# Health Recommender Systems: A State-of-the-art Review

Jhonny Pincay*, Luis Terán*†, and Edy Portmann*
*Human-IST Institute
University of Fribourg
Boulevard de Pérolles 90, Switzerland
Emails: {jhonny.pincaynieves, luis.teran, edy.portmann}@unifr.ch
†Universidad de las Fuerzas Armadas ESPE
Av. General Rumiñahui S/N, Ecuador
Email: lfteran1@espe.edu.ec

***Abstract*—The use of information technologies in the health domain started decades ago, nevertheless there are still many issues that need to be addressed. Health Recommender Systems (HRSs) constitute a promising alternative when it comes to providing tools to assist doctors in the diagnosis of diseases, as well as to help patients with recommendations in regards of how to keep their wellness. This work provides insights about methods and techniques used in the design and development of HRSs, focusing on the areas or types of the recommendations these systems provide and the data representations they employ to build their knowledge base. For this effect, a number of articles published between January 2006 and August 2018, from five different scientific databases, were retrieved. After an examination and selection of publications, 249 articles were categorized by means of a classification framework which was built upon related works and the content of the studies analyzed. Furthermore, the results of the classification are presented and major findings are outlined and discussed.**

***Index Terms*—Health Recommender System, health information systems, recommender system, literature review**

## I. Introduction

During the mid-90s the first article related to collaborative filtering and Recommender Systems (RSs) was published and came by the hand of Resnick *et al.* [1]. In this work, the authors introduced *GroupLens*, an open informatic system, as a first approach to mine the reactions of user towards publications and use them to provide suggestions of news articles, based on the likes and opinions of other users. Since then RSs have become an important research field in the computer science area.

Nowadays almost every major online retailer, streaming service, and social network make use of recommendation engines for the sake of selling more products, engaging users and helping them to select items among the huge amount of available options they offer. Amazon[1] is a clear example of an online intermediary service that makes use of RSs. When users browse the site, visualize details of products or make a purchase, the platform immediately recommends related items that may be of their likes. Another example is Netflix[2], which suggests movies or series based on the viewing history of users as well as on their demographic information. All these platforms are continuously improving their recommendation algorithms aiming to keep the user engaged and consuming their offerings. Fields where RSs are being applied are not limited to the aforementioned, they are used in more complex scenarios such as politics, economy, governance, healthcare and education [2].

The application of RSs in the domain of health has attracted the attention of researchers in the last years. RSs used in this field are also called Health Recommender Systems (HRSs). There are a number of developments attempting to provide different areas of recommendations which go from exercise plans, diets, healthcare services, to even assist medical practitioners in decision-making tasks regarding the diagnosis, treatment and well-being of their patients [3], [4]. Nevertheless, areas such as medicine and health, where users (i.e., caregivers, physicians, and patients) make decisions, imply a high risk and could have side effects, increasing the complexity of implementing such systems.

Even though a number of works regarding the development and implementations of HRSs have been published, there is a lack of a comprehensive work aiming to examine the different types of techniques and methods that are being used for their implementation, as well as the areas or types of recommendations provided. These matters need to be considered towards improving the implementation of HRSs.

In this work, a non-exhaustive search of articles published from January 2006 to August 2018 in five scientific databases (IEEE Library, ACM Portal, Science Direct, Springer Link, and PubMed) were examined and classified, to provide insights about current trends and methods regarding the design and development of HRSs. Special attention is given to the area of recommendation provided by such systems as well as the way the data conforming their knowledge base is handled.

This article is structured as follows: Section II presents related works regarding the state-of-the-art in HRSs. Then,

[1]https://www.amazon.com

[2]https://www.netflix.com

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the methodology and the classification framework used in this study is described in Section III. Results of the classification of HRS research papers are shown in section IV. Finally, concluding remarks are presented in Section V.

