Enhancing Medication Recommendations Through Multi-Criteria Collaborative Filtering

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ABSTRACT

The exponential growth of online healthcare platforms has resulted in an overwhelming volume of medication information, posing challenges for patients seeking appropriate treatments for their specific conditions. Recommendation systems have emerged as valuable tools in various applications, including healthcare, helping users navigate information overload. However, their effectiveness in recommending medications is often limited by data sparsity, which arises from insufficient user-item interaction data and hinders accurate prediction. This study proposes a collaborative multi-criteria filtering approach that improves medication recommendations without relying on external knowledge sources. The proposed approach leverages multi-criteria ratings, implicit user and item similarities, similarity transitivity, and global similarity concepts. By effectively utilizing implicit information embedded within existing user-item multi-criteria ratings, the proposed approach effectively expands user and medication neighborhoods, resulting in more accurate and diverse recommendations, even in sparse data scenarios. Empirical analysis on a real-world medicine dataset demonstrated that the proposed approach significantly outperformed existing recommendation methods, resulting in substantial improvements in predictive accuracy and recommendation coverage, particularly in sparse environments.

Keywords-recommender systems; collaborative filtering; multi-criteria; medicine recommendation; prediction accuracy; data sparsity

I. INTRODUCTION

The rapid expansion of Internet applications and digital health platforms has fundamentally transformed the way people access medical information and make health-related decisions. In recent years, online Health Information Seeking Behavior (HISB) has become a global phenomenon, driven by the accessibility, affordability, and breadth of resources available on the Internet. According to a 2020 survey, 55% of Europeans aged 16-74 have sought health-related information online, representing a 21% increase since 2010, with rates exceeding 70% in countries such as Finland, the Netherlands, Denmark, and Germany. In the United States, the proportion of the population seeking health information online increased from 61.2% in 2008 to 74.4% in 2017, while even higher rates are observed in several Asian countries [1].

However, increasing reliance on online health resources introduces new difficulties. The sheer volume of health data related to symptoms, diagnoses, treatments, side effects, and health tips can often result in information overload, confused patients, and problems in distinguishing trustworthy from untrustworthy information [1]. Online health platforms, such as WebMD, provide comprehensive information on medications for various conditions and allow users to enter their health condition and receive a list of commonly used medications for it, along with articles on the medication's uses, doses, side effects, and reviews. However, patients can often be overwhelmed by the number of medications and cannot identify which ones are best for them. Recommendation systems can help users understand and deal with misleading and excessive amounts of information. Patients and caregivers utilize online recommendation systems to assist them in efficiently sorting through various medications and recommended treatments. Thus, recommender systems reduce information overload, decrease patient cognitive overhead, and allow for better informed decision-making [2].

Recommender systems are designed to provide personalized suggestions by analyzing user preferences and past behaviors. Collaborative Filtering (CF) techniques, which include user- and item-based approaches, are widely used in

these systems. User-based CF focuses on determining the similarities between users' preferences to provide recommendations, whereas item-based CF uses the similarities between items to provide recommendations. However, both techniques face significant challenges, mainly due to data sparsity, the lack of sufficient rating data to make accurate predictions [3]. To overcome data sparsity, researchers have proposed incorporating supplementary, or side, information into CF-based approaches. This information can include user profiles, social networks, content-based data, item content, reviews, etc. [4]. Although using side information can significantly improve the accuracy of the recommendation, it is often domain-specific, difficult to collect, and sometimes unreliable.

In addition to side information, many systems still rely on single-criterion models, which fail to capture the multi-faceted nature of user preferences. Integrating Multi-Criteria (MC) ratings into recommendation systems further enhances their performance. MC ratings allow users to evaluate items based on multiple criteria, providing a deeper understanding of user preferences. For example, on WebMD, users can rate medications based on effectiveness, ease of use, and satisfaction. Taking into account these additional criteria, MC-based CF approaches can generate more precise and personalized recommendations [5].

