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Medicine Recommender System Based on Semantic and Multi-Criteria Filtering

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Abstract

Aim/Purpose	This study aims to devise a personalized solution for online healthcare platforms that can alleviate problems arising from information overload and data sparsity by providing personalized healthcare services to patients. The primary focus of this paper is to develop an effective medicine recommendation approach for recommending suitable medications to patients based on their specific medical conditions.
Background	With a growing number of people becoming more conscious about their health, there has been a notable increase in the use of online healthcare platforms and e-services as a means of diagnosis. As the internet continues to evolve, these platforms and e-services are expected to play an even more significant role in the future of healthcare. For instance, WebMD and similar platforms offer valuable tools and information to help manage patients' health, such as searching

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for medicines based on their medical conditions. Nonetheless, patients often find it arduous and time-consuming to sort through all the available medications to find the ones that match their specific medical conditions. To address this problem, personalized recommender systems have emerged as a practical solution for mitigating the burden of information overload and data sparsity-related issues that are frequently encountered on online healthcare platforms.

Methodology The study utilized a dataset of MC ratings obtained from WebMD, a popular healthcare website. Patients on this website can rate medications based on three criteria, including medication effectiveness, ease of use, and satisfaction, using a scale of 1 to 5. The WebMD MC rating dataset used in this study contains a total of 32,054 ratings provided by 2,136 patients for 845 different medicines. The proposed HSMCCF approach consists of two primary modules: a semantic filtering module and a multi-criteria filtering module. The semantic filtering module is designed to address the issues of data sparsity and new item problems by utilizing a medicine taxonomy that sorts medicines according to medical conditions and makes use of semantic relationships between them. This module identifies the medicines that are most likely to be relevant to patients based on their current medical conditions. The multi-criteria filtering module, on the other hand, enhances the approach's ability to capture the complexity of patient preferences by considering multiple criteria and preferences through a unique similarity metric that incorporates both distance and structural similarities. This module ensures that patients receive more accurate and personalized medication recommendations. Moreover, a medicine reputation score is employed to ensure that the approach remains effective even when dealing with limited ratings or new items. Overall, the combination of these modules makes the proposed approach more robust and effective in providing personalized medicine recommendations for patients.

Contribution This study addresses the medicine recommendation problem by proposing a novel approach called Hybrid Semantic-based Multi-Criteria Collaborative Filtering (HSMCCF). This approach effectively recommends medications for patients based on their medical conditions and is specifically designed to overcome issues related to data sparsity and new item recommendations that are commonly encountered on online healthcare platforms. The proposed approach addresses data sparsity and new item issues by incorporating a semantic filtering module and a multi-criteria filtering module. The semantic filtering module sorts medicines based on medical conditions and uses semantic relationships to identify relevant ones. The multi-criteria filtering module accurately captures patient preferences and provides precise recommendations using a novel similarity metric. Additionally, a medicine reputation score is also employed to further expand potential neighbors, improving predictive accuracy and coverage, particularly in sparse datasets or new items with few ratings. With the HSMCCF approach, patients can receive more personalized recommendations that are tailored to their unique medical needs and conditions. By leveraging a combination of semantic-based and multi-criteria filtering techniques, the proposed approach can effectively address the challenges associated with medicine recommendations on online healthcare platforms.

Findings The proposed HSMCCF approach demonstrated superior effectiveness compared to benchmark recommendation methods in multi-criteria rating datasets in terms of enhancing both prediction accuracy and coverage while effectively addressing data sparsity and new item challenges.

Recommendations for Practitioners
By applying the proposed medicine recommendation approach, practitioners can develop a medicine recommendation system that can be integrated into online healthcare platforms. Patients can then utilize this system to make better-informed decisions regarding the medications that are most suitable for their specific medical conditions. This personalized approach to medication recommendations can ultimately lead to improved patient satisfaction.

Recommendations for Researchers
Integrating patient medicine reviews is a promising way for researchers to elevate the proposed medicine recommendation approach. By leveraging patient reviews, the approach can gain a more comprehensive understanding of how certain medications perform for specific medical conditions. Additionally, exploring the relationship between MC-based ratings using an improved aggregation function can potentially enhance the accuracy of medication predictions. This involves analyzing the relationship between different criteria, such as medication effectiveness, ease of use, and satisfaction of the patients, and determining the optimal weighting for each criterion based on patient feedback. A more holistic approach that incorporates patient reviews and an improved aggregation function can enable the proposed medicine recommendation approach to provide more personalized and accurate recommendations to patients.

Impact on Society
To mitigate the risk of infection during the COVID-19 pandemic, the promotion of online healthcare services was actively encouraged. This allowed patients to continue accessing care and receiving treatment while adhering to physical distancing guidelines and shielding measures where necessary. As a result, the implementation of personalized healthcare services for patients is expected to be a major disruptive force in healthcare in the coming years. This study proposes a personalized medicine recommendation approach that can effectively address this issue and aid patients in making informed decisions about the medications that are most suitable for their specific medical conditions.

Future Research
One way that may enhance the proposed medicine recommendation approach is to incorporate patient medicine reviews. Furthermore, the analysis of MC-based ratings using an improved aggregation function can also potentially enhance the accuracy of medication predictions.

Keywords
medicine recommendation, semantic filtering, multi-criteria filtering, sparsity, new item

INTRODUCTION

As Internet applications and services continue to rapidly expand, people from anywhere can access a plethora of professional knowledge across various domains to aid them in making decisions (Ko et al., 2022). For instance, in the healthcare industry, platforms like WebMD – the primary website for health information services in the United States – provide valuable tools and information for managing patients' health, including medicine searches based on their specific condition. To search for medication on WebMD, patients need to enter their condition, which will then generate a list of common medications used to treat or alleviate symptoms of that particular condition. Each medicine listed on the website has a link that leads to further information, such as common uses, side effects, dosage information, and user reviews.

As online healthcare information continues to advance, patients often find it challenging and time-consuming to sift through all available medicines to find the ones that match their condition. To mitigate this issue, recommender systems have emerged as a viable solution because of their capability to lessen the burden of information overload. In this regard, medicine recommender systems have been developed to aid patients and healthcare professionals in identifying precise medications for particular medical conditions (Tran et al., 2021).

Recommender systems are personalized systems that help users select appropriate items or services from a vast pool of options based on their preferences. Collaborative filtering (CF)-based recommendation techniques leverage the opinions of other users with similar interests to guide users' decision-making. CF techniques can be categorized into user-based and item-based approaches. User-based CF evaluates the similarity between users based on their rating data for a set of particular items and generates a list of the top *N* items that match their preferences based on the ratings of a group of similar users. Item-based CF predicts an item's suitability by analyzing its similarity to the item selected by the user using a rating matrix of users and items. Various similarity metrics, such as Pearson correlation-based similarity and cosine-based similarity, can be used to measure the similarity between users or items. However, the item-based CF technique has been shown to have greater prediction accuracy than the user-based CF technique. Despite their effectiveness, CF-based recommendation techniques face two significant challenges: sparsity and cold start. The sparsity problem arises when there is insufficient data obtainable for the recommendation, while the cold start problem arises when a new user signs up for a service or when a new item is introduced in the system. In the case of a new user, the system has no information about their preferences or behavior, making it challenging to provide accurate recommendations. Similarly, when a new item is added to the system, the system has no previous user interaction or ratings to use in making recommendations (Aggarwal, 2016d; Ko et al., 2022; Sarwar et al., 2001).

