A survey on personalized health recommender systems for diverse healthcare applications

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***Abstract*—Health recommender systems are computer algorithms designed to suggest personalized health information to individuals based on their unique needs and preferences. These systems use data such as demographic information, lifestyle habits, and medical history to make tailored personal recommendations. This paper aims to critically assess the present state of the field and pinpoint the key trends, challenges, and opportunities for future development. Initially, the various types of health recommender systems, their applications and benefits are analysed. Next, the various techniques, features and challenges in the area of health recommender systems are surveyed. In addition, the application domains and evaluation metrics utilized for system assessment for each contribution are recorded. Finally, this survey delivers valuable perspectives and suggests potential avenues for future research around health recommender systems, aimed at improving the health and well-being of individuals. It highlights the current shortcomings and difficulties in the field, serving as a guide for researchers, professionals, and decision makers in creating a more effective health recommender system.**

Keywords--health recommender systems, group recommender systems, content based techniques, collaborative filtering technique, henry gas solubility optimization

I. Introduction

With the advancement of information technology used in healthcare, the presence of healthcare applications allows people to access a range of health information and services using the internet. The availability of online health information and services has dramatically changed the ways in which people search and consume health information. Recent research shows that the internet plays an important role in how people manage their own health. People seek and greatly rely on the health information available online. Today, many people search for health-related information over the internet and make their decisions based on the information available. However, with the massive increase of digital information in the health sector around the world, it is difficult to search for personalized and relevant information regarding any disease, treatment, or diagnosis. Online health information also presents some inherent challenges such as information reliability, authenticity, and user privacy issues. The overload of available information makes people more vulnerable to exploitation and misinformation.

In order to solve this problem, patients and healthcare professionals can take the help of recommender systems. Recommender systems assist users to search in an over-burden search space and come up with personalized information. Recommender systems based on the healthcare domain are called health recommender systems (HRS). In the recent times, these systems are widely used to assist healthcare professionals and patients with medical suggestions of any disease or treatment. These systems can also recommend healthcare services such as personalized exercise routines, nutrition food for diets, medications, etc., encouraging users to lead a healthier lifestyle. The goal of HRS is to improve health outcomes by providing individuals with relevant, accurate, and up-to-date health information. HRS aims to provide fast and accurate information, reducing the time and cost of the decision-making process. However, the various HRS at work today are error-prone and suffer from various kinds of issues such as lack of personalization and trustworthiness. This paper provides a comprehensive examination of the current state and trends in HRS research and provides a deep understanding of the various approaches and techniques used in the development of a HRS. Additionally, it also explains the various challenges concerning the development of a personalized HRS and the scope of future research in this field.

The rest of the paper is structured as follows: Section-II showcases the various methods used in constructing recommender systems, while Section-III explores the different types of recommender systems in the healthcare field. The survey methodology is outlined in Section-IV, followed by a detailed literature review in Section-V. The challenges and future prospects of HRS are addressed in Section-VI, and the survey is concluded in Section-VII.

II. Types of Techniques Used in Building Recommender Systems

The various types of techniques used in building recommender systems are as follows:

- Content-based techniques: In content-based systems, the users rate items according to their preferences. Looking into the history of the user's ratings, a user profile is built consisting of other items having similar features to those items which the user liked previously. This user profile is specific only to that user. Items from that user profile are then recommended to the user. In the context of HRS, this approach can be interpreted as follows: "If a patient has previously requested or liked some healthcare services/treatments available or one health condition, then in the future he will be recommended similar healthcare services related to that condition".

- Collaborative filtering techniques: Collaborative filtering-based recommender techniques assume that users who share similar interests in the past would agree in the future as well. The basic idea behind this technique is to capture the user's preferences by using some implicit or explicit measures. Distance or correlation between the preferred items and new items is then calculated and collected in a matrix, called the utility matrix. Based on the matrix values, new items are then recommended to the user. Regarding HRS, this technique can be understood as follows: "If users share similar disease profiles or health conditions, then they will be recommended similar healthcare services in future."