The increasing proliferation and utilization of online health platforms, along with the current trend indicating a demand for personalized medicine, have led to rapid growth in medicine recommendation systems. Recent years have seen rapid growth in the use of Machine Learning (ML) and Deep Learning (DL) as key tools to advance intelligent health applications [6-8], particularly in improving the accuracy and safety of systems that support medicine recommendations [9-16]. In [9], a differential privacy-preserving DL caching framework was introduced for healthcare, highlighting how advanced artificial intelligence can improve both the security and accuracy of recommendations in telemedicine and disease management contexts. In [10], the role of ML in medical emergency drug recommendations was studied, showing that decision trees can offer accurate and actionable drug recommendations in emergencies such as pandemics or natural disasters. In [11], the integration of multiple ML algorithms was also explored, using sentiment analysis and probabilistic methods to predict diseases and recommend medications based on symptoms and user ratings. The system in [12] relied on the patient's Electronic Health Record (EHR) coupled with an adversarial Drug-Drug Interaction (DDI) knowledge graph while using Singular Value Decomposition (SVD) and a post-hoc re-ranking of recommendations to find an acceptable balance between efficiency and safety. In a follow-up study [13], the Matrix Co-Factorization (MCF) method was extended to employ auxiliary data, and a post-hoc re-ranking approach was used to normalize harmful drug interactions while still delivering accurate recommendations. The method in [14] incorporated feature interaction (particularly using a drug knowledge graph) and graph convolution, while also applying a knowledge-aware attention mechanism to model drug correlations and augment user and drug representations to improve the accuracy of recommendations.

Recurrent Neural Networks (RNNs) have also been investigated for drug recommendation systems. In [15], RNNs were used in conjunction with NLP techniques to socially analyze patient reviews and ratings in conjunction with attributes such as age, gender, and medical history, to generate drug recommendations. In [16], the focus was on analyzing drug reviews using ML classifiers, employing techniques such as N-gram, Light Gradient Boosting Machine (LGBM), and Naïve Bayes (NB) to predict sentiment and recommend medications for specific conditions, achieving high accuracy.

Despite these technical advances, a significant research gap remains. Most state-of-the-art approaches depend on auxiliary information, such as semantic knowledge graphs, trust networks, or curated drug ontologies, or are not robust in highly sparse settings. Reviews and comparative studies have shown that few models can operate accurately and reliably using only MC user-item interactions, which is often the only data consistently available on real-world platforms [3, 5]. Therefore, there is a pressing need for generalizable recommender frameworks that are effective in sparse, real-world conditions and do not rely on domain-specific external resources.

Motivated by these gaps, this study introduces a medication recommendation approach designed to address the challenge of limited user rating data. Unlike other approaches that require external information, the proposed approach relies solely on available user-medication interactions to generate recommendations, ensuring broad applicability in real-world healthcare settings. Although this approach aims to help patients navigate online health information efficiently to identify suitable medication options, it is essential to consult with a qualified healthcare provider for personalized medical advice and prescriptions. The system is designed to complement, not replace, the guidance of medical professionals, ensuring that patients are equipped with relevant information to discuss with their healthcare providers. By incorporating multi-criteria ratings, implicit similarity relationships between users and items, and the concept of global similarity, this approach expands the pool of potential user and item neighborhoods. This enhancement leads to improved prediction accuracy and broader recommendation coverage. Empirical analysis on a real-world medicine rating dataset shows that the proposed approach significantly outperforms existing baseline methods. In addition, this approach effectively addresses data sparsity issues, resulting in enhanced predictive accuracy and recommendation coverage.

II. THE PROPOSED METHOD

The proposed recommendation approach is built on a hybrid MC-CF framework that integrates both user- and item-based implicit similarities. This framework utilizes a raw user-item MC rating matrix as input to generate predicted ratings for unrated items for each user.

