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Review Article

Food Recommender System: Methods, Challenges, and Future Research Directions

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***Abstract** - In recent years, the food recommender system has drawn attention to the growing need for individualized meal recommendations, dietary planning, and restaurant recommendations. The food recommender system has become increasingly important in a digital world, allowing users to select food dishes based on their preferences, dietary restrictions, and contextual factors. The demand for personalized food recommendations increased significantly with the increasing popularity of digital food delivery services and restaurant recommendation platforms. The recommendation system utilized many machine learning algorithms and various artificial intelligence techniques for mining and analysing food attributes and user preferences from past ordered and contextual factors to recommend relevant recommendations. This paper aims to inspect different food recommender system types, such as Content-Based Filtering, Collaborative Filtering, and Hybrid Filtering Models. It also explores the key challenges inherent in the food recommender system, such as sparse data, the cold start issue, cultural problems, and nutritional quality. The paper also focuses on new developments and possible options for future study, including explainable AI, multi-model data fusion, and the integration of health considerations into recommendation models. Additionally, it identifies research gaps and presents the integration of explainable AI, multimodal learning, and health-aware recommendations to further enhance the effectiveness of food recommendation systems. By addressing these challenges and exploring emerging technologies, this study aims to pave the way for more accurate, transparent, and user-centric food recommendation models. It also provides a comprehensive understanding of food recommender systems and their role in enhancing user experience, health-conscious eating, and personalized dining choices.*

***Keywords** - Collaborative Filtering, Content-Based Filtering, Hybrid Filtering, Memory Based Filtering Technique, Model-Based Filtering Technique, Recommender System.*

1. Introduction

Food has always been essential to human existence. The only physical substance that humans consume, aside from the oxygen we breathe, is food. Finding and collecting food was a challenge for early people in order to survive [1]. A Recommendation System (RS) is a tool that assists people in narrowing down a large list of products to a select few that they may find appealing. People find RSs more appealing when they are overloaded with information [2]. In the era of artificial intelligence and data-driven decision-making, recommender systems are now essential to various industries, including entertainment, e-commerce entertainment, and healthcare. Among these, food recommender systems emerged as a crucial domain, aiming to improve user experience by serving personalized meals and restaurant suggestions. With the increasing variety of food choices available in restaurants, grocery stores, and online food delivery platforms, users often struggle to identify meals that align with their taste preferences, health goals, and dietary restrictions. Food reviews and recommendations play a crucial role in online food service websites, but the process is complex due to varying contexts and meanings similar to product reviews on e-commerce platforms; food reviews are widely available on platforms like HungryGoWhere, Burpple, and Quandoo, offering valuable insights for food lovers based on the experiences of previous restaurant patrons [3]. Food Recommendation technologies explore key methodologies, including content-based filtering, collaborative filtering, hybrid models, and deep learning approaches for recommendations. Traditional collaborative filtering often struggles with cold start issues and sparse data, which GNNs mitigate by capturing complex relationships between users and movies through graph embedding [4]. The Content-based System takes advantage of situations when objects are defined using a descriptive collection of attributes. In these situations, user can find relevant recommendations using their own ratings and activities on other films. When the item is new, and there are not many ratings, this method is quite helpful. When a substantial amount of attribute information is readily available, content-based systems are frequently utilized.

These characteristics are frequently keywords extracted from product descriptions. Actually, text attributes are extracted from the underlying objects by the great majority of content-based systems. Therefore, Content-Based systems are especially ideal for making suggestions in unstructured and text-rich environments [5]. Recommender systems, which depend on content, attempt to pair consumers with products that are comparable to what they have previously enjoyed.

This resemblance depends on the characteristics of food items that users like rather than necessarily on rating correlations across users. Collaborative filtering is a prevalent approach in recommender systems that leverages user-item interactions to suggest relevant items. There are two Collaborative Filtering approaches: memory-based, which computes similarities directly from user-item interaction data, and model-based, which utilizes machine learning methods to predict user preference [6].

