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A Trust-enhanced Recommender System for Patient-Doctor Matchmaking in Online Healthcare Communities

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Abstract: In this era of vast online healthcare information, patients often find it challenging to choose the most appropriate doctors from a myriad of options available on different communities. The sheer volume of choices can be overwhelming, underscoring the importance of personalized doctor recommendations. Unfortunately, many existing communities rely on generic doctor recommendations through a global ranking system, potentially neglecting the unique needs and preferences of individual patients. To address these challenges, this study introduces a novel multi-criteria user-item trust-enhanced collaborative filtering (MCUITeCF) approach, specifically designed to facilitate patients in locating doctors who match their unique preferences. This proposed approach capitalizes on multi-criteria ratings and integrates user-item trust relationships, aiming to enhance the quality of recommendations, while tackling the common issues of data sparsity and the cold-start problem. An examination of the proposed approach, using a real-world healthcare multi-criteria dataset, the RateMDs dataset, reveals its effectiveness in overcoming challenges associated with data sparsity and cold-start problems. The results demonstrate improved prediction accuracy and coverage compared to benchmark approaches, namely MC user-based CF, MC item-based CF, MC semantic-based CF, MC trust-based CF, and trust-semantic enhanced MC CF. Specifically, the results indicate that the MCUITeCF approach improves the average MAE by 66% compared to all of the benchmark approaches when tested on the RateMDs dataset. When dealing with data sparsity, the MCUITeCF approach improves the average MAE by 41% and prediction coverage by 23% compared to all of the benchmark approaches. In scenarios involving cold-start items, the MCUITeCF outperformed specific benchmark methods such as MC item-based CF, MC semantic-based CF, and Trust-Semantic enhanced MC CF, registering a 21% drop in average MAE and a 28% rise in prediction coverage. Similarly, for cold-start user situations, MCUITeCF excelled by decreasing the average MAE by 29% and a substantial increase in prediction coverage by 20% compared to MC user-based CF, MC trust-based CF, and trust-semantic enhanced MC CF benchmark approaches.

Keywords: Online healthcare information, Patient, Doctor, Recommender system, Multi-criteria, Trust.

1. Introduction

Over the past decade, the advent of online healthcare communities has revolutionized the way patients and doctors interact. These communities have enabled patients to seek out and review doctors based on a series of criteria, influencing their choice of healthcare provider. According to available data, a significant number of patients are utilizing online healthcare communities for selecting doctors. However, the challenge of effectively navigating through a wide variety of thousands of doctors in order to find the most suitable match is becoming more evident [1].

The emergence of recommender systems offers a viable solution to this challenge. These systems use past user behavior and preferences to predict and recommend items that may be of interest, thereby personalizing the user's experience. In the context of online healthcare communities, a recommender system has the capability to generate personalized recommendations for doctors based on patient data, including ratings and reviews. These recommendations are tailored to align with the specific preferences of each patient [2].

Multi-criteria collaborative filtering (MC-CF) has emerged as a prominent methodology in the field of recommender systems design. This approach takes into account various criteria in the process of generating recommendations, intending to offer users more precise and pertinent suggestions [3-6]. Within the domain of healthcare, patients utilizing online medical communities frequently rate doctors according to diverse criteria, including staff attitude, punctuality, helpfulness, and level of medical knowledge. Therefore, the development of multi-criteria recommender systems that can effectively utilize multi-dimensional rating information to better understand user preferences is of utmost importance [4-6]. Nevertheless, the majority of current collaborative filtering (CF) approaches, including those that incorporate multiple criteria, encounter certain limitations. These limitations encompass issues such as data sparsity and the cold-start problem. Data sparsity occurs when a limited proportion of the items within the system have been evaluated by users, leading to a scarcity of ratings. On the other hand, the cold-start problem arises when new users or items lack sufficient interaction data, making it challenging to generate precise recommendations for them [7].

In addition to these advancements, there has been a rise in the use of implicit trust-based recommendation approaches [8]. These approaches show promise in addressing the aforementioned limitations by utilizing inferred trust relationships among users to generate personalized recommendations. These systems leverage implicit feedback data, including user interactions, purchase history, and browsing behavior, in order to infer trust. Trust propagation in these methodologies entails the expansion of trust relationships to encompass not only direct connections but also indirect connections, capitalizing on the transitive characteristic of trust. Trust propagation and the development of such approaches offer several advantages in the realm of recommendation systems. These benefits encompass enhanced accuracy of recommendations, as well as the ability to effectively tackle challenges related to data sparsity and the cold-start problem, particularly for new users and items. The underlying concept of this proposition is rooted in intuitive reasoning, positing that individuals who possess a higher level of trust in one another are inclined to exhibit a greater likelihood of sharing similar tastes or preferences [8]. In the context of a doctor recommender system, it is highly probable that if a patient places trust in the evaluations provided by another patient, there exists a strong likelihood that the two patients possess similar preferences when it comes to selecting a doctor.