- Knowledge-based techniques: This technique is useful when there is a limited amount of information available about an item. That is, the item features or properties are not well known. In such cases, new items are recommended based on explicit user preferences. In regard to HRS, the meaning of this technique can be interpreted as follows: "If a patient is lactose intolerance, then he will be recommended medications that are completely free from lactose."

- Hybrid techniques: A hybrid technique is a combination of two or more filtering techniques described above. The goal is to merge various techniques to overcome the shortcomings of singular recommender methods. The performance and accuracy of many recommender applications are typically improved by this hybrid combination of approaches.

III. VARIOUS RECOMMENDER SYSTEMS APPLICABLE FOR HEALTHCARE DOMAIN

The various types of recommender systems applicable to the healthcare domain are as follows:

A. *Diagnosis decision support-based recommender systems*

Diagnosis decision support-based recommender systems (DDSRS) are used to assist a physician with one or more component steps of the medical diagnostic process. This type of system primarily focuses on knowledge-based approaches, where patient data such as lab report data, family history, demographic information, etc. is fed explicitly as an input to the system. It also considers well-established medical facts automatically ingested from medical publications. The main function of the system is to find what worked for similar patients in a similar condition and recommend that to the user in the form of a ranked list of "most-likely" diagnostics.

B. *Health status prediction systems*

Health status prediction systems (HSPS) use advance machine learning algorithms to capture complicated relationships between self-reported health issues and their outcomes to predict the current health status of the users. These systems are generally designed for older patients and patients with existing co-morbidities. These systems are often equipped to take inputs from wearable body sensors and alert the user in case of any problems. Now a days such systems are used in many advanced smart bands and smart watches.

C. *Physical activity recommender systems*

Physical activity recommender systems (PARS) consider the user's current health status and other demographic information such as age, gender, etc. and recommend a daily routine of physical activities and workouts to the user. These systems are often inbuilt in wearable devices, and they continuously gather user data such as the number of calories burnt, steps taken during the day, heart rate, etc.

D. *Diet recommender systems*

A diet recommender system (DRS), also called as food recommender system, is used to offer recommendations on user's food choices for making decisions on healthier food and eating habits. A food recommender system considers both user preferences and nutritional information and recommends personalized, balanced food-intake advice to the user.

E. *Healthcare professional recommender systems*

Often patients find it challenging to select the best medical professionals for treating their health issues. A healthcare professional recommender system (HPRS) can assist a patient find the best doctor by generating a ranked list of the top preferred doctors available near that geographical location. However, such systems face many challenges such as trust issues, information reliability, and authenticity.

IV. METHODOLOGY

The aim of this study is to survey the existing state-of-art HRS and access the present state of research in this area. Research in HRS is scarily vague as it is spread across various domains, in the formality of various areas, from health status, medicine, food, diagnosis, physical activity, and healthcare personnel. Therefore, a broad range of publications and online research resources, including the IEEE Library, Elsevier, ACM, and Springer are considered for this literature study.

The paper selection process is carried out using PRISMA [31] guidelines. We have used six descriptors or keywords to conduct the search for research publications available on the internet. They are "health recommend*", "diet recommend*", "4. Health status recommend*", "physical activity recommend*", "healthcare professional recommend*", and "decision support-based recommend*". For our analysis. We did not include the following research articles: News reports, theses for master's degree, papers written in a language other than English, unpublished manuscripts and studies that were published before 2019.

Based on their abstracts and substance, we evaluated 60 articles from peer-reviewed journals with a global indexing. Only studies describing recommender systems for healthcare, however, were eligible for selection. Then, 30 scientific papers were picked from SCI, E-SCI and Scopus indexed journals. In order to demonstrate that the examination of the 30 selected articles may serve as a representation of the domain literature, both forward and backward searching techniques were used. As a result, this study may show that it is a valid and reliable assessment of the literature.