In order to address the sparsity and cold-start problems in recommender systems, recent research has focused on incorporating additional information to supplement the limited user ratings and improve the accuracy of recommendations. One such type of additional information is the semantic relationships that exist between users or items. This semantic information can be represented using taxonomies or ontologies and is essential for accurately representing item information and user preferences by including concepts and their relationships. Semantic-based recommender systems utilize this essential semantic information and attributes related to users and items to produce recommendations. For example, semantic information about items includes their attributes, the relations between items, and the association between items and meta-information (Gohari & Tarokh, 2016; Martín-Vicente et al., 2014; Shambour et al., 2021).

In addition, most CF-based recommendation techniques employ a single rating criterion, which represents the overall rating of an item, to identify user preferences. Such techniques fail to capture the detailed preferences of users for each feature of an item, despite many websites allowing users to rate items in various aspects (Shambour, 2016; Shambour et al., 2016). For example, patients on WebMD can rate their medicines based on several criteria, such as effectiveness, ease of use, and satisfaction, as shown in Figure 1. Therefore, it is required to develop Multi-Criteria (MC) recommender systems that leverage extra rating data to accurately comprehend user preferences in order to provide precise and effective recommendations. MC based-CF can improve the accuracy of recommendations by considering the critical aspects that influence users' selection of an item during the recommendation process (Shambour, 2016; Shambour et al., 2016, 2021).

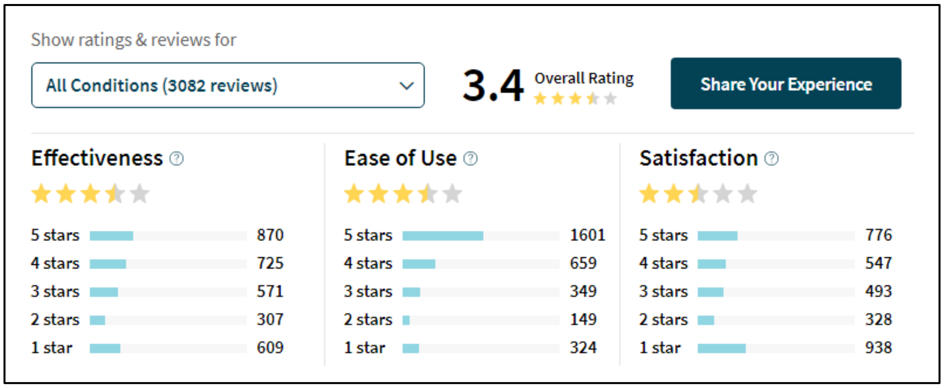

Figure 1. Example of a medicine's multi-criteria rating on WebMD

Therefore, it is essential to develop a hybrid recommender system that can provide patients with medication recommendations based on their medical conditions. This will enable patients to efficiently and promptly locate their medications on a vast online healthcare platform containing hundreds of medications. Hybrid recommender systems are designed to use multiple recommendation techniques to produce more accurate and diverse recommendations. By integrating the strengths of different recommendation approaches, hybrid recommender systems can enhance the overall performance of the system (Burke, 2007; Ko et al., 2022; Shambour, 2012; Shambour et al., 2020).

Another key point to consider is that the majority of current medicine recommendation systems rely on knowledge-based recommendation approaches. These approaches involve the use of knowledge graphs and ontologies to store information and the application of rules to enable reasoning about the information contained within the knowledge base. For instance, Doulaverakis et al. (2012, 2014), Kumari and Sharma (2019), Rodríguez et al. (2009), Wedagu et al. (2020), and Zhang et al. (2023) have employed such approaches. Despite their effectiveness, these approaches are subject to certain limitations, including the need for substantial domain knowledge, extensive human effort, expertise in knowledge representation, and ongoing knowledge maintenance (Bouraga et al., 2014; Tiddi & Schlobach, 2022). In addition, a number of researchers have proposed model-based CF approaches as potential solutions for medicine recommendations (Khanna et al., 2023; Nistal-Nuño, 2022; Poulose et al., 2022; Shahid et al., 2022) due to their scalability and ability to handle sparsity. Nevertheless, such approaches require extensive feature collection, dimensionality reduction, and substantial data for training, which may negatively impact recommendation performance. Furthermore, they may involve complex algorithms and be arduous and time-consuming (Aggarwal, 2016c; Papadakis et al., 2022). Although memory-based CF approaches have limitations such as sparsity and cold start, they offer various benefits due to their instinctive and simple methodology. These approaches are simple to implement and debug, and the rationale for recommending a particular item is easily justifiable. Such justifications for recommendations are not readily accessible in several other model-based CF approaches. Moreover, the recommendations exhibit a considerable degree of stability even when new items and users are included (Aggarwal, 2016c; Papadakis et al., 2022).

Motivated by the aforementioned issues and key points, a new hybrid memory-based CF approach that incorporates multi-criteria ratings in the recommendation process has been proposed. This approach, referred to as the Hybrid Semantic-based Multi-Criteria CF (HSMCCF), is designed to recommend medications to patients, aiding them to efficiently and precisely select the appropriate medication based on their specific medical conditions. Multicriteria filtering and semantic filtering are used in this method to improve recommendation quality and reduce the negative effects of data sparsity and new item issues. Several experiments were conducted using a real-world medicine MC rating dataset, and the results show that the proposed method is effective with respect to prediction accuracy and prediction coverage compared to other benchmark recommendation approaches. It should be emphasized that certain elements of this study exhibit notable distinctions from our prior research (Shambour & Lu, 2011), wherein a Multi-Criteria Semantic-enhanced CF (MC-SeCF) approach was proposed. The HSMCCF approach was improved by integrating the Triangle similarity method (Sun et al., 2017) and the overlap coefficient (Verma & Aggarwal, 2020) to augment the MC-based similarity among items. The HSMCCF approach utilized the binary Dice coefficient (Frakes & Baeza-Yates, 1992) to quantify the semantic-based similarity among items. The HSMCCF approach includes a reputation score to increase the number of potential neighbors available for selection during the neighbor selection phase. This paper has the following structure: the literature on medicine recommendations is briefly reviewed followed by the presentation of the design of the proposed approach; the experimental results and discussion are then illustrated followed by the conclusions and recommendations for further study.

BACKGROUND AND RELATED WORK

COLLABORATIVE FILTERING

Collaborative Filtering (CF) is a widely adopted methodology in the field of recommender systems. It operates under the assumption that individuals who have demonstrated agreement in their preferences in the past are likely to exhibit similar preferences in the future. The process involves the creation of a preference database based on the user's evaluation data, which is subsequently utilized to predict items that align with the user's preferences and ultimately employed for the purpose of providing recommendations. CF techniques can be categorized into two main types; namely, memory-based CF and model-based CF (Ko et al., 2022; Papadakis et al., 2022).

Memory-based CF

Memory-based CF techniques, commonly referred to as neighborhood-based CF techniques, utilize heuristics to make recommendations. These techniques operate on the principle that users who exhibit similar rating behavior are likely to have similar preferences for items. Memory-based CF techniques leverage the complete user-item matrix to identify similar entities through different measures, including the Pearson correlation coefficient and cosine similarity. Once the nearest neighbors have been identified, their previous ratings are utilized to make recommendations. Memory-based techniques are classified into two types: user-based CF and item-based CF. In user-based CF, the previous preferences of the nearest neighbors to an active user are utilized. On the other hand, in item-based CF, the ratings of similar items to a target item are employed. Memory-based CF techniques are characterized by their ease of implementation and robust performance on datasets with high density. However, their limitations are attributed to their reliance on only user ratings, reduced efficacy in the presence of limited data, as well as the challenges posed by new users and items (Aggarwal, 2016d; Papadakis et al., 2022).