In consideration of the aforementioned, the key contributions of our study are outlined below:

- Introduction of a novel approach: the study presents a novel multi-criteria user-item trust-enhanced collaborative filtering (MCUITeCF) approach, facilitating patients in discovering doctors who align with their preferences in online healthcare communities.
- Comprehensive hybrid framework: the proposed approach integrates multi-criteria CF and implicit trust relationships between patients and doctors, within a CF-based framework. This integration effectively addresses common challenges in online healthcare communities, such as data sparsity, and the presence of cold-start doctors and patients. By combining these techniques, our approach mitigates the limitations of scarce user ratings and the complexity of recommending for newly added patients and doctors. This hybrid approach allows for the consideration of multiple aspects of a doctor's service when making recommendations while also accounting for the relationships and past interactions between patients and doctors.
- Empirical validation: a healthcare dataset from a real-world scenario is utilized to demonstrate the efficacy and superiority of the MCUITeCF approach in terms of prediction accuracy and coverage when compared to other prevailing and state-of-the-art CF-based recommendation approaches. The results of our study emphasize the notable improvements facilitated by the MCUITeCF approach in the process of selecting doctors within the context of online healthcare communities.

In this paper, we present a comprehensive analysis of the MCUITeCF approach. In section 2, we provide a thorough review of previous research in the domain of doctor recommendation systems. Section 3 lays out the architecture of the proposed MCUITeCF approach. In section 4, we present our experimental results, highlighting the effectiveness of MCUITeCF compared to other recommendation approaches. Finally, Section 5 concludes the study and presents potential directions for future research.

2. Related work

The rapid pace of technological advancement in recent years has incited demand for innovation across various sectors, including healthcare. In particular, the deployment of recommender systems in healthcare has gained considerable interest from

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researchers [2, 9]. Despite this, research focusing on doctor recommendation systems is sparse, identifying a critical area for further exploration [10].

The burgeoning pace of technology has instigated diverse approaches to building doctor recommendation systems. Sridevi and Rajeshwara Rao [11] developed a personalized health recommender system that utilizes CF and patients' demographic data, including their ratings, reviews, and similarities with other patients, to create a customized list of top-rated hospitals and doctors. Acharjee et al. [12] proposed a different framework for matching patients with the most suitable doctors based on their needs. This recommendation framework leverages a decision tree to link symptoms to diseases, and a Naive Bayes classifier to perform sentiment analysis on patients' reviews. The resulting system returns a comprehensive list of recommended doctors. In a similar vein, Waqar et al. [10] presented an innovative doctor recommender system that uses an adaptive algorithm to create a ranking function for doctors. This function, based on patients' criteria, is converted into a numerical rating, which is then used alongside various machine learning techniques to produce personalized doctor recommendations. The system has undergone validation by domain experts and proven to effectively match patients' needs.

The study conducted by Yang et al. [13] presented a decision support model aimed at providing recommendations of appropriate doctors to patients on haodf.com. The model comprises four distinct modules, each serving a specific purpose. The first module, referred to as the transformation module, is responsible for converting raw data into intuitionistic fuzzy sets. The second module, known as the integration module, is designed to combine interdependent information. The third module, called the three-cloud presentation module, is specifically designed to accommodate patient preferences. Lastly, the fourth module, referred to as the recommendation module, is responsible for generating a personalized ranked list of doctors for each patient. The model's validation results, using the haodf.com dataset, exhibited noteworthy enhancements in the diversity and coverage of doctor recommendations in comparison to the current approach employed by haodf.com. Meng and Xiong [14] also proposed a doctor recommendation algorithm that leverages an online healthcare platform. Their approach uses the textual information from doctor-patient consultations and applies the latent Dirichlet distribution topic model, among other methods, to pinpoint doctors who best align with patients' needs. The algorithm, when tested on data from a Chinese healthcare website, displayed notable effectiveness.

The study by Yuan and Deng [15] introduces an interpretable doctor recommendation method that combats data sparsity and promotes transparency on healthcare consultation platforms. By leveraging a health knowledge graph and deep learning techniques, the method generates interpretable recommendations and captures nuanced interactions between patients and doctors. The approach surpasses traditional models, demonstrating practical and managerial benefits for online platforms contending with information overload. Wu et al. [16] present a method for aiding patients in choosing the most suitable online medical consultant. The method establishes an online decision-making process, incorporating correlated attributes derived from historical data. To blend public and personal preferences, it uses a Choquet integral-based ranking method. Key steps include utilizing a two-stage BERT-based model for extracting service features from text reviews and an innovative optimization model to amalgamate public and personal preferences. Case study results confirm its practicality and rationality compared to traditional multi-attribute decision-making methods. The research by Kulshrestha et al. [17] focuses on enhancing doctor rating prediction methodologies in healthcare, tackling the data sparsity issue. A novel deep learning model for online doctor rating prediction based on a hierarchical attention bidirectional long short-term memory (ODRP-HABiLSTM) is proposed for incorporating word and sentence level information from textual reviews. A highway network refines the learned representations, leading to improved online doctor rating predictions. Experiments on real-world Yelp.com data show the model's superior performance and robustness over existing models.

