipe-user	2022

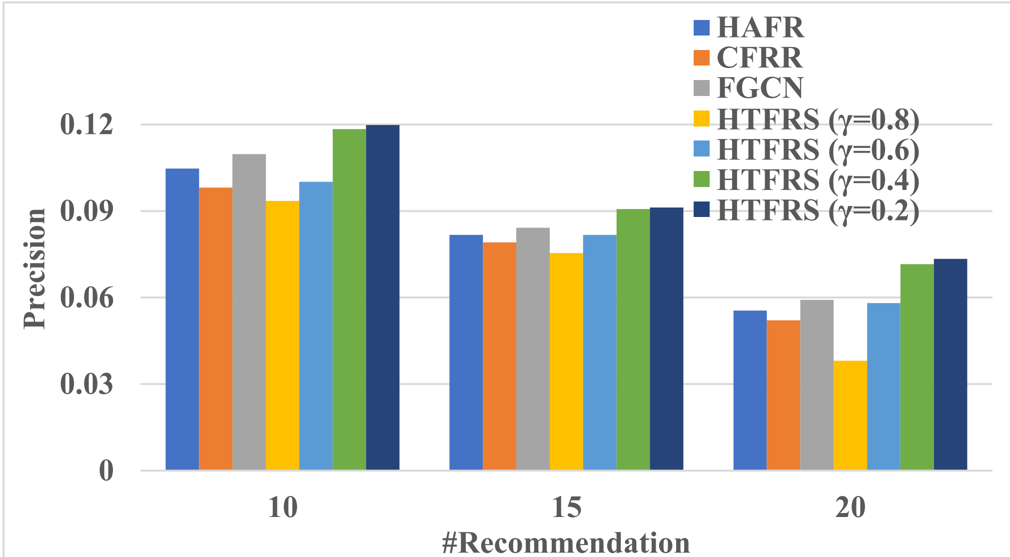
in this process, such as tokenizing, stemming, and eliminating stop words. In order to eliminate useless terms, we used a default stop words list. An inflected word was stemmed by reducing it to a stem-base or

Table 6
Performance of compared food recommender systems in Allrecipes.com dataset.

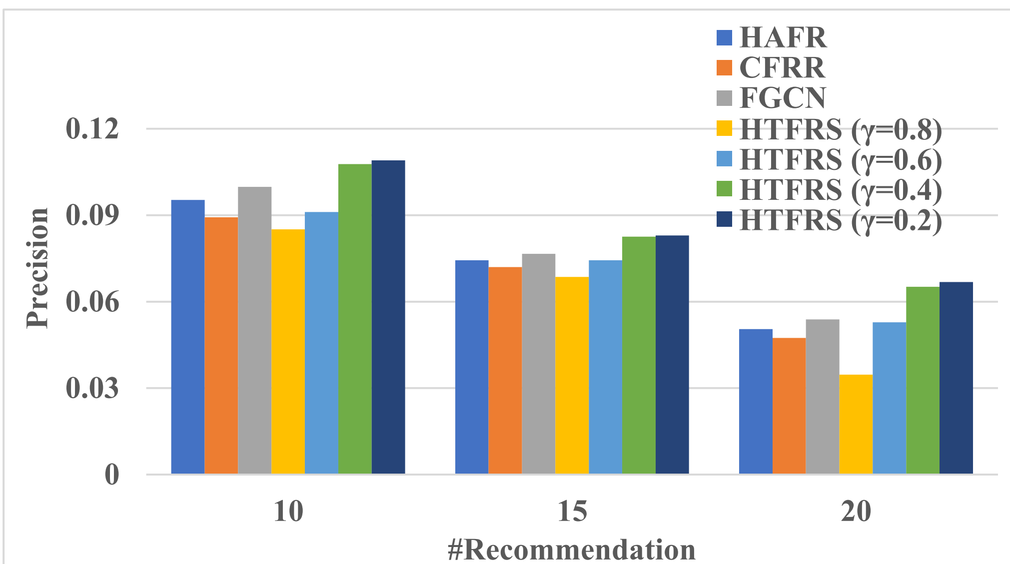
Method	Precision@10	Recall@10	F1@10	AUC	NDCG@10
HAFR	0.0698	0.0672	0.0686	0.6441	0.0452
CFRR	0.0674	0.0648	0.0639	0.6428	0.0437
FGCN	0.0706	0.0682	0.0694	0.6636	0.0466
HTFRS	**0.0732**	**0.0692**	**0.0712**	**0.6878**	**0.0509**

Table 7
Performance of compared food recommender systems in Food.com dataset.

Method	Precision@10	Recall@10	F1@10	AUC	NDCG@10
HAFR	0.0629	0.0612	0.0620	0.5644	0.0430
CFRR	0.0624	0.0608	0.0615	0.5872	0.0428
FGCN	0.0631	0.0615	0.0622	0.5934	0.0431
HTFRS	**0.0654**	**0.0637**	**0.0645**	**0.6149**	**0.0453**



(a) Allrecipes.com dataset



(b) Food.com dataset

Fig. 4. Precision evaluation of the proposed system by ranging the health factor parameter.

root. We carried out this preprocessing phase using Porter's stemming method (Porter) (M. C. Lee, 2011).

4.2. Evaluation measures

In general, the leave-one-out technique was used to evaluate recommender systems by comparing the prediction with the actual rating for each user-food pair. Our experiment compared the efficiency of HTFRS with other recommendation models. We also evaluated HTFRS according to five other well-known criteria: Precision, Recall, F1, AUC, and NDCG.

Precision, recall, and F1-scores are popular in the information-retrieval community. Using a confusion matrix, the foods can be categorized into four groups to calculate these metrics. This matrix assigns the relevant foods to the true positive (TP) and false negative (FN) categories based on the recommendation made by the system as relevant or non-relevant to the user. False positives (FP) are relevant foods recommended incorrectly by the system, and true negatives (TN) are irrelevant foods recommended correctly by the user. Precision is defined as proportion of relevant recommendations to the total number of recommended foods, defined below:

$Precision = \frac{TP}{TP+FP}$(14).

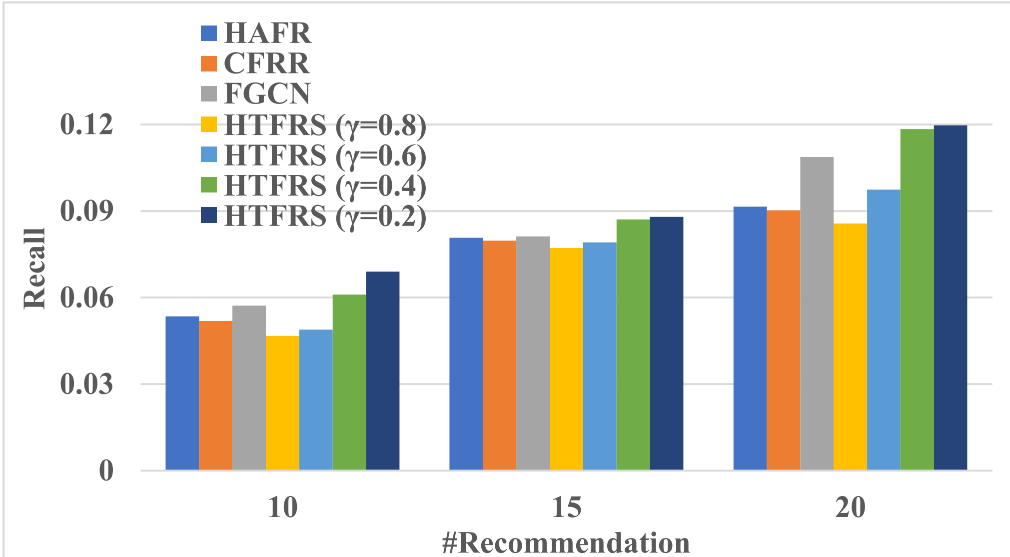
Similarly, the Recall ratio is computed as the number of relevant recommended foods to the total number of available relevant foods:

$Recall = \frac{TP}{TP+FN}$(15).

