

A Review on Personalized Health Recommender System

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Submitted by

Hashim Ahmed

Enrolment ID: ADTU/2019-23/BTech(CTIS)/017

BTech CTIS 7th Semester

Manoj Kalita

Enrolment ID: ADTU/2019-23/BTech(CTIS)/006

BTech CTIS 7th Semester

Under the guidance of

Mr. Deepjyoti Roy

Assistant professor,

Department of Computer Science & Engineering



Faculty of Engineering & Technology

Assam down town University

Gandhi Nagar, Panikhaiti, Guwahati-781026, Assam

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Programme of Cloud Technology & Information Security

Faculty of Engineering & Technology

Assam down town University

CERTIFICATE FROM GUIDE

This is to certify that the project work entitled '*Review on Personalized Health Recommender System*' has been carried by **Hashim Ahmed (ADTU/2019-23/BTech(CTIS)/017)**, **Manoj Kalita (ADTU/2019-23/BTech(CTIS)/006)**, of **7th semester BTech** in Cloud Technology & Information Security under my guidance. This work has not been submitted to any other institution in any form. I hope this project will help them in their future.

Mr. Deepjyoti Roy

Assistant professor,

Department of Computer Science
& Engineering,

Assam Down Town University



Programme of Cloud Technology & Information Security

Faculty of Engineering & Technology

Assam down town University

CERTIFICATE FROM EXAMINERS

This is to certify that **Hashim Ahmed (ADTU/2019-23/BTech(CTIS)/017)**, and **Manoj Kalita (ADTU/2019-23/BTech(CTIS)/006)**, of 7th semester of BTech in Cloud Technology & Information Security have undergone their project work entitled '*Review on Personalized Health Recommender System*' under the Programme of Computer Science & Engineering.

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Programme of Cloud Technology & Information Security

Faculty of Engineering & Technology

Assam down town University

DECLARATION BY STUDENT

We hereby declare that the project work entitled '*Review on Personalized Health Recommender System*' is hereby accorded for 7th semester under the Programme of Cloud Technology & Information Security, Assam down town University in an authentic record of our own work carried out as a pre-final year project, under the guidance of Mr. **Deepjyoti Roy**, Assistant professor, Department of Computer Science & Engineering.

Hashim Ahmed

(ADTU/2019-23/BTech(CTIS)/017)

Manoj Kalita

(ADTU/2019-23/BTech(CTIS)/006)

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Abstract

With the increasing use of information technology in healthcare, healthcare applications allow people to access a range of health information and services online. However, the vast amount of digital health information available can make it difficult for individuals to find personalized and relevant information about diseases, treatments, and diagnoses. Health recommender systems (HRS) are designed to assist users in finding personalized information that is most likely to be accepted by the user, and are used to provide medical suggestions for diseases or treatments, as well as recommenders for healthcare services such as personalized exercise routines and nutrition plans. While HRS can be useful in reducing the time and cost of the decision-making process, they can also be error-prone and lack personalization and trustworthiness. This chapter provides an overview of the current state of research in HRS, including the various approaches and techniques used in their development, as well as the challenges and future research opportunities in the field of personalized HRS.

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Chapter 1

1. Introduction:

1.1 Overview of the Project:

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.

1.2 Motivation

The motivation for this project is to improve the effectiveness and efficiency of recommender systems in the healthcare domain. Recommender systems have the potential to assist healthcare professionals and patients in finding relevant and personalized information, as well as making more informed decisions about treatment and care. However, with the increasing volume of digital information in the healthcare sector, it can be challenging to find and evaluate the most appropriate recommender systems for specific applications.

1.3 Scope & Objective

The scope of the project is to improve the effectiveness and efficiency of recommender systems in the healthcare domain, and help healthcare professionals and patients access relevant and personalized information more easily. This has the potential to greatly benefit individuals by improving their

access to accurate and relevant health information, as well as healthcare professionals by providing them with a more efficient and effective way to search for and access information.

Our objectives in this study are-

- i) To undergo a systematic review of various recent contributions in the domain of recommender systems, focusing on diverse Healthcare applications.
- ii) Analyse the various applications of each recommender system and evaluate all the datasets gathered, simulation platform, and performance metrics focused on each contribution.
- iii) Provide an overview of the current state of research in this field and point out the existing gaps and challenges to help posterity in developing an efficient recommender system.
- iv) *Conduct an algorithmic analysis of various existing recommender systems.
- v) *Collect diverse datasets and frame a taxonomy that accounts for various components required for developing an effective recommender system for diverse applications.
- vi) *Development of an efficient recommender system.

*(iv, v and vi) are the major project objectives

1.4 Existing System

There are various health care recommender systems currently in use. Some examples include:

Disease diagnosis and treatment recommender systems: These systems use machine learning algorithms to analyze patient data and provide recommenders for diagnosis and treatment based on the patient's symptoms and medical history.

Nutrition and exercise recommender systems: These systems provide personalized recommenders for nutrition and exercise plans based on the user's age, weight, height, and other factors.

Medication recommender systems: These systems provide recommenders for medication based on the user's symptoms, medical history, and other factors.

Symptom checker recommender systems: These systems allow users to enter their symptoms and receive recommenders for possible causes and next steps.

Health news recommender systems: These systems provide personalized recommenders for health news articles and other information based on the user's interests and needs.

Mental health recommender systems: These systems provide recommenders for mental health resources and treatments based on the user's symptoms and needs.

1.5 Problem Definition

Nowadays, a vast amount of clinical data scattered across different sites on the Internet hinders users from finding helpful information for their well-being improvement. Besides, the overload of medical information (e.g., on drugs, medical tests, and treatment suggestions) have brought many difficulties to medical professionals in making patient-oriented decisions. These issues raise the need to apply recommender systems in the healthcare domain to help both, end-users and medical professionals, make more efficient and accurate health-related decisions.