In order to enhance clarity and ease of understanding, this study provides a description of all symbols and notations employed, as outlined in Table 1.

3. The proposed MCUITeCF approach

In this section, we will discuss the three key components of our proposed MCUITeCF approach: the MC user implicit trust-enhanced CF, the MC item implicit trust-enhanced CF, and the hybrid prediction model. We will delve into the specifics of each component in the subsequent subsections.

Table 1. Description of notations

Notation	Description
T, *D*	The set of patients and doctors, respectively.
$C = \{c_1, c_2, \ldots, cz\}$	The set of *z* criteria.
$r^c_{a,x}$ and $r^c_{b,x}$	The ratings given by patients *a* and *b* to doctor *x* considering criteria *c*.
$\overline{r_x}^c$ and $\overline{r_y}^c$	The average ratings of the doctors *x* and *y* on criteria *c*, respectively.
$\overline{r_a}^c$ and $\overline{r_b}^c$	The average ratings of patients *a* and *b* on criteria *c*, respectively.
$P^c_{a,x}$	The predicted rating of patient *a* on doctor *x* with respect to criteria *c*.
$D_{a\cap b}$	The set of doctors commonly rated by patients *a* and *b*.
$T_{x\cap y}$	The set of patients who have commonly rated doctors *x* and *y*.
$UTriSim^c_{a,b}$	The value of the partial implicit trust between patients *a* and *b* based on criterion *c*.
$ITriSim^c_{x,y}$	The value of the partial implicit trust between doctors *x* and *y* based on criterion *c*.
D_a and D_b	The sets of doctors rated by patients *a* and *b*, respectively.
T_x and T_y	The sets of patients who have provided ratings for doctors *x* and *y*, respectively.
$r_{a,x}$ and $r_{b,x}$	The average ratings across all criteria given by patients *a* and *b* to doctor *x*, respectively.
$\bar{r}_x$ and $\bar{r}_y$	The mean ratings across all criteria for doctors *x* and *y* given by all patients, respectively.
$\bar{r}_a$ and $\bar{r}_b$	The mean ratings across all criteria of patient *a* and *b* for all doctors, respectively.
$\lvert T_a \rvert$	The total number of patients who have a connection to patient *a* within the patients' implicit trust network.
$\lvert D_x \rvert$	The total number of doctors who have a connection to doctor *x* within the doctors' implicit trust network.
NN^{UT}	The set of top nearest neighbor patients in relation to the active patient *a* from the patient-patient implicit trust network.
NN^{IT}	The set of top nearest neighbors of doctors in relation to the target doctor *x* from the doctor–doctor implicit trust network.

3.1 The MC user implicit trust-enhanced CF component

The purpose of this component is to produce MC user implicit trust-based predictions. It achieves this by leveraging implicit trust relationships among users within the patient-patient implicit trust network, along with each patient's reputation. This component is structured around four key steps:

3.1.1. Derive MC user-based direct implicit trust

In line with implicit user-based trust methodologies, our study quantifies the trustworthiness of a user by assessing the predictive accuracy of that user as a past recommender to an active user. To obtain direct implicit trust, we initially calculate the predicted rating employing Resnick's prediction method [18]. This method is used to determine the predicted rating of doctor *x* for a specific patient, *a*, by solely considering the ratings provided by a neighboring patient, *b*.

$$P^c_{a,x} = \overline{r_a}^c + (r^c_{b,x} - \overline{r^c_b}) \tag{1}$$

Given the notion that a user's past prediction accuracy determines their trustworthiness, we adopt the Triangle similarity method [19]. This method takes into account both the length of the rating vectors and the angle between them in order to calculate the preliminary degree of implicit trust between patients *a* and *b*, with respect to each rating criteria *c*.

$$UTriSim^c_{a,b} = \left(1 - \frac{\sqrt{\sum_{x\in D_{a\cap b}} (P^c_{a,x} - r^c_{a,x})^2}}{\sqrt{\sum_{x\in D_{a\cap b}} (P^c_{a,x})^2} + \sqrt{\sum_{x\in D_{a\cap b}} (r^c_{a,x})^2}}\right) \tag{2}$$

Next, the overall implicit trust value between a given patient *a* and its neighboring patient *b* is computed using the average aggregation function [20] in the following manner:

$$iTrust^{UTriSim}_{a,b} = \frac{\sum_{c=1,\ldots,z} UTriSim^c_{a,b}}{z} \tag{3}$$

To address the variation in the number of co-rated doctors between different patients and mitigate any negative impact on recommendation quality, we introduce a trust factor [21]. This factor serves as a weighting element to account for the influence of co-rated items when determining implicit trust. It penalizes patients who share a smaller proportion of co-rated doctors, thus ensuring lower implicit trust value when the proportion of co-rated doctors is small. This calculation is given by Eq. (4).