To formalize this, let U denote the set of users (patients) and I the set of items (medicines). Each medication is evaluated by a patient across multiple criteria, represented as $\{c_1, c_2, \ldots, c_z\}$. Each criterion reflects a specific item attribute, numerically rated by a user, $c_x^a(i)$. The relative importance of

each criterion is indicated by a weight $w_x^a(i)$. The overall utility of item i for user a, denoted as T, is calculated using an additive value function [17], which combines a user's ratings across multiple criteria into a single utility score, thus capturing the user's overall evaluation of the medication.

$$T^a(i) = \sum_{x=1}^{z} w_x^a(i) c_x^a(i) \text{ with}$$
$$\sum_{x=1}^{z} w_x^a(i) = 1, \ \forall a \in U \text{ and } \forall i \in I \quad (1)$$

The recommendation framework consists of three main components: a user-based MC-CF module, an item-based module, and a hybrid prediction module. As shown in Figure 1, the overall workflow includes the calculation of user and item similarities, similarity propagation, computation of global similarity, and finally, the generation of hybrid predictions.

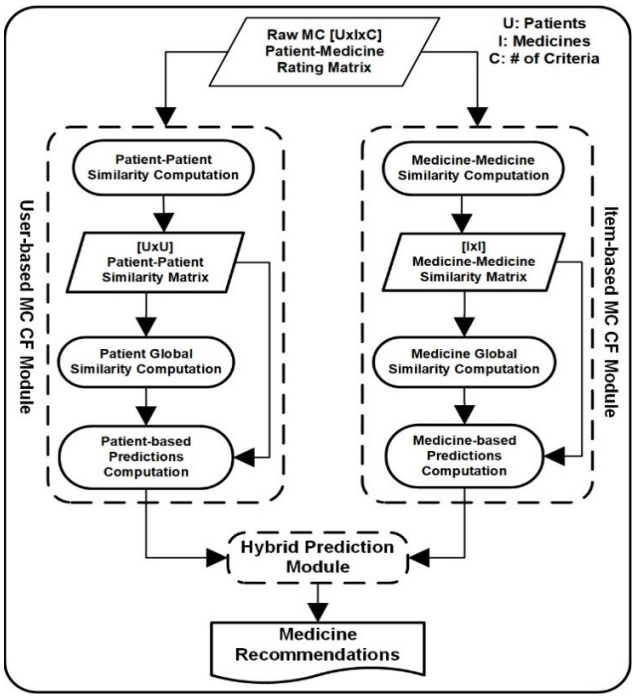

Fig. 1. Workflow of the proposed recommendation approach.

A. User-Based MC CF Module

To generate user-based MC predictions, this module leverages implicit similarities between users as derived from the user-user implicit similarity matrix. The process involves four key steps:

1) Step 1: Compute Direct Implicit Similarity Between Users

Implicit similarities between users are calculated to identify more accurate neighbors and enhance prediction accuracy. This is achieved by calculating the prediction accuracy of each user when acting as a recommender for another. A user's ability to accurately predict another user's preferences indicates a high implicit similarity between them. Specifically, if user b accurately predicts user a's preferences in the past, a high implicit similarity between users a and b is inferred. Predicted ratings are calculated based on user ratings' deviation from mean values, facilitating implicit similarity estimation between users:

$$P_{a,i} = \bar{r}_a + (T^b(i) - \bar{r}_b) \quad (2)$$

where $\overline{r_a}$ and $\overline{r_b}$ are the mean ratings of users a and b, respectively, and $T^b(i)$ denotes user b's overall rating (or utility) for item i. The implicit similarity between users a and b is calculated using the Absolute Difference of Ratings (ADF) method, which is based on the prediction errors for co-rated items by both users.

$$Sim_{a,b}^{ADF} = \frac{\sum_{i=1}^{|I_{a\cap b}|} exp\left(-\frac{|P_{a,i} - T^a(i)|}{max\left(P_{a,i}, T^a(i)\right)}\right)}{|I_{a\cap b}|} \quad (3)$$

where $P_{a,i}$ is the rating predicted for item i by user a, $T^a(i)$ is the overall rating of item i for user a, and $|I_{a\cap b}|$ is the overall number of items both users a and b have rated.