1.6 Proposed System

This systematic review will provide a much-needed overview of the current state of research in this field and points out the existing gaps and challenges to help posterity in developing an efficient recommender system. Analyze the numerous applications of each recommender system and assess the simulation platform, performance metrics, and datasets collected for each contribution. To assist future generations in creating a successful recommender system, give an overview of the status of research in this area and identify any gaps or difficulties. Analyze existing recommender systems using an algorithmic perspective. assemble several datasets, and Create a taxonomy that

includes all the different elements needed to build a reliable recommender system for a range of applications. creation of a useful recommender system.

Chapter 2

2. Theoretical Background

2.1 Types of techniques used in recommender systems:

The various types of techniques used in recommender systems are content-based filtering techniques, collaborative filtering techniques, knowledge-based techniques, and hybrid techniques.

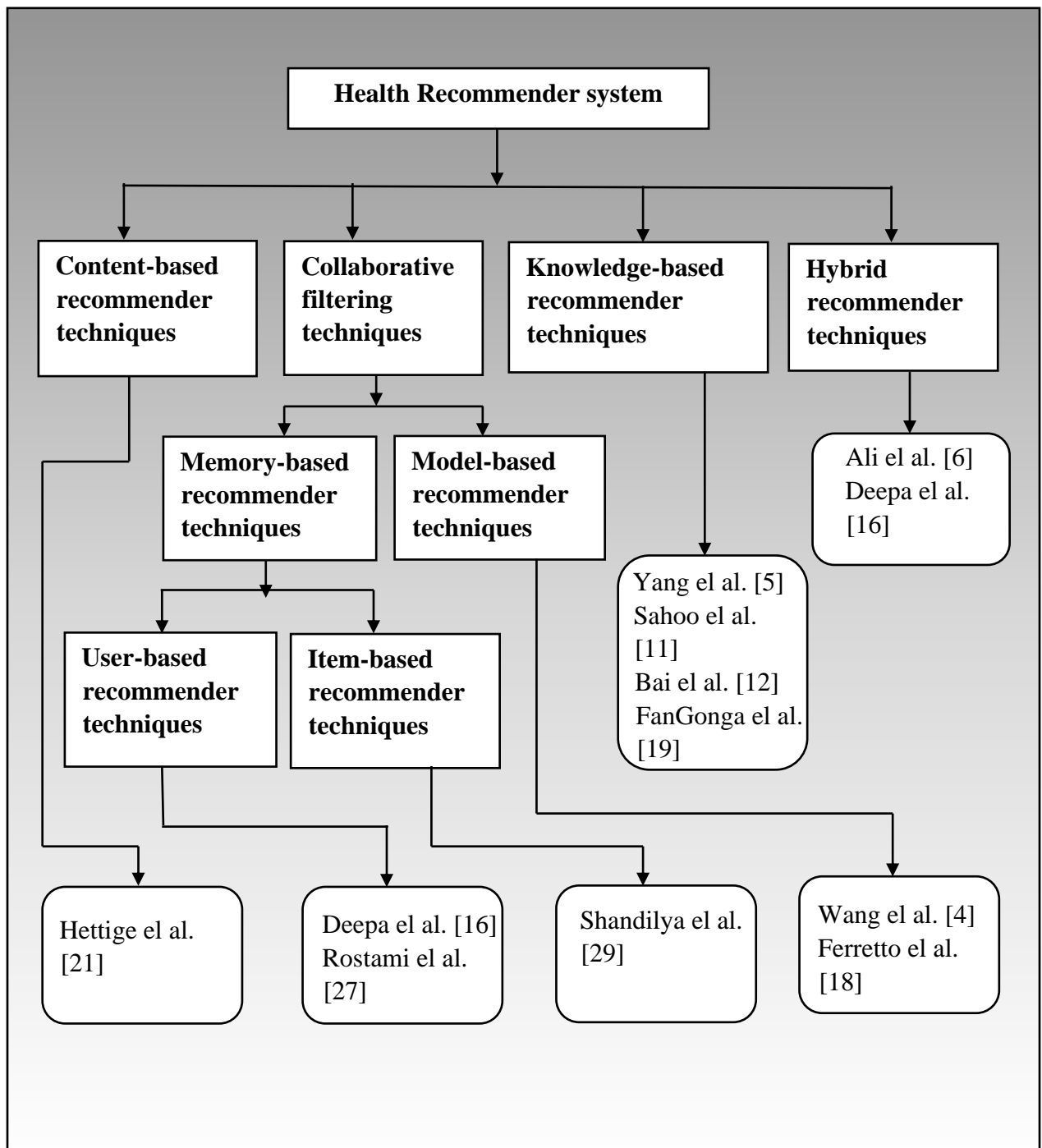


Fig. 1 Different recommender systems' algorithmic classification

- i) **Content-based recommender 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".

- ii) **Collaborative filtering techniques:** Collaborative filtering-based recommender techniques are based on the assumption 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. Collaborative filtering techniques are of two types: memory-based recommender techniques and model-based recommender techniques. Memory-based recommender techniques are again divided into two types: user-based (when the recommenders provided are based on user similarities) and item-based (when the recommenders provided are based on item similarities). Model-based techniques make use various of machine learning and data mining algorithms to develop a model to recommend a new item. In the case of HRS, this technique can be interpreted as follows: "If users share similar disease profiles/health conditions, then will be recommended similar /healthcare services in future

- iii) **Knowledge-based recommender 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 the case of HRS, 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”.

- iv) **Hybrid recommender techniques:** A hybrid technique is a combination of two or more filtering techniques described above. Each of the above-mentioned techniques has its own set of advantages and disadvantages. A hybrid technique is a combination of different approaches in order to address the limitations of individual recommender techniques. The performance and accuracy of many recommender applications are typically improved by this hybrid combination of approaches.

2.2 Various recommender systems applicable for healthcare:

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

- i) **Diagnosis decision support-based recommender systems:** Diagnosis decision support-based recommender systems 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 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.
- ii) **Medicine recommender systems:** Medicine recommender systems take advantage of data analytic techniques and artificial intelligence to explore potential knowledge from diagnosis history records and help physicians to prescribe medication correctly. A recommender of right medicine based on diagnosis can target healing and decrease trial-and-error when prescribing drugs. This can may further decrease undesirable drug side-effects.

