Received: 18 October 2019 | Revised: 5 December 2019 | Accepted: 13 December 2019

DOI: 10.1111/exsy.12519

INVITED REVIEW

Expert Systems WILEY

A survey on semanticized and personalized health recommender systems

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Abstract

Health 3.0 is a health-related extension of the Web 3.0 concept. It is based on the semantic Web which provides for semantically organizing electronic health records of individuals. Health 3.0 is rapidly gaining ground as a new research topic in many academic and industrial disciplines. Due to the recent rapid spread of wearable sensors and smart devices with access to social media, migrating health services from the traditional centre-based health system to personal health care is inevitable. In this current era of greater personalization, treating patients' health problems according to their profile and medical data gathered is possible using the latest information technologies. Consequently, personalized health recommender systems have gained importance. Empowering the utility of advanced Web technology in personalized health systems is still challenging due to pressing issues, such as lack of low cost and accurate smart medical sensors and wearable devices, existing investment in legacy Web system architecture in health sector, heterogeneity of medical data gathered by myriad health care institutions and isolated health services, and interoperability issues as well as multi-dimensionality of medical data. By tracing recent developments, this paper offers a systematic review through recent research on semantic Web-enabled personalized health systems, namely, semanticized personalized health recommender systems with the key enabling technologies, major applications, and successful case studies. Critical questions derived from the research studies were discussed, and main directions of open issues were identified leading to recommendations for future study in the field of personalized health recommender systems.

KEYWORDS

e-health, Health 3.0, health care, ontology, recommender system, semantic Web

1 | INTRODUCTION

Recent studies depict that 81% of U.S. adults use the Internet and 72% of them have searched health information on the Internet concerning diseases, diagnoses, and alternative treatments (Fox & Duggan, 2013); 2002, 2004, 2006, 2007, and 2008 surveys conducted by Pew Internet Project consistently found that between 75% and 83% of internet users search online sources for health information. Due to the ubiquity of the Internet, it is commonly believed that the above-mentioned statistics pretty much hold for people in other countries. Using the Internet as a health-related diagnostic tool, that is, retrieving information about health care and services through the Internet, becomes quite easier for users who need suitable medical treatment. Besides that, the emergence of new diseases and alternative treatments, thus changes in diagnostic methods, in the health sector cause present Web-based health services to grow exponentially and turn into a messy structure.

Current Web technologies and health-based systems, individually or together, are making momentous effects on the health care sector while addressing a quickly growing population around the world. The developments in Web technology have led to the emergence of smart and personalized health care applications for the health industry. Knowledge-based recommender systems, expert decision support systems, e-/m-health systems, IoT applications, and other smart health solutions can be considered as samples of user-centric paradigms of personalized health recommender systems (PHRSs). The generic aim of such systems is to support its users by suggesting the most appropriate health services, diagnosing techniques, treatments, and alternatives. Therefore, PHRS can be considered as medical assistance recommending suitable health services, much-needed information on treatments to its users also considering the patient history and health status.

Web services play a substantial role in gathering and monitoring medical data of patients; and PHRS is responsible for examining the growing amounts of such data and then deducing the most suitable health service required in terms of diagnoses and treatment for consumers. In general, PHRSs provide information and proper recommendations for health professionals, patients and their kin, clinics and hospitals, health support centres, and so on. The service or information recommended according to the medical requirements shows diversity depending on observed disease symptoms, patient's condition, medical reports, genetic history, and diagnosis. In this article, we review semanticized PHRSs from an overall perspective and with a particular focus on smart systems targeted to provide a recommendation to patients and health professionals. We look at the recent challenges for PHRS from the view of emerging technology itself, system necessities, design, and development techniques as well as personal health care trends. This research study presents a consolidated portrait of the most important functions and services offered by semanticized PHRS for discovering, monitoring, and detecting individual-based medical treatment requirements including its concepts, approaches, processing techniques, and technologies.

The rest of the paper is organized as follows: Section 2 surveys the background information that discusses key enabling technologies and methods for conventional PHRS. Section 3 presents the general system architecture of semanticized PHRSs as modelled in literature. Section 4 presents the research methodology used. Section 5 describes and classifies key applications and case studies of semanticized PHRSs in literature or commercially available in markets. The study presents challenges and open issues facing the current semantic or otherwise PHRS and making recommendations on how to improve future systems in Section 6. Finally, Section 7 presents the conclusion of the study.

2 | BACKGROUND

This section introduces the key effective technologies, concepts, and the most popular techniques used in PHRSs. The term “decision support system” (DSS) is a very broad concept which involves all aspects of supporting individuals during decision making and providing automated intelligent recommendation where required and when available. In other words, DSSs are tools designed to facilitate the decision-making environment for a user. For instance, a DSS can help a physician to decide which drug to prescribe based on the patient's medical history and a drug trial database, whereas a recommendation system (RS) can suggest similar products quickly by analysing previous usage behaviour as well as referring to a database of product data (Liang, 2008).

The term “recommendation system” (RS) alludes to a DSS which drew attention both in the IT industry and in academic research (Wiesner & Pfeifer, 2014) in the mid-1990s. RSs are also known as information filtering (Salunke & Kasar, 2015). Information filtering relates to the conveyance of information which is possibly interesting or useful to the user. RSs have become popular especially in the context of online shopping systems to suggest proper products of interest to a shop's visitor. RS can predict whether a particular user would be interested in an item or not based on the user's preferences and profile. A user profile is created and stored together with account information as well as past behaviour and activity data in the system database.