The Rating Jaccard method [18] is employed as a structural similarity measure to address the limitation of considering only the prediction errors of co-rated items. This method calculates similarity based on the ratio of items rated identically by both users to the total number of items rated by both users. The higher the proportion of shared items with identical ratings, the greater the similarity between users.

$$Sim_{a,b}^{URJac} = \frac{|N_{T(a,b)}|}{|I_{a\cap b}|} \quad (4)$$

where $N_T(a,b)$ counts items rated identically by both users.

$$N_{T(a,b)} = \begin{cases} N_{T(a,b)} + 1; & \text{if } \forall i \in I_{a\cap b} \ R_{a,i} = R_{b,i} \\ N_{T(a,b)} \text{ remains unchanged;} & \text{otherwise} \end{cases} \quad (5)$$

Here, I_a and I_b are the sets of items rated by users a and b, respectively. The overall direct implicit similarity is computed by aggregating the individual similarity metrics, as follows:

$$USim_{a,b}^{Direct} = Sim_{a,b}^{ADF} \times Sim_{a,b}^{URJac} \quad (6)$$

2) Step 2: Propagate Similarity Through the User-User Implicit Similarity Matrix

A user-user implicit similarity matrix is constructed, representing users as nodes and their similarities as edges. Given the sparsity of rating data in most recommender systems, similarity propagation is employed to enrich the matrix. This process identifies indirect connections between users, expanding the neighborhood of each user beyond direct similarities. The propagated similarity value that indicates the extent to which user a is implicitly similar to user k is calculated by (7). To overcome sparse data, this formula propagates similarity through intermediate users, so indirect relationships can help identify suitable neighbors when direct evidence is limited.

$$USim_{a,k}^{Prop} = \frac{\sum_{b\in adj(a \text{ and } k)}(USim_{a,b}^{Direct} \times Sim_{a,b}^{URJac}) + (USim_{b,k}^{Direct} \times Sim_{b,k}^{URJac})}{\sum_{b\in adj(a \text{ and } k)} Sim_{a,b}^{URJac} + Sim_{b,k}^{URJac}} \quad (7)$$

3) Step 3: Compute User-Global Similarity

In the third step, user global similarity is calculated, which serves to enhance the system's predictive capabilities, especially for active users with few nearest neighbors. This is computed by combining two essential elements: the average variation in ratings between the active user and the items averages, and the proportion of users who exhibit implicit similarity with the active user in the user-user implicit similarity matrix:

$$UGS_a = exp\left(-\frac{\sum_{i \in I_a} |r_{a,i} - \bar{r}_i|}{|I_a|}\right) \times \sqrt{\frac{|U_a|}{|U|}} \quad (8)$$

where, $r_{a,i}$ represents the rating assigned by user a to item i, $\bar{r}_i$ denotes the average rating for item i across all users, and $|U_a|$ indicates the total number of users directly connected to a user a within the users' implicit similarity matrix.

4) Step 4: Compute User-Based MC Predictions

Finally, this step involves predicting ratings for unseen items using the deviation-from-mean approach [19]. This method considers a user's top-n nearest neighbors, their ratings for the target item, and their respective global similarity scores. Additionally, the implicit similarity between the active user and its neighbors is also considered, as shown below:

$$P_{a,i}^{UbMC} = \begin{cases} \bar{r}_a + \frac{\sum_{b \in NN(a)} USim_{a,b} \times (r_{b,i} - \bar{r}_b)}{\sum_{b \in NN(a)} USim_{a,b}}; \text{if } USim_{a,b} \neq 0 \\ \bar{r}_a + \frac{\sum_{b \in NN(a)} UGS_b \times (r_{b,i} - \bar{r}_b)}{\sum_{b \in NN(a)} UGS_b}; \text{if } USim_{a,b} = 0 \end{cases} \quad (9)$$

Equation (9) combines the deviation-based prediction with both direct and global similarity, yielding a final prediction for each unrated item for the active user. $NN(a)$ represents the set of user a's top-n nearest neighbors, and $USim_{a,b}$ denotes the users' a and b implicit similarity.