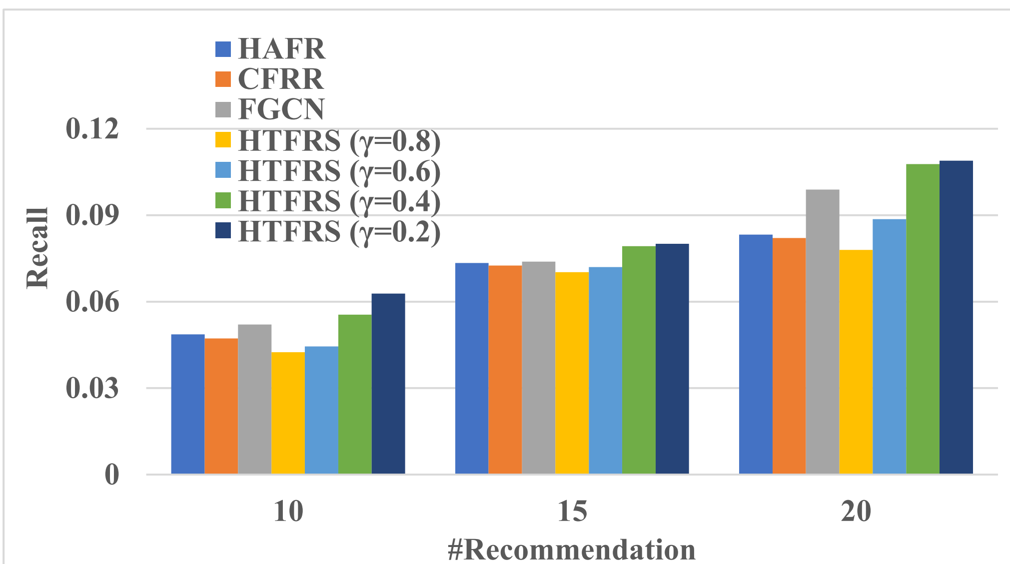
Precision and Recall criteria naturally inherit a clear conflict. With more top recommendations, the number of relevant foods will increase along with the recall measure, while the Precision measure decreases. F1 provides a weighted combination measure by combining Precision and Recall as below:

$F1 = \frac{2\times Precision\times Recall}{Precision+Recall}$(16).

In some cases, the direct evaluation of the Precision or Recall cannot be performed if the ground truth regarding the relevance of a given food is not available (i.e., if the users provide no rating). To address this issue, our experiments used Precision@N, Recall@N and F1@N (where N is the dimension of the recommendation list). The values can be calculated as follows:



(a) Allrecipes.com dataset



(b) Food.com dataset

Fig. 5. Recall evaluation of the proposed system by ranging the health factor parameter.

$Precision@N = \frac{TP}{N}$(17).

$Recall@N = \frac{TP}{|Rel_u|}$(18).

$F1@N = \frac{2\times Precision@N\times Recall@N}{Precision@N+Recall@N}$(19).where Rel_u refers to the number of relevant foods for the user u. In our case, the number of relevant foods is the foods with the actual rating of 4 or 5.

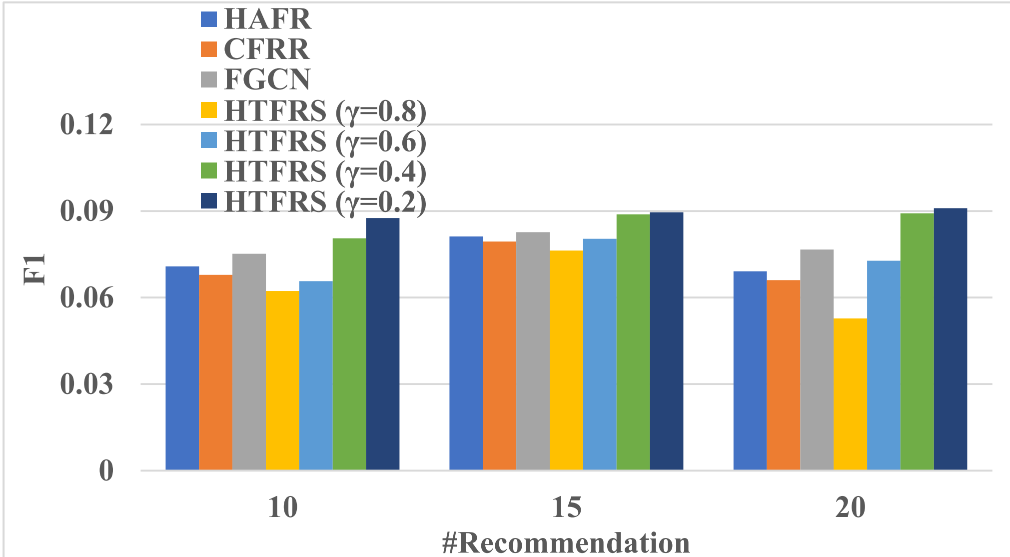
In an ideal recommender system, the ROC curve inclines directly upward to 1.0 recall and zero fallout until all relevant foods have been retrieved. This ultimately maximizes the area under the ROC curve. AUC evaluates the possibility that a prediction model will classify a randomly chosen positive sample higher than a randomly chosen negative sample.

In our experiments, we used the normalized discounted cumulative gain (NDCG), assigning values in the range of 0 to 1. Hits positioned higher on the ranking list were assigned higher values by NDCG. High NDCG values indicated higher relevancy of recommended foods in the first positions of the recommendation list. The next step details the results of our experiment.

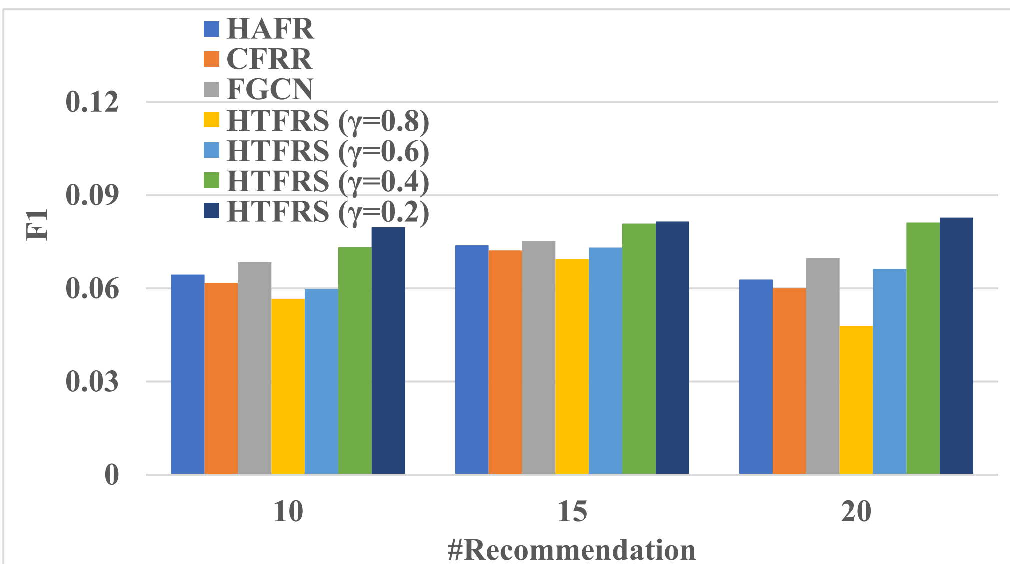
4.3. Results

We designed a variety of experiments to assess the effectiveness of our food recommendation method. First, we evaluated the impact of the two phases of our proposed recommendation model. As shown in Fig. 3, HTFRS was evaluated by considering three scenarios. In the first scenario, the food recommendations were provided based on user-based rating prediction results. The second case related to a model that made food recommendations based only on the food-based rating prediction, and the third case combined these two models. The results shown in Fig. 3 demonstrate that the recommendation approach performs much better when the final ranking is predicted by combining both user-based and food-based cases.