## II. Related Works

Several works about classifying approaches and implementations of recommender systems have been published in the academic literature. In the research of Park *et al.* [5], the authors examined 210 articles published between 2001 and 2010 in six electronic journal databases. The articles were categorized according to their application field and data mining techniques used for their implementation. As results, the researchers noticed a significantly increasing number of publications as well as continuous efforts to improve the accuracy and efficiency of the algorithms. They also put in manifest the problems that researchers face were not trivial and had a moderate complexity.

One example of a work conducting literature review specifically for HRSs is the one of Sezgin and Oezkan [6]. Their research was published in 2013 and it is probably one of the first studies aiming to evaluate the published investigations regarding HRSs. The authors reviewed articles published during the period of 2002 to 2012 in several academic databases. From this systematic review, 310 articles were retrieved and only 8 articles met the criteria the researchers defined. The selected publications were examined and their challenges and opportunities were identified.

One recent and comprehensive study about the current status of research in health recommender systems comes by the hand of Hors-Fraite *et al.* [7]. In this work, the authors performed a review of relevant HRSs publications and defined a multidisciplinary taxonomy to assess four aspects: domain, methodology and procedures, health promotion strategies, and technical aspects. A total of 890 papers were retrieved, and after the evaluation process, 19 publications were selected. Regarding the domain aspect, the authors found that most of the studies focused on nutrition and generic lifestyle promotion. When it comes to the methodology aspect, they realized that most attempts are tested with a small number of cases (no more than 90). In regards of health promotion, the authors were not able to asses it due to the lack of information. Regarding technical aspects, the authors highlighted the absence of user profile adaptation in the implementations reviewed which might affect the quality and accuracy of the recommendations over time, given that the systems should evolve alongside the user's needs.

In contrast with the aforementioned works, this study explores in depth the type of recommendations provided alongside with the manners the data is used to build the knowledge base of those systems, given that data management is one of the key challenges that need to be addressed when designing a HRS [3]. It is expected that the findings of this work will support researchers in the preliminary analysis when designing and implementing a recommender system in the health domain.

## III. Methodology and Classification Framework

In order to get insights about current trends in the implementation of HRSs, a systematic analysis of academic literature was conducted following the PRISMA framework [8]. Based on the result of the preliminary reviews, the articles were classified according to a framework which was built upon the related works presented in Section II and the content of the analyzed studies.

### A. Articles Search

With the purpose of gathering relevant works about HRSs, five electronic scientific databases were queried: IEEE Library, ACM Portal, Science Direct, Springer Link, and PubMed. Papers were selected given that their title, abstract or keywords contained one of the following combination of words: *health recommender system*, *recommendation system*, *health social network*. The keywords and search options in each database were permuted to find the best subset of results. Furthermore, only papers written in English and published between January 2006 and August 2018 were retrieved.

### B. Articles Selection

Liberati *et al.* [8] proposed the PRISMA framework as a methodology for reporting systematic reviews and meta-analyses of studies that evaluate healthcare interventions. It is a four-phase flow diagram and a twenty-seven item checklist, aimed to achieve a transparent and proper selection of relevant articles in the health domain. The four phases are: *identification*, gathering of articles according to search criteria; *screening*, removal of duplicated articles and misclassifications; *eligibility*, verify if the papers cover the topics of interest by reviewing title and abstract for example; *inclusion*, in which the final selection of publications to be included in the study based in a more rigorous review is made. PRISMA has been used in a number of studies, including the work of Hors-Fraile *et. al* [7] that is detailed in Section II. In this research work the selection of articles was conducted following the PRISMA guidelines.

### C. Classification Framework

After studying the selected articles and to get a deeper understanding about the themes addressed in the studies and current trends regarding the methodologies and knowledge representation, a classification framework was defined, likewise it was performed in similar works [7], [5], [9]. This classification framework is introduced with the purpose of providing a general overview of the type of research conducted in the field of HRSs.

The framework presented in this research work considers the following categories: 1) *method* (it is the approach that the recommender system uses to perform the retrieval of items), 2) *technique* (the way in which the relationships between items are computed), 3) *recommendation area* (the nature or domain of the items that are being recommended), and 4) *knowledge representation* (it makes reference to the method used to represent and store the data describing the items).