$$UTF_{a,b} = \frac{1}{1+exp\left(-\frac{|D_a \cap D_b|^2}{|D_a|.|D_b|}\right)} \quad (4)$$

Ultimately, by integrating the two previously mentioned metrics, as articulated in Eq. (5), we ensure a correlation between the level of trust and the amount of co-rated doctors with similar ratings by patients *a* and *b*. In essence, the more co-rated doctors with similar ratings there are, the higher the level of trust between patients. The MC user-based implicit trust derivation metric between patients *a* and *b* is defined as:

$$iUTrust_{a,b} = iTrust_{a,b}^{UTriSim} \times UTF_{a,b} \quad (5)$$

3.1.2. Propagate implicit trust

Once the direct implicit trust is determined, an implicit trust network is established, taking the form of a directed graph. The nodes of this network represent individual patients, while the edges depict the degree of implicit trust between these patients. Given the frequent presence of inadequate ratings in many recommender systems, there is a need for trust propagation in order to disseminate implicit trust throughout the network.

Trust transitivity serves as the most evident form of trust propagation. This principle suggests that if patient *A* trusts patient *B*, and patient *B* trusts patient *K*, patient *A* will, by extension, trust patient *K* due to this transitivity. This process enables the creation of new indirect connections between patients who are not directly connected but are linked through intermediary patients within the trust network.

To measure the propagated implicit trust between patients, the following aggregation metric is proposed. For patients *a*, *b*, and *k*, the propagated trust, denoting the extent to which patient *a* implicitly trusts patient *k*, is calculated as shown in Eq. (6).

$$iUTrust_{a,k}^{\mathrm{Prop}} = \frac{\sum_{b\in \mathrm{adj}(a and k)}(iUTrust_{a,b} \times UTF_{a,b}) + (iUTrust_{a,b} \times UTF_{b,k})}{\sum_{b\in \mathrm{adj}(a and k)} UTF_{a,b} + UTF_{b,k}} \quad (6)$$

3.1.3. Calculate patient reputation

The reputation of a patient can be established through a combination of factors. Firstly, it depends on the proportion of connections the patient has with other patients in the implicit trust similarity network. Secondly, it takes into account the average discrepancy between the patient's ratings of doctors and the average ratings those doctors receive [22]. This can be represented mathematically as follows:

$$PR_a = exp\left(-\frac{\sum_{x\in D_a}|r_{a,x} - \bar{r}_x|}{|D_a|}\right) \times \sqrt{\frac{|T_a|}{|T|}} \quad (7)$$

3.1.4. Calculate user implicit trust-enhanced predicted ratings

The deviation-from-mean metric is utilized in this step to predict the rating of unobserved doctor *x* for the active patient *a*, as shown below:

$$P^U{}_{a,x} = \begin{cases} \bar{r_a} + \frac{\sum_{b\in NN^{UT}} iUTrust_{a,b} \times (r_{b,x} - \bar{r}_b)}{\sum_{b\in NN^{UT}} iUTrust_{a,b}} \\ \quad ; if\ iUTrust_{a,b} \neq 0 \\ \bar{r_a} + \frac{\sum_{b\in NN^{UT}} PR_b \times (r_{b,x} - \bar{r}_b)}{\sum_{b\in NN^{UT}} PR_b} \\ \quad ; if\ iUTrust_{a,b} = 0 \end{cases} \quad (8)$$

3.2 The MC item implicit trust-enhanced CF component

This component leverages the implicit trust relationships among items within the doctor-doctor implicit trust network, along with each doctor's reputation, to provide MC item-based trust-enhanced recommendations. The component comprises three main steps:

3.2.1. Derive MC item-based implicit trust

In this step, the rating matrix is used as input to calculate the implicit item-based trust scores between each pair of doctors. The implicit trust between any pair of doctors is measured based on their ratings, evaluating the accuracy of a given doctor's predictions as a reliable recommender for another doctor. For instance, based on their past ratings, doctors *x* and *y* would yield a high implicit trust score if doctor *y* can deliver accurate recommendations for doctor *x*.

In light of this rationale, we proceed to utilize Resnick's prediction approach once more in order to derive the predicted rating for patient *a* of a specific doctor, *x*, relying solely on the input from a single neighborhood doctor, *y*, as depicted in Eq (9).

$$P_{a,x}^c = \overline{r_x{}^c} + (r_{a,x}^c - \overline{r_y^c}) \quad (9)$$

Following this, the Triangle similarity method [19], is employed to estimate the initial implicit trust of doctors *x* and *y* for each rating criteria *c*, as depicted below:

$$ITriSim_{x,y}^{c} = \left(1 - \frac{\sqrt{\sum_{a \in T_x \cap y}(P_{a,x}^{c} - r_{a,x}^{c})^2}}{\sqrt{\sum_{a \in T_x \cap y}(P_{a,x}^{c})^2} + \sqrt{\sum_{a \in T_x \cap y}(r_{a,x}^{c})^2}}\right) \quad (10)$$