In [7], it is demonstrated that GNN-based models improve recommendation accuracy by leveraging user-item interaction data, and experimental results indicate superior performance compared to conventional recommendation algorithms, highlighting the effectiveness of GNNs in personalized movie recommendations. Food recommender systems have become increasingly important in enhancing user experience, promoting healthy eating habits, and optimizing food choices in digital platforms. With the quick improvement in deep learning, machine learning and in artificial intelligence various techniques have been applied to improve recommendation accuracy and personalization. However, challenges as sparse data, cold start problems, user preference diversity and the need for explainable AI still persist.

Despite significant advancements in food recommender systems, several research gaps remain unaddressed. Many Existing studies depend upon Collaborative Filtering or may be on a hybrid approach and have a limited focus on pure Content-Based Filtering models for personalized Recommendation Systems. Most Recommendation Systems struggle to enhance precision and high recall but a low relevant recommendation.Moreover, many models focus on individual users rather to focus on group food recommendations and collective decision-making scenarios that are scarce. The demand for intelligent and personalized food recommendations has focused on future research in Recommender Systems. This paper aims to bridge these gaps by exploring existing approaches, focusing on their limitations, and examining future research directions that enhance personalization recommendation systems in terms of user satisfaction and accuracy.

Recent research in the food domain for recommendations mainly depends on Collaborative Filtering (CF) and its hybrid models. To achieve satisfactory performance, these methods face many problems, such as data sparsity, cold-start issues, and limited modelling of the diversity of user behaviour. Additionally, Content-Based Filtering (CBF), which can be highly successful when rich descriptive metadata or textual reviews are available, has not been fully investigated in the context of food recommendations.

Previous research has thoroughly studied Collaborative filtering and hybrid filtering models; however, a thorough examination of content-based methods, multimodal learning, and explainability in food recommendations is still lacking. Furthermore, to improve the performance of recommendations, few examinations utilize contextual signals such as time, location, textual qualities, or nutritional data. User pleasure and customization are so constrained.

The author aims to provide a comprehensive understanding of various machine-learning approaches used in food recommendation systems, such as content-based, Collaborative Filtering, and Hybrid models. The author analyzes their effectiveness and highlights existing challenges, with a focus on future research to enhance personalized and context-aware food recommendations.

This paper fills these gaps by providing a detailed and comparative analysis of machine learning-based food recommendation methods, including content-based, collaborative, and hybrid models. The objectives include:

- To analyse and categorize different types of food item recommender systems.
- To examine the role of machine learning techniques in improving recommendation accuracy.
- To explore new developments and potential avenues for further study, including multimodal learning, context-aware recommendations, and nutrition-focused models.
- To provide observations for scholars and professionals in developing more scalable, effective and intelligent food recommender systems.

This paper makes the following key contribution to the field of recommender systems.

- The main contribution is to provide a comprehensive analysis of different machine-learning approaches and a detailed examination of various machine-learning techniques that are used in food recommendation.
- Identification of challenges and limitations of different recommendation systems like sparse data, cold start issues, and dynamic user preferences.
- Explore emerging trends and future directions, such as advancements in food recommender systems.

The paper layout is as follows: Theoretical background and techniques used to describe in Section 2. The workflow of the Recommender System, comprising data collection, preprocessing, the technique used, and evaluation parameters, is mentioned in detail in Section 3.

A thorough literature analysis of current food recommender systems and findings from the literature review is discussed in Section 4.

The Challenges in the recommender system are mentioned in Section 5. The research finding is highlighted in Section 6.

Future study suggestions are provided in Section 7, highlighting the potential for additional innovation and improvement in food recommender systems. The conclusion is given in Section 8.

2. Theoretical Background

Recommender systems strive to tailor online experiences by employing a diverse range of methodologies. At their core, these systems analyze user behavior and item attributes to predict preferences. Recommender systems employ various methods to provide personalized suggestions. Figure 1 shows the recommender techniques to understand the recommender system better.