Figure 1 presents an overview of the classification framework of our study, it contains the categories previously mentioned alongside with all their approaches identified during the literature analysis.

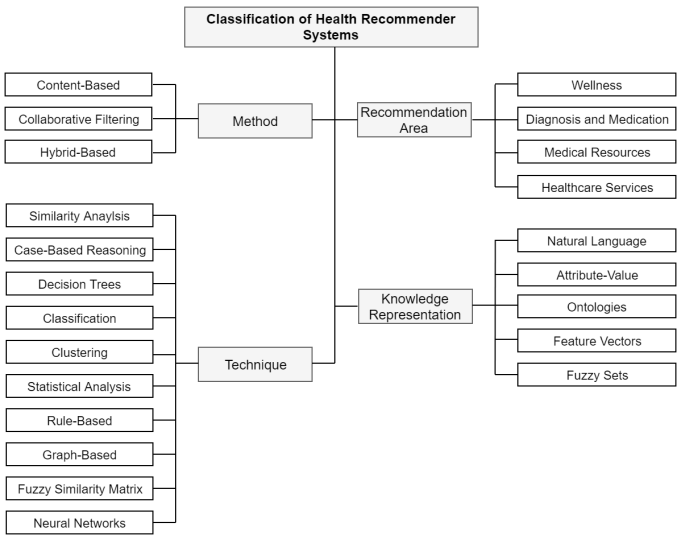


Fig. 1. Classification Framework for HRSs.

## IV. Results

In this section, the results of the database search and articles classification are presented. In total, 5.540 articles were retrieved as result of the keyword search in the databases consulted (identification), 556 turned out to be duplicates or misclassified (screening). After reviewing their title and abstract, only 450 were selected for a full-text review (eligibility). Subsequently, once the eligible works were studied, 249 (4.5% of the articles retrieved) made the final cut and were classified according to the framework defined in Section III.

Figure 2 shows the number of articles resulting after the application of each phase of the PRISMA framework. Furthermore, Table I presents the number of articles resulting from the keyword search in the scientific databases, as well as the number of articles selected for this study.

In the next subsections the results, using the classification framework, are presented. It should be pointed out that it was not possible to categorize all the features in several articles, given that some of them did not provide all the information required for this matter.

### A. Method

From the 249 reviewed articles, 55% of them (137 articles) use content-based (CB) approaches to build the recommendation engine of the systems. As an example, in the work conducted by Bianchini *et al.* [10] a recommender system for healthy food was developed, the system retrieves recipes based on comparisons among characteristics of the users and the recipes themselves.

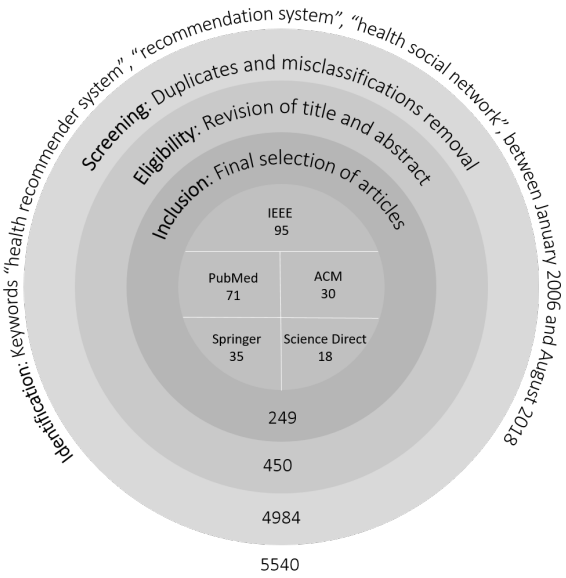


Fig. 2. Number of articles retrieved and selected per each phase of PRISMA.