We conducted different experiments to measure the effectiveness of the proposed HTFRS model. In the first part of this comparison, we compared the model's performance to three state-of-the-art food recommendation methods: namely, HAFR (Gao, et al., 2019), CFRR (Chavan, Thoms, & Isaacs, 2021), and FGCN (Gao, et al., 2022) based on Precision, Recall, F1, AUC, and NDCG measures. The characteristics of



(a) Allrecipes.com dataset



(b) Food.com dataset

Fig. 6. F1 evaluation of the proposed system by ranging the health factor parameter.

these compared models are detailed in Table 5.

To implement and tune the hyperparameters of the compared food recommender systems, we employed the following methods and values:

An embedding size of 64 and a batch size of 512 were considered for the HAFR model, and it was optimized using the mini-batch Adagrad (Duchi, Hazan, & Singer, 2011). Furthermore, we examined the learning rate among [0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05] and the regularization term among [0.0001, 0.001, 0.01, 0.1, 1]. Additionally, we found that the HAFR model performed well when the embedding, the image mapping layer and the MLP regularization terms were [0.1, 0.01, 1].

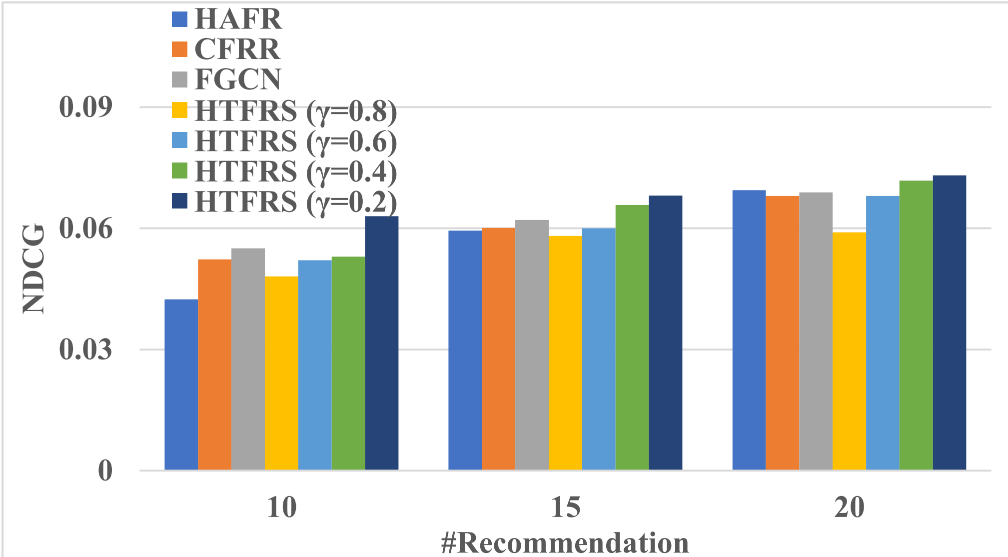
The CFRR can be employed in the recommendation system without altering the internal characteristics of the model since it is parameter-free, scalable, and portable.

Moreover, we used 64 embedding dimensions to implement FGCN. As a result, we also performed a grid search to adjust the hyper-parameters where the learning rate was tuned to [0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05] and where the L_2 coefficient was tuned to [1e6; 1e5; 1e4; 1e3; 1e2; 1e1]. FGCN exhibited the best efficiency when the learning rate was 0.0001 and the coefficient L_2 was 1e4. In addition, the hidden dimensions were [64, 32, 16].

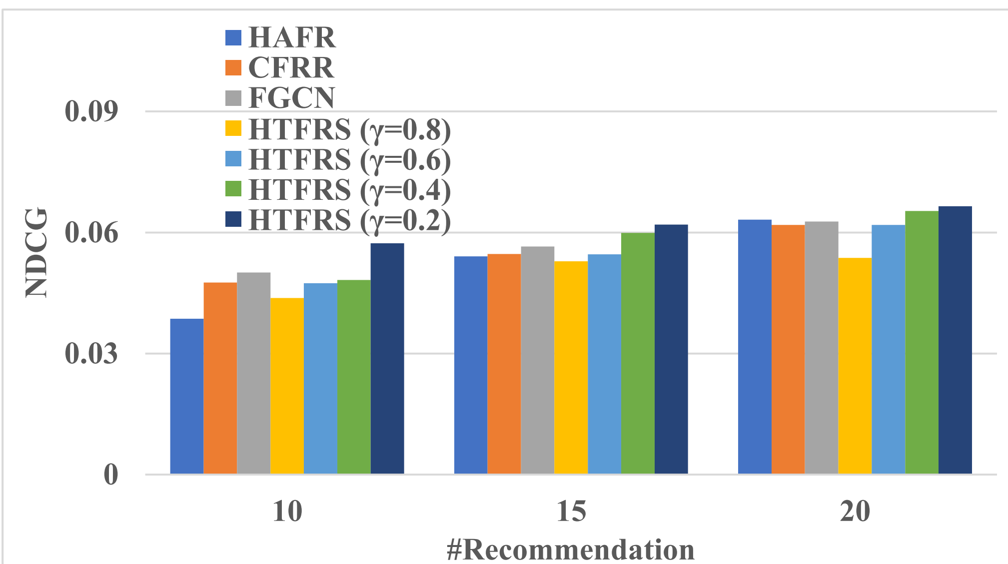
To ensure a fair comparison, the training and testing sets for all the above recommender systems were set the same.

Table 6 and Table 7 show the results of different food recommender systems for the allrecipes.com and Food.com datasets, respectively. According to the reported results of these tables, our proposed food recommender system (i.e., HTFRS) achieved the highest Precision, Recall, F1, AUC, and NDCG values when compared to the alternative state-of-the-art models. It should be noted that in these experiments, the γ parameter of the proposed system that controls the food health factors of recommendations was set to 0.2. The discussion of this parameter setting is further investigated in the sensitivity section of this paper.

In order to assess the ranking efficiency of the developed model, Figs. 4-7 show the results of the top-N evaluation metrics where ranking positions ranged from 10 to 20 and the health-factor γ ranged from 0.2 to 0.8. When the health factor was set to the lowest value ($\gamma = 0.2$), the performance of our proposed food recommendation model was higher than that of other models in terms of Precision, Recall, F1, AUC, and



(a) Allrecipes.com dataset



(b) Food.com dataset

Fig. 7. NDCG evaluation of the proposed system by ranging the health factor parameter.

NDCG criteria. Hence, the reported results clearly demonstrate that the developed model increases representation learning efficiently. Additionally, these figures demonstrate that the proposed method performs less effectively when the health factor parameter is set to a high value. This is because in this case, the suggestion of healthy food is more important than the user's preferences.

