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Exploring Recommender Systems in the Healthcare: A Review on Methods, Applications and Evaluations

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***Abstract* – Due to the vast amount of publicly available online data, people may find it difficult to obtain relevant information to find food or meals that match their taste and health while maintaining a healthy lifestyle. The overload of information makes it difficult to separate relevant, personalized information from massive volumes of data. Recommendation systems (RS) are suggestion systems that provide users with information that they may be interested in. With RS, this enormous amount of information is filtered and analyzed for further insights. This paper will explore several generations of recommender systems in the healthcare industry. This paper thoroughly analyses the current state-of-the-art recommender systems focusing on the grouping, methods, application and evaluation metrics. In addition, several challenges for further research and improvement in this domain are also outlined in the paper.**

Keywords—Recommender System, Recommendation Technique, Evaluation, Traditional Recommender System, Generative AI.

I. INTRODUCTION

Recommender systems analyze data intelligently to provide personalized recommendations for services and products [1]. Recommendation systems predict the value or preference that a user will give an item to generate relevant products or services personalized to each user. Towards recent years, recommender systems have gained popularity in several domains such as food, tourism, social media, movies, e-Commerce, e-learning, news and healthcare.

The vast volume of growing healthcare data [2] publicly made available worldwide indirectly hinders people from accessing important information easily. Since it might be difficult to retrieve information, using a Healthcare Recommender System (HRS) can help to reduce the issue of information overload [3,4]. For instance, by basing on patient data like medical history and demographics, each patient can receive personalised treatment. In addition, recommender systems also aid clinicians in decision-making by recommending medications and treatment plans to the patient. Furthermore, early disease detection could be performed by identifying at-risk individuals and suggesting preventive measures [5]. In particular, recommender systems transform healthcare by tailoring personalized care, improving faster response by providing suggestions and optimizing resource allocation [6,7].

Generally, a typical recommender system is divided into four main groups: content-based, collaborative filtering, hybrid-based and generative AI. Though the are many approaches being published by various researchers, this paper groups and analysis the

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related technologies, proposed method, evaluation metrics and datasets used in the healthcare domain.

The content-based approach recommends items based on what the user liked or interacted with in the past. It analyzes item features or content and recommends items that share similar attributes. For example, in healthcare, a content-based recommender might suggest medications based on similarities in patient demographics, medical history, or symptoms. Some of the techniques under this group are Term Frequency-Inverse Document Frequency (TF-IDF), Bidirectional Encoder Representations from Transformers (BERT), Latent Dirichlet Allocation (LDA), cosine similarity, word embedding, jaccard similarity, euclidean distance and so on. Table 1 shows a detailed description of each technique and some research carried out in this domain.

TABLE 1. Content-based approaches with some related research in the healthcare domain.

Techniques	Description	References
TF-IDF	Weigh the importance of medical terms in patient records, aiding in personalized treatment recommendations based on document similarity.	[8-14]
BERT	Leverages pre-trained language models to understand medical texts, improving diagnosis, treatment recommendations, and patient care through contextual understanding	[14-18]
LDA	Identifies topics in medical documents, helping to organize and recommend relevant content or treatments based on shared thematic similarities among patient records.	[16,19-21]
Cosine Similarity	Quantifies the similarity between patient records based on the cosine of the angle between their feature vectors, aiding in personalized treatment recommendations	[17,22-26]
Word Embedding	Transforms medical text data into dense vector representations, capturing semantic relationships between words and enabling accurate analysis for personalized treatment recommendations	[27-29]
Jaccard Similarity	Measures the similarity between patient records based on the intersection and union of their sets of medical terms, aiding in recommending treatments for similar cases.	[30-32]
Euclidean Distance	Calculates the straight-line distance between patient records' feature vectors, facilitating similarity-based recommendations for treatments.	[33,34]

Collaborative filtering recommends items by leveraging the preferences or behaviours of users with the same interests. It identifies users with similar preferences or interactions to recommend items with which similar users may have been interesting or engaged before. Some of the techniques under this group are Matrix Factorization (MF), Support Vector Decomposition (SVD), deep learning (DL), k-nearest neighbor (KNN), ensemble method and so on. Table 2 depicts a detailed description of each technique, and some research carried out in this domain.

TABLE 2. Collaborative filtering approaches with some related research in the healthcare domain.