- iii) **Food recommender systems:** The food recommender system is used to provide suggestions on user's food choices for making decisions on healthier food and eating habits. Due to a busy lifestyle, lack of food preparation time, and a wide variety of available food / packaged food items, many people fail to maintain a balanced diet. In many cases, they tend to fall short of the required daily nutrition, which in the long run may lead to chronic diseases. A food recommender system considers both user preferences and nutritional information and recommends personalized, balanced food-intake advice to the user.
- iv) **Health status prediction systems:** Health status prediction systems 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 smartwatches.
- v) **Physical activity recommender systems:** Physical activity recommender systems 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.
- vi) **Healthcare professional recommender systems:** Often patients find it challenging to select the best medical professionals for treating their health issues. This problem is common with patients who have recently moved to a new place or have been recently diagnosed with a disease. Due to the enormous number of medical consultants available online they may find it difficult to consult a new healthcare professional. A healthcare professional recommender system can assist the 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.

Chapter 3

3. Methodology

The purpose of this study is to understand the recent research trends related to recommender systems. Such recommender systems are among the key components of any healthcare system. Thus, research in healthcare recommender systems 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. Hence, this literature review gets conducted across a wide range of journals and web-based research databases such as IEEE/IEE Library, Google Scholars, ACM, Springer, and Science Direct. The search process of online research articles was undertaken, based on 6 descriptors: "Health Recommender systems", "Medicine Recommender systems", "Food Recommender system", "Physical activity Recommender system", "Healthcare professional Recommender system", and "Diagnosis decision support-based Recommender systems". The following research articles sought below were excluded from our research:

- News articles.
- Master's dissertations.
- Non-English papers.
- Unpublished papers.
- Research papers published before 2014.

We have selected a total of 104 articles from internationally indexed periodicals based on their abstracts and content. However, only research papers that described recommender systems related to healthcare could be chosen. Then, 30 research papers were chosen from Scopus and E-SCI in 2022. We now present the PRISMA flowchart of the inclusion and exclusion procedure in Fig. 1. Each paper was carefully reviewed and classified into 6 categories in the application fields, and 4 categories in the technique used to develop the system. The number of relevant articles was acquired from Expert Systems with Applications (26%), followed by IEEE (23%), collaborative filtering system (20%), and Others (31%).

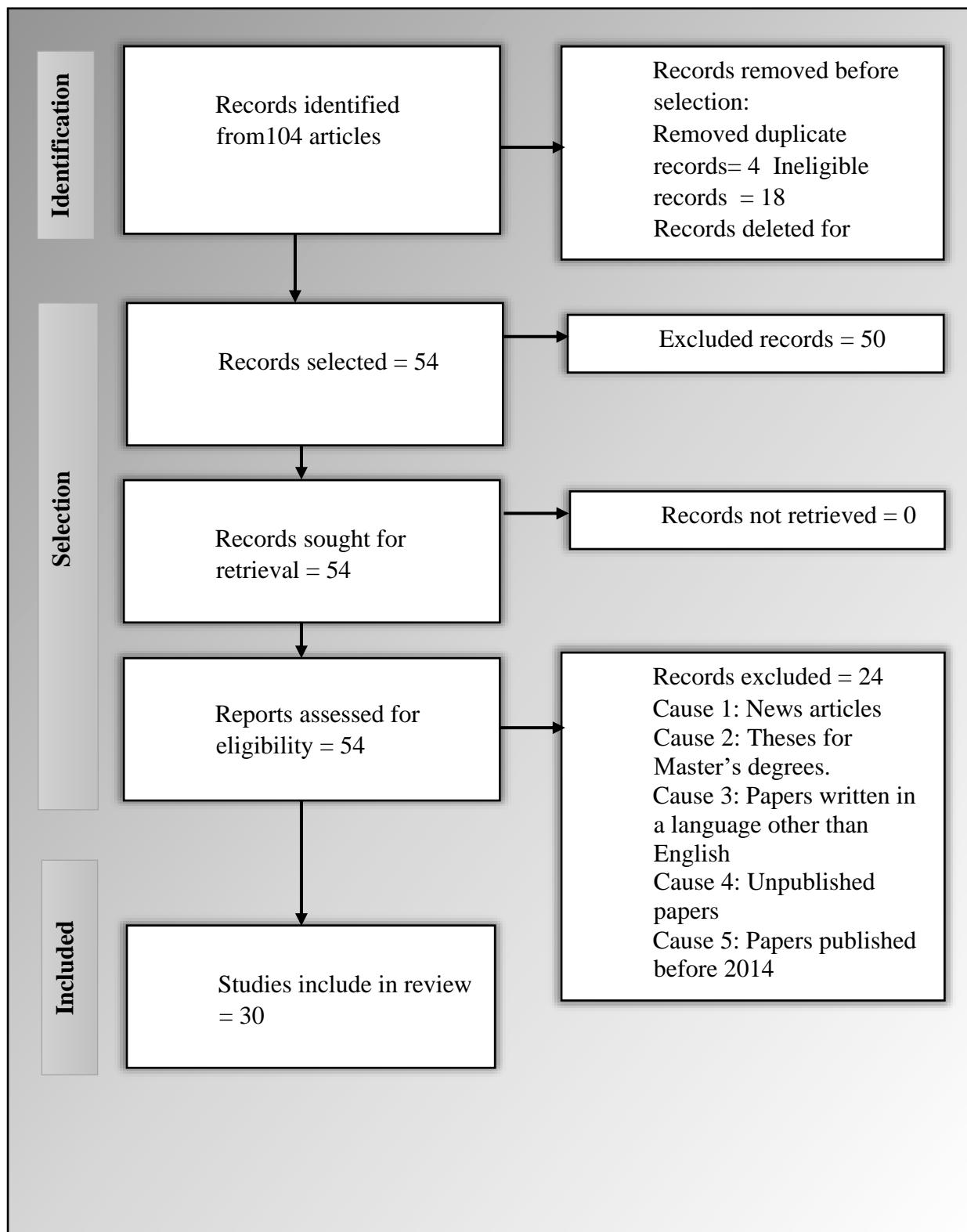


Fig. 2 PRISMA flowchart for a method of selection and rejection and study appropriate abstraction and substance.

