A Study of Health Recommender Systems: Analyzing the Advancement of Sustainable Health Recommender Systems Using NLP Techniques

Shilpa Balan
California State University, Los Angeles

Sumali Conlon
University of Mississippi

Over the years, the amount of healthcare data has immensely increased due to technological development. Although it has provided the user with ease to data access, large amounts of data can be challenging to the user due to information overload. In the case of the healthcare domain, any misinterpreted information may cause a severe situation. Recommender systems are proving to be beneficial due to their use in extracting the required information quickly. In this paper, we conducted an analysis of the existing health recommender systems using NLP techniques. We reviewed the existing solutions for health recommender systems, described and compared them based on their features and algorithms employed, and presented future research directions. Our findings indicate that the popular applications of the health recommender systems developed are in patient-doctor match, recommending drugs, cancer predictions, chronic disease diagnosis, and recommender systems for patients with heart problems. Further, given the knowledge of sustainable products, a recommender system can suggest products with these characteristics.

Keywords: NLP, health, recommender systems

INTRODUCTION

The amount of healthcare data has increased tremendously over the years. With the ease of access to the Internet nowadays, users can rapidly procure a lot of healthcare data. In addition, individuals can obtain a large amount of medical information from a variety of sources such as news sites, web forums, and other such. However, large amounts of data can cause information overload which can be an obstacle in the understanding of personal health (Sommerhalder et al., 2009). Information overload could also possibly lead to misinterpreted information (Waqar et al., 2019). Moreover, an abundant amount of medical vocabulary poses a barrier for individuals particularly in the non-medical field (Hardey, 1999). Recommender systems would hence be beneficial since they help to filter out the irrelevant information (Waqar et al., 2019).

According to the Pew Internet and American Life project (2013), 81% of U.S. adults use the Internet and 59% state that they have looked online for health information regarding diseases, diagnoses and different treatments. This influences the educated patients to discuss treatment options (Gerber et al., 2001, Kivits, 2006, McMullan, 2006) enabling them to become participants in the decision-making process. The goal of a personal health record systems (PHRS) is to centralize an individual's health data that could be accessed by the patient or the health professionals (Tang et al., 2006).

Recommender systems (RS) suggest items of interest to users. A well-known example is Amazon's recommender service that suggests products. It is believed that this idea behind recommender systems can be tailored to the health domain as has already been adapted by some. For example, a semantically enabled Health Recommender System (HRS) could help resolve medical abbreviations. This helps in decreasing the amounts of information overload as it provides a user with those items of interest that are most relevant for a given medical context (Wilson, 2001). In this paper, we applied Natural Language Processing (NLP) methods to conduct our analysis on the benefits and approaches used to develop the current health recommender systems.

BACKGROUND

Health care recommendation systems can help with the decision-making process by providing personalized health care services. Based on a patient's current health status, prehistory, symptoms and past treatments, the recommender system can examine patients with similar factors in its database to suggest the most helpful medicines (Stark et al., 2019). Such systems analyze patient data to provide predictive health care recommendations. Health professionals benefit from recommender systems in the retrieval of valuable information for clinical guidelines leading to the delivery of high quality health treatments for patients (Sahoo et al., 2019).

Existing literature examines factors affecting patients' trust in doctors (Croker et al., 2013). An adaptive doctor-recommended system developed by Waqar et al. (2019) helps patients to identify a doctor who meets their requirements. The authors proposed a hybrid recommender system constructed by combining different machine learning techniques including content, collaborative and demographic filtering. Patients aim to find the right doctor with whom they could build a trusting relationship, given that the trust in a patient-doctor relationship plays an essential role in improving their satisfaction with the care provided (Birkhauer et al., 2017). Patients tend to rely on word-of-mouth recommendations from friends and relatives.

There are some previous studies on the literature review on health recommender systems (HRS). One example of a work conducting literature review for HRS is the one of Sezgin and Ozkan (2013). Their work published in 2013 is probably one of the first studies aiming to evaluate the published investigations regarding HRS. Applications of health recommender systems have been used for diagnostic assistance and for personal health advising (Ricci, et al., 2011). In addition, HRS has been used by physicians for diagnostic and educational purposes. Suggesting online health resources and educational resources are examples for web based diagnostic recommender system use (Fernandez-luque et al., 2009).