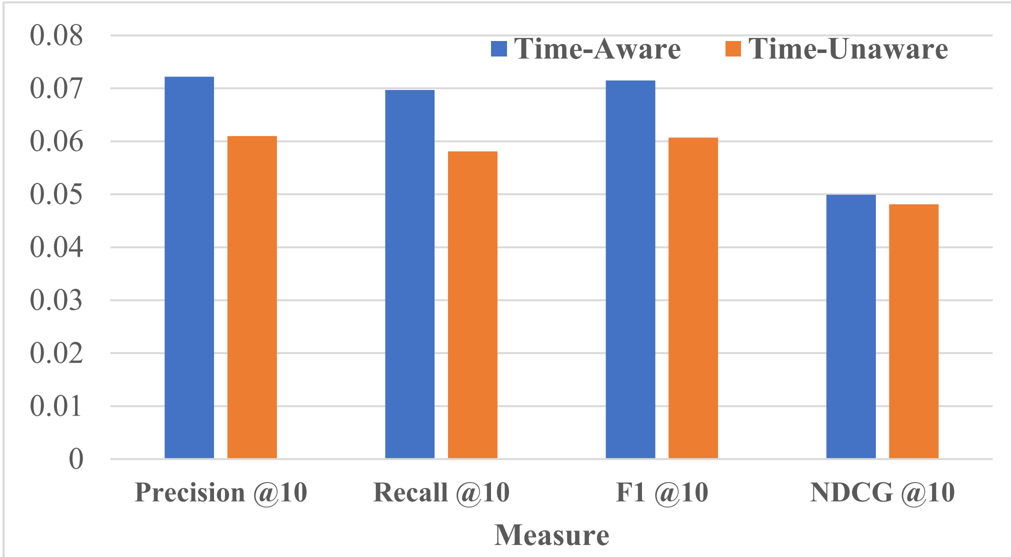
4.4. Ablation study

This subsection examines the HTFRS system's contributions by designing an ablation study. It should be noted that HTFRS provides three main contributions: considering the time factor by defining a time-aware user-similarity calculation, introducing a novel ingredient-aware food similarity measure, and developing a novel attributed community-detection algorithm for food clustering. By examining each provided contribution, the performed ablation study could help demonstrate performance improvement. We disregarded each contribution of the proposed FRSHR system and compared the obtained model to the original version of HTFRS to investigate the effect of each contribution on performance improvement.

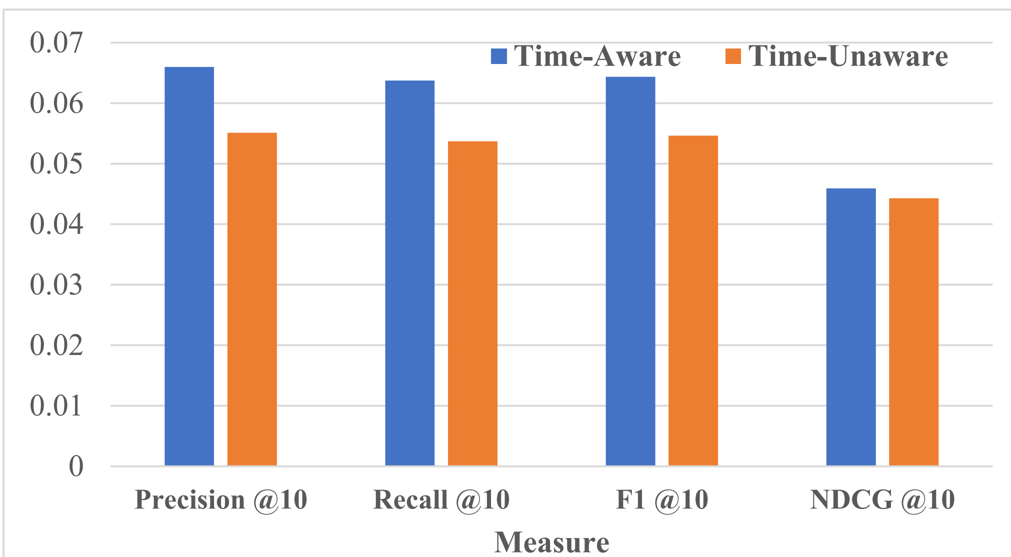
In the first experiment, we examined the effect of the time factor on the quality of predictions. Fig. 8 compares the case where the developed recommender system considered the time factor with the case where the time factor was ignored. The reported results show that the developed time-aware food recommendation model achieves better predictions than those models that ignore the time factor. Furthermore, this experiment showed that on average, the Precision@10, Recall@10, F1@10, and NDCG@10 improved by 15.51%, 16.64%, 15.10%, and 23.64%, respectively, when time was considered as opposed to ignored.

Fig. 9 shows the results of comparing the original version of the developed food recommender system with the model obtained by ignoring ingredients. These results demonstrate that the proposed ingredient-aware food recommender system significantly increases the performance of HTFRS across all evaluation measures. Therefore, the ingredient-aware recommender system benefits HTFRS in terms of all performance metrics.

Finally, in the last experiment, we examined the effect of our developed attributed community detection algorithm. Fig. 10 compares



(a) Allrecipes.com dataset



(b) Food.com dataset

Fig. 8. Evaluation of the Time awareness in final recommendation.

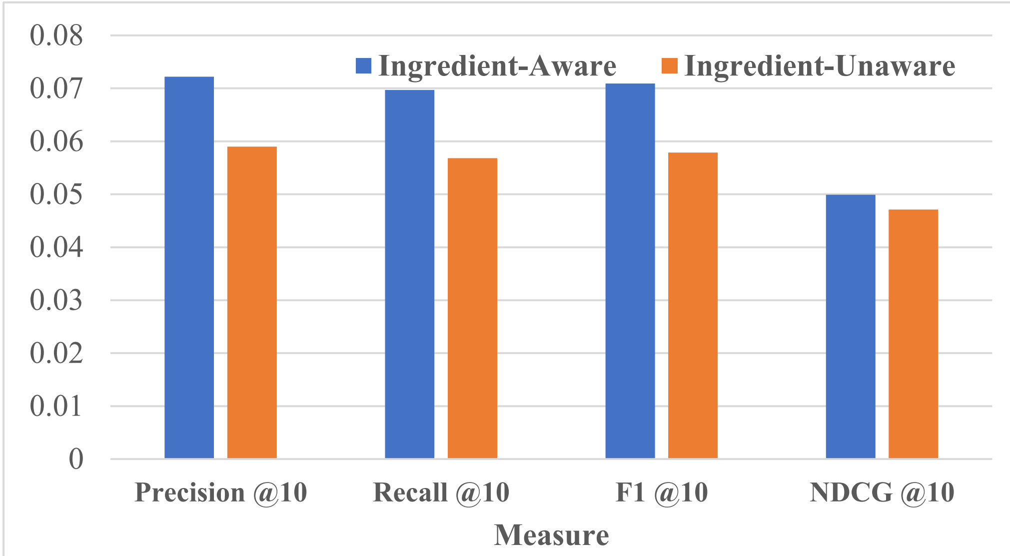
the case that employed our algorithm with the case that employed standard non-attributed LPA community detection (i.e., ignored the ingredients of foods). The results indicate that the developed attributed community-detection-based model achieves better predictions than the attributed community-detection food-clustering algorithm. Furthermore, this experiment showed that on average, the Precision@10, Recall@10, F1@10, and NDCG@10 improved by 20.83%, 21.01%, 18.95%, and 13.15%, respectively, when attributed community detection was employed as opposed to non-attributed community detection.