Table. 1: Distribution of articles by

Journal title	Journal title No	% (approx.)
Expert Systems with Applications	8	26
IEEE Access	7	23
Collaborative filtering system	6	20
Others (various Elsevier journals)	9	31
Total	30	100

Table. 2: Domain-wise article distribution

Domain	No	% (approx.)
Diagnosis decision	5	16.6
Medicine	5	16.6
Food	5	16.6
Health status	5	16.6
Physical activity	5	16.6
Healthcare professional	5	16.6
Total	30	100

Table. 3: Features and challenges

Reference	Methodology	Features	Challenges
Mazzaglia et al. [1]	trial arm and baseline exposure	general practitioner; lipid-lowering drugs; primary care physician; antiplatelet drug.	Need more data to build a precise system
Dean et al. [2]	Bayesian belief network	High accuracy	Limited data set
Nair et al. [3]	Apache Spark, Scala	High performance, it offers remote health monitoring to users with a hassle-free	The dataset used in the work is not so big a dataset so small generic errors occur.

		experience in real-time.	
Wang et al. [4]	collaborative filtering, clustering	High performance, recommend the most suitable doctor according to the patient's condition	when applying the algorithm to a real system, the efficiency will be rather low owing to the massive data
Yang et al. [5]	SVM-machine-learning algorithm with decision-trees	high performance, personalized recommender, personalized therapy solutions	The system needs to improve its recommended content and techniques.
Ali et al. [6]	Machine learning, Data Acquisition, and Processing, Context Generation.	High performance, it can also provide educational recommenders to users.	There is no feedback mechanism introduced that's why it's not able to monitor whether or not the user acted on the given recommender and records the user's opinion on the generated recommender.
Mokdara et al. [7]	Deep learning	High accuracy	Model is dependent on user's dataset
Huang et al. [8]	CML-kNN	High accuracy	No integrating textual and monitoring data , Need more diverse data
Chen et al. [9]	Apriori algorithm, Density-Peaked Clustering Analysis (DPCA), and Apache Spark cloud computing platform.	high performance, low latency response	Good for the limited data set

Akbulut el al. [10]	machine learning approach, Microsoft Azure ML	high accuracy and high performance.	The communication between system components is not encrypted.
Sahoo el al. [11]	Clustering, big data analysis	It offers real-time remote monitoring of vital signs with high precision.	The collaborative filtering method will have scalability issues as participants and items increase in number. Another issue is that the cold start problem arises when HRS has sufficient data on a specific physician or patient to make accurate predictions.
Bai el al. [12]	Textual resemblance and multi-labels classification	It improves the accuracy of all macro F1 and macro-AUC models by a large margin	Highly dependent on Wikipedia clinical notes: - ICD-9 and ICD-10 codes
Zamanifar el al. [13]	hidden semi-Markov model, Baum-Welch algorithm, DHSP-tree construction	It significantly raises the accuracy of all macro F1 and macro-AUC models.	Highly dependent on Wikipedia clinical notes: - ICD-9 and ICD-10 codes
Toledo el al. [14]	AHPSort as multi-criteria choice evaluation tool	Day-by-day meal sketch	No recipe recommendations are included in the meal plan that is built daily and uses long-term data to create the menu.
Swarnalatha el al. [15]	Sentiment Analysis, Data	High performance, high accuracy,	facts about hospitals are received from comments

	Analysis, and Natural-language Processing		and critiques published by people the world over in special public forums via internet crawling through the numerous websites of the worldwideweb and it may be incorrect information.
Deepa el al. [16]	Red-black tree, spanning tree, binary tree, B+ tree, Merkle hash tree, and collaborative filtering	High performance	The proposed system isn't uses real-world dataset because it has difficult computations.
Kadri el al. [17]	Decision tree method, machine learning and deep learning techniques, and bidirectional long short-term memory	good performance, able to give good physical activity recommenders to user	There is no GPS sensor to track the kilometers for walking and jogging like dynamic activity in the current system.
Ferretto el al. [18]	Collaborative Filtering	High performance can be employed for additional uses by adding various groups of individual aspects.	According to the validation results, the recommender model only received about 75% of the vote.
FanGonga el al. [19]	Knowledge graphs and EMRs , Embedding	High Accuracy , less harmful medicine recommending	Depends on medical records so , this model is not suitable for new types of diseases

Mondal el al. [20]	Relational data model, Neo4j NoSQL graph database, MySQL and PostgreSQL, multilayer graph data model.	Good performance	Only patient preferences for treating doctors and a patient population with a range of doctor visits are used in the paper's investigation of the trust issue. The degree to which patients and doctors may trust one another, however, may depend on a number of other crucial aspects. These reflect both the cultural, linguistic, ethnic, and social origins of doctors as well as their behaviours, attitudes, and values.
Hettige el al. [21]	Medical Data Graph Embedding, V -C attributed bipartite graph temporal sequence	Visit Embedding Uncertainty, Code Embedding Uncertainty, Interpretation of code embeddings, Mortality prediction	Limited data set
Kwan el al. [22]	multilevel meta-analysis model	Heterogeneity between studies, clustering outcomes	Need more improvements
Sengan el al [23]	State of the art advising frameworks and cryptographic techniques.	High performance, PRIPRO can provide recommender solutions with high bandwidth.	The users will attain respiration issues while doing exercise, due to skipping alone, and there are some disturbances whereas skipping within

			the user is hard to calculate.
Choudhury el al. [24]	Google Firebase, Deep Neural Network, Radio Frequency Identification card, NodeMCU, Global Positioning System	High accuracy, high performance, and able to recommend best nearest hospital.	The current system is lacking of google map navigation features and system is only on web application on not in mobile app.
Pitchai el al. [25]	Cloud computing	The Generic Med Cloud (GMC) and Local System	Issue about the privacy of patient data, Health information, employee information, and credit card information
Mahyari el al. [26]	Attention networks, Active-learning, and deep-learning	High accuracy and high performance	Personalized recommender systems are very difficult to design when there is no training dataset, especially for first-time users.
Rostami el al. [27]	Graph clustering and deep-learning	content-based, collaborative filtering-based	Improvement and need for additional datasets
Zhang el al. [28]	Pareto-based algorithms	Healthy food suggestion	Limits data , need more user related objects.
Shandilya el al. [29]	Collaborative Filtering	High accuracy and more advanced then old system	Not suitable for all kind of users