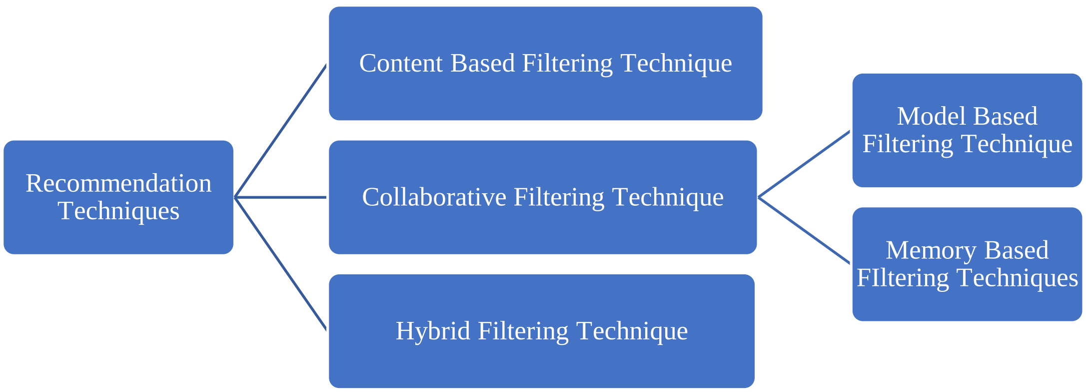

Fig. 1 Types of recommendation techniques

2.1. Different Recommendation Techniques

2.1.1. Content-Based Filtering Technique

Depending on the item description and user profile, the Content-Based Recommendation model suggests products to users. Recommendations for websites, news, restaurants, TV shows, and products for selling are just a few of the many applications for Content-Based Recommendation Systems.

Although specifics of different systems vary, Content-Based Recommendation Systems all have a way to describe the kinds of things that could be suggested, a way to build a user profile that outlines the kinds of things the user enjoys, and a way to compare items for the user in order to decide what would be recommend. Frequently, the profile generation and updating are done automatically according to user feedback regarding the appeal of the products they are shown [8]. Content-based filtering can be analyzing food attributes such as ingredients, cuisine type, and nutritional information. However, a major limitation is the lack of variety in recommendations, as users often receive similar suggestions.

2.1.2. Collaborative Filtering Technique

The Collaborative Filtering Model produces recommendations based on relationships and similarities between users and items. These relationships depend on how users interact with the system that manages items or goods [9]. Collaborative filtering is a method of filtering items based on reviews from people. The collaborative filtering approach gets together the reviews of large connected communities with the web and supports the filtering of many more data. This method has also been used for little more than a decade, and Collaborative Filtering stems from a practice that humans have engaged in for centuries – exchanging opinions with one another [10].

Two important categories regarding the collaborative filtering technique are memory-based and model-based techniques. In the memory-based technique, data of the previous user is maintained and based on some calculations each time a new item recommendation is needed; in the model-based technique, the same data is maintained, but firstly, a description of the model is developed using this data and then this data used to make recommendations for user[11].

2.1.3. Hybrid Filtering Technique

Hybrid Recommender Model merges Content-Based Filtering and Collaborative Filtering Algorithms to get the output. As compared to Content-Based Filtering and Collaborative Filtering Techniques, Hybrid Recommender System recommendation accuracy is higher. The main reason behind this is the lack of data regarding food domain dependences in Collaborative Filtering and the user preferences of Content-Based Filtering. The concatenation of both techniques leads to increased knowledge, which leads to better recommendations. The increased knowledge leads to exploring new ways to enhance the strength of the Collaborative Filtering algorithm by incorporating content data and content-based algorithms that take into account user behavior [12]. Table 1 describes the trade-offs between all the recommendation models, including Content-Based Filtering, Collaborative Filtering, and Hybrid Filtering Techniques. It also includes the use case of different techniques.