Model-based CF

Model-based CF techniques utilize data mining and machine learning techniques, including Bayesian models, clustering models, and singular value decomposition models, to construct a model that can identify intricate patterns and provide insightful predictions for CF-based tasks. Classification techniques are typically utilized as CF-based models when the user ratings are categorical. On the other hand, regression models and singular value decomposition methods are suitable for numerical ratings. Model-based CF techniques have certain limitations. For instance, they may not be suitable for datasets with high sparsity. Additionally, the recommendation performance of these techniques may be reduced when using dimensionality reduction or transforming multiclass data into binary data. Moreover, the cost of building models can also be high, and many techniques face a tradeoff between prediction performance and scalability (Aggarwal, 2016c; Papadakis et al., 2022).

Content-Based Filtering

Content-based filtering techniques generate recommendations by analyzing the descriptive characteristics of items and user profiles. Content-based filtering techniques aim to recommend items to users based on their previous preferences. They achieve this by identifying items that are similar to those that the user has previously favored. The efficiency of recommending a newly added item to the system is high when using content-based filtering. Despite the absence of any previous ratings for the new item, content-based filtering techniques can leverage the descriptive information to make recommendations to the appropriate users. While content-based filtering techniques have demonstrated their efficacy in recommending new items, they are limited in their ability to generate personalized predictions due to insufficient data regarding the user's profile. In addition, the recommendations provided have limitations in terms of diversity and innovation as the techniques fail to utilize collective knowledge from users with similar interests (Aggarwal, 2016a; Ko et al., 2022).

Hybrid Filtering

The hybrid recommendation strategy has been proposed as a means of surpassing the limitations of conventional recommendation techniques and attaining superior performance. This strategy combines the most effective features of two or more recommendation techniques to create a single hybrid technique (Ko et al., 2022). Burke (2007) identified seven fundamental hybridization mechanisms for building hybrids in recommender systems. These mechanisms include switching, mixed, weighted, feature combination, cascade, feature augmentation, and meta-level. Hybrid recommendation techniques commonly involve combining CF with other recommendation techniques to address issues related to cold-start and sparsity (Ko et al., 2022).

Medicine Recommendation Systems

Recommender systems strive to address the challenge of information overload in online environments by offering users personalized products and services. Considerable progress has been made in delivering customized services for diverse web-based applications such as e-commerce, e-business, e-learning, e-tourism, and e-government (Ko et al., 2022). Nevertheless, despite several studies on the implementation of recommender systems in the healthcare field (Etemadi et al., 2022; Tran et al., 2021), there remains a noticeable dearth of research on medicine recommendation systems within this field (Goyal et al., 2020).

A decision support system based on semantic web technologies that enable the proper medicine and treatment recommendation for a specific disease was proposed by Rodríguez et al. (2009). The proposed system assists the doctors in avoiding the entire process of drug interaction validation by bypassing those that potentially cause a risk to the patient due to his or her allergies or other secondary reactions or potential side effects caused by medication(s) still present in the patient's body. Doulaverakis et al. (2012) presented GalenOWL, a system for medicine recommendation based on semantic web technologies. GalenOWL employs well-known and standardized medical terminologies, as well as a vast knowledge base of drug-drug and drug-disease interactions expressed as rules and Web Ontology Language (OWL) axioms. GalenOWL is deployed as an online service with both comprehensiveness of results and promptness of query response in mind. The semantic-enabled implementation was compared to a traditional business logic implementation, and semantic technologies were found to be a more viable choice for capturing knowledge in the system than basic rule engines.

Later, Doulaverakis et al. (2014) presented Panacea, a semantically enabled medicine recommendation framework based on a patient's medical record. In terms of scalability and design, Panacea can be viewed as the expansion of GalenOWL (Doulaverakis et al., 2012). In order to infer tacit knowledge, Panacea employs a layered reasoning approach in which the medical ontology and patient data instances are fed into an extended Resource Description Framework Schema (RDFS) reasoner.

The second reasoning layer, which can use any common rule engine, is used to generate medicine recommendations. Stark et al. (2017) introduced a medicine recommendation system based on a native graph database that is highly scalable. Based on a traditional collaborative filtering algorithm, patients are ranked according to the similarity of their features (e.g. prescriptions, allergies, migraine type). The presented system utilizes simulated patient data to aid doctors in determining which drug is optimal for migraine patients based on their characteristics. The evaluation results indicate that the proposed system performs as expected. This implies that only drugs with the highest relevance scores and no negative effects due to the patient's diseases and medications will be recommended. Kumari and Sharma (2019) designed a fuzzy-based recommendation framework that uses a fuzzy membership function, input variables, output variables, and a fuzzy rule base to diagnose thyroid disease and predict proper medicine. First, thyroid disease is identified and classified into three categories: normal, hyperthyroidism, and hypothyroidism. Then, a suitable medication is recommended based on the disease category. Wedagu et al. (2020) proposed a Diabetes Medicine Recommendation System (DIMERS) model, which combines doctors' prior medical knowledge with bidirectional Long Short-Term Memory (BiLSTM). Using time series variables as input, DIMERS first preprocesses a set of diabetic patient test results and medications. A weighted block containing prior medical knowledge is then used to boost the learning and explainability of deep neural networks (DNN). Specifically, the DIMERS has been evaluated using a real-world dataset from a Ruijin hospital. The results of the experiments confirm the effectiveness of the DIMERS, as it outperforms five baseline methods. Granda Morales et al. (2022) developed a medicine recommendation system for diabetic patients using clustering and collaborative filtering techniques. The study's patient data set was provided by the Machine Learning Repository at the University of California, Irvine. The dataset was analyzed using data mining techniques, and unsupervised learning was used to cluster patients and reduce dimensionality. Using a user-based collaborative filtering approach, drug predictions were generated by creating patient profiles that could be compared to those of other patients with similar characteristics. Ultimately, recommendations were made based on the patient groups that were identified. Nistal-Nuño (2022) introduced an artificial intelligence-based online pharmacy recommendation system employing a patient model based on Bayesian Networks to provide an introductory user-adaptive system. This system is designed to aid patients in locating information on prescribed medications in a more manageable format while making online purchases.

The goal of providing a user-adaptive system is to facilitate a more effective and user-friendly interaction between patients and healthcare professionals. The system consistently achieved a high level of accuracy in predicting the medication categories required by patients. Therefore, by relying on the recommendations provided by the system, patients can potentially save time and effort. A study by Poulose et al. (2022) outlined and implemented a medication recommendation system that employs data mining techniques to propose an improved prescription for patients receiving inpatient care. The medication recommender system is composed of various modules, including data splitting modules, feature modules, sentiment classification modules, and count vectorizers. Shahid et al. (2022) presented a drug recommendation system based on deep learning and N-Gram techniques. The system utilizes patient review data as input and employs sentiment analysis to determine the most suitable treatment for the given medical condition. The study conducted by Zhang et al. (2023) aimed to explore the issue of medicine recommendation, which entails the prediction of a collection of medications on the basis of a set of symptoms. MedRec was developed by the researchers to tackle the problem of sparse data by utilizing a medical knowledge graph and a medicine attribute graph. The researchers employed the two graphs to acquire the embedding representations of symptoms and medications, which were subsequently utilized for medication recommendation. The study proposed by Khanna et al. (2023) developed an efficient medicine recommendation system utilizing a natural language processing (NLP) algorithm and several machine learning models. This system is intended to provide medical professionals with up-to-date information on popular medicines available on the market. The study utilized consumer reviews as the primary data source, which underwent analysis through the Vader tool and language processing-assisted opinion mining techniques.