Therefore, DSSs involve RSs, which in turn employ specialized filtering approaches. Filtering approaches rely on one or more of supporting techniques of artificial intelligence or statistical approaches such as knowledge-based, machine learning, data mining, matrix factorization, and other knowledge classification techniques. Figure 1 below illustrates the various technologies and techniques applied in PHRS systems and their associations in terms of different filtering approaches.

RSs have been discussed in many research studies and classified commonly based on filtering approaches, to name a few, as collaborative filtering, content-based filtering, and hybrid filtering. Additional techniques found in literature such as demographic-based filtering, social-based filtering, context-aware filtering, and knowledge-based filtering (Bobadilla, Ortega, Hernando, & Gutiérrez, 2013; Chandak, Girase, & Mukhopadhyay, 2015; Koren, Bell, & Volinsky, 2009; Mavridis, 2017; Ozgen, 2011; Wiesner & Pfeifer, 2014) are also discussed below together with their applied techniques.

Collaborative filtering relies only on past user behaviour examining similar user profiles in the system database and determines the user's preferences and appropriate recommendations. Content-based (or feature-based) filtering uses only item data and provides a profile for each item. The method makes recommendations based on specific features of an item such as a product's category, weight, height, and name of the production company. The profile generated defines the nature of each user and item. Whereas content-based filtering is based on the similarity of item features, collaborative filtering methods calculate similarity from user-item interactions. In other words, the behaviour of a user is predicted based on evidence that resembles other users. Therefore, the filtering approach is not interested in information about

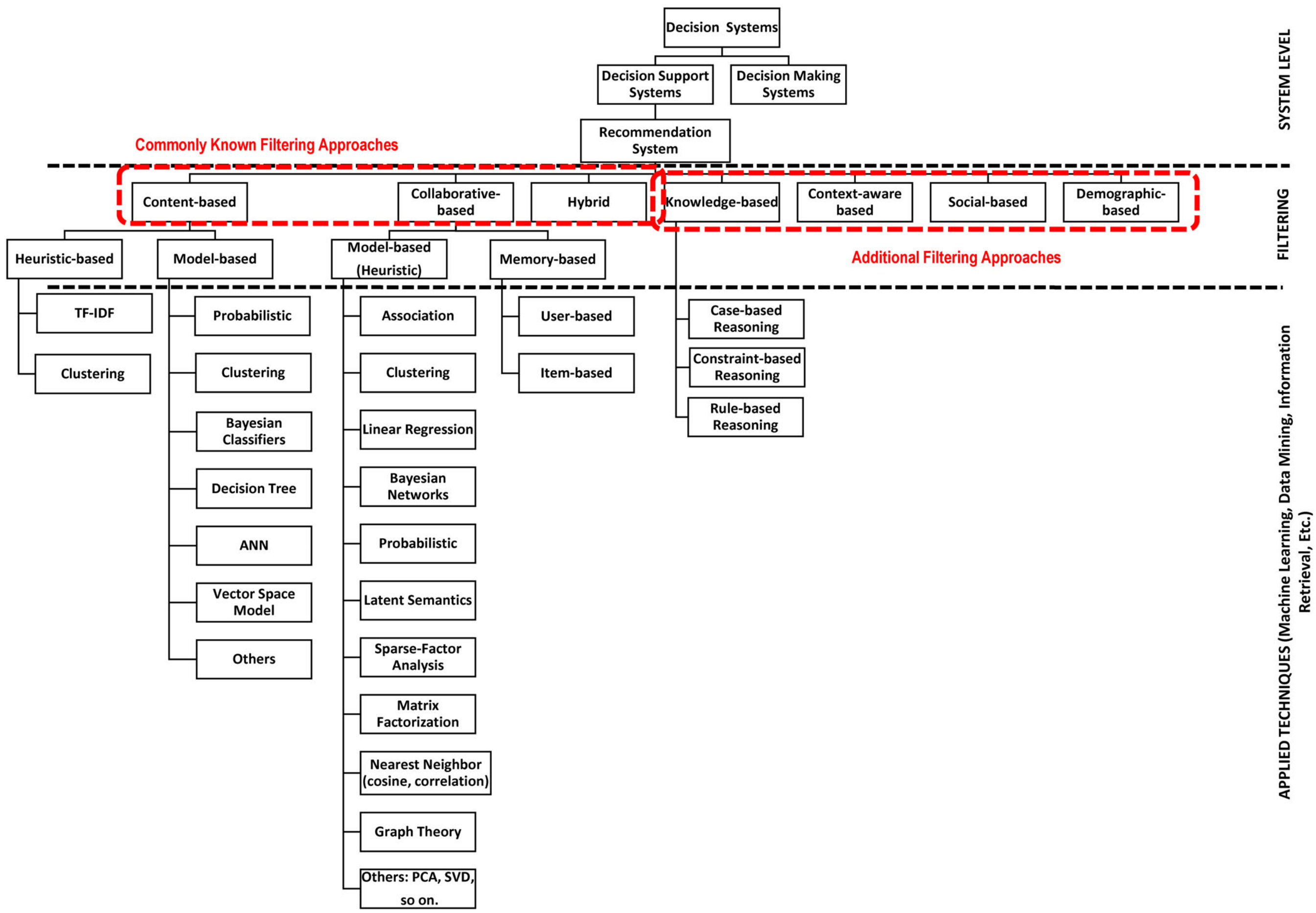

FIGURE 1 DSS subsumes recommendation techniques

products or items. In a nutshell, collaborative filtering examines relations between users and interdependencies among items to detect new user-item associations.