Advancements in online recommender systems are enhanced by the semantic web (Berendt et al., 2002), which facilitates the extraction of vast amounts of information through mining techniques (Berners-Lee et al., 2001). Using these techniques, it is possible to rank and classify items based on terms grouped into ontologies (Yu et al., 2015) creating an important resource for recommender systems. A recommender system proposed by Narducci et al. (2015) utilized the semantic relationship between a patient's symptoms and their treatment to find similar patients followed by recommended doctors who are rated highly by them. The recommender system presented by Salunke et al. (2015) used natural language processing and user ratings to construct a doctor profiler.

Generally, recommendation systems are of two types, i.e., collaborative filtering and content-based recommendation systems. Whereas content-based filtering is based on the similarity of item features, collaborative filtering methods calculate similarity from user-item interactions (Ertugrul and Elci, 2019). In a healthcare setting, for example, collaborative filtering is based on the interaction between the patient and doctor. Collaborative filtering examines similar user profiles to determine the user's preferences. Content-based filtering on the other hand uses item data and provides a profile for each item (Ertugrul and Elci, 2019). In this paper, we analyze existing articles on the health recommender systems and present our findings in the discussion and results section.

RESEARCH METHODOLOGY

In this study, we combined several natural language processing (NLP) techniques in text analytics to analyze the articles on health recommender systems. Natural Language Processing is "a range of computational techniques for analyzing naturally occurring texts at one or more levels of linguistic analysis for the purpose of achieving human-like language processing for a range of tasks or applications" (Liddy, 2001, p1). For our paper, we include building a lexicon of the medical terms, analyzing term frequencies, analyzing term co-occurrences, and semantic relationships. These are further described in the methodology section.

Data

For our study, we analyzed various research articles in health recommender systems from several sources. Following are examples of journals we extracted relevant articles from for this research.

- Artificial Intelligence in Medicine
- Behavior and Information Technology
- BMC Medical Informatics and Decision Making
- Decision Support Systems
- Expert Systems
- Future Generation Computer System
- Information and Software Technology
- International Journal of Cardiovascular Sciences
- International Journal of Advanced Computer Science and Applications
- Journal of Intelligent Information Systems
- Knowledge Based Systems
- International Journal of Environmental Research and Public Health