To sum up, the majority of medicine recommendation systems that have been reviewed are classified as knowledge-based systems. These systems, as described by Doulaverakis et al. (2012, 2014), Kumari and Sharma (2019), Rodríguez et al. (2009), Wedagu et al. (2020), and Zhang et al. (2023), utilize a knowledge base, such as knowledge graphs and ontologies, to store information. Rules are then applied to reason about the information contained within the knowledge base. Despite the fact that knowledge-based systems are not affected by sparsity and cold-start issues, owing to their pre-constructed knowledge bases with the assistance of domain experts, they do have certain constraints. Limitations in the knowledge acquisition process often require significant domain knowledge and extensive human effort, as well as expertise in knowledge representation. In addition, the process of maintaining knowledge involves ongoing updates and maintenance of knowledge bases, as they are not static entities and must remain current and relevant (Bouraga et al., 2014; Tiddi & Schlobach, 2022).

In addition, a number of model-based CF approaches have been proposed in the literature as potential solutions for medicine recommendations (Khanna et al., 2023; Nistal-Nuño, 2022; Poulose et al., 2022; Shahid et al., 2022). Such approaches are known for their scalability in handling large datasets and sparsity compared to memory-based CF methods. However, these approaches demand extensive feature collection and dimensionality reduction, which may negatively impact recommendation performance. Furthermore, accurate training of the underlying approaches requires a substantial amount of data, as insufficient or sparse data can lead to less accurate recommendations and poor performance. Finally, the process of developing a robust model requires expertise in data mining and machine learning and may entail the utilization of intricate algorithms, which can be arduous and time-consuming (Aggarwal, 2016c; Papadakis et al., 2022). On the other hand, the adoption of memory-based CF approaches in medicine recommendation systems has received little attention, as only a few memory-based CF approaches have been presented in the current literature in the form of hybrid approaches (Granda Morales et al., 2022; Stark et al., 2017). Even though memory-based CF approaches have limitations such as sparsity and cold start, they offer various benefits due to their instinctive and simple methodology. These approaches are simple to implement and debug, and the rationale for recommending a particular item is easily justifiable. Such justifications for recommendations are not readily accessible in several other model-based CF techniques. Moreover, the recommendations exhibit a considerable degree of stability even when new items and users are included (Aggarwal, 2016d; Papadakis et al., 2022).

Equally important, the absence of research studies on the adoption of multi-criteria recommender systems in the medicine recommendations field is a significant concern that deserves further attention. Based on the aforementioned information, we have become interested in developing a hybrid memory-based CF approach that incorporates multi-criteria ratings in the recommendation process. Accordingly, a hybrid semantic-based multi-criteria CF is being developed in this study as a solution for the medicine recommendation problem. The proposed approach differs from previous works by focusing on two aspects. Initially, the approach employed multi-criteria ratings to effectively capture patient preferences and deliver accurate recommendations. Furthermore, the approach utilizes semantic filtering and a medicine reputation score to tackle problems associated with data sparsity and new item challenges in the field.

DESIGN METHODOLOGY

This study proposes an information system that serves as a medicine recommendation system. The proposed system, as depicted in Figure 2, contains three modules: the semantic filtering module, the Multi-Criteria filtering module, and the recommendation generation module. Figure 2 presents the modules involved in the proposed Hybrid Semantic-based Multi-Criteria CF approach.

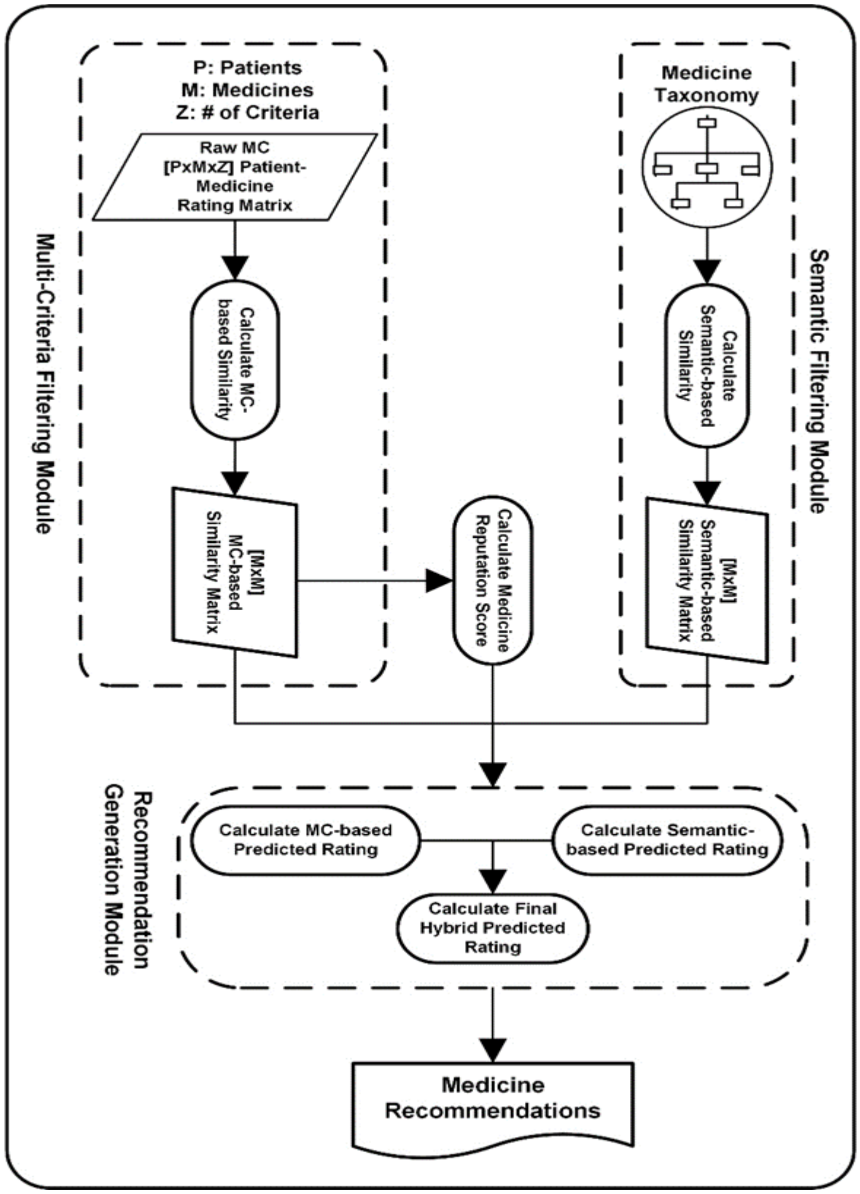

Figure 2. Design of the proposed HSMCCF approach

SEMANTIC FILTERING MODULE

In order to utilize the semantic relationships that exist between medicines, a hierarchy of medicines known as a medicine taxonomy is created by experts in the medical field to group a set of medicines at a lower level under specific medical conditions at a higher level. The medicines are represented as leaves in the tree structure, while the non-leaf nodes represent medical conditions. Each medicine may be associated with one or more medical conditions.

The medicine taxonomy provides a structured representation of medicines and their relationships, which can be leveraged in the proposed system to improve the accuracy and quality of medicine recommendations. One advantage of using a medicine taxonomy is that it helps mitigate the sparsity problem by providing a more granular representation of medicines. This is because medications associated with a particular medical condition tend to have similar features and are hence more likely to be recommended to a patient who has demonstrated interest in other medicines related to the same medical condition. Figure 3 illustrates a medicine taxonomy as an example. The taxonomy follows a tree structure that originates from a "medical condition" node, which is linked to different branches of medical conditions, including joint pain, backache, nerve pain, psoriasis of scalp, and skin condition, through an "Associated with a medicine" relationship type. This type of relationship connects medicines with their corresponding medical conditions. It is worth noting that a medicine may have multiple associations with various medical conditions due to its potential to treat multiple conditions.