Table 1. Trade-offs between recommendation techniques

Recommendation Technique	Strengths	Weaknesses	Use Cases
Content-Based Filtering	– Personalized recommendations that depend on user preferences. – No need for extensive user interactions. – Works well for new users with few interactions.	– Limited diversity in recommendations (users get similar suggestions). – Cold-start problem for new items (if there is not enough metadata). – Requires good feature engineering.	– Personalized news feeds – Food recommendation (based on ingredients, nutrition, cuisine) – Movie recommendations (based on genre, director, actors)
Collaborative Filtering	– No need for item metadata. – Provides diverse recommendations beyond user history. – Works well for large-scale datasets.	– The cold-start problem for the newest users and items. – Sparse data affects accuracy. – Scalability issues with large user-item matrices.	– E-commerce (Amazon product recommendations) – Streaming services (Netflix, Spotify) – Social media friend suggestions.
Hybrid Recommendation	– Combines strengths of multiple techniques. – Reduces cold-start and data sparsity issues. – Improves recommendation accuracy.	– Higher computational cost. – More complex implementation. – Requires careful tuning of model weights.	– E-commerce (personalized product recommendations) – Online learning platforms (course recommendations) – Healthcare (personalized treatment plans)

3. Work Flow of Recommender System

Fig. 2 Work flow of recommender system

3.1. Data Collection

This phase involves gathering relevant data, such as customer orders, item details, outlet types, and timestamps. The dataset should be diverse and well-structured to ensure meaningful recommendations.

Data sources can include transaction histories, user preferences, and contextual information like time and location.

3.2. Data Processing

Raw data often contains missing values, inconsistencies, or redundant information that must be cleaned and preprocessed to ensure accuracy and reliability. This step includes handling missing values, normalizing text data, and combining relevant features (e.g., item name, type, and outlet type) to improve recommendation accuracy.

3.3. Filtering Technique

The best filtering techniques can be applied, such as content-based filtering, Collaborative Filtering, and Hybrid Methods, depending on suitable parameters as input and output. The hybrid approach combines multiple techniques, including both Collaborative and Content-Based Techniques. The hybrid model can also be applied to improve recommendation quality by including a variety of multiple techniques.

3.4. Evaluation Parameter

Different evaluation metrics can be applied to assess the accuracy of the recommendation system, including precision, recall, and F1-score. Evaluation parameters are used to measure the relevance of recommended items in comparison to actual user preferences, ensuring that the model provides accurate and personalized recommendations.

3.5. Generate Recommendation

The Recommendation model generates recommendations to users by different filtering techniques using different machine learning algorithms based on different parameters like users' past order, preferences, time of day, weekend or not, and season to improve used satisfaction and engagement.

4. Literature Review

4.1. Food Recommender System

Recommender systems are essential in today's digital world that experiences personalizing content and products for users. They filter vast information to improve user satisfaction and engagement. Some recommendation Systems for businesses drive sales by recommending relevant items and boosting revenue and customer loyalty. More efficiently predicting user preferences that improve inventory management. By providing tailored suggestions at scale, they create a more enjoyable and efficient online environment, benefiting consumers in a world of information overload.

4.2. Related Work

While exploring different recommendation systems that encompass both methodological frameworks and areas of interest and provide the foundation of this study. The author enhances food recommendation accuracy by incorporating temporal patterns and community elements. The methodology consists of two steps: a Content-Based Recommendation using graph clustering to group similar food items and a user-based recommendation employing deep learning to cluster users based on preferences. Evaluation parameters include Precision, Recall, F1-score, AUC, and NDCG. The proposed system performs advanced Recommender Systems across these metrics, demonstrating its effectiveness. It addresses limitations such as ignoring food item ingredients, time factors, and cold start problems, and could explore integrating additional contextual information and real-time data to further personalize recommendations [13].