Techniques	Description	References
MF	Decomposes the patient-observation matrix into lower-dimensional matrices to capture latent features, enabling personalized treatment recommendations based on similarities among patient records.	[35-39]
SVD	Decomposes the patient-observation matrix into singular vectors and values, identifying latent factors for accurate personalized treatment recommendations based on similarities.	[40,41]
DL	Extracting complex patterns and relationships to provide personalized treatment recommendations based on individual medical histories and needs.	[42-46]
KNN	Identifies similar patients based on medical profiles and recommends treatments based on the collective preferences of nearest neighbors in the dataset.	[47-50]
Ensemble	Combine predictions from multiple models to generate more accurate and robust recommendations. It leverages the diverse strengths of individual models to enhance overall performance.	[51-53]

Hybrid-based combines some recommendation techniques to overcome the limitations of individual approaches to provide more diverse and accurate suggestions. By doing so, hybrid systems can offer improved recommendations. In the healthcare domain, a hybrid recommender might combine content-based filtering with collaborative filtering to provide more personalized treatment recommendations based on both patient characteristics and similarities to other patients [54-58].

Recently, a growing number of recommender systems in healthcare have been incorporating generative artificial intelligence (AII) to provide personalized recommendations for patients and healthcare professionals [59-61]. Generative Adversarial Network (GAN) and Variational Autoencoder (VAE) are some of the well-known model utilized to generate new content suggestions based on learned patterns [62]. As such, Generative AI is capable to address the "cold start" issue, since new content can be generated with minimum input required. In other words, it can address the challenge of limited data available [63,64]. In addition, more diverse and most probably useful or desired recommendations can be provided to solve complex problems related to health [65,66].

II. Applications and Evaluation Metrics

A. Application of HRS

Personalized Treatment Recommendations: HRSs can suggest personalized treatment plans based on one individual medical history, genetic, and lifestyle factors [8]. For instance, using HRS specific medication or lifestyle changes can be suggested to a patient based on a patient's well-being profile [67].

Clinical Decision Support: Healthcare providers can use recommender system to recommend possible diagnostic tests, screening protocols, and treatment options [68,69]. Clinicians can rely on these recommendations to enhance diagnostic accuracy, particularly in complex medical scenarios with multiple treatment options.

Chronic Disease Management: With HRS, patients receive recommendations for personalized care plans for chronic diseases, such as diabetes, cardiovascular, asthma, and others [70]. Such recommendations may include medication, recommended nutrition, physical activity patterns, and further treatment that, if followed over the long term, contributes to improving the patient’s health [71].

Telemedicine and Remote Monitoring: HRS allows virtual and remote monitoring appointments with the help of devices and develops plans under the influence of informed patients and historical healthcare records and at the patient’s availability [72], [73] . This way, HRS applies to ensure that patients receive timely help and counseling when needed, regardless of their location.

Health Promotion and Disease Prevention: HRS with the prediction capability can advise on health screenings and vaccinations for early disease prevention. Population health management efforts and disease prevention initiatives are made possible through these systems by targeting specific populations or individuals at higher risk [74,75].

B. Evaluation Metrics

Several metrics can be used to evaluate the effectiveness of HRS [76-78]. Among some of the common evaluation metrics are Mean Absolute Error (MAE), Root Mean Error Square (RMSE), accuracy, precision, recall, F1 score, Mean Average Precision (MAP), Area under the Curve (AUC) and Confusion Matrix [79-81]. Besides, some other evaluation through user testing can also be conducted. For instance, user satisfaction and engagement can be evaluated through click-through rate [82,83], conversion rate [84] or user feedback survey.

1) MAE

MAE is a primary evaluation measure in HRSs used to measure the performance and accuracy to a system. It is simply an important measure to which one can compare the results of the recommendation algorithms designed for the system. By calculating the mean measure of the absolute distinction between the predicted and actual values, MAE disclosed the customer resemblance to a recommendation. For example, in a medication recommendation system, MAE measures the mean absolute differences between a medication's predicted effectiveness and the same medication's actual effectiveness in real patient data, enabling the healthcare provider to improve the recommendation process.

Moreover, its simplicity and intuitive interpretation make it particularly well-suited for healthcare applications. It provides a simple measure of the average prediction error without being overly sensitive to outliers or extreme values. This attribute is crucial in healthcare, where individual patient cases can vary widely, and accurate recommendations are essential for ensuring patient safety and well-being. By minimizing MAE, HRSs can optimize their recommendations to match patients with the best suitable treatments, ultimately improving patient satisfaction and reducing the risk of adverse events or ineffective treatments.

2) RMSE

RMSE is the measure used to quantify the average error between the predicted health outcomes recommended by the system and those observed. It quantifies the differences between the observed and recommended output generated from the system. This is done by squaring the differences to ensure the positive and negative errors counterbalance each other. Later, the mean is computed, after which the RMSE is taken as the square root.