4.5. Sensitivity analysis

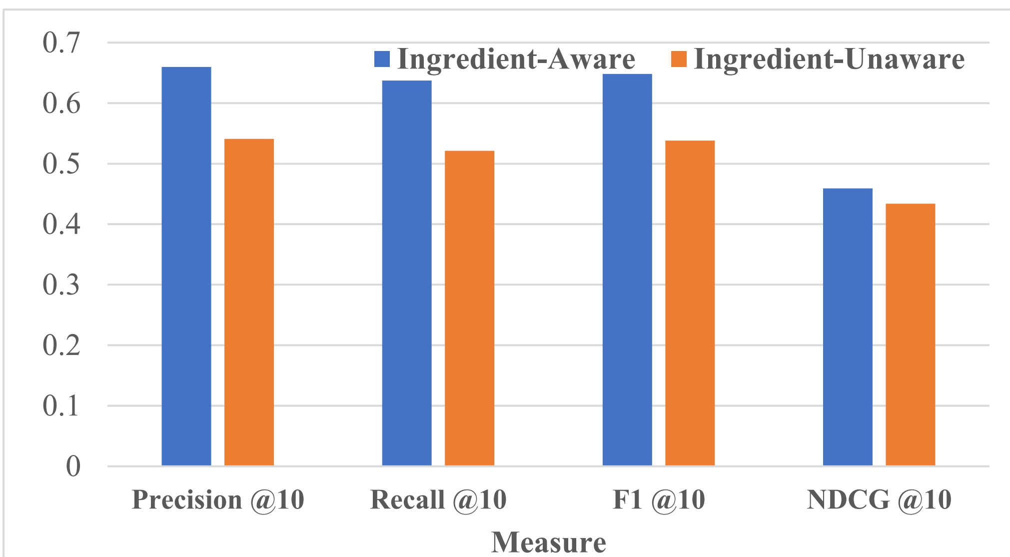
Like many recommender systems, HTFRS also needs its input parameters to be adjusted. It includes three parameters: time weight (λ), user-based/food-based control (β), and health factor (γ).

To measure the impact of the λ parameter on the efficiency of our developed model, we first needed to determine the impact of the time factor on the similarity calculation. Note that λ can be initialized with a value between 0 and ∞, where a high λ value denotes a greater impact of the time factor on similarity calculations. Conversely, a lower λ value results in the time factor having a diminished effect. In Fig. 11, we present the sensitivity analysis of λ. The results evaluate HTFRS in terms of Precision@10, Recall-10, F1@10 and NDCG@10 for various λ within the range of [0.5, 4]. In most cases, setting the time-weight parameter to 2.5 improved the efficiency of the food recommendation model.

Moreover, we designed different experiments to show how various values of the user-based/food-based weight parameter (i.e., β) would affect the performance. The β parameter ensures a tradeoff between collaborative filtering and the food-based part of rating prediction. It is adjusted to a value in the range between 0 and 1. When the β parameter is tuned to a value close to 1 (resp. 0), the collaborative-filtering term becomes more significant (resp. less significant). If this parameter is tuned to a value close to zero, the food-based terms will have a greater impact. Fig. 12 shows an analysis of β parameter sensitivity. We examined various β values to determine the performance of the developed food recommendation on the Precision@10, Recall@10, F1@10 and NDCG@10 measures. The results indicate that in most cases, HTFRS achieved the best performance when the β was set to 0.6.



(a) Allrecipes.com dataset



(b) Food.com dataset

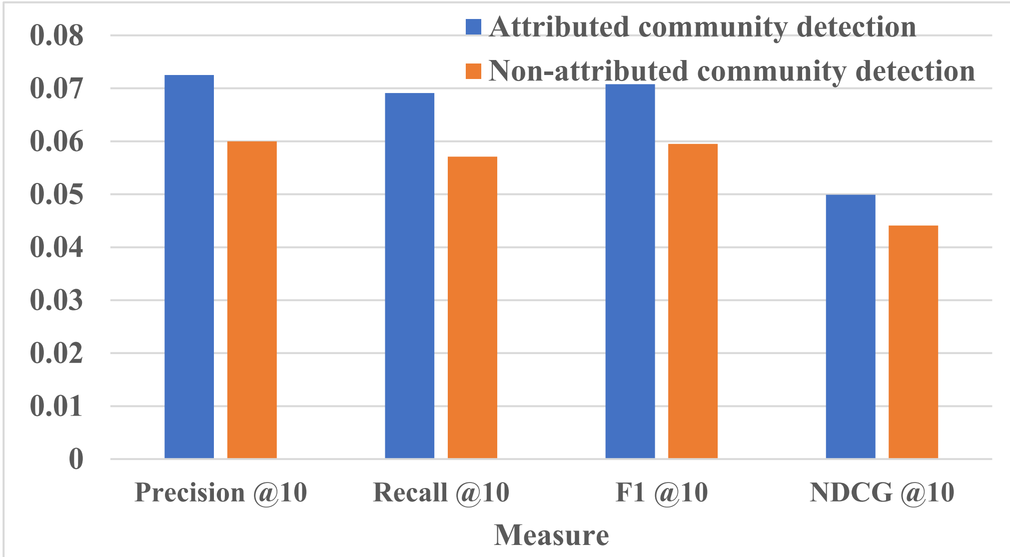
Fig. 9. Evaluation of the Ingredient awareness in final recommendation.

In the last part of the sensitivity analysis, we investigated the effects of the health factor (γ). Healthy foods are considered more strongly for final recommendations when this parameter is set close to 1. On the other hand, when this factor is set to 0, only the user's preferences are considered in the final food recommendation. Overall, the performance of the developed system decreases as the health factor's effect on the final recommendations increases. This is because in most cases, people tend to eat and review unhealthy foods. Therefore, recommending healthy foods to them will affect the final performance of the recommendation system. Fig. 13 illustrates the sensitivity analysis of the γ parameter. The results show that increasing the value of the health-factor parameter from 0 to 0.8 reduced the HTFRS in terms of Precision@10, Recall-10, F1@10 and NDCG@10 by 52.67%, 63.89%, 45.58%, and 39.61%, respectively.