Using the average aggregation function [20], the overall implicit trust value between doctor x and its neighboring doctor y is then computed, as follows:

$$iTrust_{x,y}^{ITriSim} = \frac{\sum_{c=1,\ldots,z} ITriSim_{x,y}^{c}}{z} \quad (11)$$

Similar to the previous method, the same factor [21] is used as shown in Eq. (12), in addition to the Triangle similarity, as a weighting trust factor. This factor takes into account the patients who provide ratings for both doctors when determining their degree of trust, as illustrated in Eq. (8). Consequently, the more common patients with similar ratings for doctors y and z, the higher the level of trust between them.

$$ITF_{x,y} = \frac{1}{1 + exp\left(-\frac{(T_x \cap T_y)^2}{|T_x| \cdot |T_y|}\right)}, \quad (12)$$

Finally, the MC item-based implicit trust derivation metric between doctors x and y is provided as follows:

$$iITrust_{x,y} = iTrust_{x,y}^{ITriSim} \times ITF_{x,y} \quad (13)$$

3.2.2. Calculate doctor reputation

The reputation of a doctor is established by considering two factors. Firstly, it depends on the proportion of connections the doctor has with other doctors within the doctor-doctor implicit trust network. Secondly, it takes into account the average discrepancy of the doctor's ratings across all criteria compared to the average ratings given by all patients for all doctors. This can be mathematically represented as shown in Eq. (14).

$$DR_x = exp\left(-\frac{\sum_{a \in T_x} |r_{a,x} - \bar{r}_a|}{|T_x|}\right) \times \sqrt{\frac{|D_x|}{|D|}} \quad (14)$$

3.2.3. Calculate item implicit trust-enhanced predicted ratings

The deviation-from-mean metric is utilized again in this step to predict the rating of unobserved doctor x for the active patient a, as shown below:

$$P^{I}{}_{a,x} = \begin{cases} \bar{r}_x + \frac{\sum_{y \in NN^{IT}} iITrust_{x,y} \times (r_{a,y} - \bar{r}_y)}{\sum_{y \in NN^{IT}} iITrust_{x,y}} \\ \quad ; if\ iITrust_{x,y} \neq 0 \\ \bar{r}_x + \frac{\sum_{y \in NN^{IT}} DR_y \times (r_{a,y} - \bar{r}_y)}{\sum_{y \in NN^{IT}} DR_y} \\ \quad ; if\ iITrust_{x,y} = 0 \end{cases} \quad (15)$$

3.3 The hybrid prediction component

In light of the fact that the best performance in rating prediction is achieved through the hybridization of multiple recommendation approaches, we adopt the switching hybridization strategy [23]. This strategy allows us to alternate between different recommendation systems based on certain conditions. The primary determinant for the selection of an approach is its capacity to produce a projected rating. When both recommendation approaches have the ability to generate a projected rating, we employ the harmonic mean metric to merge the predicted ratings.

$$P_{a,x}^{final} = \begin{Bmatrix} 0\ ; if\ P_{a,x}^{U} = 0\ and\ P_{a,x}^{I} = 0 \\ P_{a,x}^{U}\ ;\ if\ P_{a,x}^{U} \neq 0\ and\ P_{a,x}^{I} = 0 \\ P_{a,x}^{I}\ ;\ if\ P_{a,x}^{U} = 0\ and\ P_{a,x}^{I} \neq 0 \\ \frac{2 \times P_{a,x}^{U} \times P_{a,x}^{I}}{P_{a,x}^{U} + P_{a,x}^{I}};\ if\ P_{a,x}^{U} \neq 0\ and\ P_{a,x}^{I} \neq 0 \end{Bmatrix} \quad (16)$$

The switching hybridization strategy allows us to benefit from the strengths of different recommendation approaches and adaptively choose the most suitable one based on the available information and conditions. This approach enhances the accuracy and robustness of the hybrid recommendation system, resulting in improved user satisfaction and personalized recommendations.

4. Experiments

4.1 Experimental design

The RateMDs MC dataset [24], utilized in this study for experimental validation, was collected from ratemds.com, an online healthcare platform that enables patients to provide ratings for doctors on a scale ranging from 1 to 5. These ratings are based on four primary criteria, namely staff performance, punctuality, helpfulness, and medical knowledge. With a substantial dataset comprising 31,180 multi-criteria ratings, it reflects the assessments of 3,464 patients toward 3,118 doctors. This dataset's significance lies in its ability to quantitatively capture patient perspectives on the medical care they receive.

By evaluating aspects such as staff professionalism, doctor punctuality, willingness to assist, and medical expertise of doctors, it offers a comprehensive view of the patient experience.

The RateMDs MC dataset can be utilized by researchers and healthcare stakeholders for a variety of purposes, such as examining patterns in patient satisfaction, identifying doctors who demonstrate exceptional performance, and identifying areas within healthcare delivery that require enhancement. The dataset provides a valuable resource for enhancing the quality of patient care and enhancing healthcare systems' performance.

The evaluation of the proposed approach was conducted using two criteria: (1) the quality of predictions, assessed through the mean absolute error (MAE); and (2) the extent of prediction coverage, determined via the coverage measure [25].