On the other hand, only 14% of the HRSs proposals studied (35 articles) use collaborative filtering (CF), whereas 31% (77 articles) employed hybrid-based (HB) approaches. Stark *et al.* [11] used CF to build a system capable of recommending drugs against migraine. For this implementation, users were grouped according to a similarity measure and the prescription recommendation was provided to the target user based on the drugs that worked for related users. Li and Cheng [12] built a system to recommend nutritional menus (combos) and made use of both CB and CF to appease some of the issues these approaches might present when using them separately, such as cold start and data sparsity.

### B. Technique

The way in which the relations between items in a system are computed is a crucial aspect for a RS to achieve a reasonable performance level. In the case of HRSs, the techniques employed are diverse since the data that describe the items does not necessarily have a single nature.

From the 249 articles reviewed, ten different techniques were identified. The most employed technique to determine associations among items was through the use of similarity measures (such as Cosine, Pearson correlation, and Euclidean and Hamming distance, among others). From this, 24% of the studies analyzed (60 articles) used one of the aforementioned techniques or some variant. This result is not surprising, given that similarity measure models are widely used in the implementation of RSs in most domains.

Examples of studies using similarity measures are the proposals of Dhas and Jeyanthi [13] and Li and Yang [12]. In the first case, the Pearson correlation coefficient is used to compute similarity between healthcare services, whereas Euclidean distance is used in the second case to identify similar users.

TABLE I
NUMBER OF PAPERS RETURNED BY SCIENTIFIC DATABASE AND KEYWORD SEARCH.

| Search Criteria | ACM Portal | | IEEE Xplore | | Pubmed | | Science Direct | | Springer | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Results | Selected | Results | Selected | Results | Selected | Results | Selected | Results | Selected |
| health recommender system | 11 | 11 | 174 | 55 | 32 | 30 | 4 | 4 | 21 | 20 |
| recommendation system | 1550 | 8 | 1994 | 20 | 68 | 36 | 1032 | 10 | 356 | 11 |
| health social network | 25 | 11 | 41 | 20 | 13 | 5 | 12 | 4 | 207 | 4 |
| **TOTAL** | | 30 | | 95 | | 71 | | 18 | | 35 |

Decision trees and rule-based implementations are both the second most used techniques in the cases studied. Nearly 14% of the articles (35) used one of these techniques. Most authors use them since medical decisions are based on the evaluation of multiple conditions. As an example: If patient *U* presents the symptom *A* and also symptom *B*, then he might be suffering from the disease *Z*; the techniques previously mentioned allows to model such procedures.

The work of Patil and Gore [14] is an example of usage of decisions trees. In this case, a set of yoga exercises is recommended to users according to their physical and mental characteristics. Moreover, Malmir *et al.* [15] use fuzzy rules to build a RS capable of supporting medical decision making, taking into consideration the uncertainty that making such kind of judgment brings alongside.

Furthermore, case-based reasoning and clustering were also used frequently by researchers. Figure 3 presents the distribution of articles per technique employed in more detail.

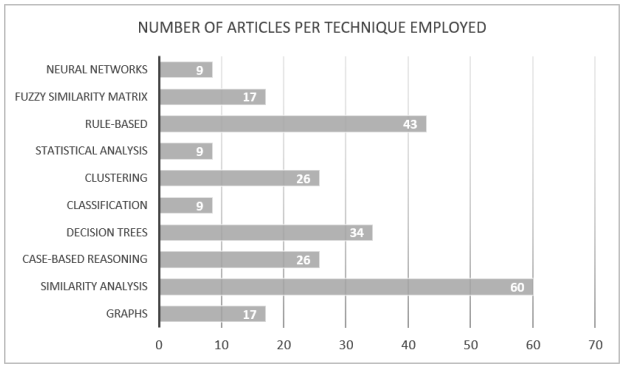


Fig. 3. Number of articles per technique employed.

## C. Recommendation Areas

In the health domain, there are a wide number of topics and issues addressed by HRSs. Thus, the recommendations that current systems provide are from different nature. In this research work, the following recommendation areas were identified: wellness, healthcare services, diagnosis, medication, and medical resources. Figure 4 shows an overview of the number of articles per each recommendation area identified.