Silva el al. [30]	SWOT Analysis	Assured semantic interoperability, Smart data access binding, and easy integration with different health informatics structures	Lack of support in mobile devices and control over a text field Input.
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Table. 4: Description of the dataset and implementation

Reference	Application	Dataset description and size
Mazzaglia el al. [1]	Computerized decision support system for pharmacological management	N/A
Dean el al. [2]	an aid in clinical decision-making tool for pneumonia patients treated in emergency rooms.	digital clinical record
Nair el al. [3]	Remote health status prediction system with real-time feature	Cleveland.data is a legitimate dataset that has been processed. Heart Disease Data Set is the dataset in question. The dataset has 14 properties that are labelled, and the class label attribute indicates if heart disease exists or not
Wang el al. [4]	Doctors Recommender Algorithm	The dataset used in the proposed system is real-world based that is the information of 200 doctors in Tianjin Nankai Hospital. The data set includes the basic information of doctors, academic information, and the

		assessment information given by the patients.
Yang et al. [5]	Intelligent Health Recommender System	The dataset used in the system is from 1047 volunteers' data which is used to training and testing the data.
Ali et al. [6]	Hybrid recommender framework	Not available.
Mokdara et al. [7]	food recommender system	Thai food
Huang et al. [8]	Clinical decision support framework for managing health data	Electronic health record (EHR)
Chen et al. [9]	Recommender system for diagnosis of disease and treatment	Medical disease data from hospitals
Akbulut et al. [10]	Health status prediction system	Dataset is real-world based, it is a clinical dataset. The dataset consists of 96 numbers of pregnant women, ages of the women are between 18–41.
Sahoo et al. [11]	Intelligence-based health recommender system	Dataset is real-world based, that is a healthcare dataset. The dataset contains 1-5 ratings for 500 doctors from 10,000 patients.
Bai et al. [12]	Knowledge Source Integration framework for medical code prediction	The datasets are ICD-9 diagnosis code pages from Wikipedia and the MIMIC-III dataset..
Zamanifar et al. [13]	Health status prediction system	The datasets used in the method are MIMIC III and Arrhythmia data set. The MIMIC III dataset is taken from PhysioNet.

Toledo el al. [14]	Food recommender system	N/A
Swarnalatha el al. [15]	Med-Recommender System	<p>The dataset is real world i.e., hospital data. The dataset contains 150 tuples and the 150 tuples have a diverse range of 8 specialties and 78 hospitals.</p> <p>Then 300 tuples were set to feed the algorithm, which has 11 different specialties and 121 different hospitals.</p>
Deepa el al. [16]	Hybrid Context-Aware Recommender System	N/A
Kadri el al. [17]	Physical activities recommender system	<p>The dataset used in the approach is collected from WISDM (Wireless Sensor Data Mining).</p> <p>The dataset consists of 1,098,207 samples of different physical activities that were gathered using six parameters and 36 individuals. User, x, y, and z accelerations, activity, and timestamp are the properties. Jogging, walking, going upstairs, going downstairs, standing, and sitting were among the activities.</p>
Ferretto el al. [18]	Physical Activity Recommender System	<p>The dataset is authentic. The information was gathered at the Clinics Hospital in Passo Fundo, RS, Brazil. In the dataset 9 resident physicians of cardiology perform a questionnaire with 51 hypertensive patients that were randomly presented.</p>

FanGonga el al. [19]	Safe Medicine Recommender	<p>Date set is real word based , eg: MIMIC-III , Drugbank and ICD-9 ontology and two medical knowledge graphs.</p> <p>Data set for MIMIC-II - It contains distinct 46,520 patients, 650,987 diagnoses and 1,517,702 prescription records that associated with 6,985 distinct diseases and 4,525 medicines.</p> <p>Data set for contains 13,000 international standard codes of diagnoses and the relationships between them.</p> <p>Data set for The medical knowledge graph version3 contains 8,054 medicines, 4,038 other related entities (e.g., protein or drug targets) and 21 relationships.</p>
Mondal el al. [20]	Trust-based doctor recommender system	<p>The patient-doctor multilayer dataset is an authentic dataset. 5300 records from various hospitals and health facilities are part of the collection. Some data elements, including patient names, contact information, and physician names, are omitted from the dataset and replaced with synthetic values for privacy and security concerns.</p>
Hettige el al. [21]	Med Graph- an effective EMR embedding framework.	<p>chronic liver disease (CL). and heart failure (HF) are included in the data collection .</p>

Kwan el al. [22]	Computerized clinical decision support system	Medline up to August 2019
Sengan el al [23]	Privacy-protected Physical Activity recommender system	<p>The dataset used in the model are - PAMAP Dataset and HAR.</p> <p>The PAMAP dataset contain 18 comprehensive physical activities under taken by 9 subjects.</p> <p>The HAR dataset is a collection of data from fifteen people that contains details on fifteen different categories, including motion, services, geolocation, gyroscope, sunshine, magnetic flux, and ambient noise.</p>
Choudhury el al. [24]	Hospital recommender system framework	It is not an actual dataset. Hospital rating data from Kaggle, which is made available by the Centers for Medicare and Medicaid Services, was utilized to develop the neural network models.
Pitchai el al. [25]	Generic medicine recommender system	Medical data of the patients
Mahyari el al. [26]	recommender system for physical exercise	<p>The dataset used in the proposed system are- mHealth and MovieLens datasets.</p> <p>100,000 user IDs, movie IDs, user movie ratings, and timestamps are included in the MovieLens dataset.</p>
Rostami el al. [27]	User-based food recommender system	The dataset consists of 52,821 food items divided into 27 classes. From 2000 to 2018, 1,093,845 reviews, 68,768 people, 45,630 food items, and