Hybrid methods try to combine other filtering approaches in some way (Wiesner & Pfeifer, 2014). The main filtering approaches also have differentiated among themselves based on the techniques used.

Demographic-based filtering (Bobadilla et al., 2013) provides analysis and recommendations based on the user's demographic information such as age, gender, residency, education level, nationality, and income level.

Social-based filtering exploits social information such as contacts and interactions between users (e.g., followers, followed, trust, reputation, credibility, content-based filtering of social data, social tagging, and taxonomies). In social filtering techniques, aspects and components of traditional recommenders are clearly designed to exploit social entities and social contexts. For instance, social filtering is based on substituting the user-neighbourhood, the ratings of which are considered to be similar to the current user's tastes (Bobadilla et al., 2013; Shardanand & Maes, 1995).

Context-aware filtering is based on additional contextual information, such as time, location, and wireless sensor networks. The contextual information can be obtained explicitly, implicitly, using data mining, or by a mixture of these methods. Currently, mobile applications increasingly use geographic information, which enables geographic RS to behave as location-aware RS (Bobadilla et al., 2013).

Knowledge-based filtering is another approach of filtering for RSs. This filtering technique uses a knowledge base about users and products to follow a knowledge-based approach deducing about what products match the user's requirements, thus generating a recommendation (Burke, 2000). Knowledge bases and machine learning algorithms together are also adapted as solutions to learn user profiles.

A knowledge base (KB) is a technology used to keep complex structured and unstructured information. The early use of the concept was associated with expert systems, which were the initial knowledge-based systems. A knowledge-based system (KBS) naturally needs significant domain knowledge and an intelligent reasoning engine. Recent approaches to KBS development typically revolve around the rapid configuration of reusable, independent components such as domain ontologies, problem-solving methods, problem solvers, and task specifications (Burke, 2000; Corsar & Sleeman, 2008).

Web 3.0 or semantic Web (SW; Berners-Lee, Hendler, & Lassila, 2001) is a fast-evolving Web technology that is widely considered under the content-based (or feature-based) RSs because it is geared to use an ontology (Gruber, 2009) knowledge base that comprises machine-readable (semantic) annotations. SW-based word treasure (vocabulary) can be considered as a special form of an ontology, or sometimes also simply as a set of uniform resource identifiers (URIs; Berners-Lee, Fielding & Masinter, 2004) complete with a prescribed meaning. Recently, many ontological languages have been proposed and standardized such as RDF(S) (McBride, 2004), Web Ontology Language (OWL; McGuinness & Van Harmelen, 2004), and its new version OWL 2.0 (Grau et al., 2008). OWL expresses concepts in an ontological form with specific special terms and features. In this way, it is possible to adapt heterogeneous information from distributed information systems. Additionally, each concept described in an ontology encapsulates a subset of instance data from the domain of discourse. The ontology knowledge base provides appropriate results in terms of human communication with the information in a machine-understandable format (OWL); in contrast, standardized methods are used for matching data from the database, where data are written in freestyle such as doctor prescriptions, medical patient reports, or clinical laboratory results. Thus, SW is used in order to share and integrate information not only in natural language but also by using the associated software, so it can be understood, interpreted, and expressed in a way that makes it easier to find the required data using application software.

2.1 | Technıques used ın RSs

Filtering approaches differ internally based on the techniques used as displayed in Figure 1. The most prominent ones are machine learning techniques that are highly proposed and applied by considering different types of filtering approaches introduced above, such as content-based, collaborative, and hybrid filtering solutions, in the literature. RSs can use unsupervised or supervised learning methods of machine learning techniques to improve the prediction performance when applied to content-based, model-based collaborative filtering, and hybrid filtering approaches (Isinkaye, Folajimi, & Ojokoh, 2015).

Collaborative filtering is divided into two categories, which are model-based (or heuristic-based) and memory-based filtering approaches (Adomavicius & Tuzhilin, 2005; Sinha & Dhanalakshmi, 2019). Memory-based filtering uses a database that keeps the preferences of all users and calculates across the entire database in order to drive a prediction. However, model-based filtering initially designs users' preferences in a descriptive user-element-user-class model and then presents suggestions based on the generated model for each prediction. Memory-based filtering is simpler and performs quite well in practice because new data can be added easily to the database. Nevertheless, this approach can become expensive in terms of both time and space complexity as the database grows. In addition, memory-based and model-based filtering often cannot provide additional information about explanations of predictions or data. For memory-based filtering, calculations for a similarity score are done over the entire database of users' ratings for each prediction (Pennock, Horvitz, Lawrence, & Giles, 2000). This score gives similarity clues between an active user and every other user. Predictions are produced by weighting each user's ratings in proportion to their similarity to the active user. Various approaches to similarity measurements are possible in this filtering mechanism.

In model-based filtering, a “user preferences model” is created from which predictions are inferred. For model-based collaborative filtering systems, several techniques are discussed in the literature. One of them is the matrix factorization technique, which is the dominant methodology; it maps both items and users by vectors of factors inferred from item rating designs (Koren et al., 2009; Mavridis, 2017). High relevance between item and user factors indicates a fitting recommendation. Collaborative methods in model-based usually use the interaction matrix for matrix factorization that is also called the rating matrix in the occasional case when users provide a clear rating of items. Methods used based on matrix factorization try to reduce the dimensionality of the interaction matrix, which can be very large, highly sparse, or even missing most of the values. For example, singular value decomposition (SVD; Pennock et al., 2000) technique may be used for this purpose. Other techniques are probabilistic and statistical oriented for clustering and model estimation. Probabilistic models (Billsus & Pazzani, 1998) such as Bayesian clustering and Bayesian networks (Ungar & Foster, 1998) are significant applications on learning of the model that provides to predict the utility of items to each user. The number of classes and the parameters of the model are learned from the dataset.