The MAE is a commonly employed metric in the field of recommender systems for assessing the accuracy of predictions generated by the system. In the context of recommender systems, MAE measures the average absolute difference between the predicted ratings and the actual ratings provided by users for a set of items. A lower MAE value signifies a higher level of accuracy and improved performance of the recommender system, as it indicates that the system's predictions are in closer proximity to the actual user ratings [25].

Prediction coverage is a fundamental performance metric utilized for the evaluation of recommender systems. It measures the proportion of items for which the recommender system can predict ratings or generate recommendations. Prediction coverage evaluates the system's capacity to provide recommendations across the entire range of items in the item space. If a system only provides recommendations for a limited portion of the complete range of available items, it may not fully meet the diverse needs and interests of its users. A high level of prediction coverage is typically considered advantageous, as it signifies the recommender system's ability to generate recommendations for a diverse range of items [25]. However, achieving high prediction coverage can pose a challenge, especially when dealing with sparse datasets that exhibit cold-start scenarios, where many items have been rated by a few users or not rated at all.

The performance and efficiency of the proposed approach were benchmarked against the following established CF-based recommendation approaches:

- The multi-criteria item-based CF recommendation approach [20], which employs a similarity-based approach to integrate and utilize multi-criteria ratings between users, thereby enhancing the accuracy of recommendations.
- The multi-criteria user-based CF recommendation approach [20], which utilizes a similarity-based approach to incorporate and leverage multi-criteria ratings between items, leading to improved recommendation accuracy.
- The multi-criteria semantic-based CF approach [4], which improves predictive accuracy and handles data sparsity and cold-start item issues by utilizing multi-criteria ratings and the inherent relationships between items.
- The multi-criteria trust-based CF approach [5], which enhances predictive accuracy and tackles data sparsity and cold-start user issues by leveraging multi-criteria ratings and inferred trust relationships among users.
- The trust-semantic enhanced multi-criteria CF (TSeMCCF) [26] approach that incorporates trust relationships, multi-criteria user ratings, and semantic item relations within the CF framework. This approach ensures effective results, particularly in situations where there is a limited availability of rating data, such as in cases of data sparsity and challenges related to cold-start items and users.

4.2 Experimental results

A set of experiments was carried out to evaluate the effectiveness of the proposed approach in comparison to benchmark approaches. Initially, the MAE values based on different neighborhood sizes on the RateMDs dataset were compared between the proposed approach and benchmark approaches. Subsequently, the proposed approach was evaluated alongside benchmark approaches on diverse datasets with varying sparsity levels, considering both MAE and prediction coverage metrics. Finally, an evaluation was conducted to assess the performance of the proposed approach in comparison to benchmark approaches on datasets containing varying numbers of ratings for cold-start items and users, again using MAE and prediction coverage as evaluation criteria.

4.1.1. Performance evaluation utilizing the RateMDs dataset

Fig. 1 depicts a comparative analysis of MAE results for the proposed MCUITeCF approach and benchmark approaches. The analysis is conducted on the RateMDs dataset, with the number of nearest neighbors ranging from 5 to 50. The results reveal

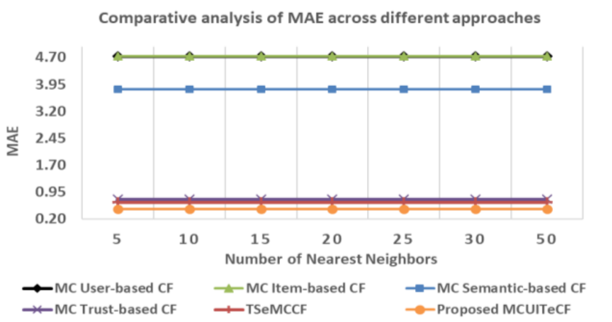

Figure. 1 Comparative analysis of MAE across different approaches at varying nearest neighbors sizes

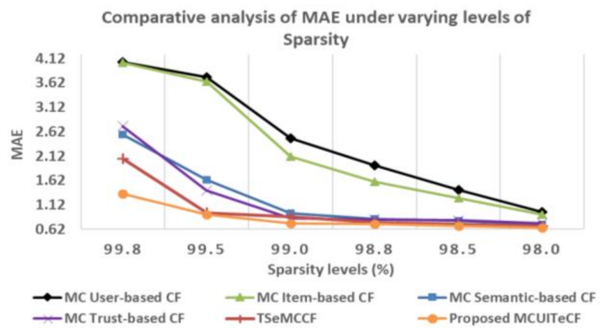

Figure. 2 Comparative analysis of MAE across different levels of sparsity

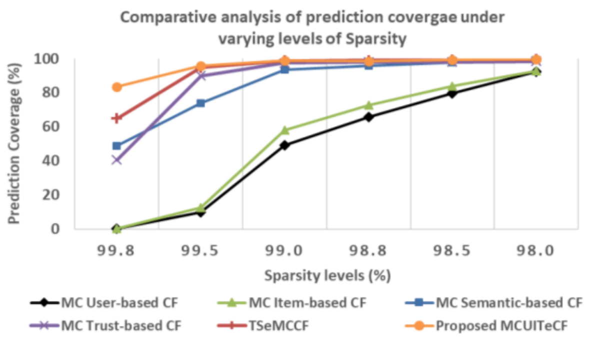

Figure. 3 Comparative analysis of prediction coverage across different levels of sparsity