System Architecture

FIGURE 1
ARCHITECTURE FOR HEALTH RECOMMENDER SYSTEMS

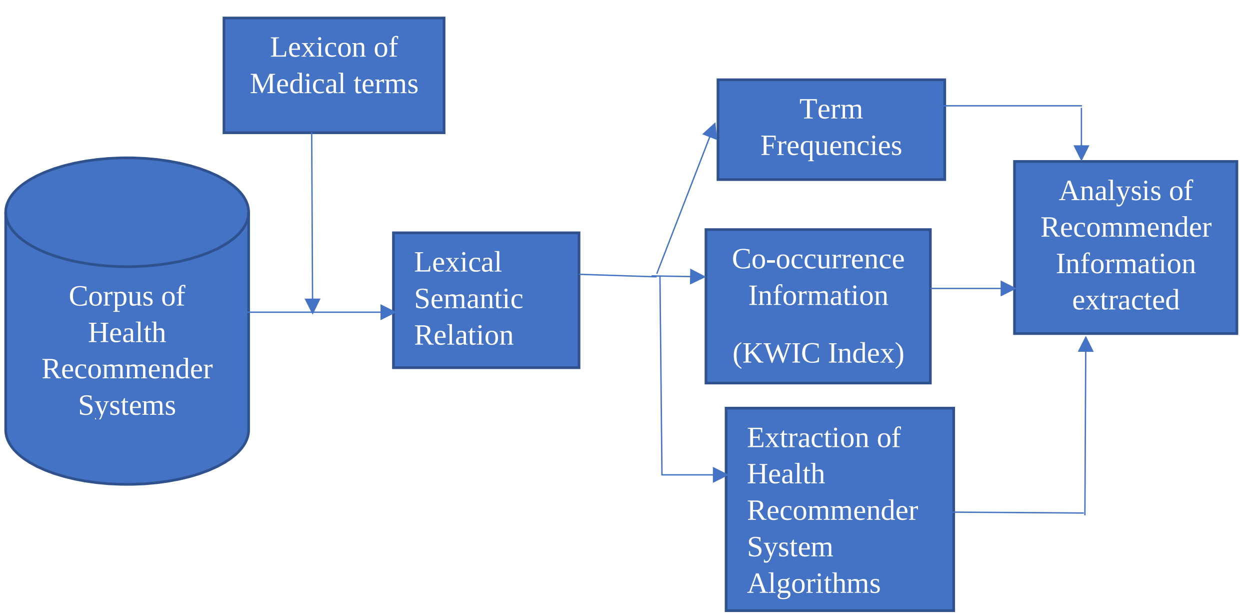

Figure 1 shows the system architecture we applied in this research. First, we extracted the corpus of documents on health recommender systems based on the lexicon of medical terms. We then extracted the frequently occurring terms and the collocated terms using the KWIC (Key Word in Context) index. The detailed steps of the methodology are described below.

Lexicon

There were many unique terms included in the corpus of our study. To find out the relevant terms, we created a lexicon of terms as shown in Figure 2 that includes the frequently used terms applied for searching health related information listed at the Centers for Disease Control and Prevention (CDC) (CDC, 2022). Examples of these terms are asthma, cancer, and diabetes.

Using the most searched terms from Figure 2 that uses CDC as a guideline, we found the frequently occurring terms included in our corpus documents illustrated in Table 1. The terms listed in Table 1 shows the different diseases and causes of diseases that researchers study related to health recommender systems. We reviewed thirty documents in all from sources described in the data section. As shown in the table, the topmost frequently used medical terms are 'weight', 'diabetes', and 'heart'. We also found that the term 'cancer' occurs frequently.

FIGURE 2
MOST SEARCHED DISEASES & CONDITIONS LISTED BY THE CENTER FOR DISEASE CONTROL AND PREVENTION

ADHD	Epilepsy	Methicillin-resistant Staphylococcus aureus (MRSA)
Arthritis	Fetal Alcohol Spectrum Disorder	Microcephaly
Asthma	Flu (Influenza)	Middle East Respiratory Syndrome (MERS)
Autism	Genital Herpes (Herpes Simplex Virus)	Overweight and Obesity
Avian Influenza Birth Defects	Giardiasis Gonorrhea	Parasites – Scabies Salmonella
Cancer	Healthy Water	
Chlamydia	Heart Disease	Stroke
Chronic Fatigue Syndrome	Hepatitis	Traumatic Brain Injury (TBI)
Chronic Obstructive Pulmonary Disease (COPD)	HIV/AIDS	Trichomonas Infection (Trichomoniasis)
Coronavirus Disease 2019 (COVID-19)	Human papillomavirus (HPV)	Tuberculosis (TB)
Diabetes	Kidney Disease (Chronic Kidney Disease)	Zika Virus
Ebola (Ebola Virus Disease)	Meningitis	

CDC, 2022

TABLE 1
TERM FREQUENCIES AND THE NUMBERS OF ARTICLES THE TERMS APPEAR IN THE CORPUS

Term	Frequencies	Number of documents
Weight	268	30
Diabetes	187	18
Heart	39	16
Healthy	50	14
Cardio	49	10
Blood	33	10
Pressure	22	10
Cancer	57	9
Brain	8	6
Breast	35	4
Alcohol	10	4
Kidney	10	4
Obesity	23	3
Thyroid	29	2
Glucose	18	2
Infection	12	2

In addition to the main terms that appear in the lexicon, we expanded our key terms by incorporating lexical semantic relation terms provided by WordNet. WordNet (Miller et al., 1990) is a lexical database that contains semantic relation between words such as synonyms and hyponyms. The term ‘cancer’ for example, has the following lexical semantic relation as shown in Figure 3.