As mentioned earlier, content-based systems are intended typically to recommend text-based items; the content in the content-based systems is generally described with keywords. In addition, content-based filtering systems use various types of models to find similarity in text-based items via the keywords for generating meaningful recommendations (Breese, Heckerman, & Kadie, 1998). It could use vector space model such as term frequency inverse document frequency (TF/IDF; Neto, Santos, Kaestner, Alexandre, & Santos, 2000) or also probabilistic models such as Naïve Bayes classifier (Friedman, Geiger, & Goldszmidt, 1997), decision trees (Bouza, Reif, Bernstein, & Gall, 2008), or neural networks (Chang, Chen, Chiu, & Chen, 2009; Fidele, Cheeneebash, Gopaul, & Goorah, 2009) to model the relationship between different documents within a corpus. These techniques make recommendations by learning the underlying model with either statistical analysis or machine learning techniques.

3 | GENERIC SYSTEM ARCHITECTURE OF SEMANTICIZED PHRSs MODELLED IN LITERATURE

Personalized recommendation techniques matching medical information of patients to suitable medical services are crucial for health care systems through employing efficient and accurate recommendation techniques to provide valid and useful suggestions. In the health domain, knowledge sources include patients' features like age and gender; concept/service features like keywords, drug name, and disease name; and patient-health data like drugs used and genetic diagnosis. From this patient-health data, a patient profile is generated which has a crucial effect on recommendations.

The sound recommendation stems from special filtering strategies gathering external information that might not be readily available or easily accessible. Wiesner and Pfeifer (2014) claim that collaborative filtering is not suitable for health RSs because it examines similar user profiles across entire users, which would incur too high a security and privacy risk, whereas PHRS requires a high degree of privacy. In measuring the similarity between user profiles via a health RS, one can argue that no one can see which users are considered; however, due to privacy concerns, users may opt to exclude their data from such filtering. Furthermore, researchers have put forward that it might become easier for hackers to exploit potential security holes to get from one user's profile data to another. Another problem is that collaborative filtering may suffer due to the cold start problem: New treatments that have not been applied before cannot be recommended. Researchers also mention that content-based systems do not hold the aforementioned risks.

In semanticized PHRSs, the recommendation procedure is usually based on a conceptual diagram or an ontology knowledge base (Ghani & Fano, 2002). In the rest of this article, we survey the semantic-enabled RSs (De Gemmis, Lops, Musto, Narducci, & Semeraro, 2015; Ghani & Fano, 2002) as health systems that base its performance on a knowledge base, normally defined through conceptual maps (like a taxonomy or thesaurus) or an ontology, and those that use technologies from the SW stack, a layered cake of semantic Web technologies.

Increasing interest in semantic technologies and the accessibility of several open-source knowledge bases, such as Wikipedia, DBpedia, Freebase, and BabelNet, led to recent advances in knowledge-based PHRS. Several research studies have presented semantic techniques that focus on switching from a keyword based to a concept-based representation of items and user profiles (De Gemmis et al., 2015). Figure 2 above depicts semanticized PHRS's architecture, which involves fact base, knowledgebase, rule base, inference engine, and user interface.

The components of the semanticized PHRS architecture are introduced briefly below:

1. *The knowledge base* contains all of the relevant domain-specific information for the problem domain. Medical-based knowledge bases are constructed in direct collaboration with the physicians who are experts in the problem domain or a medical field. The medical knowledge base consists of two essential parts: a domain ontology and associated rules set. A medical ontology knowledge base is written in a formal language