B. Item-Based MC CF Module

This module utilizes the implicit similarities within the item-item implicit similarity matrix, in conjunction with each item's global similarity score, to generate item-based MC predictions. The module consists of three main steps.

1) Step 1: Compute Direct Implicit Similarity Between Items

The implicit similarity between items is calculated using two complementary metrics. This builds upon the principles established in the preceding module, enhancing the robustness of similarity assessment. First, ADF is used to measure the similarity between two items based on the prediction errors of co-rated items (10). This metric provides a quantitative assessment of similarity based on rating accuracy. Second, the Rating Jaccard method is utilized, complementing the ADF. This method calculates the similarity between items based on the overlap of identically rated items shared between users (11). This offers a structural perspective on item similarity, focusing on rating patterns rather than absolute values. Finally, these two metrics are combined to derive a comprehensive similarity score (13). This integrated approach leverages the strengths of both metrics and enables a more robust and accurate computation of implicit item similarity.

$$Sim_{i,j}^{ADF} = \frac{\sum_{a=1}^{|U_{i \cap j}|} exp\left(-\frac{|P_{a,i} - T^a(i)|}{max(P_{a,i}, T^a(i))}\right)}{|U_{i \cap j}|} \quad (10)$$

This equation calculates the implicit similarity between two items by measuring how closely they are rated by the same users. Here, $P_{a,i}$ represents the predicted rating that user a would assign to item i, and $T^a(i)$ denotes the total utility of item i for user a. $|U_{i \cap j}|$ denotes the total number of users who rated both items i and j.

The Rating Jaccard method effectively captures the similarity between items based on how consistently users rate them similarly. Equation (11) calculates the structural similarity between two items based on how frequently users rate both items with the same score, as follows:

$$Sim_{i,j}^{IRJac} = \frac{|N_{T(i,j)}|}{|U_{i \cap j}|} \quad (11)$$

where $NT(i,j)$ is the set of users who rated both items i and j with the same rating, given as follows:

$$N_{T(i,j)} = \begin{cases} N_{T(i,j)} + 1; & \text{if } \forall a \in U_{i \cap j} \ R_{a,i} = R_{a,j} \\ N_{T(i,j)} \text{ remains unchanged}; & \text{otherwise} \end{cases} \quad (12)$$

The overall implicit similarity is derived by integrating the two complementary similarity metrics, as follows:

$$ISim_{i,j} = Sim_{i,j}^{ADF} \times Sim_{i,j}^{IRJac} \quad (13)$$

2) Step 2: Compute Item Global Similarity

To enhance the module's performance in predicting unseen items, particularly in sparse datasets with limited nearest neighbors, an item global similarity score is introduced, which considers two factors: how much an item's average rating deviates from the general user preference (average rating across all items), and how well-connected the item is within the network of similar items based on the implicit similarity matrix.

$$IGS_i = exp\left(-\frac{\sum_{a \in U_i} |r_{a,i} - \bar{r}_a|}{|U_i|}\right) \times \sqrt{\frac{|I_i|}{|I|}} \quad (14)$$

Equation (14) measures the global similarity of an item by combining its distinctiveness or general appeal with its connectivity in the item-item similarity network. $\bar{r}_a$ represents the average rating that user a assigned to the set of items that he/she rated, $|U_i|$ is the number of users who provided a rating for item i, $|I_i|$ is the number of items identified as similar to item i within the item-item implicit similarity matrix, while $|I|$ is the total number of items included within the entire dataset.