In practicality, a lower RMSE value represents the close recommendation to the desired if it was taking actual data. This, therefore, shows the system’s accuracy in recommending the users closer to their goal. On the other hand, a higher RMSE value represents a bigger deviation and error from the observed values. This value would thus necessitate an improvement of the system, which might be aligned with the algorithm or more accurate input by incorporating more relevant data sources.

3) Accuracy

In HRSs, accuracy serves as a crucial evaluation metric to assess the system's ability to provide precise recommendations. The accuracy metric measures the proportion of correctly predicted recommendations among all recommendations made by the system. In the context of healthcare, where the consequences of incorrect recommendations can be severe, ensuring high accuracy is paramount. A high accuracy score indicates that the recommender system effectively identifies and suggests relevant options that align with patients' needs, preferences, and medical conditions. This metric enables healthcare providers to gauge the reliability and trustworthiness of the recommendations.

4) Precision

Precision is the percentage of relevant items the system recommends compared to the number of all recommended items. The rationale for using precision is that it guarantees that treatment, medicine, or a given provider recommended indeed corresponds to the patient’s needs and conditions. Additionally, high precision means that the system recommends the most relevant and appropriate options, which lessens the possibility of error in the decision-making and quality of treatment for patients. Implying precision will promote trust between the HRS and its users, encourage them to make more unbiased decisions, and consequently, secure a positive outcome for patients.

5) Recall

Recall scores the ability of the system to recall all relevant items from all the relevant items that are available. In the case of healthcare, it allows adequate recognition to ensure no suitable treatment, medication, or health care providers are left out. A high recall score ensures the recommender system identifies nearly all relevant options, which assures one hardly misses out on significant medical records. It provides confidence in the HRSs and the users to research more before concluding, resulting in better patient care outcomes.

6) F1 score

F1 score provides a symmetrical appraisal of both precision and recall. The F1 score aggregates precision and recall into a single measure; hence, a good F1 score means that the healthcare recommender system has achieved a balance between precision and recall. F1 score allows for a complete assessment of the two metrics described above. A high F1 score shows that the healthcare recommender system combines high precision in accurately selecting relevant sets of alternatives and high recall in returning a large fraction of the relevant object sets. Therefore, it will improve the quality of patient care and support clinical decision-making.

7) MAP

The MAP provides an indication of how relevant recommended items are and how accurately they are ranked. It measures the average precision on different levels of recall, showing how well the system optimizes and ranks relevant treatments, drugs, or healthcare providers. By binding the precision and recall at different thresholds, the MAP levelled indicates how well the system performs overall. A higher score on MAP indicates that the recommender system identifies logical options and sorts them efficiently, making clinical insights more beneficial and accurate in their prescriptions.

8) AUC

The Area Under the Curve (AUC) quantifies the model's ability to discriminate between positive and negative instances, reflecting the system's ability to rank relevant items higher than irrelevant ones across various thresholds. A high AUC score indicates that the recommender system effectively distinguishes between relevant and irrelevant options, thereby enhancing the quality of recommendations and supporting informed decision-making by healthcare professionals.

9) Confusion Matrix

The confusion matrix presents a detailed view of how well the system opens the recommendation: it contains information about true-positive, false negative, false-positive, and true-negative recommendations. It shows how the system prioritizes options, rates accuracy, and makes its recommendations. By analyzing the confusion matrix, stakeholders can refine the recommender system's algorithms and parameters to deliver a better HRS to the patients and healthcare providers.

10) Mean Squared Error (MSE)

MSE is the average squared difference between the predicted value and the actual value. Therefore, it should minimize MSE, guaranteeing that the recommender system will create predictions much closer to what the patient intends or prefers.

11) Mean Absolute Percentage Error (MAPE)

MAPE is the average percentage difference between predicted and actual recommendations. MAPE should be minimized to ensure the recommender system creates predictions much closer to their medical needs. In other words ensuring that the quality of recommendations is much assured to that the patient's health outcome can be realized.

Figure 1 depicts the word cloud for the evaluation metrics elaborated above. As can be seen, the most utilized evaluation metrics for HRS is RMSE, followed by MAE, while the least utilized metrics are click-through rate and conversion rate.

FIGURE 1. Word count of evaluation metrics in HRS.