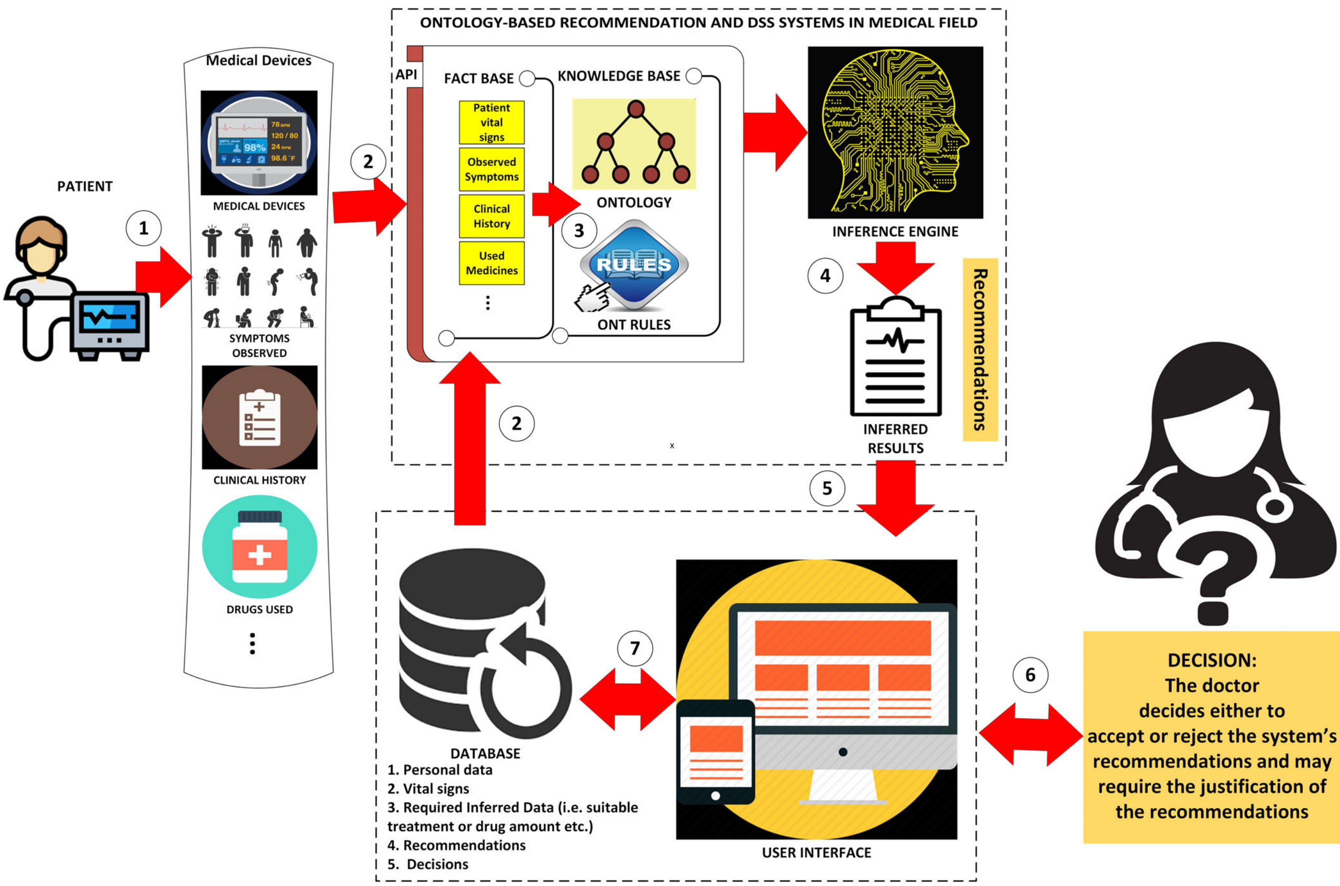

FIGURE 2 An overview of semantic recommendation and semanticized PHRS architecture

and involves the concepts used at problem domain (e.g., symptom, vital sign, output of a medical monitoring device, drug usage, and genetic history of patients) and their relationships (e.g., body temperature "is_a" vital sign, BMI value "is_a" measure of body fat, and Patient 1 "has_BMI_measure" 34). Moreover, rules in an ontology are a group of IF THEN ELSE rules; they represent the procedure used by medical experts to diagnose diseases, treat patients, and monitor them.

2. *The fact base* consists of medical data retrieved from the database in a given timeframe or instant data gathered from patients through medical devices. A collection of medical facts can be the values (e.g., observed symptoms, instant vital signs, the output of a medical monitoring device, drug usage data, and genetic history) of patients at a given time. These facts match the left sides of the medical rules determining appropriate rules to fire.
3. *The inference engine*, also referred to as "reasoner," is the essential part of the semantic recommender and decision support systems. The inference engine associates the ontology rules (e.g., medical rules) given in a knowledge base with the fact base and makes inferencing to find out a solution for the focused problem. In literature, many reasoners are available such as Pellet (Sirin, Parsia, Grau, Kalyanpur, & Katz, 2007), Hermit (Shearer, Motik, & Horrocks, 2008), FaCT++ (Tsarkov & Horrocks, 2006), Jena (McBride, 2002), and Racer Pro (Haarslev, Hidde, Möller, & Wessel, 2012). Reasoners are important for semantic applications for deducing new medical data from existing data in the fact base.
4. *The graphical user interface* allows interaction between medical experts and the system. The interface presents inferred suggestions obtained by the system to the medical expert who will use that information to supervise and treat a patient. In addition, the interface provides the user with an opportunity to ask the system how the result was reached.

The sequence of operations in a semanticized PHRS normally follows these steps as numbered in Figure 2: (1) gathering data from a patient, (2) insertion of the newly gathered user data as well as historic data from the database into the fact base, (3) incorporation of user data into ontology, (4) production of recommendation, (5) feeding the recommendation and its base data into the user interface, (6) communicating with doctor, and (7) updating the (history) database with new findings.

4 | RESEARCH METHODOLOGY USED

This research traces the impact of two technologies, SW and RSs, on health care via a methodical review of the recent literature. The objective of this review is to put forward how SW and RSs have contributed to the conveyance of health care with a highlight in health care decision making and operations management. We searched for articles on SW and RSs technologies in various library archival databases (e.g., Web of Science) and other journal sources in February 2019. The study focused on reviewing the articles selected according to the target research topic from both databases.

The steps applied to manage our methodical literature review of semanticized PHRS in the health care applications comprise the following: (1) selecting the pertinent literature, (2) identifying the semanticized PHRS, and (3) information extraction. In the literature selection procedure, suitable keywords and search criteria were used during the literature review to guarantee that the target concept(s) would be within the boundaries of the research objective. The search keywords used to support our research were the following: "recommendation system," "decision support system," "semantic Web*, Web 3.0*, or ontology*," and "data mining*, machine learning*, or big data*" (Figure 3). The symbol "*" is used as a placeholder for unknown text or wildcards in a search. The concepts "health*, healthcare*, e-health*, m-health*, or m-health" are used as filter inputs in titles.