		33,147 ingredients were gathered from Allrecipes.com crawling..
Zhang et al. [28]	Balanced diet recommender system	The dataset used in the system is MyFitnessPal app data. The MFP data set contains 1.9 million records of meals. It was recorded from 9.8K MyFitnessPal users on 71 K food items from September 2014 to April 2015.
Shandilya et al. [29]	Mature-Food- a food recommender system	medical history of any UIHC patients with CKD.
Silva et al. [30]	Clinical decision support system	N/A

Chapter 4

4. Literature Review or Related Work

In 2014, Mazzaglia et al. [1] The proposed model is mainly designed for the patients to improve high-risk in cardiovascular diseases as a primary treatment, It is seen that this model is also helping diabetic patients. The author selects the following - Type 2 diabetes mellitus (T2DM) and acute myocardial infarction (AMI) stroke, as over 8% adult population are suffered by these diseases The system first read the data from its database, then it scan the medications data from the last 6 months as well as prescribe data. after analyzing patients' data, it displays reminder messages for the best medications

In 2015, Dean et al. [2] a decision support system is proposed for emergency patients with pneumonia, the proposed system uses a Bayesian belief network for recommenders, it also embedded with an electronic clinical record. Then system makes a calculation for disease severity assessment which also includes disposition, antibiotic selection and diagnosis testing, *“primarily based on the Infectious Disease Society of America/American Thoracic Society 2005 and 2007 pneumonia treatment guidelines.”*

In 2017, Nair et al. [3] developed a real-time remote system that predicts the user's health status. The system works by using Spark and its machine learning library MLlib, and from the available health data, a decision tree model is created, which is then applied to the steamed data to allow the user to remotely predict health status. The user posts on twitter health data, which would be filtered in near real-time by the app, and then a machine learning model is applied to the obtained health data to predict health status. The process works by analyzing the data with a decision tree model and transferring a direct message to the user regarding their health status.

Wang et al. [4] designed an algorithm that recommended doctors based on collaborative filtering and clustering techniques. The algorithm will also evaluate comprehensive physician quality, such as basic physician information and scores provided to physicians by patients. Diseases also required doctor's favors, recommending the most suitable doctor to the patient. The algorithm mainly relies on two pieces of data information. This is information for associates of academic papers published by a particular doctor and patient score information for doctors. The process involves three steps. These are the calculation of the similarity of doctors in academic

achievements, the prediction of the score of an unknown doctor with the similarity information and the score of a certain doctor, and the calculation of the basic and comprehensive scores based on the ranking indices.

Yang et al. [5] developed a system which is known as emHealth system. The developed system is an intelligent health recommender system that can make depression predictions for emotional health. The system monitors and improves the psychological and physiological state of users by providing personalized therapeutic solutions for patients experiencing emotional distress. Within the emHealth system, the system is designed as a personalized mobile phone application that collects emotional data of users with a tendency to be depressed, and based on the collected data, a prediction model is created, which is developed using a machine learning approach using a decision tree and SVM. provides personalized recommenders and intelligent decision-making solutions.

In 2018, Ali et al. [6] proposed a hybrid recommender framework. The framework can provide recommenders for physical activities and diets that support wellness and requirements to the user in a comprehensive manner and provide educational recommenders that assist in increasing the user's level of awareness of the wellness domain. The proposed framework addresses three key aspects of wellness promotion. These are educational recommenders, physical activity recommenders, and dietary recommenders. The framework consists of two modules – the main module, which serves as the framework's operational engine, and the supporting modules, which manage the primary module.

Mokdara et al. [7] The suggested approach draws pertinent components from a database of recipes for the user's favourite foods that is made available before system use. A deep neural network model analyses the consumer profile after features from the evaluation of preferred substances are extracted (DNN). Additionally, the technology keeps a database of user profiles and a history of the meals they have chosen. The model will predict the ensuing dishes using a temporal prediction model on the profile and consumption history. Customer satisfaction is analysed using the hit ratio, which is a measurement of whether a person selected the advised food or not. Additionally, the recommender's accuracy and reach are looked at. Based on the experiment's results,

Huang et al. [8] the proposed model combine heterogeneous health information structure distinctive sources , along with lab-tests, patients health data. K-Nearest

neighbours in a extending the algorithm for multi-label research utilising label correlations (CML-kNN). After first employing the dependencies between every pair of labels to replace the initial label matrix, the CML-kNN algorithm executes multilabel learning to estimate the possibilities of labels by using the built-in features. Finally, it gives doctors recommenders for the top N diseases. The effectiveness and viability of the suggested CDS framework are established through experimental effects on real-world clinical data in the area of health.

Chen el al. [9] a system for diagnosing diseases and making treatment recommenders based on patient inspection reviews introduced. To perceive sickness signs and symptoms extra precisely , For clustering disease-symptoms, a Density-Peaked Clustering Analysis (DPCA) approach is presented. Additionally, the Apriori algorithm is used to perform affiliation analyses independently for disease-diagnosis (D-D) recommenders and disease-treatment (D-T) rules.

Akbulut el al. [10] designed a system that predicts the health status of the fetus. The system uses machine learning techniques to offer pregnancy care and medical services. The proposed system consists of a site in mobile that is intended for patients, an application website that is intended for doctors, and a database that collects data and subsequently a prediction system. The proposed system has five modules – mobile application, web application, database, mobile services, and prediction system. The suggested system seeks to offer services for pregnant women and physicians via an online help system that is composed of a mobile site app for patients, a web app to their doctors, a database that collaborates between the patients' and doctors' sides, and a prediction system.

In 2019, Sahoo el al. [11] created a health recommender system that offers people useful data depending on their input. The system gathered a lot of data, such as patient research health records, risk assessments, and the severity of different diseases, and then used analytics tools to analyze the enormous data and suggest potential outcomes. The method makes recommendations for diet, exercise, diagnosis, and treatment or medication. The framework's architecture is divided into three sections. The first step is gathering data. This section compiles information and categories from the healthcare system's data source. The process of data analysis, which might produce recommendations customized to a person's health, is the next component of the

framework. Visualization is the framework's last component. It includes components that may have an impact on the suggested items and how they are displayed.