*1) Wellness:* This subcategory groups all the implementations developed towards providing recommendations to improve the well-being of users: diets, exercise routines, children and elderly care recommendations. 52% of the 249 studied articles (129 articles) corresponded to this group.

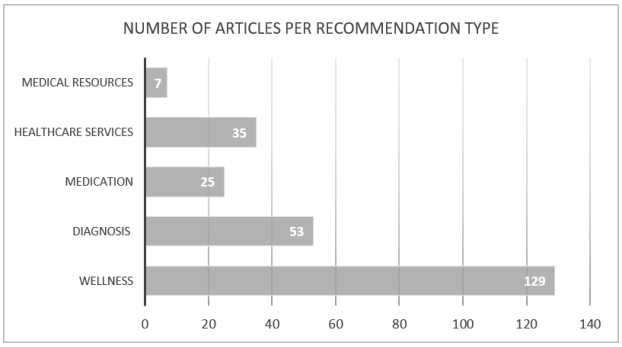


Fig. 4. Number of articles per recommendation area.

One of the most comprehensive studies that we found was the work of Agapito *et al.* [16]. The authors developed a system called DIETOS capable of delivering nutritional advice to both healthy individuals and patients suffering from chronic diseases such as kidney failure and diabetes. Other related initiatives are the approaches of Kim *et al.* [17] and Bundasak [18].

The work of Patil and Gore [14] is about recommending exercise routines. It makes recommendations about yoga sets according to the health status of a certain person. In regards of children and elderly care, one development comes by the hand of Wongpun and Guha [19] whose implementation was capable of recommending food, exercises, emotional, and physical therapy to informal elders' caregivers.

*2) Diagnosis and Medication:* Providing tools to medical practitioners to accurately diagnose a disease is a topic that has been widely studied over the years. Unfortunately, there is not a definitive solution for this matter. HRSs constitute a promising alternative to face the challenges of assisting doctors in decision-making tasks as well as suggesting possible treatments to certain conditions. From the research papers retrieved in this work, 53 articles (21%) focused on designing methods to support diagnosis of conditions.

The diagnosis problem is one of the hardest to solve given all the aspects that needs to be taken into account to achieve an accurate result. This may be one of the reasons why all the works that can be found attempt to develop general methodologies; nevertheless, they end up being tested an working only for particular conditions.

Malmin *et al.* [15] proposed the use of fuzzy rules to develop a method capable of diagnose diseases given input from patients' symptoms and doctors' expertise; the approach

was tested using two case studies: kidney stone and kidney infection. The results obtained had a higher precision that the ones obtained by means of other machine learning methods.

Another example is the initiative of Managaran *et al.* [20] were a system capable of determining the presence of heart diseases was built. The system performed well and had an accuracy of 98% according to the authors.

When it comes to treatment or medication recommendation, only 10% of the cases studied (25 articles) attempted to provide a solution to this issue. The work of Stark *et al.* [11] is one of the few initiatives in this context. The authors introduced the BetterChoice platform which was targeted to provide migraine medication suggestions to doctors, taking into account the patients' clinical history.

*3) Healthcare Services:* Finding suitable doctors and medical services for patients is another of the aspects studied by several authors. Approximately 14% of the cases analyzed (35 articles) focused on designing solutions to face this issue.

Narducci *et al.* [21] proposed the use of a recommender system to suggest doctors and hospitals that could fit in a better way the profile of a given patient. This was the main feature of a health social network called HealthNet, which aims to connect patients and doctors in an easy and seamless way.

*4) Medical Resources:* Further investigations were oriented to handle the fact that nowadays people have access to a huge number of online resources (e.g., articles, videos and books) about health and wellness; nevertheless, not all the information available suits their needs. Nearly 3% of the revised articles (7 articles) focused on providing suggestions to users in this matter. One example is the proposal of Rivero-Rodriguez *et al.* [22] whose implementation suggests YouTube videos enhanced with additional information coming from Medline Plus[3] according to the users' needs.