The author in [14] addresses the challenge of enhancing food recommendation accuracy by incorporating temporal dynamics and introduces a novel time-aware Recommender System that leverages deep learning for feature extraction and clustering in the user-item interaction model. The methodology employs neural networks to capture complex patterns and graph algorithms to identify user communities. Evaluation, using precision and recall, demonstrates a significant improvement over baseline models, showing the efficacy of time-aware features. The author used a hybrid approach and effective temporal modelling and can explore personalized dietary restrictions and expand the dataset to include diverse culinary preferences and contexts. Collaborative filtering by integrating user correlation and evolutionary clustering enhanced by the author in [15]. The main objective is to improve recommendation accuracy and robustness using the methodology that employs Pearson correlation for user similarity and evolutionary clustering to dynamically track user preference shifts with techniques of matrix factorization and graph-based clustering. The evaluation metrics include precision, recall, and F1-score, demonstrating improved performance and accuracy compared to other traditional methods. Here, the author employs an adaptive clustering approach that accommodates evolving user preferences and can be utilized to incorporate contextual information and explore hybrid models with deep learning for more nuanced recommendations.

In [16], the author focuses on enhancing movie recommendation systems by incorporating temporal characteristics into collaborative filtering to capture the dynamic evolution of user preferences over time. The methodology utilizes matrix factorization techniques, augmented with temporal information such as timestamps of ratings, employing time-aware matrix factorization and sliding window approaches. Evaluation metrics such as RMSE and precision are employed, demonstrating improved prediction accuracy compared to static collaborative filtering methods to achieve effective integration of temporal dynamics and can explore more complex temporal patterns, incorporate external contextual data, and investigate deep learning models for capturing long-term temporal dependencies in the future.

The authors in [17] investigate the impact of Justifications in natural language on user acceptance in food Recommender Systems to determine if Providing justifications for suggestions increases user confidence and satisfaction. The methodology involves developing a food recommender system that generates both recommendations and corresponding natural language justifications, utilizing machine learning for recommendation generation and natural language processing for justification generation. Evaluation parameters include user ratings, perceived helpfulness, and trust. Results indicate that justifications significantly improve user satisfaction and trust compared to recommendations without explanations. It focuses on explainability in food recommendations and can explore personalized justification styles, integrating richer contextual information to generate more nuanced and effective explanations.

In [18], the author addresses the challenge of group recommendations by leveraging external social trust networks to improve group recommendation accuracy. This is achieved by incorporating trust relationships, utilizing a methodology that employs graph-based models to represent social networks and trust propagation algorithms to infer group preferences. It also includes some techniques like social network analysis and collaborative filtering with evaluation metrics, such as precision, recall, and nDCG, demonstrating improved performance compared to traditional group recommendation methods. The author also describes the effective use of external social-trust data to enhance group preference prediction and that future research can explore dynamic trust relationships, incorporate contextual information, and investigate hybrid models that combine social trust with other recommendation techniques for more robust and personalized group recommendations. The author aims to enhance recommendation accuracy by integrating contextual information into collaborative filtering techniques within mobile computing environments. The authors propose a context-aware collaborative filtering algorithm that considers factors such as location, time, and activity to provide personalized recommendations, utilizing tensor factorization methods to model the multidimensional interactions between users, items, and contexts. Evaluation metrics include precision, recall, and F1 Score, with experiments conducted on datasets such as MovieLens. The outcomes demonstrate that the proposed algorithm outperforms traditional collaborative filtering methods, achieving a precision of 0.85 and a recall of 0.80. It is an effective incorporation of contextual information, leading to more accurate recommendations and could explore real-time context integration and scalability to larger datasets[19].