FIGURE 3
EXAMPLE OF WORDNET FOR THE TERM ‘CANCER’

direct hyponym / full hyponym

S: (n) lymphoma (a neoplasm of lymph tissue that is usually malignant; one of the four major types of cancer)

S: (n) carcinoma (any malignant tumor derived from epithelial tissue; one of the four major types of cancer)

S: (n) leukemia, leukaemia, leucaemia, cancer of the blood (malignant neoplasm of blood-forming tissues; characterized by abnormal proliferation of leukocytes; one of the four major types of cancer)

S: (n) sarcoma (a usually malignant tumor arising from connective tissue (bone or muscle etc.); one of the four major types of cancer)

direct hypernym / inherited hypernym / sister term

S: (n) malignant tumor, malignant neoplasm, metastatic tumor (a tumor that is malignant and tends to spread to other parts of the body)

(Source: WordNet, 2022)

We use the lexical semantic information in WordNet to capture the relationship for the key terms in our corpus. Some sample semantic relation terms from our corpus document are listed in Figure 4.

FIGURE 4
SAMPLE SEMANTIC RELATIONSHIPS FROM OUR CORPUS DOCUMENTS

diabetes	causes	headaches
obesity	causes	diabetes
obesity	causes	heart disease
diabetes	caused by	sugar
diabetes	caused by	obesity
heart disease	caused by	obesity
heart disease	caused by	**s**tress

Co-Occurrence Analysis

The list of the terms of diseases that occur in the corpus document list of our study helps us to identify which diseases are referenced in the articles selected for analysis. In addition, we were also interested in discovering which terms appear together in the same sentences with those key terms. This is because the terms that co-occur with the key terms could provide some additional information leading to what might cause or occur together with a disease. To find the terms that co-occur with the terms we were interested in, we generated the Key Word in Context (KWIC) file (Luhn, 1960). Key Word in Context (KWIC) shows the keyword in the middle of each line, with the text forming its context on either side. For example, in our document collection, the term 'diabetes' co-occurs with words that appear on the left and the right as seen in Figure 5.

FIGURE 5
KWIC INDEX SAMPLE FOR THE TERM "DIABETES" FROM THE CORPUS DOCUMENTS

th; Remote Chronic Disease Diagnosis prediction;	Diabetes	healthcare management system; Decision Tree; Ran
of patient risk factors and recommending	diabetes	prescriptions. Bianchini, De Antonellis, De Franc
case-based reasoning framework for semantic	diabetes	diagnosis. Artificial Intel ligence in Medicine,
semantic retrieval algorithm for a semantic	diabetes	diagnosis. Compared with the existing CBR
patient. Fig. 3 shows sample of the	diabetes	medical dataset of an undiagnosed patient
Video. Example diabetes video from the	Diabetes	Research Foundation and links extracted from
model performance [22]. In our system, the	diabetes	dataset is filtered by determining the
a treatment plan according to the	diabetes	type of the patient. OWL-DL
an active patient suffering from the	diabetes	disease. She is now facing some
significant and highest effect on the	diabetes	diagnosis. The scale of diagnose is
technique to suggest proper medications to	diabetes	patients. A patient has to register
al. 2017) CF suggests proper drugs to	diabetes	patients (Bresso et al. 2013) decision trees,
might be fewer links related to	diabetes	than other topics (e.g., hypertension),
codes for kidney complications relating to	diabetes.	The parameters of the BNs that
engesFigure 2: "10" sample records of total "935"	diabetes	training dataset Figure 3: Sample dataset of
.A. Al-Lawatia and J. Tuomilehto, "	Diabetes	risk score in Oman: A tool
: A tool to identify prevalent type 2	diabetes	among Arabs of the Middle East,"
No information IRS-T2D [11] Type 2	Diabetes	Knowledge base with ontologies and SWR
2D: Individualize Recommendation System for Type2	Diabetes	Medication Based on Ontology and SWRL.
D. Individualize Recommendation System for Type2	Diabetes	Medication Based on Ontology and SWRL.
2D: Individualize recommendation system for type2	diabetes	medi cation based on ontology and
a drug recommendation system for type 2	diabetes	and intends to give doctors a
official documents on management of Type 2	diabetes.	Protégé is used for modelling the
-OWL API Test patients DiaTrack [12] Type 2	Diabetes	Database management system Dynamic service middl
to individualize patient treatment of type 2	diabetes	mellitus patients. The solution combines rule
for anti-diabetic drugs selection [3] Type 2	Diabetes	Protégé Protégé No information An Intelligent
Elbeh (2016) Suitable treatment plans for Type 2	diabetes	OWL, SWRL, JESS engine, XSLT √ (Continues)