### *D. Knowledge Representation*

A crucial aspect that needs to be carefully taken into account when dealing with health-related data, is to find a proper representation to manage and storage the heterogeneous information needed to build the knowledge base of a HRS. Moreover, the manner in which data is input to the systems needs to be considered as well. From the 249 reviewed articles, only 220 (88%) pointed out the way in which the data was handled.

The information needed to compute the recommendations depends on the area of recommendation that the system is providing. In the case of HRSs supporting the diagnosis of diseases, the symptoms depicting a disease and the ones a patient is suffering need to be properly described, to perform an accurate recommendation; this is not a straightforward task. In the case of RSs providing recommendations for wellness for example, the representation of the knowledge is less complicated than in the previous case, given that patient characteristics, nutritional information of food, or a set of exercise routines are not complex to depict in terms of common database structures (i.e., attribute-value pairs).

The different representations that we found are: natural language, attribute-value pairs, ontologies, feature vectors and fuzzy sets. Figure 5 shows an overview of the number of articles per each knowledge representation type that we identified.

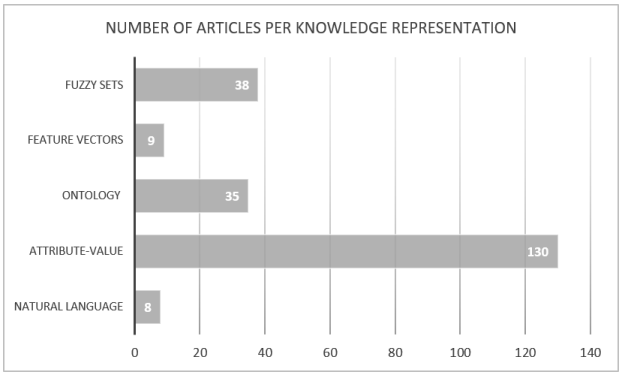


Fig. 5. Number of articles per knowledge representation type.

*1) Natural Language:* HRSs using natural language representation of the knowledge were the ones offering recommendations about medical resources such as articles, answer to questions, and videos. Only eight papers (4%) from the articles retrieved in this work made use of representations in natural language for both, users input and description of items in the knowledge base. Text mining and natural language processing techniques were employed to determine relevant elements for the users.

The initiative of Wang *et al.* [23] is a case of a HRS using this approach. The authors designed a system capable of recommending answers to questions about medical topics to patients. The questions were entered in natural language descriptions. Then, natural language processing was used to find similar questions, retrieve their answers, and finally to perform an answer recommendation given all the ones retrieved. According to the authors, their system had a good accuracy performance. This approach could be used to assist practitioners in diagnosis processes.

*2) Attribute-Value Pairs:* This representation was the most frequently found in the literature. Systems using this type of depiction were the ones with recommendations related to wellness (e.g., diets and exercises), medication and healthcare services. Nearly 55% of the works studied (121 articles) used this approach.

The attribute-value pairs were used to depict patient information, nutritional characteristics of food, and healthcare services attributes. Moreover, many authors opted for this information representation since it allows to use a variety of techniques to find similarities among items and compute recommendations, such as case-based reasoning, clustering, statistical, and similarity analysis. These techniques are not complex and do not require a lot of computational power to perform computations.

[3]https://medlineplus.gov

TABLE II
SUMMARY OF THE KNOWLEDGE REPRESENTATIONS FOUND BY RECOMMENDATION AREA.

| Recommendation Area | Knowledge Representation | | | | |
|---|---|---|---|---|---|
| | Natural Language | Attribute-Value | Ontology | Feature Vector | Fuzzy Set |
| Wellness | | ✓ | ✓ | ✓ | |
| Diagnosis and Medication | | ✓ | ✓ | ✓ | ✓ |
| Medical Resources | ✓ | | | | |
| Healthcare Services | | ✓ | ✓ | ✓ | |

Phanich *et al.* [24] used attribute-value pairs to describe nutritional facts of meals combos, which are suggested to diabetic patients according to their condition and nutrition needs. To describe the meals, the authors made use of the following attributes: energy (Kcal), water (ml), proteins (g), carbs (g), fiber (g), ash (g), calcium (mg), sugar (mg), phosphorus (mg), iron (mg), and niacin (mg). Their values where real numbers and expressed the quantity of the nutrition fact in the meal. Moreover, they use a hybrid-based recommendation method alongside with clustering analysis to retrieve the relevant items.