The author enhances recommendation accuracy by integrating multimodal information, like text and images, into item similarity assessments; the author proposed the Multimodal Interest-Related Item Similarity (IRIS) model, comprising three modules: multimodal feature learning with a knowledge sharing unit, an Interest-Related Network (IRN) to evaluate relevance and interest between the target and historical things and similar item recommendation module. Also, use evaluation metrics like precision and recall, with experiments conducted on real-world datasets like MovieLens and Amazon products and demonstrate that Multimodal IRIS greatly increases interpretability and accuracy in top N recommendation tasks compared to state-of-the-art methods and could explore incorporating additional modalities and real-time context to further refine recommendations[20].

To improve restaurant recommendations in Riyadh by employing matrix factorization techniques, the author developed a collaborative filtering system using Non-Negative Matrix Factorization (NMF), Singular Value Decomposition (SVD), and its optimized variant (SVD++), leveraging user reviews and ratings in [21]. Evaluation parameters included Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The results show that SVD achieved an RMSE of 0.92 and MAE of 0.72, while NMF had an RMSE of 0.94 and MAE of 0.74, both outperforming a popularity-based baseline in the creation of a comprehensive, publicly available dataset of Riyadh restaurants and future, it could explore integrating additional contextual factors to further enhance recommendation correctness.

The author aims to enhance the accuracy of recommendations by integrating multimodal data (text, images, and metadata) into knowledge graphs. The authors propose a Multimodal Knowledge Graph Attention Network (MKGAT) that uses graph attention mechanisms for effective information propagation and uses accuracy metrics like precision, recall, and F1-score, with experiments conducted on real-world datasets such as MovieLens and show MKGAT outperforms traditional models. It describes a novel use of multimodal data, and future work includes enhancing scalability and expanding data modalities[22].

The author enhances recommendation accuracy by integrating contextual information into collaborative filtering techniques and proposes a novel algorithm that incorporates user context, such as time and location, into the recommendation process. This algorithm utilizes matrix factorization methods enhanced with contextual variables and evaluates its approach using measures of recall and precision on datasets such as MovieLens and Netflix. The results demonstrate improved recommendation performance compared to traditional methods, highlighting the strength of incorporating context and exploring additional contextual factors, as well as real-time context integration, to further refine recommendation systems [23].

In [24], the author provides a comprehensive overview of the evolution and current state of Recommendation Systems, highlighting recent advancements and identifying future research challenges. The authors conduct an extensive literature review, analyzing various Recommender System (RS) methodologies, including Content-Based Filtering, Collaborative Filtering, and Hybrid Approaches. They emphasize the integration of deep learning techniques and the incorporation of temporal and contextual information to improve recommendation accuracy. Evaluation parameters, such as recall, precision, and Normalized Discounted Cumulative Gain (NDCG), are discussed, with analyses performed on popular datasets, including MovieLens and Amazon product reviews. Future research directions include addressing biases, enhancing diversity, and improving transparency in RS.

The author enhances the interpretability of SVM classifications by introducing two novel explanatory methods. The first method identifies the support vectors most influential in a specific test point's classification, while the second, termed "border classification," determines the feature modifications required to move a test point to the decision boundary. These techniques are implemented in a user-friendly software tool that graphically visualizes these insights and its innovative approach to demystify SVM decisions, making them more accessible to practitioners, and could focus on applying these methods to other "black-box" models to further enhance model interpretability[25].

The author proposes a novel ranking framework [26] that simultaneously learns user preferences and embedding by minimizing pairwise ranking loss and employing a neural network model. It jointly represents users and items in an incorporated space, optimizing ranking losses to maintain item ordering based on user preferences. The methodology involves empirical risk minimization and neural network-based embedding learning, utilizing evaluation parameters such as ranking accuracy metrics. It also employs a simultaneous learning approach, leading to improved recommendation performance, and explores the integration of additional contextual information to address data sparsity challenges.

They enhance recommendation accuracy by integrating collaborative and content-based filtering techniques that involve analyzing user preferences through filtering methods to provide personalized suggestions and use data mining algorithms and machine learning models. Additionally, evaluation parameters focus on metrics such as precision, recall, and F1-score to assess the quality of recommendations. Here, the author used a hybrid approach with the advantages of both filtering methods to improve system performance and could explore adding more sources of information and advanced algorithms to further refine user preference mining[27].