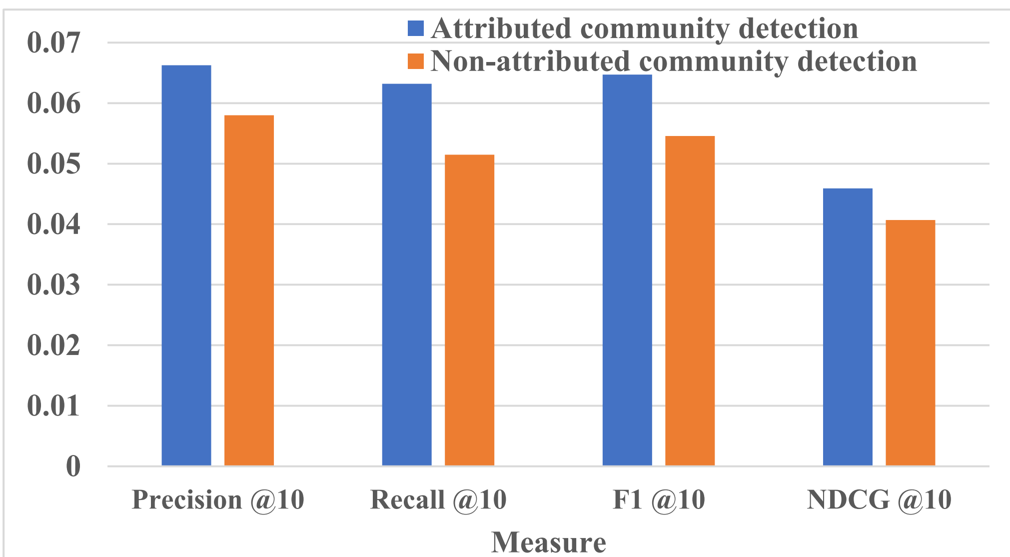
4.6. Statistical analysis

In this statistical analysis, we tested the experimental results to determine their statistically significance based on a relevant theoretical framework. The Friedman test is a well-known technique for conducting statistical analyses since it provides nonparametric approach to measure statistical differences among results obtained by models used in the datasets (Friedman, 1940). The purpose of this test is to determine if there is a significant difference between different models based on the used criteria and datasets. For this reason, the models should be sorted in descending order based on the values of each dataset, with the highest-performing model at the top and the lowest-performing the model at the bottom. A hypothesis H0 (null hypothesis) is drawn from the similarity between the average ranks among groups in this test. The null hypothesis is rejected if there are significant differences between at least two groups. In this way, if the p-value exceeds the significance level of alpha = 0.05, then the null hypothesis is accepted; otherwise, it is rejected.

Tables 8 presents the average obtained ranking for different recommender systems on these two datasets. The results of Table 8 indicated that the developed model had the best average ranking. Moreover, Table 9 denotes a p-value of 0.0018 and 0.0028 for the different performance measures on allrecipes.com and food.com, respectively. Since these values are below 0.05, we can conclude that the results of the



(a) Allrecipes.com dataset



(b) Food.com dataset

Fig. 10. Evaluation of the attributed community detection algorithm in final recommendation.

recommendation model were significantly different from those of other techniques.

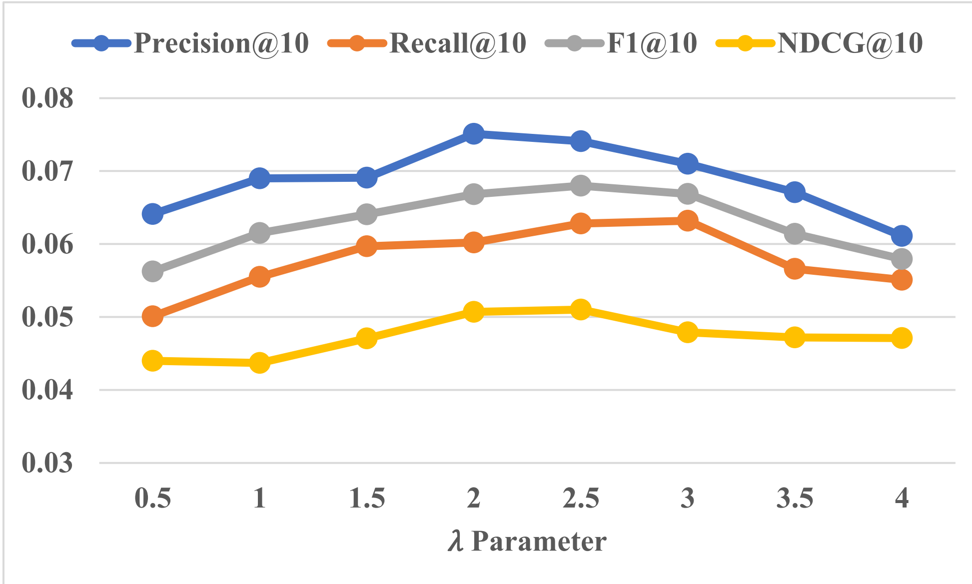
4.7. Analysis and discussion

In this study, our team developed and evaluated a novel food recommender system based on crawled user ratings and recorded food information from allrecipes.com and food.com, two food social networks. According to the experimental results, our model's performance metrics were remarkably higher than the recently implemented food recommendation models (Tables 6 and 7). The results show that our time-aware food recommender system outperformed the baseline model (i.e., FGCN) in terms of precision, recall, F1, AUC, and NDCG by approximately 3.66%, 3.41%, 3.13%, 3.63%, and 4.86%, respectively. The major reason for the superiority of our model is that in contrast to the baseline model that ignores the time factor of historical user ratings, our model is a time-aware food recommender system that addresses changes in users' food preferences, diets, or lifestyles over time, which are common in real-life situations. Moreover, in contrast to the baseline model, which did not address the data sparsity or cold-start problem, our developed model utilized food group information to improve its final performance.

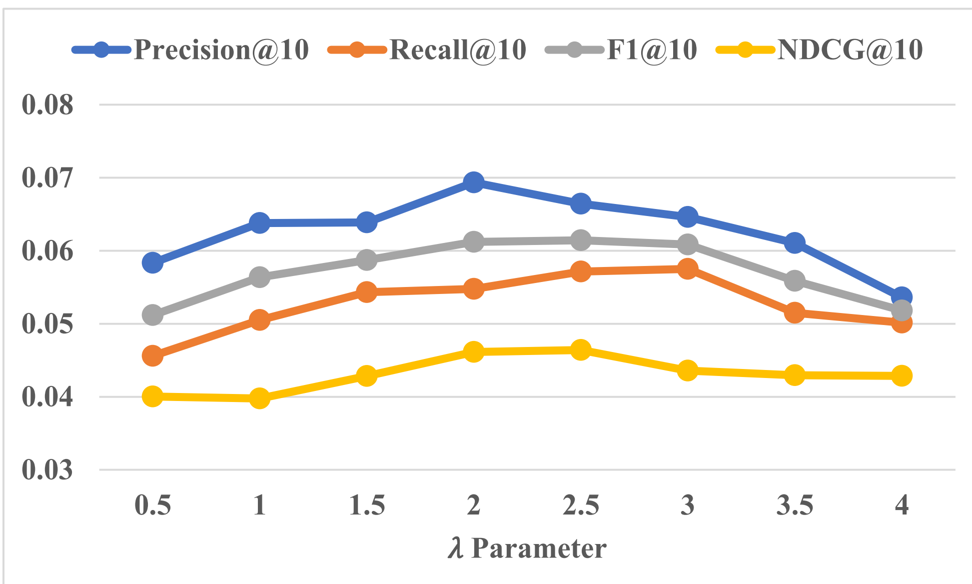
The proposed model predicted the user rating by incorporating two different components: time-aware collaborative filtering and food ingredient-based rating prediction. In our experiments, we evaluated the impact of these two parts of the recommender system. According to the results, the performance of the developed hybrid food recommendation was about 14.84% more effective than that of the case where only collaborative filtering was used. Additionally, our model was about 8.38% more efficient than the case where only the food ingredient-based rating prediction was used (Fig. 4).

Additionally, we found that considering the time factor of ratings improved the final performance of the proposed system by an average of 14.96 % compared with ignoring the time factor (Fig. 9).