Our search returned 1,269 articles. These articles were in Computer Science (772), Engineering (379), Health Care Sciences and Services (38), and Medical Informatics (19); only 949 articles were published recently, from 2015 to 2019. Only 38 of the 1,269 articles matched directly addressing our research topic and consequently were taken into account for further scrutiny/analysis. Finally, important research queries and related concentrated headlines were identified aiming at providing a better understanding of semanticized PHRSs in the health field as given in Table 1.

Ultimately, 38 articles in total were selected as the final reference set for this survey study. The main contributions of this study are summarized below:

1. SW has emerged as an extension of the current Web by associating well-defined meaning to contained information, better-enabling computers, and people to work in cooperation. In addition, RSs have evolved in order to provide personalized e-services in many applications in the Web environment. The use of new generation Web technologies in RSs makes the production of more personalized and advanced RSs, which is a useful guide for practitioners and researchers in the field. In this study, Web 2.0- and SW-based recent PHRS were investigated and analysed.
2. This study analyses research attainments on RSs in literature from the point of view of "system" and then classifies the RS applications into five filtering techniques, which provide a framework for RS development.

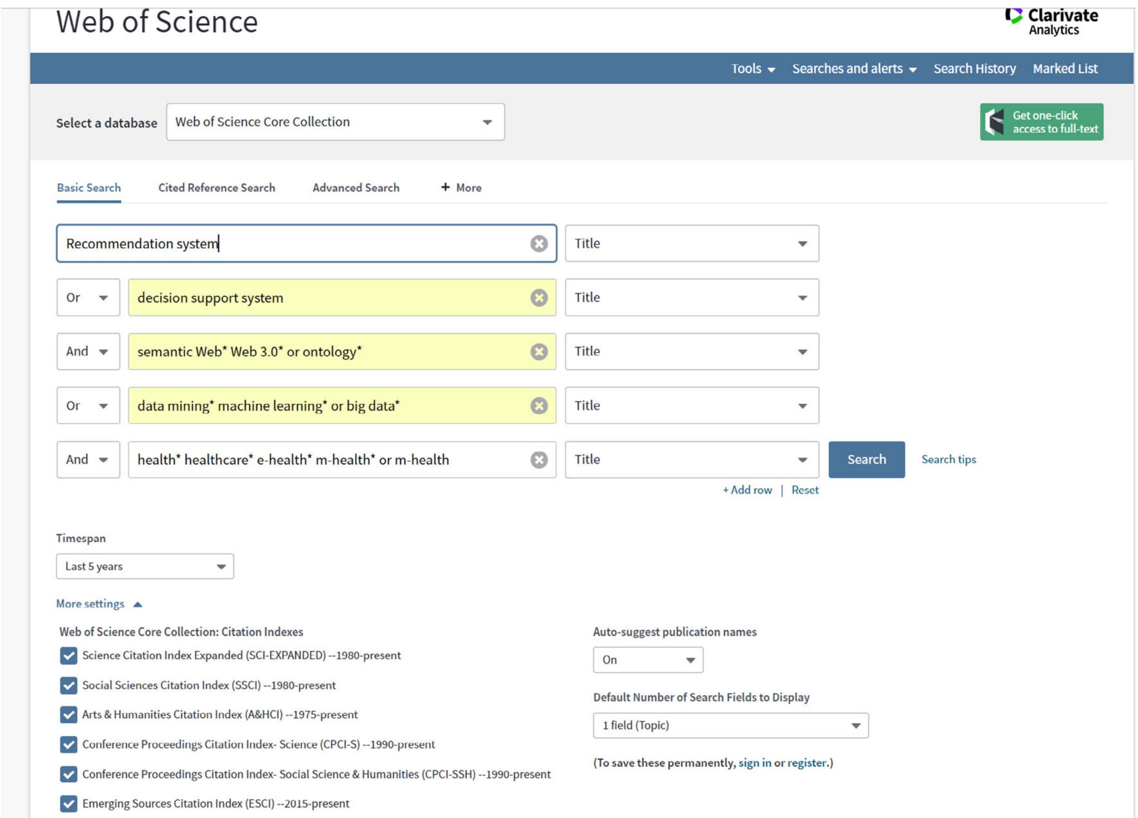

FIGURE 3 The search query on the WoS database

TABLE 1 Research queries and in-context concentrated headlines

Research queries	Concentrated headlines
RQ 1: Is there a systematic literature review on semanticized PHRSs in health practices?	It is imperative to have a clear vision of the key issues used in semanticized PHRSs architecture and health care applications.
RQ 2: Which performance evaluation objectives are accomplished through semanticized PHRS practices?	Conceptual-based data processing in health services is important. Therefore, the recommendation process via inferencing on knowledge bases can be provided with Web 3.0. In addition, personal medical datasets can be collected from various environments (web portal, mobile devices, smartwatches, smart wristbands, existing health devices, existing health software, etc.).
RQ 3: Which methods are used to achieve objectives in semanticized PHRS practices?	Identifying the state-of-the-art technologies in semanticized PHRS practices.
RQ 4: Which are the current studies on semanticized PHRS applications?	Collecting information on semanticized PHRS applied areas.
RQ 5: What are the future directions in semanticized PHRS architecture, applications, challenges, and motivation?	Collecting information on semanticized PHRS technologies that are successfully implemented in health care applications as exemplary use cases.

3. This study has revealed recent innovative research studies on semantic-enabled RS development, especially the health field for RSs is our main concentration during the entire study.
4. The five main filtering techniques for the RS development are categorized into application techniques according to the implementation approaches, and the requirements for RSs in the field of health have been carefully analysed and stated according to these filtering and application techniques.
5. This study is able to directly motivate and support relevant researchers and practitioners in order to increase the number of the implementation of health care RSs.
6. The use of content awareness-based recommendation techniques and SW-based technologies in RSs reveals that more advanced RSs would be necessary and prove very successful practices.
7. The study highlights a number of innovative emerging research topics and directions in the area of semanticized RSs.