DISCUSSION AND RESULTS

Using some of the information we extracted semi-automatically using the NLP techniques described in the methodology section, we have used the key search terms to analyze the healthcare related articles. The word patterns that co-occur appear in the KWIC index file as seen in Figure 5. Some of the major information extraction techniques and benefits in health recommender systems that we extracted using the techniques described previously are illustrated in Table 2.

Table 2 describes the techniques and algorithms used by various researchers who have attempted to build recommender systems for healthcare purposes. Table 2 also provides the benefits of these recommender systems. Recommender systems are now found in clinical settings primarily to assist health professionals (Espin et al., 2016, Borbolla et al., 2014, Valdez et al., 2016). From our results, we can infer that the popular applications of the health recommender systems developed are in patient-doctor match, recommending drugs, cancer predictions, chronic disease diagnosis, personal health record system (PHRS) to help with patient-oriented decision making and recommender systems for patients with heart problems. Other applications of recommender systems in healthcare include nutritional recommender systems, IoT enabled applications and recommendations for exercise routes.

Among chronic diseases, heart attack is a common reason for hospitalization, especially in aging population (Mozaffarian et al., 2011). Cardiovascular diseases are a leading cause of death globally (World Health Organization, 2021). Moreover, many people suffer from chronic attack arthritis and back pain due to improper exercise and diet (World Health Organization, 2013). To overcome these issues, there is an attempt to apply innovative technologies such as recommender systems to encourage a healthy lifestyle.

Semantic networks and ontologies have become important in medicine to categorize symptoms, diseases and medical procedures. Recommender systems are now used in several applications for extracting relevant information quickly. Our findings indicate that many researchers have applied k-means clustering, SVM and matrix factorization methods to develop health recommender systems. For example, to obtain the necessary medical information, Weisner et al. (2014) employ a support vector machine (SVM) model. Other systems focus on prevention aspects by delivering recommendations. Thereby, patients suffering from chronic diseases such as diabetes receive personalized advice based on their individual condition.

Other researchers who developed their own algorithm to build recommender systems have applied collaborative filtering algorithms and hybrid approaches. The collaborative filtering method helps to filter users' preferences for items. Most current systems have adopted machine learning algorithms (Gu et al., 2016, Zhang et al., 2016, Li et al., 2015) such as naive Bayes, and matrix factorization (Hernando et al., 2016, Ioannidis et al., 2016) approaches. The content information is integrated into the matrix factorization collaborative filtering methods, which provides useful insights about the contents, as well as make the recommendation more easily interpretable.

Kumar et al. (2018) developed a context-aware recommender system to provide real-time data from smart city infrastructure, usage of routes for people based on health condition. Context-aware recommender system software performs based on preference of routes. The system takes the user's healthcare data as input to avoid dangerous routes benefiting the user based on their health condition. Sahoo et al. (2019) mention that with the increased use of social networks, health recommender systems are beneficial for recommending diagnosis and treatments based on the patient's health profile. Sustainability in health recommendations would be an effective option. However, there is less discussion on sustainability in health recommender systems in the current literature. The sub-section below details the importance of sustainability in health recommender systems.