Bai et al. [12] proposed an end-to-end information source integrated technique that compares the outputs of a base method with the results of calculating the similarity score between clinical data and disease-related data from Wikipedia entries. Any neural multi-label prediction model may include external data sources using the model. The intersection of a clinical note and an external information source is a crucial part of the KSI system, which entails using a learning algorithm to choose crucial properties in the intersection set. The score for each piece of information that matches the note is then determined. The KSI framework frequently outperforms the baseline model at predicting unusual codes. The KSI framework also clarifies the outside information that backed the forecast.

Zamanifar et al. [13] proposed an approach that can predict healthcare status in an IoT application. The proposed approach predicts based on the HSMM model and uses a special sensor to record the patient's health status, i.e., physical status, objects, and environmental status. The approach that detects the patient's health status is not cost-effective because it needed a significant number of sensors and which is expensive and it also inconvenient for patients to wear it. The suggested model makes predictions about the health condition of nursing home patients using a tree structure network.

Toledo et al. [14] the present paper proposes a universal framework for daily meal graph suggestions, in contrast to prior studies that lacked this global viewpoint. Its fundamental component is the simultaneous storing of nutritional- and preference-aware data. The proposal incorporates a pre-filtering step where items that aren't the best fit for the characteristics of the contemporary person are eliminated using AHPSort as a multi-criteria choice evaluation tool. Additionally, it contains a stage for developing a daily meal sketch based on optimization, with the goal of suggesting meals the user could enjoy unexpectedly, haven't eaten in a while, and that meet his or her daily nutritional requirements.

Swarnalatha et al. [15] designed and developed a recommender system that helps users in the finding of the best hospital for a specific treatment. The system works by collecting data from various websites, data such as comments and reviews submitted by people to hospitals in various public forums using web browsing. The data is then

processed by the Textblob natural language processing tool. Then the intelligence algorithm selects the hospitals and ranks them.

Deepa et al. [16] proposed a mechanism that uses collaborative filtering to rank physicians based on their performance and the system is a hybrid context-aware recommender system. The recommender system is essentially for E-Health care, that is in the implementation of HCARS-EHC. The suggested solution is effective because it relies less on computing complexity and more on privacy protection, recommender systems, and assessment.

In 2020, Kadri et al. [17] developed a recommender system for predicting daily physical activities for users based on WHO references. The system uses data from a smartphone accelerometer to make health recommenders. The system first collects the smartphone sensor data and processes the data, then predicts physical activity using the machine learning and deep learning algorithms. The three-step process is the foundation of the predicted approach. These include data processing, movement activity prediction utilising machine and deep learning algorithms, and dynamic activity calorie computation for making decisions about physical behaviour.

Ferretto et al. [18] created a system that recommends physical exercise to hypertension patients. In order to create a physical activity recommender system, they first created a user profile model for the hypertensive user, which they named HyperModel2PAR. Although the HypeModel2PAR user profile model is largely focused on advising physical activities, the technology may be used for other reasons as well. This new trait gives the model flexibility and adaptability since it enables adaption in a specific setting.

FanGong et al. [19] develop a model to generate a heterogeneous graph consisting of Medical knowledge graph and Electronic Medical record(EMRs) . It consists of 'DRugbank, ICD-9 ontology, and MIMIC-III' , then the model recommend medicine by embedding disease , patients, medicines by calculating the lower space of dimension and it generates a disease-patient graph.

Mondal et al. [20] proposed to develop a doctor recommender system for patients. The recommender system will be built on a multi-layer graph data model. The recommender system is meant to be used to choose a doctor from a list of available doctors in a distant healthcare situation. The paper also includes a patient-physician

relational model and a trust factor model for the proposed system. A multilayer graph approach is used in the system architecture to achieve the proposed goal.

Hettige et al. [21] a medicine recommender system called MedGraph is developed. The model makes patients data embeddings, then they use RNN-based algorithm to study about their relationship close and effectively. Further the model is feed with real world data set and let it examine for 30 days and results are noted. It is seen that after the experiment the model perform very well. It is able to predict

Kwan et al. [22] EHRs and clinical decision support systems are integrated in the suggested approach. a screen-based tool made to improve doctors' adherence to a recommended healthcare system. to keep track of the advancements made through the use of medical selection assistance systems and to analyse heterogeneity resulting from the pooling of effects across various clinical contexts and intervention objectives.

In 2021, Sengan et al [23] suggested a homomorphic encryption (HE)-based recommender system that protects the privacy of customer data. To speed up computation and customise judgments, the system bases itself on user needs and uses offline and online data processing techniques. The HE approaches for protecting user data in the preferred decisions make up the proposed PRIPRO paradigm. Only mathematical operations are used. The HE procedures used by the PRIPRO model are 100% correct. A DDDMS can also be produced using a training set.

Choudhury et al. [24] a programme that uses neural networks to choose hospitals based on hospital ratings, available physicians, and distance has been developed to ensure that people can travel to the best hospital in an emergency. The recommended architecture uses a real-time database created in Google Firebase to store information on hospitals, such as their location, rating, list of attending physicians, and number of beds available. Another system that was created uses NodeMCU and radio frequency identification cards to track doctor attendance. A web-based application was also created, and it provides information about the proposed hospital or hospitals, including name, address, and phone number.

Pitchai et al. [25] proposed a model that take the data of the patient after admitting into the Hospitals, it sense the the wellbeing of the patients. The patients data is stored on the cloud server, medicine data prescribed by doctors, diagnosis condition of the patient and tests. The software analyse the data and display the result of 'cost effective generic medicine' also suggested for the upcoming tests for the

patients. This financial tracking methodology aids patients in keeping track of their medical expenses.

In 2022, Mahyari et al. [26] Create a system that can suggest daily fitness plans to users based on their interactions with other users and their histories, profiles, and histories. The developed recommender system uses a deep recurrent neural network with attention mechanisms based on user profiles and temporal awareness. The system adapts the recommender system for each user via independent learning. A collection of train data from various persons is used to train the recommender system. The system is used to decide when to consult experts for advice and is derived from the marginal distance distribution of probabilities.