that the proposed MCUITeCF approach consistently achieves higher prediction accuracy compared to the benchmark approaches, namely MC user-based CF, MC item-based CF, MC semantic-based CF, MC trust-based CF, and TSeMCCF. At different neighborhood sizes, the proposed approach demonstrates superior MAE performance, achieving approximately 89%, 89%, 87%, 36%, and 28% improvement over the benchmark approaches, respectively. The analysis of the average MAE results indicates that the MCUITeCF approach demonstrates a notable improvement in prediction accuracy in comparison to the benchmark approaches on the RateMDs dataset.

4.1.2. Performance evaluation based on diverse levels of Sparsity

To assess the robustness of our proposed MCUITeCF approach in addressing the issue of data sparsity, a set of experiments was conducted using six sparse datasets, each having varying sparsity levels ranging from 99.8% to 98.0%. Fig. 2 and Fig. 3 present a comparative analysis of the prediction accuracy (measured by MAE) and prediction coverage results of our approach in contrast to benchmark approaches, namely MC user-based CF, MC item-based CF, MC semantic-based CF, MC trust-based CF, and TSeMCCF on these sparse datasets.

Fig. 2 illustrates the average MAE results of the proposed MCUITeCF approach in comparison to benchmark approaches. The performance of our approach surpasses that of the benchmark approaches by approximately 65%, 62%, 31%, 30%, and 16% respectively. This clearly demonstrates the superiority of our approach in accurately predicting recommendations even when faced with highly sparse scenarios.

Furthermore, Fig. 3 presents the prediction coverage results of our proposed approach in comparison to benchmark approaches. The proposed MCUITeCF approach demonstrates a significant enhancement in prediction coverage of 48%, 44%, 11%, 9%, and 3% respectively, when compared to the benchmark approaches. This indicates that our approach is more effective in providing recommendations across a wider range of items, even in datasets characterized by a scarcity of ratings.

The substantial improvements in MAE and prediction coverage validate the effectiveness of our proposed approach in addressing data sparsity. By incorporating underlying trust relationships and the reputation of both patients and doctors, our approach compensates for the lack of ratings, thus reducing the impact of sparsity and enhancing recommendation accuracy and coverage.

4.1.3. Performance evaluation under various cold-start item scenarios

In order to evaluate the efficacy of our proposed approach, MCUITeCF, in mitigating the cold-start item challenge, we performed a series of tests using six diverse datasets. Each dataset contained a variable range of ratings for cold-start items, from a minimum of 4 to a maximum of 25. The results, as shown in Fig. 4 and Fig. 5, provide a comparative examination of our approach's prediction accuracy (represented by

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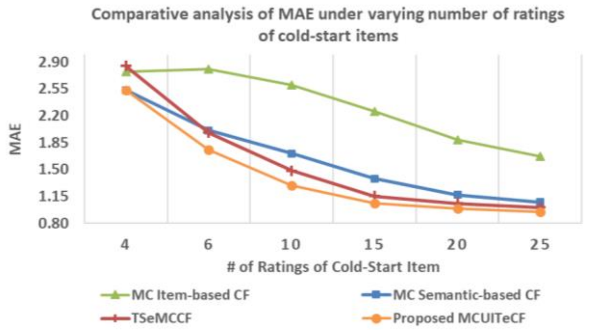

Figure. 4 Comparative analysis of MAE across different numbers of ratings of cold-start items

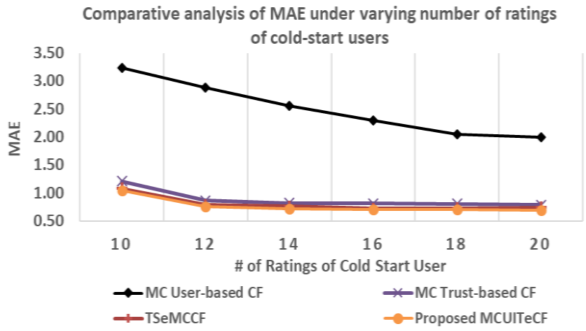

Figure. 6 Comparative analysis of MAE across different numbers of ratings of cold-start users

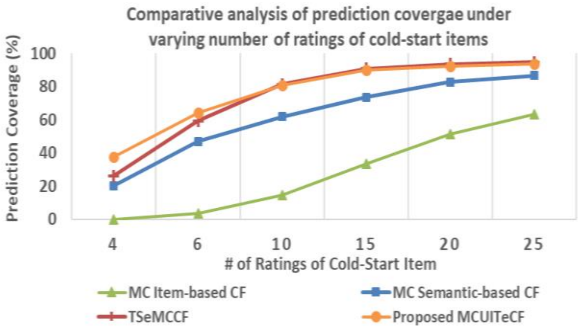

Figure. 5 Comparative analysis of prediction coverage across different numbers of ratings of cold-start items