V. LITERATURE SURVEY

In this section, various techniques, features, and challenges of the current state of HRS are reviewed through research papers published since 2019, and the overall flow of related research is analyzed. The survey is classified based on the various types of recommender systems relevant to healthcare, as follows:

A. DDSRS

In 2021, Chang et al. [1] proposes a DDSRS for medical diagnosis that uses transfer learning to improve the accuracy of the recommendations by leveraging information from the source domain, which may have more data or a higher level of expertise. The system is evaluated on real-world medical datasets and results show that the proposed system outperforms traditional recommender systems in terms of accuracy and efficiency.

Song et al. [2] presents a knowledge-based DDSRS for pregnancy diagnosis. The system uses a knowledge base of medical knowledge and expert-verified rules to support the diagnosis process. The authors aim to design an interpretable system that can provide clear explanations of its diagnosis decisions, allowing for greater transparency and accountability. The system is analyses on a real-world dataset of pregnancy cases and results show that it is effective in supporting accurate and interpretable diagnoses.

In Zhu et al. [3], the authors present a DDSRS for multi-disciplinary medical treatment. The system uses machine learning and data mining techniques to provide intelligent recommendations for medical treatment based on patient data and medical knowledge. The authors aim to support the medical decision-making process by considering the interdisciplinary nature of medical treatment and incorporating expert knowledge from multiple medical domains. The system is accessed on real-world medical datasets and results show that it is effective in providing accurate and personalized recommendations for medical treatment.

In Ertuğrul et al. [4], the researchers focus on developing a DDSRS for the management of iron deficiency, a common nutritional disorder. The system is designed as a rule-based system, meaning that it uses a set of predefined rules to make recommendations for patient management based on their symptoms and test results. The system was tested and evaluated using a dataset of patients with iron deficiency and found to be effective in aiding the management of the disorder. The authors conclude that the rule-based approach offers a transparent and interpretable solution in a clinical setting.

In 2022, Ragab et al. [5], the authors present a Deep Learning-based DDSRS for breast cancer utilizing ultrasound images. The system employs an ensemble of Deep Learning models, combining various models to enhance the diagnosis's accuracy and reliability. The system was trained and evaluated using a comprehensive dataset of ultrasound images of breast tissue, and was found to have a high level of accuracy in diagnosing and classifying breast cancer. The authors conclude that the ensemble deep learning approach offers a promising solution for the automated diagnosis of breast cancer in a clinical setting, offering high accuracy and interpretability for medical professionals.

Nagaraj et al. [6] developed of a DDRS for predictive diabetes diagnosis using a fuzzy inference rule-based approach. The system uses a combination of demographic information, medical history, and physiological data to make predictions about the likelihood of a patient having diabetes. The authors use fuzzy logic to model the uncertainty and imprecision inherent in the data and to provide interpretable and transparent recommendations to medical experts. The system was evaluated using a dataset of patients with and without diabetes, and the results showed that it had good accuracy and was able to provide clinically relevant recommendations.

Nagaraj et al. [7] focuses on the development of an adaptive diabetes DDSRS by using a bi-level performance enhancing algorithm. The Kalman filter is used to predict and control the glucose levels in patients with diabetes, while the adaptive tree seed algorithm is used to optimize the filter's parameters. The results show that the proposed system can provide improved recommendations for diabetes management and improved glucose control compared to traditional methods.

Guisande et al. [8] proposed a Clinical DDSRS aimed at evaluating the risk of breast cancer in patients. The CDSS uses artificial intelligence techniques to analyse patient data and provide doctors with recommendations for further testing or treatment. The system includes a database of patient information and risk factors, and uses algorithms to calculate the patient's risk score based on the input data. The study findings indicate that the CDSS can aid physicians in evaluating breast cancer risk effectively and enhance the precision of risk assessments compared to conventional methods.