3) Step 3: Compute Item-Based MC Predictions

This final step predicts the rating that an active user a will assign to a target item i by taking into account both the direct and global similarities of the items and the item i's top-n nearest neighbors. The deviation-from-mean approach [19] is

employed to provide corrections to the ratings to minimize bias and improve prediction accuracy.

$$P_{a,i}^{IbMC} = \begin{cases} \bar{r}_i + \frac{\sum_{j \in NN(i)} ISim_{i,j} \times (r_{a,i} - \bar{r}_j)}{\sum_{j \in NN(i)} ISim_{i,j}}; \text{ if } ISim_{i,j} \neq 0 \\ \bar{r}_i + \frac{\sum_{j \in NN(i)} IGS_j \times (r_{a,i} - \bar{r}_j)}{\sum_{j \in NN(i)} IGS_j}; \quad \text{if } ISim_{i,j} = 0 \end{cases} \quad (15)$$

where $NN(i)$ signifies the neighborhood of item i, which encompasses the items most similar to it based on the item-item implicit similarity matrix.

C. Hybrid Prediction Module

Inspired by successful hybrid recommendation strategies [20], this module adopts a dynamic switch hybridization scheme. This adaptive strategy selects the most suitable recommendation technique based on its ability to predict ratings for unseen items, with the primary objective of improving recommendation accuracy and coverage. When both user-based and item-based modules provide predictions, the Root Mean Square (RMS) of both predictions is calculated to yield a robust final recommendation, taking advantage of both perspectives. The RMS metric provides an added benefit as it measures the extent to which the two predicted ratings are in agreement or in disagreement, which leads to more reliable recommendations.

$$P_{a,i}^{Final} = \begin{cases} 0 ; & \text{if } P_{a,i}^{UbMC} = 0 \text{ and } P_{a,i}^{IbMC} = 0 \\ P_{a,i}^{UbMC} ; & \text{if } P_{a,i}^{UbMC} \neq 0 \text{ and } P_{a,i}^{IbMC} = 0 \\ P_{a,i}^{IbMC} ; & \text{if } P_{a,i}^{UbMC} = 0 \text{ and } P_{a,i}^{IbMC} \neq 0 \\ \sqrt{\frac{(P_{a,i}^{UbMC})^2 + (P_{a,i}^{IbMC})^2}{2}}; & \text{if } P_{a,i}^{UbMC} \neq 0 \text{ and } P_{a,i}^{IbMC} \neq 0 \end{cases} \quad (16)$$

III. EXPERIMENTAL RESULTS AND DISCUSSION

A. Experimental Design

A real-world WebMD healthcare medication rating dataset [21] was used to assess the proposed recommendation approach. This dataset was compiled by aggregating voluntary patient reviews and ratings posted on WebMD, where users evaluate medications based on their personal experiences. Each entry records the patient's assessment of a medication using three criteria: effectiveness, patient satisfaction, and ease of use. The final dataset comprises 32,054 ratings contributed by 2,136 unique patients for 845 different medications. Given the vast number of potential patient-medication pairs, the resulting user-medication rating matrix is highly sparse, with only about 1.4% of possible ratings present (i.e., a sparsity level of 98.6%). Such sparsity is characteristic of real-world healthcare data, where most patients review only a limited number of medications. To ensure credibility and reproducibility, the dataset was randomly partitioned into training and testing subsets using an 80:20 split. The distribution of both patients and medications was maintained across the two subsets, ensuring that each split remained representative of the overall data composition.

Performance was assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coverage [22]. The MAE and RMSE metrics reflect the difference between actual and predicted item ratings by the recommendation algorithms, and the smaller the MAE or RMSE, the more accurate the predictive accuracy of the method. The RMSE value is more desirable than the MAE value simply because it gives more weight to greater errors and thus reflects predictive accuracy better. The Coverage metric is also included to assess the percentage of predicted ratings to the set of all ratings within the test dataset. This metric reports its value as a percentage that reflects the ability of a recommendation method to predict for a given set of user-item interactions. Within the percentage value of coverage, the larger the value, the more accurately the recommendation system can predict items other than the highly rated ones (most popular).

The proposed approach was compared with two state-of-the-art benchmark approaches: the MC Trust-Based Collaborative Filtering (MC-TCF) approach [23] and the Hybrid Semantic-based MC CF (HSMCCF) approach [24]. The MC-TCF approach improves predictive accuracy and alleviates the issue of data sparsity by leveraging the information from MC ratings and user trust relationships. The HSMCCF approach fuses MC ratings with the semantic relationships between items to improve recommendation quality and address the issue of sparsity.