In [28], the author develops a recommendation system for fast food menus using collaborative filtering techniques that involve calculating item and user similarities through cosine similarity measures and include memory-based collaborative filtering and K-Nearest Neighbor (K-NN) algorithms and also used Evaluation parameters based on similarity scores, with item-based recommendations yielding a perfect score of 1.0 for certain menu items. The author implements a practical application in the fast-food industry, demonstrating that effective recommendations can address challenges such as data sparsity and explore hybrid models to enhance recommendation accuracy.

4.3. Finding from Literature Review

From the literature review, many key challenges in the recommender system have been found. Recommender system techniques, such as content-based filtering and collaborative filtering, have been explored, and numerous studies have implemented hybrid approaches to enhance recommendation accuracy by integrating temporal dynamics, user preferences, and contextual data. It has also been demonstrated how effective multimodal data integration, matrix factorization, and graph-based clustering are in capturing complex user behaviors and enhancing customization. There are still a number of research gaps in spite of these developments. Although explainability in recommendations is gaining popularity, further research is needed to enhance user confidence and trust in AI-powered meal suggestions. Another thing is the underuse of textual and multimodal data, as the majority of research mostly relies on structured datasets like user demographics and ratings. Future food recommender models can be greatly improved by addressing these issues using context-aware, group-based, and explainable AI-driven recommendation systems.

5. Challenges in Recommender System

From the analyzed literature, several challenges have been identified in food recommender systems. These challenges impact the effectiveness, accuracy, and adoption of recommendation models. The key challenges are categorized as follows: data-related challenges, algorithmic issues, user-centric challenges, scalability and computational challenges, and ethical and social challenges.

5.1. Data-Related Challenges

In a recommender system, collaborative filtering technique-based models rely on user-item interactions, making it difficult to provide recommendations for new users or new food items. Hybrid models are used in many studies to try to address this problem, but it remains very challenging. Sparse user interactions, in which a tiny proportion of users rate or review food products, are a problem for many food recommendation databases. Inadequate interaction data lowers Collaborative Filtering models' accuracy and results in less-than-ideal suggestions. Unlike movie or e-commerce recommendation systems, food recommendation datasets are limited. The majority of studies still rely on structured data (ratings, reviews, and demographics), although others utilize text and imagery to provide more accurate suggestions. It's still difficult to use textual descriptions (like ingredient information) with pictures (like meal presentation) effectively.

5.2. Algorithmic Issues

Content-based filtering (CBF), which suggests similar products, tends to decrease variety. Since growing variety often leads to decreased accuracy, better trade-off techniques are required. Since most studies use hybrid or collaborative filtering, pure content-based filtering for food recommendations has not been fully investigated. Commonly ordered items may be biased since Collaborative Filtering models depend on user ratings and interactions. Time-aware recommendation systems improve personalization but require complex temporal modeling. Even though many studies include time-based dynamics, real-time adaptation to user behavior remains challenging. Users like clarity in food options, especially when it comes to health-related meal recommendations. The area of explainability is still in its infancy because not much research has been done on how arguments are constructed in natural language.

5.3. User-Centric Challenges

Many existing systems fail to account for dietary restrictions, allergies, or individual nutritional needs. Personalized meal recommendations based on medical conditions (such as diabetes or hypertension) are still in their infancy. Most models are created for individual clients, but infrequently are group meal options (such as dining at a restaurant or event catering) examined. There are still problems with group dynamics, preference conflicts, and the fairness of suggestion generation. Studies show that explainable ideas increase user happiness despite the fact that many systems lack effective reasoning mechanisms. There is still work to be done on building trust in AI-powered meal recommendations.

5.4. Scalability and Computational Challenges

One of the biggest challenges is scaling models without compromising accuracy and efficiency. Real-time recommendation adaption is challenging since many models need to be trained offline. The problem of continuously updating recommendations based on user activity is not well covered in studies.