B. HSPS

In 2019, Sneha et al. [9] have presented a HSPS for early prediction of diabetes mellitus using optimal feature selection. The system uses a machine learning approach to analyse a dataset of patients with diabetes and identify the most relevant features (e.g., demographic information, lifestyle factors, medical history, etc.) for early prediction of the disease. The authors employ a feature selection algorithm to determine the most optimal subset of features that are strongly associated with the diagnosis of diabetes. The model's efficacy was evaluated using various metrics, and the results revealed that the model demonstrated a high level of accuracy in early detection of diabetes. The authors conclude that the optimal feature selection approach offers a promising solution for the early prediction of diabetes, which can help healthcare providers to take preventative measures and improve patient outcomes.

In 2020, Chatrati et al. [10] demonstrated a smart HSPS for predicting hypertension and type 2 diabetes using machine learning techniques. The system collects various health-related data, such as blood pressure, weight, and physical activity, from wearable devices and other sensors in the home environment. The data undergoes processing and analysis using machine learning algorithms such as decision trees (DT), random forests (RF), and artificial neural networks (ANN) to estimate the probability of developing type 2 diabetes and hypertension. The results of the study showed that the smart HSPS was able to predict type 2 diabetes and hypertension with high accuracy, and the performance was improved by combining the predictions of multiple algorithms. The study also demonstrated that the system has the capability to provide real-time monitoring and prompt detection of changes in health status, thereby enabling early intervention and promoting better health outcomes. In conclusion, the research paper highlights the potential of using a smart HSPS and the importance of considering multiple machine learning algorithms and real-time monitoring for this task.

In 2022, Lu et al. [11] proposed a machine learning HSPS model for predicting type 2 diabetes mellitus (T2DM) using patient network data. The model employs patient network data to capture the connections between patients and the similarities in their health conditions. The results of the study showed that the patient network-based machine learning model performed well in predicting T2DM, with high accuracy and precision. The results further demonstrated that the utilization of patient network information enhances the performance of the predictive model compared to models that solely rely on individual patient data. In conclusion, the research paper highlights the potential of using patient network data for T2DM prediction and the effectiveness of machine learning techniques for this task.

Mehbodniya et al. [12] presented a machine learning approach for classifying fetal health from cardiotocographic (CTG) data, which is commonly used in prenatal care to monitor the fetal heart rate and uterine contractions during labor.The researchers used a large dataset of CTG signals and extracted various features, such as heart rate variability, power spectral density, and waveform morphological characteristics, to represent the CTG signals. The authors employed various machine learning algorithms, such as K-Nearest Neighbors (k-NN), Support Vector Machines (SVM) and Random Forest (RF), to construct classifiers that are capable of predicting fetal health status. The results of the study showed that the machine learning-based classifiers performed well in classifying fetal health from CTG signals, with high accuracy, precision, and recall. In conclusion, the research paper highlights the potential of using machine learning for fetal health classification from CTG signals and the importance of considering multiple features and ensemble learning techniques for this task.

In Chui et al. [13], the authors present a HSPS for detecting Alzheimer's disease. The algorithm used magnetic resonance imaging (MRI) scans and a convolutional neural network (CNN) with transfer learning. It used a Generative adversarial network (GAN) to generate additional sample data for polarized datasets. The authors used a pre-trained CNN model as the base model and fine-tuned it using a dataset of MRI scans from Alzheimer's patients and healthy controls. The results showed that the fine-tuned model could accurately detect Alzheimer's disease with high accuracy, suggesting that this approach may be useful for detecting Alzheimer's in clinical practice.

Hanumanthappa et al. [14] proposed the implementation of Internet of Things (IoT) technology in the healthcare sector for building HSPS. The proposed model is specially designed for patients and elderly people with restricted movement. Desai et al. [15] presented a HSPS that uses machine learning and cloud computing to monitor the health status of heart patients. The system is designed to gather health data from patients, such as heart rate and blood pressure, and use that data to predict potential health problems.