III. RELATED WORKS

Research on healthcare recommender systems has gained traction in recent years due to their potential to enhance patient care and treatment outcomes. Various studies have explored different aspects of these systems, focusing on personalized treatment recommendations, clinical decision support, patient engagement, and resource optimization in healthcare settings. For instance, a personalised and well-designed doctor recommendation system called iDoctor is proposed [85]. It is capable of doing sentiment analysis of text, topic models, matrix factorization, and other approaches on crowdsourced reviews of healthcare products. Sentiment analysis is required to determine the offset for changing the initial rating by taking into account the emotional offset in patient feedback regarding the doctor. iDoctor consists of hybrid model: (1) an LDA model to extract subjects related to user preference and user review comments on specific doctors, and (2) Hybrid Matrix Factorization (HMF) to generate a more personalised recommendation based on user preference and doctor features. By selecting the optimal parameters, it showed improvement as it yields a lower Root Mean Square Error (RMSE). The experiment's results indicate that the HMF model outperforms the other models, with a significantly lower RMSE, demonstrating the ability of iDoctor to provide more precise doctor recommendations.

Kaur et al. introduced a multi-party Arbitrary Distributed Data (ADD) approach for healthcare recommendation systems that relies on randomization, masking, and homomorphic encryption techniques with little computational costs [86]. According to the authors, the main innovation of this research is using a privacy-preserving collaborative filtering technique for generating health recommendations based on the data distribution among several parties. Three protocols are proposed: Protocol one calculates the similarity between items, Protocol two determines the item vectors' length, and Protocol three creates predictions and analysis. The findings were evaluated using different parameters, and the results obtained showed that the accuracy and coverage of the scheme outperformed other competing methods, especially when multiple parties collaborated. The benefits of this study include improved security and no loss of accuracy due to the implementation of privacy measures. The researchers were also successful in reducing the computational time of the off-line model generation process. One of the limitations of this research is the requirement for synchronization between computations performed by multiple parties to ensure proper computation.

Han et al. developed a hybrid recommender system to streamline the appointment process for primary care physicians [87]. They used large data collection to understand patients' beliefs in the family doctor. In addition, they also blended the patient and doctor metadata to observed the pattern. The system offers personalized doctor recommendations and more accurate results than the collaborative filtering technique and heuristic baselines.

Hybrid Collaborative Filtering Model for Healthcare (HCFMH) improves search for physicians by outperforming baseline approaches on the dataset with sparse data [88]. The model identifies items proactively and provides reminders to clinicians about missed information. However, the researchers face a "cold-start" problem, as missing patient encounter data prevents the generation of recommendations.

Rustam et al. proposed an automatic diagnoses diseases system that could recommend preventative measures based on patient symptoms [51,89]. The system uses machine learning algorithms, categorical data conversion, and speech data extraction. It uses a microphone to record patient voice data and assesses the performance of speech recognizers. The accuracy of the method is assessed using F1-score, recall, precision, and accuracy. Their analysis indicated that text data is often more accurate than categorical data. It was also observed that accuracy improved when classifiers accessed a large feature vector.

Shambour et al. [90] presented a hybrid system based on content-based and collaborative filtering to address the challenge of finding the best-suited doctors for patients amidst the vast amount of available healthcare information. The proposed system incorporates a multi-criteria collaborative filtering approach to help patients accurately identify doctors that align with their preferences. It utilizes multi-criteria decision-making, doctor reputation scores, and doctors' content information to improve recommendation quality and mitigate the impact of data sparsity. Their evaluation results demonstrate the effectiveness of the proposed approach with regards to predictive accuracy and coverage under extreme levels of sparsity.

In another work, Shambour et al. [91] proposed a medicine recommendation system called Hybrid Semantic-based Multi-Criteria Collaborative Filtering (HSMCCF) to help patients find appropriate medications based on their medical conditions. The system uses a dataset of patient ratings on medicines from WebMD. It contains two main modules: a semantic filtering module that groups medicines by medical condition, and a multi-criteria filtering module that considers patient preferences across multiple rating criteria. The semantic module addresses data sparsity, while the multi-criteria module improves recommendation accuracy. A medicine reputation score is also used to expand the pool of similar medicines considered. Experiments show the HSMCCF approach improves prediction accuracy and coverage compared to benchmark methods, especially on sparse datasets and for new medicines with few ratings.

Roy et al. [92] introduced health recommender systems (HRS) which is personalised healthcare advice based on one lifestyle choices, medical histories, and other characteristics. There is a description of several forms of HRS, such as diagnosis decision support systems, health status prediction systems, nutrition and physical activity recommendations, and healthcare professional recommendation systems. The paper then surveys the current literature on these different HRS, describing techniques, features, applications and challenges of existing work. It highlights areas for further research, such as incorporating more diverse data sources, improving personalization and algorithm transparency, and conducting rigorous evaluations of HRS impact on patient outcomes. In conclusion, the survey provides an overview of HRS research trends and guidance to improve health recommender systems.