TABLE 2
RECOMMENDER SYSTEM APPLICATIONS IN HEALTHCARE

Author	Technique	Benefit / Function of the System
Stark et al., 2019	C4.5 and Bagging, K-means algorithm, SVM	recommending drugs, system name: DiaTrack
Ertuğrul and Elci, 2019	Association mining, decision tree, clustering	personalized health, classify precise disease symptoms
Mustaqeem et al. 2020	Collaborative algorithm (k-mean clustering)	for cardiovascular diseases
Hussein et al. 2012	Random Forest algorithm	reliable recommender systems for chronic diseases
Tran, 2020	time series prediction algorithm	predicting drug side effects
Suleiman et al., 2020	Bayesian Networks	recommendation for medical coding
Waqar et al., 2019	Collaborative filtering algorithm and Hybrid approach	effectively tackle the issue of doctor recommendation
Stitini et al., 2020	SVM	breast cancer risk prediction and diagnosis, patient-doctor match
Wiesner et al., 2014	SVM	patient oriented decision making; personal health record systems (PHRS) to centralize an individual's health data
Chang et al., 2020	Hybrid method / cross domain recommender system	chronic disease diagnosis recommender system
Sahoo et al. 2019	Collaborative filtering algorithm / Convolutional Neural Network	patient based recommender system that gives their choices and ratings. recommending diagnoses, health insurance, clinical pathway-based treatment methods and alternative medicines based on the patient's health profile
Bocanegra et al., 2017	hybrid approach, matrix factorization	recommend health videos. Ex. nutritional recommender system for elderly
Kaur et al., 2018	Collaborative filtering algorithm	patient oriented decision making
Erdeniz et al., 2020	Collaborative filtering, k-nearest neighbor	IoT enabled mHealth applications
Han et al., 2018	Matrix factorization algorithm	patient-doctor match
Kumar et al., 2018	Collaborative filtering (k nearest neighbor approach)	recommendation for exercise routes
Medina et al, 2016	hybrid approach	recommender system for patients with heart problems
Lopez-Nores et al., 2011	Collaborative filtering. Clustering	health aware recommender system

Sustainability in Recommender Systems

The implementation of sustainable IT systems is called sustainability information systems. The concept of sustainability includes three dimensions namely economic sustainability, ecological sustainability and social sustainability (Junker and Farzad, 2015). The authors describe these three dimensions. Economic sustainability simplifies the demand of adding value by minimal allocation of resources. Ecological sustainability aims to allocate resources that demand on natural livelihood. Social sustainability involves theories of humane existence, equal opportunities, or participation.

Although living sustainably has become a goal for many, it does not necessarily translate into sustainable purchases (Hughner et al., 2007). Ekstrand and Willemsen (2016) claim that recommender systems have the potential to make recommendations based on user preferences that they wish to achieve, rather than reinforcing observed behavior.

Knowledge about what makes a product sustainable can be a barrier to consumers (Pickett-Baker and Ozaki, 2008). Given the knowledge of sustainable products, a recommender system can suggest products with these characteristics to customers. If we can identify a group of sustainability-minded shoppers, then recommender systems can learn from their purchasing patterns (Tomkins et al., 2018). Thus, we can use purchasing patterns to identify sustainable customers and additional sustainable products from their shopping.

CONCLUSION AND FUTURE RESEARCH

From our analysis in this study, we can infer that recommender systems are beginning to be applied in many areas of healthcare including cancer, diabetes, and heart diseases. Recommender systems are already seen applied in health and fitness and for nutrition recommendations. The primary goal in the development of recommender systems is patient oriented decision-making.

HRS constitute a promise to assist doctors in decision-making tasks (Pincay et al., 2019). IBM's artificial intelligence machine Watson Health (IBM, 2017) is already able to find a suitable treatment for patients. IBM claims that 81% of healthcare executives familiar with Watson Health agreed that it has a positive impact on their business (Stark et al., 2019).

However, the application of health care recommendation system in various medical domains is still immature in terms of trustworthiness and reliability (Sharma et al., 2019). For future research, further investigation in user privacy in health recommendations must be conducted. Specifically in health care systems, the user's privacy should be protected from unauthorized attackers. This would also increase the trust in using health recommender systems. Sustainability in health recommender systems is another factor that could be further examined in future.

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