*3) Ontologies:* Ontologies allow to represent knowledge using a hierarchy of concepts in a domain. Besides, an ontology facilitates the depiction of properties and interrelationships among concepts [25]. About 16% of the publications studied (35 articles) used this type of representation. The work of Chen *et al.* [26] is an example of it. The authors used ontologies to depict the information of patients, dietary records, and food nutrition to compute the recommendation of diets by means of decision trees.

Furthermore, ontologies were used in systems in which the recommendation types were targeted to wellness and medication recommendation.

*4) Feature Vectors:* When performing recommendations specific data might be more relevant than other. That is why, some researchers opted for representing the knowledge using feature vectors given that they allow to assign weights to certain characteristics describing entities in a system. Nevertheless, in this work, only 4% of the articles found (9 studies) use this approach and the recommendations they provide were related to healthcare.

Wongpun and Guha [19] use feature vectors for the implementation of a RS to assist informal caregivers of elderly people by providing them therapy and care plans. The aspects given more importance (weight) were the ones related to symptoms (e.g., blood pressure, heart rate, limb weakness) and health behaviour (e.g., if the patient exercises, smokes, or consumes alcohol), whereas the personal data and daily activities were less considered when computing recommendations. This implementation in particular made use of case-based reasoning to retrieve the suggestions.

*5) Fuzzy Sets:* Diagnosing a medical condition or a disease is a complex process, which is effected under a high uncertainty. Aiming to provide means to assist physicians in the decision-making process, several authors have lately opted to use fuzzy logic methods to modelling the variables involved, as well as to appease the uncertainty impact when computing the recommendations.

Similar to classical sets, fuzzy sets have a number of elements but whose elements have certain degree of membership, which is established by means of a membership function. This properties are particularly interesting since a symptom can be associated to a disease in a certain degree and at the same time, a disease could be related to a number of symptoms. Fuzzy logic allows to establish relationships and reaching conclusions taking into considerations these aspects.

Fuzzy sets were used by 17% of the papers studied (38 articles). One example is the work of Malmir *et al.* [15]. The authors made use of fuzzy sets to depict the symptoms of kidney infection and the presence of kidney stones and determine if a person is suffering one of those conditions. For the effect, the authors considered the judgment of five physicians regarding the severity of the various symptoms. Afterwards, they built a model taking into account the different degrees of severity informed by each specialist and make a decision based on that. The levels of severity of the symptoms were expressed as: zero, very low, low, moderate, high, and very high. These levels were possible to represent by means of fuzzy logic.

Additionally to the stated in the previous points, Table II shows a summary of the knowledge representations found per each area of recommendation provided by the HRSs studied. Furthermore and because of space constraints, only a sample of the articles analyzed and their references is presented in the Appendix A.

## V. CONCLUSIONS

This study presents the results of a systematic state-of-the-art review on recommendation systems used in the health domain, also called health recommender systems. Articles published in five scientific databases between January 2006 to August 2018 were retrieved for analysis. The PRISMA framework was used to get insights about the methods, techniques employed, recommendation areas, and knowledge representation that have been used in the design and implementation of such systems.

In this work, 249 articles were carefully reviewed and classified according to the framework introduced in Section III. The majority of the studies used CB methods and similarity analysis to build their recommendation engine, which is rather common when implementing RSs. Nevertheless, a significant percentage of the initiatives employed artificial intelligence

and fuzzy logic techniques as a way of achieving higher levels of accuracy and performance of the systems.

Regarding the recommendation areas, most investigations were targeted to improve the well-being of the users, by means of recommending diets and exercise plans. However, an important number of authors invested efforts in designing systems capable of assisting physicians in the task of diagnosing of diseases and prescribing medication.