Ooi et al. [93] outlined the framework for the HRS, encompassing various recommender system techniques, datasets used, and evaluation metrics employed in the healthcare domain. The paper emphasizes the significance of accurate medical recommendations and the potential of recommender systems to enhance patient care and decision-making processes. It also presents insights into the theoretical framework, dataset, data cleaning process, recommender engine, and user interface, offering a comprehensive overview of the entire system's development and evaluation.

Navin et al. [94] proposed a knowledge-based recommender system model for disease diagnosis and treatment recommendations using adaptive fuzzy logic systems. It presents an architecture consisting of multiple parallel "fuzzy blocks" which act as fuzzy rule-based classifiers for sub-medical conditions. A knowledge-based combiner segment combines the outputs of these fuzzy blocks using a rule base to provide holistic diagnoses and treatment recommendations. The system is configured and evaluated for basic lung disease diagnosis using a sample patient dataset. The results show good agreement with expert evaluations.

Table 3 depicts the summary of related works reviewed.

TABLE 3. Summary of related works.

Reference	Findings	Evaluation
[85] , 2017 Dataset: The data used is from Yelp, aservicethat collects reviews from the public. http://www.yelp.com/ dataset challenge	Proposed iDoctor, a specialized and personalised system for making doctor recommendations. It can do text sentiment analysis, topic modelling, matrix factorization, and other techniques on crowdsourced reviews of healthcare.	RMSE is far lower than that of other models, demonstrating the accuracy of iDoctor's doctor recommendations.
[86], 2018 The healthcare simulation dataset includes discrete evaluations from 1 to 5 for 500 clinicians and 10,000 patients.	Proposed several party ADD methods based on low-cost homomorphic, masking, and randomization encryption approaches for healthcare recommendation systems.	The planned work's correctness is determined using MAE.
[87], 2018 Dataset: European health care provider	Proposed a collaborative filtering recommender system to match patients to doctors.	Compare model performance with a heuristic baseline model.
[88],2020 Physician searches at Eskenazi Health in Marion County, Indiana, USA, logged from April 2013 to May 2016 comprise the data used in the research.	Suggested search terms to physicians, a methodology known as the Hybrid Collaborative Filtering Model for Healthcare (HCFMH) was developed. With the help of this research, practitioners will be given helpful reminders regarding information that may have been indications they may have overlooked.	Performance metric, hit rate at k (HR@k) is employed.
[89], 2022 The dataset for the current study was taken from Kaggle. The dataset includes separate files for symptoms and safety measures.	Introduced an automated healthcare system that can successfully take the place of a physician at the first stage of diagnosis and contribute to time savings by advising the appropriate measures.	Performance metrics such as accuracy, precision, and F1 score
[90], 2023 Dataset: RateMDs Ratemds.com	Used a doctor's reputation score and the substance of their medical practice as multiple decision-making factors to improve the quality of their suggestions and lessen the impact of data sparsity.	Performance metrics such as prediction coverage, the RMSE, and the MAE.
[91], 2023 Dataset: WebMD	Medicine recommendation system called Hybrid Semantic-based Multi-Criteria Collaborative Filtering (HSMCCF) to help patients find appropriate medications based on their medical conditions.	Performance evaluation based on accuracy,
[92], 2023 Dataset: Research paper since yar 2019	The survey provided an overview of HRS research trends and guidance to improve health recommender systems.	Various evaluation metrics were surveyed.
[93], 2023 Dataset: "mtsamples.csv" dataset, taken from Kaggle.com	Proposed the framework for the HRS, encompassing various recommender system techniques, datasets used, and evaluation metrics employed in the healthcare domain	Similarity score, word count
[94],2024 Dataset: Proprietary dataset from Hospital	Disease diagnosis and treatment recommendations using adaptive fuzzy logic, which utilizes rule base to provide holistic diagnoses and treatment recommendations	Expert evaluation

IV. CONCLUSION AND FUTURE WORK

In conclusion, HRS are vital tools in modern healthcare. They streamline treatment processes, improve patient outcomes, and optimize resource allocation. By providing personalized recommendations based on vast data, they empower patients to take control of their health and help practitioners stay updated on the latest research and treatments. In this paper, we have reviewed the recommender techniques, application of the recommender system, evaluation metrics and related works of recommender systems in healthcare domain.

Some of the future works include surveying machine learning techniques that could incorporate adaptive learning mechanisms that enable continuous improvement over time. In addition, our current review is limited to single source. As such, we could explore the integration of multi-modal data sources, including electronic health records (EHRs), genomic data, social determinants of health, environmental factors, and even patient-reported outcomes in our future work.

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