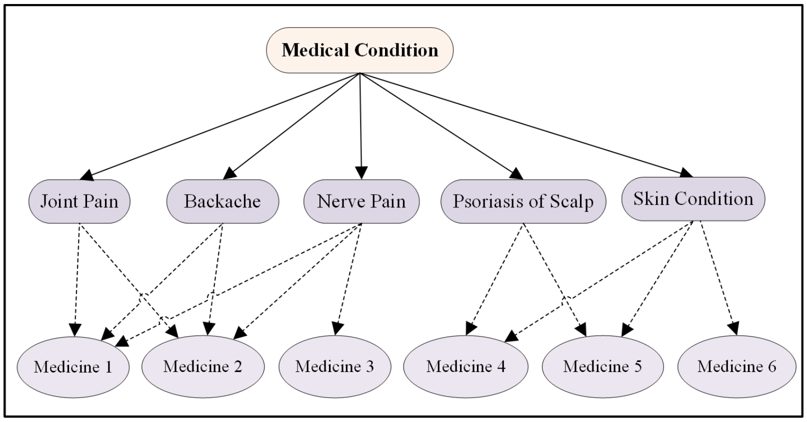

Figure 3. Example of a medicine taxonomy

Initially, to assess the semantic-based similarity of medicines based on their associated medical conditions, the first step is to represent each medication as a binary number vector [0, 1], as illustrated below.

$$\overline{M}_x = (m_{x,1}, m_{x,2}, \ldots.., m_{x,d}), \tag{1}$$

Where $\overrightarrow{M}_x$ denotes a vector for medicine x and its associated medical conditions m. $m_{x,d}$ is defined as a binary variable, as follows:

$$m_{x,d} = \begin{cases} 1 & \text{If } \textit{medicine } x \text{ associated with } \textit{medical condition } d \\ 0 & \text{If } \textit{medicine } x \text{ does not associated with } \textit{medical condition } d \end{cases} \tag{2}$$

Once the binary vector has been assigned to each medication, the semantic-based similarity between any two medicines x and y can be calculated using the binary Dice coefficient (Frakes & Baeza-Yates, 1992), as demonstrated in Eq. (3).

$$MedSim_{x,y}^{Semantic} = \frac{2 \times D_{11}}{D_{01} + D_{10} + 2 \times D_{11}}, \quad where \tag{3}$$

$$\begin{Bmatrix} \mathrm{D}_{11} = \text{ Total number of events where } m_{x,d} \text{ is 1 and } m_{y,d} \text{ is 1} \\ \mathrm{D}_{01} = \text{ Total number of events where } m_{x,d} \text{ is 0 and } m_{y,d} \text{ is 1} \\ \mathrm{D}_{10} = \text{ Total number of events where } m_{x,d} \text{ is 1 and } m_{y,d} \text{ is 0} \end{Bmatrix}$$

Consider the example of "Medicine 3" and "Medicine 4" in Figure 3, where they are shown to have no semantic similarity as they do not share any specific medical conditions. In contrast, "Medicine 1" and "Medicine 2" are considered similar because they share three common specific medical conditions: joint pain, backache, and nerve pain. Suppose a patient wishes to switch from "Medicine 1" to another medicine for better efficacy or cost-effectiveness. In this case, the semantic-based filtering module will likely suggest "Medicine 2" as it is the most similar to "Medicine 1". This can be better understood by examining each medicine's vector representation: "Medicine 1" = (1, 1, 1, 0, 0), "Medicine 2" = (1, 1, 1, 0, 0), "Medicine 3" = (0, 0, 1, 0, 0), and "Medicine 4" = (0, 0, 0, 1, 0). We can determine the semantic-based similarity between "Medicine 3" and "Medicine 4" using Equation (3) with D11 = 0, D01 = 1, and D10 = 1. As a result, the semantic-based similarity between "Medicine 3" and "Medicine 4" is 0/(1 + 1 + 0) = 0. In contrast, the semantic-based similarity between "Medicine 1" and "Medicine 2" is 6/(0 + 0 + 6) = 1.

MULTI-CRITERIA FILTERING MODULE

The multi-criteria (MC) based-filtering is an advanced version of single-rating based-filtering where users rate various criteria for each item. Although the overall rating of an item indicates how much the user likes it, MC ratings offer more comprehensive information about why the user likes it. As a result, MC ratings allow for a more precise assessment of the similarity between users or items, as mentioned by Adomavicius and Kwon (2007).

Formally, the rating function in MC based-filtering for a set of patients *P* and a set of medicines *M* is defined as:

$$R : P \times M \rightarrow R_0 \times R_1 \times ... \times R_z \tag{4}$$

Where R_0 is an overall rating and R_c refers to the rating value for each criterion c ($c = 1,2,..z$) on a particular numeric scale (e.g.,1 to 5).

Adomavicius and Kwon (2007) classified MC based-filtering approaches into two types: similarity-based approaches and aggregation-function-based approaches. In the similarity-based approach, any similarity metric, such as Pearson correlation or cosine similarity, is used to calculate the similarity between users or items on each criterion. Then, an overall similarity is aggregated using the individual similarities on various criteria, either by taking their average (average similarity) or considering only the minimum similarity among all similarities (worst-case similarity). After obtaining the overall similarity, the problem is then transferred from being a multi-criterion filtering problem into a single-criteria filtering problem (Gupta & Kant, 2020). The proposed MC based-filtering module follows the similarity-based approach.

The aggregation-function-based approach is based on the rationale that the overall rating of an item is not independent of other ratings; rather, it has a latent relationship with the MC ratings. So, there is a need to learn an aggregation function that can estimate the relationship δ between the overall rating and the underlying MC ratings of items $R_0 = \delta(R_1, R_2, \ldots, R_z)$. Hence, finding a proper aggregation function is vital in model-based MC approaches; however, a variety of statistical techniques and machine-learning methods have been applied for this purpose (Adomavicius & Kwon, 2007; Gupta & Kant, 2020).

To compute the MC-based similarity, the first step involves determining the partial similarity values between two medicines, x and y, in relation to each rating criterion, c. The triangle similarity method (Sun et al., 2017), which takes into account both the vector length and the angle between them, is used to calculate the partial similarities. This method is preferred over the cosine measure, which is solely based on the angle between vectors and may produce counterintuitive results. For instance, if we consider the vectors x = (5, 5, 5) and y = (1, 1, 1), the cosine similarity is 1, which is irrational. On the other hand, the triangle similarity between the two vectors is 0.33, which is more sensible. Formally, the partial similarity value of criteria c between medicine x and medicine y can be expressed as:

$$TriSim_{x,y}^{c} = 1 - \left(\frac{\sqrt{\sum_{p \in P_{x,y}} (r_{p,x}^{c} - r_{p,y}^{c})^2}}{\sqrt{\sum_{p \in P_{x,y}} (r_{p,x}^{c})^2} + \sqrt{\sum_{p \in P_{x,y}} (r_{p,y}^{c})^2}} \right) \tag{5}$$

Where $r^{c}_{p,x}$ and $r^{c}_{p,y}$ represent the ratings of patient *p* for medicines *x* and *y* respectively, concerning criteria *c*. $P_{x,y}$ refers to the set of patients who have rated both medicines *x* and *y*. Next, to determine the overall similarity value between medicines *x* and *y*, the average similarity is employed as an aggregation approach to the partial similarities, as proposed by Adomavicius and Kwon (2007). The following equation illustrates this process:

$$OverallSim_{x,y} = \frac{\sum_{c=1,\ldots,z} TriSim^{c}_{x,y}}{z} \tag{6}$$

Where *z* is the number of individual criteria being considered.