B. Experimental Results

1) Evaluation of Prediction Accuracy on the WebMD Dataset

Figures 2 and 3 compare the performance of the proposed approach with MC-TCF and HSMCCF in varying sizes of nearest neighbors. The proposed approach consistently achieved the best results in both MAE and RMSE. Specifically, it achieved an average MAE of 1.074, outperforming MC-TCF (1.163, 7.68% improvement) and HSMCCF (1.203, 10.77% improvement). In terms of RMSE, the proposed approach recorded an average of 1.409, compared to 1.464 for MC-TCF (3.73% improvement) and 1.546 for HSMCCF (8.85% improvement). This consistent performance across various neighbor sizes highlights the robustness and reliability of the proposed approach in predicting user ratings accurately.

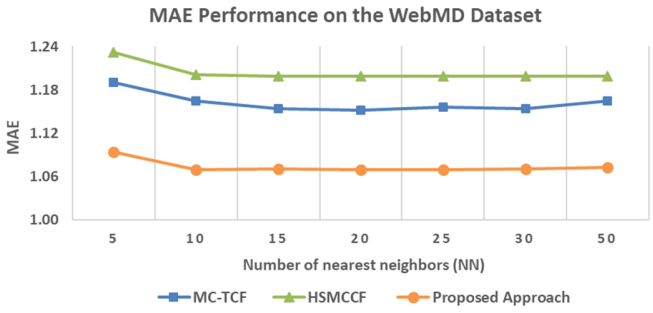

Fig. 2. MAE performance on the WebMD dataset with varying nearest neighbor sizes.

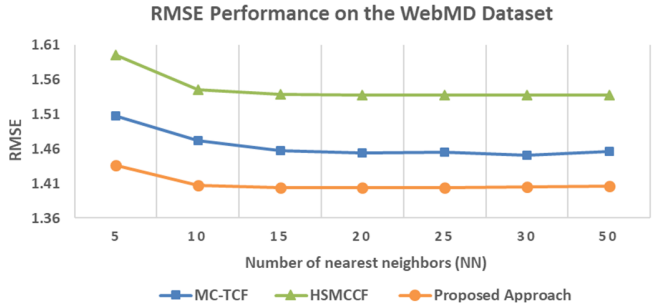

Fig. 3. RMSE performance on the WebMD dataset with varying nearest neighbor sizes.

2) Analysis of Prediction Accuracy and Coverage Across Different Levels of Sparsity

Experiments at multiple sparsity levels (99.8-98.0%) were carried out to thoroughly examine the efficacy of the proposed approach in sparse data conditions. As shown in Figures 4 and 5, the proposed approach not only maintains the lowest MAE values across all levels but also demonstrates the highest average coverage. For instance, at the highest sparsity (99.8%), the MAE of the proposed method was 1.299, substantially outperforming MC-TCF (2.731) and HSMCCF (1.335). Across all tested sparsity levels, the average MAE for the proposed approach was 0.835, representing a remarkable 32% improvement over MC-TCF and an 8.94% improvement over HSMCCF. In terms of coverage, the proposed approach achieved an average of 97.21%, which is 10.39% higher than MC-TCF and 1.32% higher than HSMCCF. These results confirm the robustness and effectiveness of the proposed approach for sparse real-world data.

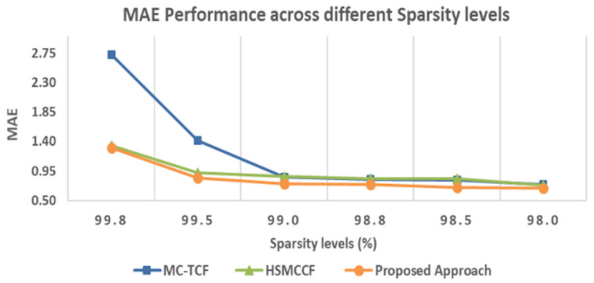

Fig. 4. Impact of data sparsity on MAE.