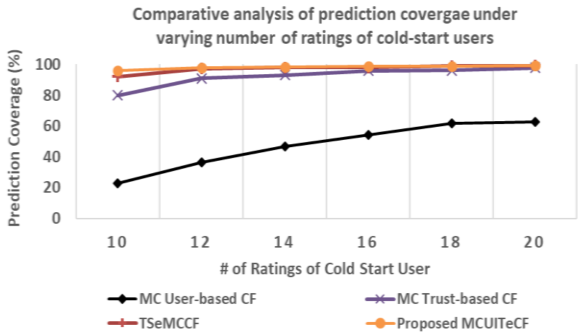

Figure. 7 Comparative analysis of prediction coverage across different numbers of ratings of cold-start users

MAE) and prediction coverage against benchmark approaches, namely the MC item-based CF, MC semantic-based CF, and TSeMCCF.

Fig. 4 displays the average MAE results of the proposed MCUITeCF approach in comparison to benchmark approaches. The performance of our approach outperformed the benchmark approaches by approximately 38%, 13%, and 10% respectively. This demonstrates that even in scenarios with limited ratings for cold-start items, where items have been rated by only a few users, our approach excels in making accurate recommendations.

Further reinforcing the strength of our approach, Fig. 5 delineates the prediction coverage results. The MCUITeCF approach shows a significant increase in prediction coverage by 62%, 17%, and 3% respectively, against the benchmark approaches. This indicates that our approach can effectively provide recommendations for a broader set of cold-start items. These marked improvements in both MAE and prediction coverage underline the effectiveness of the MCUITeCF approach in mitigating the issues arising from scarce ratings, thus offering a promising solution to the cold-start item problem.

4.1.4. Performance evaluation under various cold-start user scenarios

To validate the robustness of our proposed approach, MCUITeCF, in resolving the cold-start user issue, we carried out a comprehensive set of experiments on six varied datasets. Each of these datasets included different numbers of ratings for cold-start users, ranging from 10 to 20. Our results, depicted in Fig. 6 and Fig. 7, compare the predictive accuracy, as signified by MAE, and prediction coverage of our approach with three benchmark approaches: MC user-based CF, MC trust-based CF, and TSeMCCF.

Fig. 6 presents the average MAE outcomes of the MCUITeCF approach against the benchmark approaches. Notably, our approach surpassed the benchmarks, reducing the MAE by an impressive 69%, 12%, and 4% respectively. This implies that our approach effectively generates accurate recommendations, even in situations characterized by cold-start users who have a limited number of past ratings.

Building on the strength of our approach, Fig. 7 showcases the prediction coverage results. Here, the MCUITeCF approach exhibits a substantial improvement in prediction coverage, rising by 51%, 5%, and 1% respectively when measured against the benchmark approaches. This demonstrates our approach's proficiency in generating recommendations for a larger cohort of cold-start users. These noteworthy enhancements in both MAE and prediction coverage highlight the potency of our

MCUITeCF approach in mitigating the issues arising from sparse ratings, hence providing a compelling remedy for the cold-start user problem.

5. Conclusion

As online healthcare communities continue to grow, they often struggle to effectively fulfill patients' medical needs, particularly in the vital task of helping them find reliable doctors. Addressing this issue, we present an efficient recommendation approach, MCUITeCF, aimed at aiding patients in selecting the most appropriate doctors based on their unique preferences.

The MCUITeCF approach integrates the MC user implicit trust-enhanced CF and MC item implicit trust-enhanced CF approaches. It enhances the quality of recommendations by broadening the active patient's and the target doctor's neighborhood using supplementary information extracted from historical ratings. To tackle issues related to data sparsity and cold-start users, the proposed approach exploits the intuitive properties of implicit trust and trust propagation among patients, as well as patients' reputation in the MC user implicit trust-enhanced CF. Moreover, the MC item implicit trust-enhanced CF approach leverages the intuitive properties of trust among doctors and their reputation to further alleviate data sparsity and cold-start item problems.

The experimental evaluation indicates that the proposed MCUITeCF approach outperforms benchmark CF-based recommendation approaches in terms of prediction accuracy and coverage when handling data sparsity, cold-start items, and cold-start users challenges. This makes it a promising solution for personalized doctor recommendations in the healthcare domain. In our future research, we plan to delve into the feasibility of enriching our proposed approach by integrating deep learning technology, and investigate its potential impact on the quality of the recommendations.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, Hussein and Shambour; methodology, Hussein and Shambour; software, Hussein; validation, Hussein and Shambour; formal analysis, Hussein; investigation, Shambour; writing—original draft preparation, Shambour; writing—review and editing, Hussein; supervision, Shambour.

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