5 | KEY PHRS APPLICATIONS AND CASE STUDIES IN LITERATURE

For the medical field, various PHRS or DSS applications found in the 38 research articles selected for this survey study were analysed and compared by way of the filtering and techniques used in reaching a recommendation in reference to Figure 1. Each article is reviewed below by mentioning its contribution, techniques used, and methodology followed. The other 31 references in this section indicate tools, techniques, and known algorithms used in the selected 38 research articles. Table 2 inserted at the end of this section provides a ready-reference summary of this review.

Salunke and Kasar (2015) proposed a PHRS for medical assistance using keyword extraction where users can search for doctors and hospitals. Natural language processing (NLP), hybrid filtering (collaborative and content-based), top-k query algorithm, keyword extraction, and user-based personalization were used in implementing the system to assess user ratings and reviews to calculate system ratings. The aim of top-k query use in the system is to search out exact records from the given dataset that matches the filtering keywords and arrange them according to their scores. At the end of this process, the system recommends doctors and hospital names. The retrieved results after any search are structured and stored by using XML.

Chen, Jin, Goh, Li, and Wei (2016) proposed a personalized RS of antihypertensive drugs based on context-awareness and own-design context ontology. Their system is capable of real-time sensing users' context with wearable and medical sensor devices and provides reliable antihypertensive drug recommendation. They used SW and ontology engineering technologies to analyse user preferences. The rules of reasoning mechanism of their system use semantic Web rule language (SWRL; Horrocks et al., 2004) to render drug recommendation more personalized. The researchers applied three categories of information recommendation rules that fit diverse priority levels and used a sorting algorithm to optimize the recommendations returned. JESS engine (Friedman-Hill, 2008) is used to run the SWRL rules to infer new knowledge. JESS is a lightweight and the fastest rule engine developed by Ernest Friedman-Hill. It uses the Rete Algorithm to match patterns and provides two application extensions for Protégé editor, JessTab, and SWRLJessTab.

Quinn, Bond, and Nugent (2017) proposed an information RS for diabetic and obese patients, most especially for older adults focusing on personalized patient education. Patient information is captured relating to four main lines, namely, the patient, medical conditions, physical activities, and educational content. The patient profile is then modelled as an ontology. SWRL rule-based reasoning was then applied to achieve personalization. The Protégé (Noy et al., 2003) ontology editor was used in creating the ontology knowledgebase; and Pellet was used to reason with the SWRL rules to determine logical inferences.

Sherimon and Krishnan (2016) proposed *OntoDiabetic*, as an ontology-based clinical DSS for diabetic patients. The system was modelled to assess risk factors and provided suitable treatment recommendations. The system produces two different outputs. The first output is an assessment of a risk score (and, a prediction) of diabetic risk, namely, activity risk assessment, cardiac risk assessment, and cardiovascular risk assessment of patients. The second output is about alerts/recommendations and suitable treatment suggestions for diabetic patients. OWL 2.0 is used to create both the system ontology knowledge base and the semantic rules. The language used for the rules is SWRL. Pellet and Hermit reasoners of OWL 2.0 are used to reach correct conclusions (risk scores and treatment suggestions) by processing the input (semantic profile) with the stored knowledge (clinical guidelines).

Stark, Knahl, Aydin, Samarah, and Elish (2017) proposed *BetterChoice* personalized health care system, which is a migraine drug RS cased-based on the highly scalable native graph database Neo4j (Van Bruggen, 2014). The aim of the system is to assist physicians with treatment recommendations for migraine patients using simulated patient data. The collaborative filtering (user-based) approach is employed where a patient–user is categorized in a group of patients and the group's preferences are used as the basis for the recommendation. The system was implemented with queries to the Neo4j database and further processed in Python.

Subramaniyaswamy et al. (2019) proposed an ontology-driven and IoT-based health care system "ProTrip" that is a personalized food RS. The system has a Web-based interface that allows users to plan events before or in the middle of trips. ProTrip is based on an ontology knowledge base that semantically manipulates health and nutrition information for individuals. The researchers avoided including any complex information extraction procedure in ProTrip and used hybrid suggestion techniques to make it more effective. The hybrid filtering mechanism of the system involves three basic types of filtering: collaborative filtering, content-based filtering, and knowledge-based filtering. In a nutshell, the gap between heterogeneous user profiles and descriptions is bridged using semantic ontologies in this study.

Ahire and Khanuja (2015) proposed an ontology-based personalized framework for health care RS. The system provides precise information based on user needs and constraints. SW technology is used to analyse user preferences, as well as to create a user profile for nutrition and health. The system uses the profile to classify relational information; thus, users can make inquiries to prepare delicious meals and get actionable recommendations. Food recommendation is based on the user preferences, considering personal preferences for food, health condition, and culture influence on food choice. The researchers also used the decision tree approach to analyse the characteristics of the user and retrieve related information from the database. In this way, the system can provide relevant information to the user by recommendation, follow-up, and monitoring. The rules used for recommendation are modelled by using SWRL.