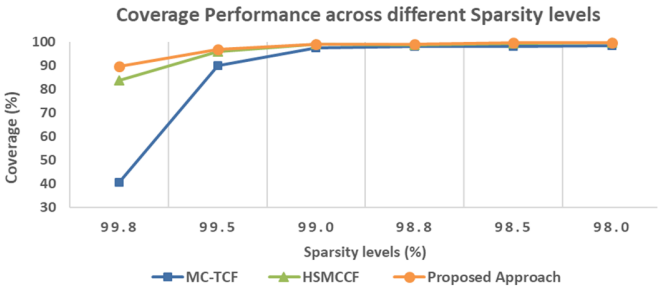

Fig. 5. Impact of data sparsity on coverage (%).

3) In-Depth Analysis of Performance Gains

The significant improvements demonstrated by the proposed approach on both benchmarks can be attributed to several key methodological innovations:

- MC rating utilization: Unlike single-criterion methods, the proposed leverages multi-dimensional user feedback (effectiveness, satisfaction, ease of use), which captures more nuanced preferences and improves the granularity of user-item matching. This results in more accurate and context-aware recommendations.
- Implicit similarity propagation: The proposed approach incorporates implicit similarity propagation to uncover indirect relationships between users and between items. This mechanism is particularly advantageous in sparse settings, where direct overlap in ratings is minimal. By propagating similarity, the system effectively expands each user's (or item's) neighborhood, leading to more reliable and diverse recommendations, even in the face of limited data.
- Global similarity integration: Integration of global similarity measures ensures that users and items with few direct connections are still effectively anchored within the overall rating network. This mitigates cold-start effects and helps maintain high accuracy and coverage, as evidenced by the proposed method's stable performance across all levels of sparsity.
- No reliance on external data: Both MC-TCF and HSMCCF improve prediction by introducing trust or semantic data, which may not always be available or reliable in real-world healthcare settings. The proposed approach, relying solely on the observed multi-criteria ratings, maximizes utility from intrinsic data and remains broadly applicable and scalable.
- Balanced hybrid aggregation: The dynamic hybrid module adaptively aggregates user- and item-based predictions using root mean square aggregation. This balanced combination leverages the complementary strengths of both models, further enhancing accuracy and coverage.

IV. CONCLUSION

The increasing availability of online health information has brought both opportunities and challenges for patients seeking suitable medications, often leading to decision fatigue and confusion. This study proposed a robust medication recommendation approach that addresses data sparsity by relying solely on implicit user and item similarities, similarity propagation, and global similarity within an MC-CF framework. Unlike previous models, the proposed approach does not require external information, making it broadly applicable in real-world healthcare settings. By providing personalized recommendations for prescription medications, the proposed approach empowers patients to make informed choices in consultation with healthcare professionals, ensuring compliance with medical regulations. Comprehensive experiments on a WebMD MC rating dataset confirmed the superiority of the proposed method over state-of-the-art benchmarks in terms of MAE, RMSE, and coverage, even in

extremely sparse data conditions. By leveraging MC ratings (effectiveness, satisfaction, and ease of use), the system achieves a deeper and more nuanced understanding of patient preferences, resulting in more personalized and accurate recommendations. The practical importance of this approach lies in its potential to power real-world medical recommendation systems that can operate effectively without dependence on external knowledge bases. This enhances the scalability, reliability, and reach of digital health platforms, supporting better treatment decisions and patient outcomes. The method's generalizability also opens possibilities for adoption in other domains with sparse MC feedback.

Future work will focus on several promising directions: piloting the recommender in live clinical settings, incorporating real-time patient feedback and clinical outcomes for adaptive learning, expanding the framework to additional e-health and chronic care domains, and optimizing for large-scale, real-time deployment. In addition, improving model transparency by developing explainable recommendation mechanisms enables clinicians and patients to better understand the basis for medication suggestions.

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