Our HTFRS model performs better than other food recommender systems due to the following key innovations:



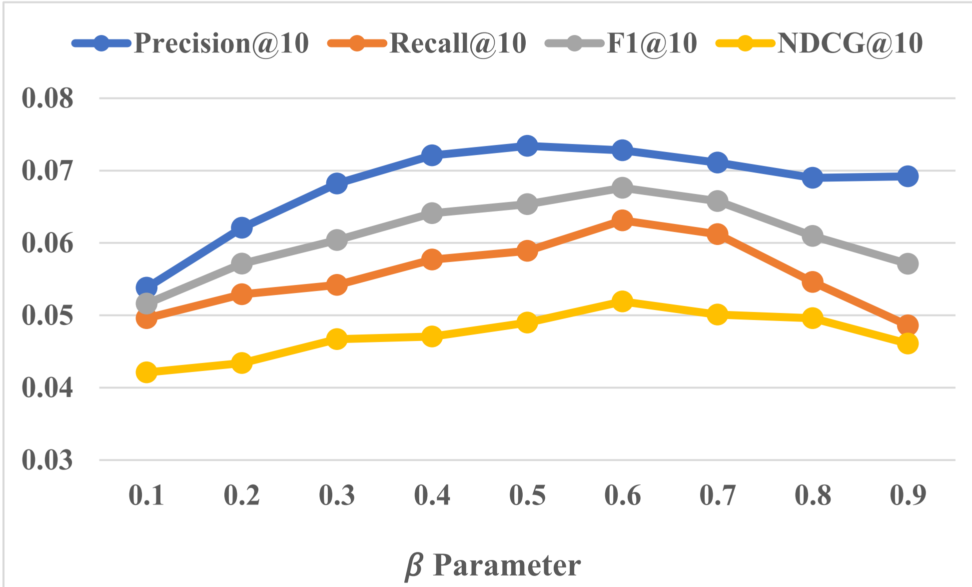
(a) Allrecipes.com dataset



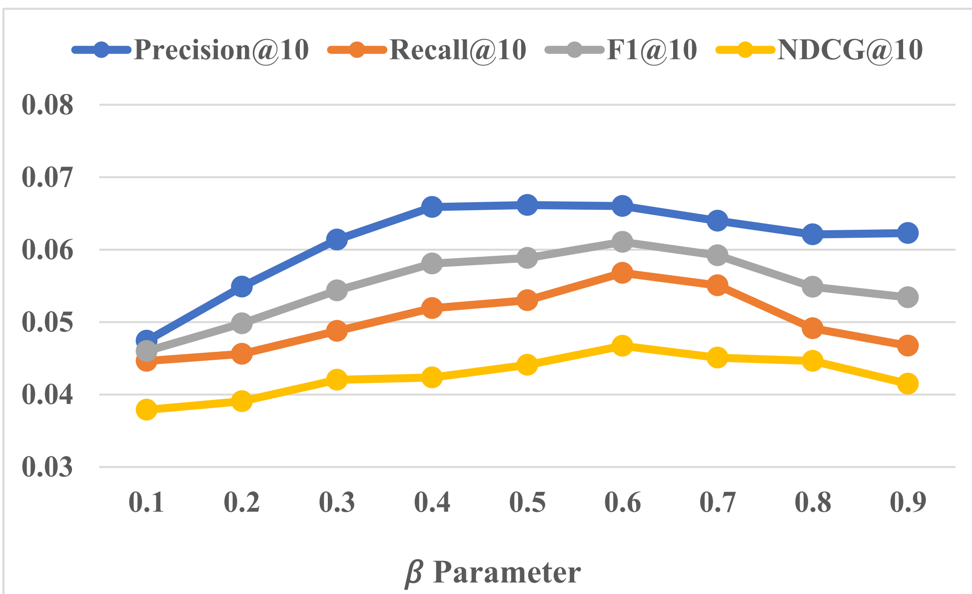
(b) Food.com dataset

Fig. 11. Sensitivity analysis of λ parameter.

- People generally choose a specific food because it contains ingredients that they enjoy eating. This tendency affects the final performance of food recommendation systems that only employ user ratings and do not consider food content. Most previous food recommendations, such as CPRR, ignore food ingredients, making them ineffective at learning user preferences and recommending favorite foods. Therefore, food recommendation platforms must consider ingredients when making recommendations. Our model explicitly considers user ratings and food ingredients when recommending foods. Our system recommends foods based on a target user's tastes and preferences as well as on their rating history.
- Prior recommender systems, including HAFR, CPRR, and FGCN, have ignored the time factor of historical user ratings. An efficient food recommender system must consider the fact that users' preferences, including their diets and tastes, may change over time in realistic scenarios. The other food recommender systems that we compared (i.e., HAFR, CPRR, and FGCN) ignore the time factor of user ratings, making them ineffective when user tastes and preferences change over time. In this study, our team developed a novel time-aware similarity metric that considers changes in dietary preferences over time. This metric gives our developed recommender system an edge with respect to other recommender systems, which often disregard the time factor.
- Cold start and data sparsity are significant issues in recommender systems, especially in food recommender systems, where users often only rate a few foods. To overcome this issue, we developed a novel community-detection algorithm that takes advantage of clustering-based techniques (i.e., food similarity measures based on food ingredients). To the best of our knowledge, this is the first study to represent food items as attributed social networks in food recommender systems. In a food recommender system, grouping foods and considering food groups are critical tasks because when a user likes a



(a) Allrecipes.com dataset

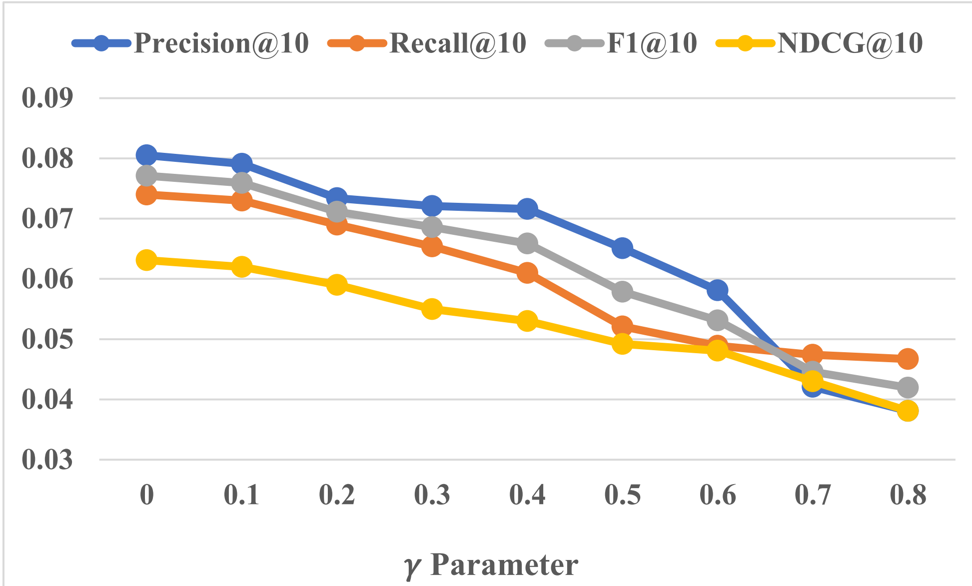


(b) Food.com dataset

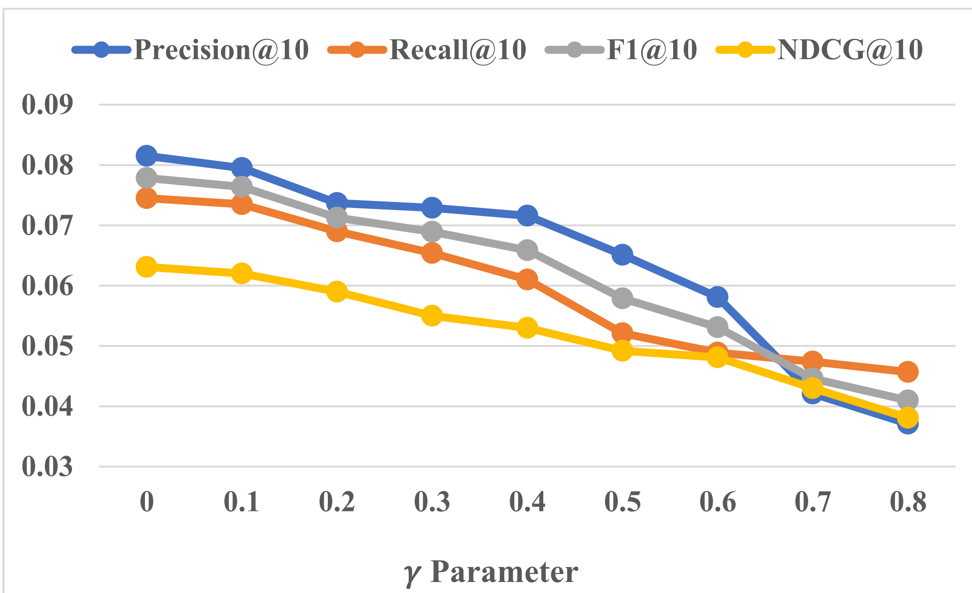
Fig. 12. Sensitivity analysis of β parameter.