Rostami et al. [27] The proposed approach consists of two phases: user-based suggestion and recommender based on food content. Graph clustering is utilised in the first stage, while deep learning is used in the second stage to cluster both people and food goods. Additionally, a comprehensive approach is applied to account for time restrictions and user community concerns, raising the calibre of the counsel given to the user.

Zhang et al. [28] a food recommender model MaOO-based approach is developed . The model is responsible for stabilizing food balance and meal suggestion task . the proposed model mainly focuses on users food diet , users food preference , diet pattern , food diversity etc. This paper's key contributions can be summed up as follows: To solve the recommender issue, a novel MaOO-based recommender framework is created, in which three MaOO techniques are delicately connected to transform the actual recommender challenge into a MaOO problem. A number of tests are also carried out. In order to achieve the suggested recommender task's goal of offering clients a scientifically sound yet personalised diet, four separate meal-related objectives must be simultaneously optimised.

Shandilya et al. [29] a Collaborative filtering based food recommender system is developed named – “*MANDATORY FEATURE CHOICES*” . The system is mainly focuses on the user preferences data such as ratings , suggestions , likes as it help the system to make more personalise food recommenders . The system use machine learning algorithms to recommended food to every possible users .

Silva et al. [30] A clinical decision support system is build on OpenEHR international diagnosed standard. The model architecture consists of three sections – (i)

create guideline , (ii) guidelines and (iii) subject proxy.the system create the guidelines , also the system's component allow the users to visualize , and execute it , users can manage the functionalities of subject proxy sections. Because of OpenEHR the system is able to work as interoperable system which stores Digital records.

Chapter 5

5. Result Analysis

5.1. Performance analysis with existing system/algorithms

The performance evaluation metrics used for the analysis of different recommender systems is depicted in **Table.5**. From the set of research works, 20% of the works use recall measure, 6% of the works employ Mean Absolute Error (MAE), 6% of the works take Root Mean Square Error (RMSE), 23% of the papers consider precision, 30% of the contributions analyse F1-measure, and 60% of the works apply accuracy. Moreover, some additional measures are also considered for validating the performance in a few applications.b

Table.5: Performance analysis with existing system/algorithms

References	Recall	MAE	RMSE	Precision	F1-measure	Accuracy	Miscellaneous measures
Mazzaglia el al. [1]							Statistical analysis
Dean el al. [2]						✓	Primary Data Analysis
Nair el al. [3]						✓	Amazon EC2
Wang el al. [4]						✓	Data clustering, decomposition of singular value
Yang el al. [5]					✓	✓	Self-Rating Depression Scale
Ali el al. [6]							MET
Mokdara el al. [7]				✓		✓	Hit ratio
Huang el al.	✓			✓	✓		Ham loss

Chen el al. [9]						✓	time complexity, RDD, K-Means and DPCA
Akbulut el al. [10]					✓	✓	Tree-based feature selection
Sahoo el al. [11]	✓	✓	✓	✓	✓	✓	Specificity measures
Bai el al. [12]						✓	Recurrent neural network (RNN), Convolutional neural network (CNN), Convolutional Attention (CAML)
Zamanifar el al. [13]	✓			✓	✓	✓	specificity
Toledo el al. [14]							Multi-criteria decision Analysis
Swarnalatha el al. [15]	✓			✓	✓	✓	False Positive Rate
Deepa el al. [16]		✓	✓				NMAE
Kadri el al. [17]	✓			✓	✓	✓	Decision tree and BiLSTM
Ferretto el al. [18]							Physical Activity Result

							Indexes (PARI)
FanGonga el al. [19]						✓	K-Most frequent m
Mondal el al. [20]							Trust factor
Hettige el al. [21]					✓	✓	RNN
Kwan el al. [22]							multilevel meta-analysis, statistical analyses
Sengan el al [23]		✓	✓			✓	Top-K Mining value comparison.
Choudhury el al. [24]						✓	Normalized scores
Pitchai el al. [25]							Generic Med Cloud
Mahyari el al. [26]						✓	RNN
Rostami el al. [27]	-			✓	✓	✓	NDCG
Zhang el al. [28]							SPEA2 , NSGA-II , and SDE
Shandilya el al. [29]							CxF, Mandatory Features (MF), Preferred Features (PF)
Silva el al. [30]							SWOT Analysis

Chapter 6

6. Conclusion & Future Scope

In the past years, researchers and academicians are getting interested in new technology recommender systems. In this study, the related studies on health recommender systems that focused on various applications in the healthcare system that were published between 2014 and 2022 have been identified and carefully examined. This study has accumulated a variety of information, including the application domains, methodologies, modelling techniques, targeted applications, key metrics, datasets, system characteristics, and difficulties of several health recommender systems. Overall, this study offers a thorough overview of the trend in research on health recommender systems and offers researchers insight and guidance for the field's future. The result of this study has a number of important and useful consequences:

- Focusing on recent-past publication rates, we anticipate that future research on health recommender systems will expand significantly.
- We found health status, food, and physical activity recommender systems had a high concentration of research publications, but diagnosis decision support-based, medicine, and healthcare professional recommender systems had a far lower concentration. This is because publicly accessible datasets on the three subjects of food, physical activity, and health status are readily available. Consequently, it is essential to create datasets in other fields as well.
- For recommender systems, numerous collaborative filtering methods are being put out. Applying collaborative filtering techniques can significantly boost a recommender system's performance.
- Deep learning and machine learning-based techniques for creating recommender systems are the subject of extensive research. It is discovered that systems created utilizing these techniques attain better accuracy.

This study will also guide researchers on future research in the area of health recommender systems. There are some limitations to this research, though. First off, due to a lack of resources and time, Only journal papers have been evaluated by us that have a particular interest in health recommender systems. Second, we only looked at English-language papers. Finally, only six descriptors—"Health Status Recommender Systems," "Food Recommender Systems," "Physical Activity Recommend," "Diagnosis Decision Support-based Recommend," "Medicine Recommend," and

"Healthcare Professional Recommend"—were searched for in this review. Research papers without these keywords were not taken into consideration. Additional keywords and descriptions for searching may be included in future studies. This will enable expanding the study to include literature on recommender systems from a wider range of sources.

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