Although the triangle similarity method takes into account co-rating patients, it does not provide complete information on non-co-rating patients. To overcome this limitation, we incorporate the overlap coefficient (Verma & Aggarwal, 2020) as a structural similarity measure to enhance triangle similarity. As a result, we obtain a new hybrid measure that is calculated by multiplying the triangle similarity and overlap coefficient. The overlap coefficient quantifies the proportion of the intersection size of the total common patients who rated both medicines, with respect to the smaller of the two sets of total patients who rated either medicine. This means that the higher the number of common patients who have rated both medicines, the greater the level of similarity between them.

$$OverlapSim_{x,y} = \frac{\left|P_x \cap P_y\right|}{\min\left(\left|P_x\right|,\left|P_y\right|\right)} \tag{7}$$

Where $\left|P_x \cap P_y\right|$ represents the total number of patients who have rated both medicines *x* and *y*, while $\left|P_x\right|$ and $\left|P_y\right|$ denote the overall number of patients who have rated medicine *x* and medicine *y*, respectively.

In conclusion, the MC-based similarity metric for a given pair of medicines can be expressed as follows:

$$MedSim^{MC}_{x,y} = OverallSim_{x,y} \times OverlapSim_{x,y} \tag{8}$$

Medicine reputation score

In order to enhance the module's ability to predict medicines that have not been observed, a medicine reputation score has been introduced. This is necessary to address the sparsity and new item issues that arise due to a limited number of reliable nearest neighbors. The reputation score of a medicine is determined by considering various factors, including the difference in ratings between the medicine and the patients' mean ratings, as well as the medicine's similarity with other medicines, as illustrated below.

$$MedRep_x = \exp\left(-\frac{\sum_{p \in P_x}\left|r_{p,x} - \overline{r}_p\right|}{\left|P_x\right|}\right) \times \sqrt{\frac{\left|M_x\right|}{\left|M\right|}} \tag{9}$$

Where $\overline{r}_p$ denotes the average rating on all medicines rated by patient *p*, while P_x denotes the set of patients who have given ratings for medicine *x*. Similarly, M_x indicates the set of medicines that are related to medicine *x* in terms of similarity, while *M* represents the entire collection of medicines available in the dataset.

RECOMMENDATION GENERATION MODULE

This module involves the process of computing the predicted rating for an unobserved medicine x for a patient p. To achieve this, the weighted sum approach (Sarwar et al., 2001) is employed, which involves adding up the ratings given by patient p to the most similar medicines y in the nearest neighbors set (NN) for the unobserved medicine x. The *Top-n* approach is utilized for selecting neighbors, whereby a predetermined number of items exhibiting the highest degrees of similarity are selected. This module employs two sets of nearest neighbors (NN) for items that exhibit the highest similarity to the target item, based on both semantic-based and MC-based similarity. These sets are derived from the corresponding similarity matrices, as illustrated in Figure 2. The weighted sum approach is applied twice, first for the semantic-based filtering approach and then for the MC-based filtering approach. The computation process is described below.

$$PredRating_{p,x}^{Semantic} = \frac{\sum_{y \in NN} (r_{p,y} \times MedSim_{x,y}^{Semantic})}{\sum_{y \in NN} \left| MedSim_{x,y}^{Semantic} \right|} \tag{10}$$

$$PredRating_{p,x}^{MC} = \begin{cases} \dfrac{\sum_{y \in NN} (r_{p,y} \times MedSim_{x,y}^{MC})}{\sum_{y \in NN} \left| MedSim_{x,y}^{MC} \right|} & ; \quad \text{if } MedSim_{x,y}^{MC} \neq 0 \\ \dfrac{\sum_{y \in NN} (r_{p,y} \times MedRep_{y})}{\sum_{y \in NN} MedRep_{y}} & ; \quad \text{if } MedSim_{x,y}^{MC} = 0 \end{cases} \tag{11}$$

Subsequently, it has been proven that achieving the best rating prediction performance requires a hybrid approach that combines several recommendation methods. Thus, the proposed HSMCCF approach employs the switching hybridization strategy (Burke, 2007), as depicted below, to alternate between the two modules based on a specific condition. The selection criterion for determining which module to use is its ability to generate a predicted rating for a potential medication. When both modules are capable of producing predicted ratings, the arithmetic-harmonic mean is utilized to merge the predicted scores. The harmonic mean metric is employed to ensure that a high total predicted rating for a particular medicine is obtained only when the predicted ratings from both combined modules are high.

$$PredRating_{p,x}^{Final} = \left\{ \begin{array}{ll} 0 & ; \text{if } PredRating_{p,x}^{Semantic} \text{ and } PredRating_{p,x}^{MC} = 0 \\ PredRating_{p,x}^{Semantic} & ; \text{if } PredRating_{p,x}^{MC} = 0 \\ PredRating_{p,x}^{MC} & ; \text{if } PredRating_{p,x}^{Semantic} = 0 \\ \dfrac{2 \times PredRating_{p,x}^{MC} \times PredRating_{p,x}^{Semantic}}{PredRating_{p,x}^{MC} + PredRating_{p,x}^{Semantic}} & ; Otherwise \end{array} \right\} \tag{12}$$

EXPERIMENTAL RESULTS

This section presents our experimental investigation into the accuracy and coverage of predictions. It encompasses the experimental datasets, evaluation measures, benchmark recommendation methods, as well as the experimental findings and discussion.

DATASETS AND EVALUATION MEASURES

To assess the effectiveness of the proposed HSMCCF approach, we utilized the WebMD MC rating dataset. This dataset was obtained from the well-known healthcare website, webmd.com, which allows patients to rate medicines on a scale of 1 to 5 based on three criteria: medication effectiveness, ease of use, and satisfaction. The WebMD MC rating dataset comprises 32,054 ratings across multiple criteria, provided by 2,136 patients for 845 medicines. Additionally, we employed a two-level medicine taxonomy organized by medical conditions. The top level comprises 915 main categories representing various medical conditions, such as joint pain, nerve pain, backache, and psoriasis of the scalp, while the second level consists of medications such as leaf nodes.

To assess the effect of sparsity on the performance of the proposed HSMCCF method and benchmark recommendation methods, we utilized the sparsity metric to generate six sparse datasets with varying levels of sparsity. Ratings were randomly omitted from these datasets to create increasing levels of sparsity, ranging from 98.0% to 99.8%. The sparsity level of a dataset is measured as (1 - dataset density). Dataset density is defined as the proportion of the number of nonzero entries/total number of entries, where nonzero entries are the total number of overall ratings in the dataset, and the total number of entries is computed by multiplying the number of users by the number of items. In addition, we introduced another six datasets to evaluate the impact of the new item problem on the effectiveness of the HSMCCF method and benchmark recommendation methods. Each dataset had a distinct number of ratings for new items, ranging from 2 to 25 ratings.

In order to evaluate the performance of the method and benchmark recommendation methods concerning prediction accuracy and coverage, the Mean Absolute Error (MAE) and the Coverage measures are used. The MAE is a commonly used evaluation metric in recommender systems for measuring prediction accuracy. It measures the average absolute difference between the predicted and actual ratings provided by users for items in a dataset. In other words, it quantifies how well the recommendation method's predictions match the true ratings. A lower MAE value indicates better prediction accuracy and, thus, a more effective recommendation method. The MAE can be calculated based on the set of predicted p_i and actual r_i ratings for all items *T* in the test set using the following formula:

$$MAE = \frac{1}{T}\sum_{i \in T}\left|p_i - r_i\right| \tag{13}$$

Coverage is a widely used evaluation metric for evaluating the performance of recommender systems when dealing with both sparsity and new items. It can be used to measure the percentage of unrated items that are still recommended by a recommendation method, as well as the method's ability to generate recommendations for a diverse set of items, including new ones, despite the sparsity of the dataset. A higher coverage indicates that the recommendation method is able to recommend a larger proportion of the items in the dataset, including those that are new or unrated and can thus offer more personalized recommendations to users (Aggarwal, 2016b). Coverage can be calculated using the variables *T* and *P*, where *T* represents the total number of available items in the test set and *P* represents the number of items for which a prediction can be obtained in the test set, formulated as follows:

$$Coverage = \frac{P}{T} \tag{14}$$

BENCHMARK METHODS

In order to perform a comparative analysis, and considering that the HSMCCF recommendation approach is an item-based recommendation method, we compared its results with those of three item-based benchmark recommendation methods:

- The Single-Criteria Item-based CF (SC-ICF) recommendation method, which utilizes cosine similarity among items to generate personalized recommendations (Sarwar et al., 2001).
- The Multi-Criteria Item Based CF (MC-ICF) recommendation method, which employs MC

ratings between items to improve the accuracy of predictions (Adomavicius & Kwon, 2007).