C. PARS

In 2020, Ferretto et al. [16] presented a PARS that provides personalized physical activity recommendations for patients with arterial hypertension, which is a condition characterized by high blood pressure. The system uses data from wearable devices, such as heart rate monitors, to track the patient's physical activity levels and provide recommendations based on the patient's age, gender, and physical condition. The study found that the system was effective in increasing physical activity levels among patients with arterial hypertension, and that it had a positive impact on their overall health. The results suggest that this type of recommender system could be useful in helping patients with arterial hypertension to manage their condition and improve their health.

Kadri et al. [17] proposed a PARS that uses smartphones to suggest physical activities to individuals based on their personal information and physical activity data collected through the phone's sensors. The system takes into account factors such as age, gender, weight, and daily physical activity levels to provide personalized recommendations. The paper describes the development and evaluation of the recommendation system and discusses the potential benefits of using a smartphone-based approach for promoting physical activity.

Igor et al. [18] proposed a PARS that aims to increase the engagement of senior adults in daily activities. The system is designed to be responsive and provide recommendations based on the individual preferences and routines of the seniors. The paper describes the development and evaluation of the recommendation system, which uses a combination of machine learning algorithms and data from wearable devices and sensors to provide personalized recommendations to seniors. The results of the evaluation show that the system is effective in increasing the engagement of senior adults in daily activities, and that it has the potential to improve the quality of life for this population.

In 2021, Sengan et al. [19] discussed the design and implementation of a PARS for physical activity classification. The system aims to provide personalized recommendations to users based on their physical activity and contextual information such as location, time, and weather. The system uses a secure architecture to protect users' privacy by encrypting sensitive data. The system was evaluated and found to provide accurate recommendations and effectively protect users' privacy.

In 2022, Bhimavarapu et al. [20] proposed a PARS that provides personalized physical activity recommendations to prevent respiratory diseases. The system uses deep learning algorithms to analyze data from wearable devices and make recommendations based on the patient's physical activity levels, heart rate, and respiratory rate. The results suggest that this type of recommender system could be useful in helping patients prevent and manage respiratory diseases by providing personalized and data-driven recommendations for physical activity. Forestiero [21] proposed a PARS to provide recommendations to users based on their past behavior and preferences, taking into account factors such as the type of device being used, the time of day, and the user's location. The author argues that swarm intelligence algorithms are particularly well suited to this type of application due to their ability to learn from past experiences and dynamically adapt to changing conditions.

D. DRS

In 2019, Toledo et al. [22] proposed a DRS that takes into account both nutritional information and individual user preferences. The system uses a combination of data mining techniques and machine learning algorithms to suggest meals that are nutritionally balanced and align with a user's specific dietary needs and preferences. The system is designed to provide personalized recommendations that can help users make healthier food choices. The results of the study indicate that the system is effective in generating recommendations that are both nutritionally balanced and aligned with user preferences.

Osadchiy et al. [23] presented a DRS that utilizes pairwise association rules to make recommendations. The system finds the association rules between items in a transaction dataset and uses them to generate recommendations for users. The recommendations are generated based on the items that are frequently purchased together, with the goal of improving the accuracy and diversity of the recommendations. The system is evaluated using a real-world dataset and is shown to perform better than traditional recommendation methods, such as collaborative filtering.

In 2020, Iwendi et al. [24] proposed a DRS that uses Internet of Medical Things (IoMT) devices to gather patient data and then uses machine learning to recommend a personalized diet for the patient. The study evaluates different algorithms such as Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) to find the most efficient model for the task. The results show that the proposed system is effective in providing personalized diet recommendations and has the potential to improve patient health outcomes.

In 2022, [25] presents a method for building DRS using graph convolutional networks (GCN). The authors create a food graph that models the relationships between different food items and use GCN to analyse the graph and make recommendations. The GCN model takes into account various factors such as food categories, ingredient relationships, and user preferences to make personalized recommendations. The experimental results show that the proposed method outperforms traditional collaborative filtering and content-based recommendation methods in terms of recommendation accuracy.