particular food, they will usually be interested in similar foods. Our developed model explicitly incorporates food-group information, in contrast to previous systems (i.e., HAFR, CPRR, and FGCN) that ignore it. Our model employs attributed community-detection-based food clustering to address the cold-start problem by leveraging knowledge stored outside of the user's ratings. Moreover, in the developed attributed community-detection algorithm, we employed an improved version of $tf-isf$ term weighting measure for attribute (i.e., ingredient) weighting. The final performance of the food clustering has therefore been improved where the number of food groups is determined automatically.

- Many previous recommender systems, including HAFR and FGCN, only recommend foods that match users' preferences without considering how healthy or nutritious these foods may be. Because of this limitation, these systems cannot help people adopt a healthy lifestyle or follow a healthy diet. This paper overcomes this shortcoming by including health and nutrition factors in the food recommendation framework so that users can be guided towards a healthier lifestyle. The CFRR method considers the calories of each food when recommending healthy foods; however, considering calories is insufficient in determining whether each food is healthy or unhealthy. Our developed health-aware food recommender system assesses the healthiness of foods by considering their protein, fat, and carbohydrate macronutrients as well as their energy contribution, which is also one of the newest criteria approved by the WHO. As a result, we expect that our developed system will recommend healthier foods than the CFRR method.
- Our analysis of all foods in the Allrecipies.com and Food.com datasets shows that the most popular and the most highly rated foods are the unhealthiest foods. In other words, the foods that are interacted with most often and rated highest tend to be unhealthier, which is concerning because these recipes are most likely to be cooked and eaten.



(a) Allrecipes.com dataset



(b) Food.com dataset

Fig. 13. Sensitivity analysis of γ parameter.

Table 8
Average ranks of the different recommender systems based on Allrecipes.com and Food.com.

Dataset	HAFR	CFRR	FGCN	HTFRS
Allrecipes.com	3	4	2	1
Food.com	3.2	3.8	2	1

Table 9
The results of the Friedman test for two used datasets.

Dataset	χ2	P-value
Allrecipes.com	15.000	0.0018
Food.com	14.040	0.0028

Therefore, healthy food recommendations to the user can result in a low performance, which aligns with our experimental results and sensitivity analysis of the health factor (γ) parameter (Fig. 13).

Even though our developed system already outperforms several state-of-the-art food recommendation models, as demonstrated in the results section, the question remains as to whether it can be improved even further:

- In the absence of compelling explanations behind healthy food recommendations or recommendations involving foods that a given user enjoys (omitted due to their unhealthy nature), the user may hesitate to try healthy foods and be discouraged from following the recommendation system's guidelines. Personalized and balanced food recommendation outcomes can be achieved by balancing food health factors and preference factors. Future food recommender systems should therefore provide the user with an explanation of why a given food was recommended or why other foods that might be of interest to them were not recommended. Therefore, explainable healthy food recommendations can be considered a new research topic in future works to provide additional feedback.

- In this study, we used the data from allrecipes.com and Food.com's websites to evaluate the systems' performances. According to an analysis of the visitors of allrecipes.com, over 85% live in North America even though this website is one of the largest food social networks. Therefore, evaluating our model using data from sites hosted by other countries with a strong food culture could bias our results to some extent. We plan to crawl other food social networks and to analyze diet styles in different cultures and countries to compensate for this shortcoming.
- Our developed recommendation system as well as most of the previous models typically ignore user characteristics (e.g., age, height, weight, gender, location, allergies, medical history, etc.) and only consider food content or user ratings when recommending foods to a user. A food recommendation system should consider a person's user characteristics when generating recommendations because nutritional requirements vary significantly based on one's profile. Additional information about users will be incorporated into the food recommendation framework in future research.
- This paper and previous studies have focused on increasing the accuracy of recommendations to improve the health of the recommended foods. When accuracy is overemphasized, recommendations may be inappropriate, which may lead to over-fitting. We plan to utilize novelty and diversity in future works to solve the over-fitting problem as well as to increase the quality of the user's experience with the recommender system.
- In real-world food recommendation models, user-food ratings are very noisy. Previous research (D. Li, et al., 2019) has shown that only about 60% of user ratings remain the same when users are asked to rate items again, indicating that many ratings do not accurately reflect user preferences. Therefore, generating a recommendation model with these noisy data will result in low generalization performances. Therefore, in future research, we intend to focus on addressing noisy data problems in recommender systems.

5. Conclusion

Friends who have dinner together may use food-related apps to discover what to eat or to share their experiences on social media. Because food plays such a significant role in people's lives, many hail it as a means of influencing people towards a healthier lifestyle. Therefore, food recommendation systems play an important role in a range of lifestyle applications, and they are a vital component of many lifestyle services. In order to build an effective food recommendation system, it is crucial to accurately understand a user's food preferences. Such systems are typically generated through machine-learning algorithms. Some previous food recommendation systems are not able to guarantee the health of the foods they recommend since they do not consider health or nutrition factors. In other words, most of the previous recommendation systems have only recommended foods that match the user's preferences without attempting to recommend healthy foods. To guide users to a healthier eating style, this paper integrates health and nutrition factors into the food recommendation model. This study introduces a novel health-aware food recommendation model that utilizes users' preferences and the nutritional information of the foods. The Healthy and Time-aware Food Recommender System predicts the desirable foods in two phases: (1) time-aware collaborative-based rating prediction, and (2) food ingredient-based rating prediction. In the first phase, the system predicts the user-based ratings using historical ratings. In the second phase, the system groups initial foods into several clusters using a novel attributed community-detection algorithm. Considering these two components, the unrated foods are predicted accordingly. After calculating the final rating prediction and considering the nutritional content (protein, fat, and carbohydrates) of the foods, the system recommends the top-N healthy and favorable foods. Compared to the latest proposed food recommender systems, including HAFR, CFRR, and FGCN, the proposed model was evaluated in terms of precision, recall, F1, AUC, and NDCG. The results show that our food recommendation model achieved the highest efficiency and outperformed the existing food recommender systems by a significant margin.

CRediT authorship contribution statement

Mehrdad Rostami: Conceptualization, Methodology, Investigation, Formal analysis, Writing – review & editing. **Vahid Farrahi:** Writing – review & editing, Supervision. **Sajad Ahmadian:** Writing – review & editing, Methodology. **Seyed Mohammad Jafar Jalali:** Formal analysis, Writing – review & editing. **Mourad Oussalah:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

Data availability

Data will be made available on request

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Data availability
Data will be made available on request

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