- The Multi-Criteria Item-based Semantic-enhanced CF (MC-ISCF) (Shambour et al., 2016) recommendation method, which utilizes both MC ratings and semantic relationships among items to enhance prediction accuracy and tackle issues related to data sparsity and cold-start item problems.
- The Fusion Multi-Criteria User-Item Collaborative Filtering (Fusion MC-UICF) (Shambour et al., 2022) recommendation method, which leverages all the data available in the user-item matrix by fusing the MC ratings of both users and items to enhance the accuracy of predictions and mitigate the impact of sparsity.

EXPERIMENTAL RESULTS

The proposed HSMCCF recommendation approach was subjected to a series of experiments, as presented below, to validate its improvement and effectiveness in enhancing both prediction accuracy and coverage when compared to benchmark methods. These experiments also aimed to address the challenges posed by sparsity and new items in the introduced datasets.

Evaluation of prediction accuracy using the WebMD medication dataset

Figure 4 compares the prediction accuracy, as measured by MAE results, of the HSMCCF approach with benchmark methods on the WebMD MC dataset. The benchmark methods included in the comparison are SC-ICF, MC-ICF, MC-ISCF, and Fusion MC-UICF. The results demonstrate that the HSMCCF approach achieves exceptional MAE performance across neighboring sizes ranging from 5 to 50, outperforming the benchmark methods by an average of approximately 59%, 51%, 35%, and 37%, respectively. These findings indicate that the HSMCCF approach significantly enhances prediction accuracy on the WebMD MC dataset, as confirmed by the analysis and comparison of all benchmark methods against it.

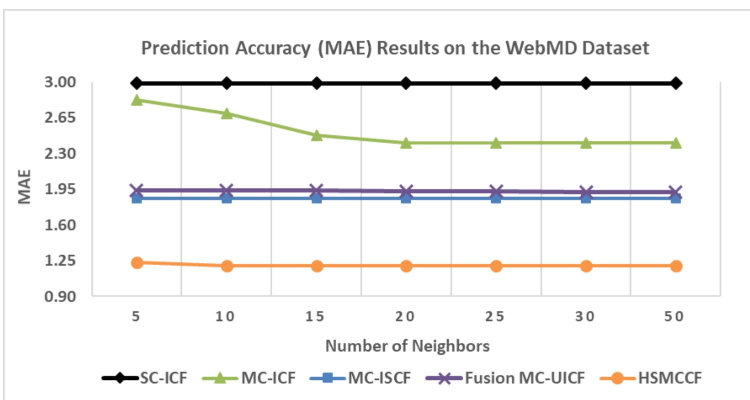

Figure 4. Evaluation of prediction accuracy (MAE) on the WebMD dataset

Evaluation of prediction accuracy and coverage across a variety of sparsity levels

Figures 5 and 6 demonstrate that incorporating MC ratings, reputation scores, and semantic filtering into the prediction process of the HSMCCF approach can mitigate the negative impact of sparsity on prediction accuracy and coverage. The SC-ICF, MC-ICF, and Fusion MC-UICF methods rely solely on raw ratings for finding neighbors and generating predictions, which leads to unsatisfactory prediction accuracy and coverage when dealing with sparse datasets. MC-ISCF, on the other hand, leverages both MC ratings and semantic relationships between items to enhance prediction accuracy and coverage to some extent. Meanwhile, the HSMCCF approach employs MC ratings, reputation scores, and semantic filtering to expand the pool of potential neighbors in the neighbor selection phase, which helps to address issues related to data sparsity and ultimately leads to higher prediction accuracy and coverage compared to other benchmark approaches.

Figure 5 shows that the HSMCCF approach achieves average MAE results that are approximately 65%, 58%, 26%, and 51% better than the benchmark methods. This indicates the superior performance of the HSMCCF approach in accurately predicting ratings across different levels of sparsity when compared to the benchmark methods. Figure 6 displays the average Coverage results of the HSMCCF approach in comparison to benchmark methods, with enhancements of approximately 58%, 46%, 15%, and 36%, respectively, indicating its superior performance in terms of prediction coverage as well. In summary, the results provide evidence supporting the superiority of the proposed HSMCCF approach in handling the sparsity problem over benchmark methods regarding both prediction accuracy and coverage.

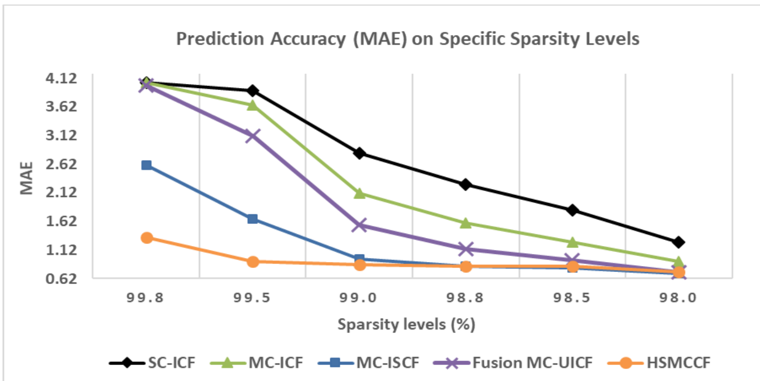

Figure 5. Evaluation of prediction accuracy (MAE) across a variety of sparsity levels

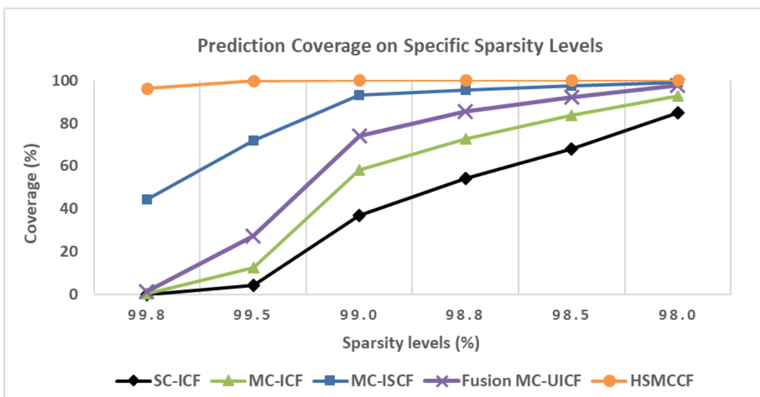

Figure 6. Evaluation of prediction Coverage across a variety of sparsity levels

Evaluation of prediction accuracy and coverage for new items with varying numbers of ratings

The effectiveness of the HSMCCF approach in addressing the negative impact of the new item problem on prediction accuracy and coverage is demonstrated in Figures 7 and 8. As shown, the SC-ICF, MC-ICF, and Fusion MC-UICF methods rely solely on raw ratings for neighbor selection and prediction generation, which results in unsatisfactory prediction accuracy and coverage values when producing predictions for new items. MC-ISCF, conversely, improves prediction accuracy and coverage to some extent by utilizing both MC ratings and semantic relationships between items. HSMCCF takes this a step further by incorporating MC ratings, reputation scores, and semantic filtering in the neighbor selection phase to expand the pool of potential neighbors, which effectively mitigates issues related to new items and leads to higher prediction accuracy and coverage compared to other benchmark approaches.