Rostami et al. [26] depicts a DRS that takes into account the time of day and user habits. The authors use deep learning and graph clustering to analyse the relationships between food items and users, and make recommendations based on the time of day and the user's habits. The deep learning model uses a multi-layer perceptron to learn the representations of food items, and the graph clustering algorithm groups similar food items together. The experimental results show that the proposed method outperforms traditional recommendation methods in terms of recommendation accuracy, especially for time-aware recommendations. The authors conclude that considering the time of day and user habits can significantly improve the performance of food recommendation systems.

E. HPRS

In 2019, Ye et al. [27] proposed a HPRS framework using big data analytics to identify high-quality physicians. The framework combines traditional IT systems with big data technologies to gather and analyse large amounts of data from multiple sources. The data is then used to evaluate the quality of care provided by physicians and to identify those who consistently provide high-quality care. The study shows that the framework can be effective in helping healthcare organizations to improve the quality of care provided by their physicians.

In 2020, Selvi et al. [28] presented a framework for HPRS that utilizes deep learning techniques to analyze big data while maintaining patient privacy. The framework is designed to address the privacy concerns associated with using big data in healthcare, as well as the technical challenges of analyzing large amounts of data. The framework is evaluated on a real-world dataset, and the results show that it can effectively provide health recommendations while protecting patient privacy.

In 2021, Yuan et al. [29] proposed an integrated framework for doctor recommendation on healthcare consultation platforms that combines knowledge graph and deep learning. The framework aims to address the challenge of providing personalized recommendations by utilizing a combination of structured and unstructured data. The knowledge graph captures the relationships between doctors, patients, and medical conditions, while deep learning is used to predict the preferences of patients based on their historical data. The experimental results show that the proposed framework outperforms traditional recommendation methods in terms of accuracy and effectiveness.

In 2023, Zhang et al. [30] presented a multi-task learning approach for medicine recommendation that incorporates knowledge from domain-specific resources. The method is designed to address the challenge of limited data availability in the medical domain by leveraging external knowledge to improve the performance of the recommendation system. The approach uses attributed multi-task learning to simultaneously predict multiple aspects of medicine, such as efficacy, side effects, and dosage, while also incorporating external knowledge in the form of drug-disease relationships. The experimental results demonstrated the effectiveness of the proposed method in terms of recommendation accuracy and stability.

Table I, II, III, IV and V summarizes the techniques, features and challenges of DDSRS, HSPS, PARS, DRS and HPRS respectively:

TABLE I. TECHNIQUES, FEATURES AND CHALLENGES OF EXISTING DDSRS

Reference	Techniques Used	Features	Challenges and Limitations
Chang et al. [1]	Collaborative filtering techniques, transfer learning	Real-time model which overcomes the data sparsity problem	Suffers from privacy issues and data scalability issues.
Song et al. [2]	A combination of knowledge-based and machine learning algorithms	Reliable model with high specificity, sensitivity and F1 score	Complex model with high time complexity.

Zhu et al. [3]	Machine learning algorithms	Scalable model with decision-making capacity in multi-disciplinary treatment	Expert-bias and complexity in implementation and deployment.
Ertuğrul et al. [4]	DT, ANN	Robust model with high accuracy	The model is platform dependent and does not consider specific user needs.
Ragab et al. [5]	Ensemble deep learning-based techniques	High accuracy and model good for large datasets	Use of ultrasound images for training limit the widespread deployment and adoption of the system.
Nagaraj et al. [6]	Fuzzy Rule-Based System, decision trees and Particle Swarm Optimization	Model achieved good accuracy and provided interpretable and transparent recommendations	Model has limited application area and is not applicable on large datasets.
Nagaraj et al. [7]	Kalman Filter, adaptive tree seed algorithm	The system achieved improved performance by using bilevel optimization strategy	Algorithms used have high Complexity and requires significant computational resources.
Guisande et al. [8]	DT, ANN, Bayesian network	Use of AI techniques for data analysis and risk assessment significantly increased the system performance.	Model has limited applicability and high reliance on data input accuracy.