Data management and knowledge base representation are key aspects that need to be taken care carefully when designing a HRSs. The knowledge representation depends on the type of data the system is dealing with as well as the area of recommendation that is being provided. Systems making wellness recommendations opted for attribute-value pairs, ontologies, and feature vectors representations. HRSs dealing with diagnosis and medication recommendations, besides the representations previously stated, make use of fuzzy sets with the goal of depicting uncertainty in a more accurate manner, which is part of decision-making processes in the health area.

In spite of all the works that have been conducted in the last years, this is a research area that is still in its infancy and more comprehensive studies are needed. Dealing with health-related issues is complex and there is no a unique method capable to tackle all the problems that HRSs present nowadays. From the research works studied and from our perspective, we can conclude that we are still far from having a fully functional and reliable health recommender system. Moreover, efforts should be pointed towards addressing the uncertainty that making health-related decisions implies and defining more suitable testing mechanisms, that will allow to properly evaluate the accuracy and performance of the implementations.

Lastly, the intention of this work is to serve as a starting point for researchers aiming to make further developments in the field HRSs, specially when deciding which kind of knowledge representation to use, according to the recommendation area of the system. It should be pointed once again that for the execution of this study, only five databases were explored, which constitutes its main limitation.

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| Recommendation Type | Article | Knowledge Representation | | | | |
|---|---|---|---|---|---|---|
| | | Natural Language | Attribute-Value | Ontology | Feature Vector | Fuzzy Set |
| *Wellness* | [16] DIETOS: A dietary recommender system for chronic diseases monitoring and management | | ✓ | | | |
| | [10] PREFer: A prescription-based food recommender system | | | ✓ | | |
| | [26] The Nutrients of Chronic Diet Recommended Based on Domain Ontology and Decision Tree | | | ✓ | | |
| | [24] Food Recommendation System Using Clustering Analysis for Diabetic Patients | | ✓ | | | |
| | [18] A healthy food recommendation system by combining clustering technology with Weighted slope one Predictor | | ✓ | | | |
| | [19] Elderly Care Recommendation System for Informal Caregivers Using Case-Based Reasoning | | | | ✓ | |
| | [14] Recommendation System for Yoga and Raga for Personalized Health based on Constitution | | ✓ | | | |
| *Diagnosis and Medication* | [15] A medical decision support system for disease diagnosis under uncertainty | | | | | ✓ |
| | [27] Intuitionistic fuzzy recommender systems: An effective tool for medical diagnosis | | | | | ✓ |
| | [11] BetterChoice: A Migraine Drug Recommendation System Based on Neo4J | | ✓ | | | |
| | [20] Hybrid Recommendation System for Heart Disease Diagnosis based on Multiple Kernel Learning with Adaptive Neuro-Fuzzy Inference System | | | | | ✓ |
| | [28] A Hybrid Fuzzy Soft Sets Decision Making Method in Medical Diagnosis | | | | | ✓ |
| | Medication Recommender System | | | ✓ | | |
| | [29] Decision Support System for Medical Diagnosis Using a Kernel-Based Approach | | | | ✓ | |
| *Medical Resources* | [23] An Answer Recommendation Algorithm for MedicalCommunity Question Answering Systems | ✓ | | | | |
| | [22] A health information recommender system: Enriching YouTube health videos with Medline Plus information by the use of SnomedCT terms | ✓ | | | | |
| | [30] Chinese Medical Question Answer Matching Using End-to-End Character-Level Multi-Scale CNNs | ✓ | | | | |
| *Healthcare Services* | [31] A Framework for Personalized Healthcare Service Recommendation | | ✓ | | | |
| | [32] Towards a Patient Satisfaction Based Hospital Recommendation System | | ✓ | | | |
| | [33] Personal Health Explorer: A Semantic Health Recommendation System | | | ✓ | | |

## APPENDIX A
## SAMPLE OF ARTICLES ANALYZED BY RECOMMENDATION TYPE AND KNOWLEDGE REPRESENTATION.