Figure 7 illustrates that the HSMCCF approach exhibits superior performance compared to benchmark methods, with an average MAE improvement of approximately 36%, 35%, 13%, and 27%. The results are noteworthy as they demonstrate that the proposed approach surpasses benchmark methods in prediction accuracy. Furthermore, Figure 8 illustrates the mean Coverage results of the HSMCCF approach in contrast to benchmark methods, exhibiting improvements of roughly 72%, 66%, 23%, and 48%, correspondingly. The results validate that the HSMCCF approach exhibits superior performance compared to benchmark methods with regard to prediction Coverage. Consequently, it has the ability to produce recommendations for a significant proportion of the recently added items. In general, it can be demonstrated that the MAE exhibits a negative correlation with the number of ratings assigned to new items, while the Coverage metric displays a positive correlation with the number of ratings. The proposed approach exhibits greater robustness and effectiveness in terms of prediction accuracy and coverage compared to other benchmark methods when dealing with new items that have very limited ratings. This is evidenced by the noteworthy enhancements in MAE and Coverage results.

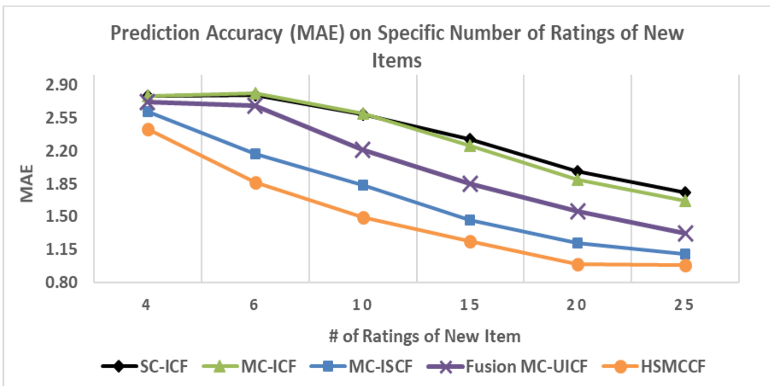

Figure 7. Evaluation of prediction accuracy (MAE) for new items with varying numbers of ratings

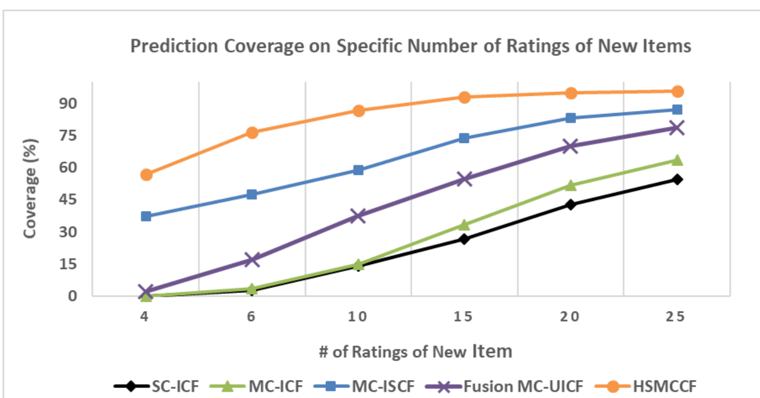

Figure 8. Evaluation of prediction Coverage for new items with varying numbers of ratings

Discussion

The experimental evaluation results outlined above provide evidence that the proposed HSMCCF approach is effective in improving prediction accuracy and coverage in sparse datasets as well as datasets containing new items with few ratings. The SC-ICF, MC-ICF, and Fusion MC-UICF approaches exclusively depend on ratings to identify neighbors and produce predictions. This results in unsatisfactory prediction accuracy and coverage, particularly when handling datasets and items with very limited ratings. However, the MC-UICF approach still yields better results than SC-ICF and MC-ICF with respect to predictive accuracy and coverage, particularly in scenarios involving sparse datasets or new items with limited ratings. This is due to its ability to fuse the MC ratings of both users and items, thereby utilizing all the data present in the user-item matrix to produce predictions.

Whereas the MC-ISCF, which bears the closest resemblance to our proposed approach, employs a combination of MC ratings and semantic associations among items in order to improve the accuracy and coverage of predictions to a certain degree. On the other hand, the HSMCCF approach incorporates reputation scores in conjunction with MC ratings and semantic filtering to further enlarge the pool of potential neighbors during the neighbor selection phase, thereby yielding superior results in terms of predictive accuracy and coverage, especially when dealing with extremely sparse datasets or with new items with very few ratings. For instance, regarding data sparsity, the proposed approach exhibited a mean enhancement of 48% and 53% in MAE and Coverage, respectively, compared to the MC-ISCF approach in a dataset with a sparsity level of 99.8%. Moreover, in the dataset with a sparsity level of 99.5%, the proposed approach exhibits an average percentage improvement of 44% and 27% over the MC-ISCF approach in terms of MAE and Coverage, respectively. With respect to the new item problem, the proposed approach exhibited an average improvement of 7% and 34% in MAE and Coverage, respectively, when compared to the MC-ISCF approach in a dataset of new items that have only four ratings. In addition, the proposed approach demonstrates an average percentage improvement of 14% and 37% over the MC-ISCF approach with respect to MAE and Coverage, respectively, in a dataset comprising new items that have only received six ratings.

CONCLUSION

As the internet continues to evolve, online healthcare platforms and e-services are expected to play an even more significant role in the future of healthcare. Such platforms offer valuable tools and information to help manage patients' health, such as searching for medicines based on their medical conditions. Nonetheless, patients often find it arduous and time-consuming to sort through all the available medications to find the ones that match their specific medical conditions. The aim of this study is to devise a personalized solution for online healthcare platforms that can alleviate problems arising from information overload and data sparsity by proposing an effective medicine recommendation approach, referred to as HSMCCF, for recommending suitable medications to patients based on their specific medical conditions. This approach is designed to overcome issues related to data sparsity and new item recommendations that are commonly associated with medicine recommendations in the online healthcare field.

To overcome the data sparsity and new item issues, the proposed approach incorporates a semantic filtering module and a multi-criteria filtering module. The semantic filtering module aims to reduce data sparsity and new item issues by utilizing a medicine taxonomy that sorts medicines according to medical conditions and by leveraging semantic relationships between medicines to identify those that are most likely to be relevant to patients based on their current medical conditions. Furthermore, the multi-criteria filtering module enhances the approach's capability to capture the intricacy of patient preferences and provide more precise recommendations. This is achieved by considering multiple patient preferences and criteria through a unique similarity metric that incorporates both distance and structural similarities. Additionally, a medicine reputation score is also employed to further expand the pool of potential neighbors during the neighbor selection phase, thereby yielding superior results in terms of predictive accuracy and coverage, especially when dealing with extremely sparse datasets or with new items with very few ratings. The effectiveness of the proposed HSMCCF approach was proven to be superior to that of benchmark recommendation methods, including the SC-ICF, MC-ICF, and Fusion MC-UICF approaches, in terms of boosting both prediction accuracy and coverage, specifically when tackling the challenges of data sparsity and new items.

However, the primary limitation of the study was the absence of MC rating datasets within the medicine recommendation domain that could have been employed for further model validation. In the future, researchers may focus on two key routes. The first is to use deep learning techniques to analyze MC-based ratings with the aim of devising a robust aggregation function, which has the potential to enhance the precision of medication predictions. The second is investigating the effects of integrating patient medicine reviews on the efficacy of the proposed recommendation methodology.

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