TABLE II. TECHNIQUES, FEATURES AND CHALLENGES OF EXISTING HSPS

Reference	Techniques Used	Features	Challenges and Limitations
Sneha et al. [9]	DT, RF, naive Bayes classifier	High performance mode with high specificity and accuracy	Complex system which is not scalable.
Chatrati et al. [10]	DT, RF, ANN	Model is good for elderly population as can automatically call healthcare provider in case of any emergency	Not suitable for sparse datasets
Lu et al. [11]	Machine learning and boosting techniques	High performance model useful for chronic disease risk prediction	Model lacks robustness and reliability. Also difficult for real-time practical implementation.
Mehbodniya et al. [12]	k-NN, SVM, RF	Model used cardiotocographic signals to achieve high precision values	The quality of the cardiotocographic signals in the dataset may affect model performance.
Chui et al. [13]	GAN, CNN	Used GAN to create additional sample data	Limited diversity and lack of clinical validation
Hanumanthappa et al. [14]	Artificial intelligence algorithms, Natural language processing.	IoT based smart diagnosis with real-time monitoring	High system cost with data privacy and security concerns.
Desai et al. [15]	Cloud computing, SVM, Gradient boosting, ANN	High accuracy, recall and specificity, small Execution time, low latency, and low memory usage.	High system cost with security concerns as data is generated and stored in cloud.

TABLE III. TECHNIQUES, FEATURES AND CHALLENGES OF EXISTING PARS

Reference	Techniques used	Features	Challenges and limitations
Ferretto et al. [16]	Collaborative filtering-based machine learning techniques	High accuracy and personalized recommendations	System has a limited scope and lack of long-time evaluation.
Kadri et al. [17]	Decision trees, neural networks	Continuous, real-time recommendations	The system has high reliance on smartphone data. This may raise privacy concerns.
Igor et al. [18]	Rule-based collaborative filtering, KNN	Uses a data-driven approach and has potential for widespread adoption	Comparatively low accuracy and high dependence on technology
Sengan et al. [19]	Cryptographic techniques for privacy protection.	The system provides real-time, context-aware and privacy-protected recommendations.	High complexity system with dependence on data availability. Also, the success of the system depends on user adoption.
Bhimavarapu et al. [20]	Deep learning - based algorithms	Uses a combination of data sources, such as physiological measures and environmental factors, to make more accurate recommendations.	System suffers from personalization bias and complex integration with existing systems.
Forestiero [21]	Heuristic techniques, Ant Colony and Particle Swarm Optimization	High accuracy, recall, precision, and F1 score with the capacity to generate dynamic recommendations.	Not scalable for large-scale IoT applications. Complex system which requires continuous update of dynamic user data.

TABLE IV. TECHNIQUES, FEATURES AND CHALLENGES OF EXISTING DRS

Reference	Techniques used	Features	Challenges and limitations
Toledo et al. [22]	K-Means Clustering, decision tree, Naive Bayes classifier	The model was able to deliver accurate, data-driven, personalized recommendations.	Model is not real-time. Performance could be improved by adding explicit user data and integrating with other health and wellness systems.
Osadchiy et al. [23]	Collaborative filtering, Association Rule Mining	Model is resistant to the cold-start problem. High accuracy and high scalability.	The system is not real-time and does not provide personalized recommendations.
Iwendi et al. [24]	Logistic regression, RNN, LSTM, Gated Recurrent Units	Used IoMT devices to gather patient data resulted in high precision, recall and F1 score.	High cost and complexity of implementing the system, including the need for adequate infrastructure and technical expertise.
Gao et al. [25]	Graph Convolutional Network	Using graph representation, the system captured more complex relationships compared to traditional methods. This improved the system accuracy.	The model is highly complex and suffers from cold-start problems.
Rostami et al. [26]	Content-based technique, graph clustering and multi-layer perceptron.	Time-aware recommendations with high Precision, Recall and F1 score.	Model is complex and is not scalable. It also suffers from cold-start issues.