5.5. Ethical and Social Challenges

Collaborative Filtering models tend to favor popular restaurants or food items, leading to recommendation biases. Ensuring fairness in food recommendations for diverse cultural and dietary preferences remains an open research problem. Food recommender systems rely on personal data (e.g., order history, location), raising privacy concerns. Secure data handling and user consent mechanisms are crucial but not widely addressed in existing literature. Food recommender systems can contribute to sustainable consumption by recommending healthier or locally available meals. Table 2 describes the summary of all types of challenges discussed above. Figure 2 describes the number of challenges in all the category of challenges.

Table 2. Summary of all types of challenges

Category of Challenges	Challenges
Data Challenges	Cold start, data sparsity, lack of high-quality datasets, underutilization of multimodal data
Algorithmic Issues	Accuracy vs. diversity trade-off, reliance on CF, lack of real-time context adaptation, limited explainability
User-Centric Issues	Lack of health-aware and group recommendations, low user trust, limited personalization
Scalability Issues	Handling large-scale data, real-time processing limitations
Ethical Issues	Bias in recommendations, privacy concerns, sustainability awareness

6. Research Finding

Significant progress and enduring difficulties in food recommender systems are revealed by the literature review. To improve recommendation accuracy, a number of research combine collaborative filtering, deep learning, and graph-based clustering; hybrid models perform better. While temporal dynamics enhance personalization, real-time adaptation is still a work in progress. The majority of research relies heavily on structured data, such as ratings and demographics, even though multimodal approaches that incorporate textual and visual data have proven successful. The majority of research has focused on individual preferences, leaving group meal recommendation systems understudied. Additionally, few models produce tailored reasons for suggestions despite the growing interest in explainability and consumer trust. Scalability is still an issue for large-scale food platforms, and Collaborative Filtering-based methods are still hampered by the cold start issue and data sparsity. To close these gaps and enhance suggestion diversity, customization, and fairness, contextual, multimodal, and real-time elements must be integrated more thoroughly.

7. Future Scope

By using cutting-edge machine learning and artificial intelligence approaches, food recommender systems offer a great deal of room for future advancement. By constantly adjusting to users' shifting tastes, real-time personalization through deep learning models can improve suggestion accuracy. Such multimodal learning can lead to more diverse and relevant meal recommendations by combining textual descriptions, images, and nutritional information. Moreover, additional studies need to be carried out on group recommendation models that can handle joint eating experiences while considering dietary restrictions and group decision-making dynamics. Natural language explanations and interpretable AI models can enhance user acceptance and trust in a critical space of explainability of food recommendations. Moreover, applying transfer learning and federated learning for sparse data and cold start challenges would generate more effective recommendations. Furthermore, it is possible to incorporate diet and health care consultation in the future, which makes use of the user's health data to provide personalized nutrition. Additionally, the efficiency of recommendations could be enhanced with real-time contextual factors such as geography and weather. This makes food recommenders more intelligent and personalized in changing situations.

8. Conclusion

A comprehensive survey of food recommender systems: Strategies for the retrieval of personalized food recipes. The study focuses on different techniques, such as Collaborative Filtering, Content-Based Filtering, Hybrid Models, and deep learning-based techniques, which emphasize their effectiveness in enhancing recommendation model accuracy and personalization. The study explores critical challenges like sparse data, cold start problems, lack of explainability, and the underutilization of multimodal and contextual data. Despite progress on the topic, there is still a lack of dedicated models for food recommendation that are adaptive, explainable, and can be used in real time. To this end, we could explore multimodal learning better group recommendation frameworks, and we could embed health-aware recommendations in the context of personalized nutrition. Tackling these deficiencies will, in turn, facilitate more intelligent, user-centric, and effective food recommender systems, which will enhance the user’s dining experience and facilitate healthier choices.

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