TABLE V. TECHNIQUES, FEATURES AND CHALLENGES OF EXISTING HPRS

Reference	Techniques used	Features	Challenges and limitations
Ye et al. [27]	Big Data Analytics	The model integrates traditional IT systems with big data technologies to generate efficient quality recommendations.	Technical Complexity and high system cost.
Selvi et al. [28]	Collaborative filtering, deep learning techniques	Model displayed high-performance efficiency with high precision and recall values.	System lacks security and personalization.
Yuan et al. [29]	Knowledge-based graph and deep learning techniques	Robust model which can resolve the data sparsity problem	Model has low scalability and transparency issues.
Zhang et al. [30]	Graph modeling techniques	Stable model which solves the data sparsity problem by using external knowledge	Model is complex and limited to only those relationships which can be expressed by using graphs

VI. CHALLENGES AND FUTURE SCOPE OF RESEARCH IN THE AREA OF HRS

HRS have the potential to greatly improve the quality of patient care and health outcomes by providing personalized and evidence-based recommendations for medical treatment and lifestyle changes. However, our survey indicates that there are several challenges in the development and implementation of HRS, including:

- *Data privacy and security*: Healthcare data is highly sensitive and personal, and must be protected to ensure the privacy of patients.
- *Data quality and availability*: The quality and availability of data can greatly affect the accuracy and reliability of recommendations. This can be a challenge, especially for real-world data that may be incomplete, inconsistent, or noisy.
- *Personalization*: Providing recommendations that are tailored to the specific needs and preferences of each patient can be challenging, especially when dealing with a large and diverse patient population.
- *Algorithm transparency*: It is important for healthcare providers and patients to understand how HRS make their recommendations, in order to build trust in the technology. However, some algorithms used in HRS can be complex and difficult to interpret.
- *Clinical workflow integration*: HRS must be integrated into existing clinical workflows and decision-making processes in a way that is efficient and effective, without adding undue burden on healthcare providers.
- *Evaluation*: Evaluating the impact and effectiveness of HRS in improving patient outcomes and satisfaction can be challenging, as it requires large, controlled trials that can be difficult to conduct in real-world settings.
- *Ethics and fairness*: It is important to ensure that HRS are ethical and fair in their recommendations, and do not perpetuate existing biases or discriminate against certain groups of patients.

The existence of these challenges emphasizes the importance of thoughtful design and planning in the creation of HRS for medical diagnosis. Different algorithms were applied based on recommendation methods or machine learning techniques for each recommendation scenario. Despite the numerous advantages of the proposed HRS, there are still a number of hurdles that requires to be addressed to enhance their development in the future.

Our research survey also indicates a significant opportunity for further study in the area of HRS, particularly for specific populations such as the elderly. Future scope of research in HRS could include:

- Incorporating more diverse and real-world data sources (like electronic data gathered from wearable devices) to improve the efficiency and relevance of recommendations.
- Improving the interpretability and transparency of the algorithms used, to ensure that they can be easily understood and trusted by healthcare providers and patients.
- Developing methods to personalize recommendations based on a wider range of patient characteristics, such as age, socioeconomic status, cultural background, and individual preferences.
- Integrating recommender systems into clinical workflows and decision-making processes, to ensure that they are used effectively and efficiently in real-world settings.
- Conducting more rigorous evaluations of the effectiveness and impact of HRS in improving health outcomes and patient satisfaction.

VII. CONCLUSION

This review has collected a variety of information, including the techniques employed, features, specific applications focused on, performance metrics and system characteristics faced by different HRS. Additionally, the challenges and future scope were highlighted to outline the future direction of HRS research. In conclusion, this paper offers a comprehensive overview of the trend in HRS research and provides posterity with insight and guidance for future developments in this field.

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