Alharbi, Berri, and El-Masri (2015) proposed an ontology-based clinical DSS that is a diagnosis and treatment RS for diabetic patients. Referring to the clinical practice guidelines (CPG) for recommendations, the system takes into account patient information, symptoms and signs, risk

TABLE 2 Comparison of PHRS based on the methods used

			Filtering approaches										
			CB		CL			KB					
REFERENCE	Recommendation topic	Technology used	Heuristic-based	Model-based	Model-based	Memory-based	Hybrid filtering	Case-based	Constraint-based	Rule-based	Context-aware fil.	Social-based fil.	Demographic-based fil.
Salunke and Kasar (2015)	Medical assistance: recommends suitable doctors and hospitals	Top-K query algorithm Similarity matching	√			√	√						
Chen, Jin, Goh, Li, and Wei (2016)	Antihypertensive drugs	OWL, SWRL, Protégé, JESS engine, wearable, and medical sensors								√	√		
Quinn, Bond, and Nugent (Quinn et al. 2017)	Medical assistance for personalized patient education in diabetic and obesity cases	OWL, SWRL, Protégé, Pellet								√			
Sherimon and Krishnan (2016)	Suitable treatment plans for diabetic patients	OWL, SWRL, Protégé, Pellet, and Hermit								√			
Stark et al. (2017)	Migraine drugs	Graph theory			√								
Subramaniyaswamy et al. (2019)	Personalized food plans	OWL, IoT-based		√	√		√	√					
Ahire and Khanuja (2015)	Personalized food plans	OWL, decision tree, and SWRL		√			√			√			
Alharbi, Berri, and El-Masri (2015)	Suitable treatment plans for diabetic patients	OWL, SWRL, JESS engine, Protégé, and Pellet								√			
Hu, Elkus, and Kerschberg (2016)	Personal HealthRecommender System (PHRS) suggests most appropriatecourse of treatment for an illness.	OWL, Protégé, multiagent system, SWRL, and similarity								√			
Geetha and Sivasubramanian (2017)	Suitable treatment plans for diabetic patients human papilloma virus (HPV)	OWL, SWRL, Protégé, and XSLT		√	√		√			√			
Lee and Kim (2015)	Family doctor role	OWL, cloud computing, and depth-first search			√			√					
Mahmoud and Elbeh (2016)	Suitable treatment plans for Type 2 diabetes	OWL, SWRL, JESS engine, XSLT								√			

(Continues)

TABLE 2 (Continued)

REFERENCE	Recommendation topic	Technology used	Filtering approaches										
			CB		CL			KB					
			Heuristic-based	Model-based	Model-based	Memory-based	Hybrid filtering	Case-based	Constraint-based	Rule-based	Context-aware fil.	Social-based fil.	Demographic-based fil.
El-Sappagh, Elmogy, and Riad (2015)	Diagnosing diabetes mellitus disease	Fuzzy ontology-based CBR framework and five classifiers (C4.5, k-NN, SVM, Bayesian classifier, and ANN)			√		√	√					
Dename and Mengistu (2017)	Diagnosing anemia disease	OWL, Protégé, and SPARQL						√	√				
Chen, Huang, Bau, and Chen (2012)	Diabetes drugs	OWL, Protégé, SWRL, JESS engine, and XSLT								√			
Thangaraj and Gnanambal (2014)	A DSS to diagnose Vitamin D deficiency	OWL, NEFCLASS algorithms, BRMS, neuro-fuzzy classifiers, SWRL, and JESS			√		√			√			
Khalili and Sedaghati (2013)	Semantic-based drug prescriptions	SPARQL, linked open data (LOD), NLP, and graph theory	√		√		√			√			
Bocanegra, Ramos, Rizo, Civit, and Fernandez-Luque (2017)	Complement health videos on YouTube by adding educational semantic content	OWL and Cohen's kappa formula		√				√					
Hors-Fraile et al. (2018)	Generate motivational health messages for smoking cessation	Health recommendation system algorithm (HRSA) and demographic similarity	√				√						√
Gómez, Oviedo, and Zhuma (2016)	Monitoring health and workout routine of patients with chronic diseases	OWL, SWRL, IoT, and mobile app								√	√		
Chi, Chen, and Tsai (2015)	Suitable dietary plan for chronic disease patients	OWL, SWRL, Protégé, SQWRL, JESS, and Java server pages (JSP)								√			
Shen et al. (2018)	Infectious disease diagnosis and antibiotic prescription	OWL, graph theory, Naïve Bayes, Neo4j			√		√	√					
Chang, Fan, Lo, Hung, and Yuan (2015)	Diagnosing and detecting depression	OWL, cloud-based, mobile app, graph theory, Bayesian network, multiagents, DAG, Protégé, GeNNe and SMILE engine, and Java			√		√			√			

(Continues)

TABLE 2 (Continued)

			Filtering approaches										
			CB		CL			KB					
REFERENCE	Recommendation topic	Technology used	Heuristic-based	Model-based	Model-based	Memory-based	Hybrid filtering	Case-based	Constraint-based	Rule-based	Context-aware fil.	Social-based fil.	Demographic-based fil.
Bucci, Sandrucci, and Vicario (2011)	A DSS for medical diagnosis	Graph theory, probabilistic analysis, Bayesian networks, OWL, Racer Pro, Pellet, and Hugin Expert library for BNs			√		√			√			
Hu et al. (2010)	Online cognitive behaviour therapy (CBT) application for treating depression	RDF(S) context ontology, C#, NET, Java, and mobile app.						√	√				
Abbas, Bilal, Zhang, and Khan (2015)	Suitable health insurance plans	XML schema tree-based matching algorithm, ranking algorithm, DaaS model, and SaaS	√								√		
Chen et al. (2018)	Disease diagnosis and treatment RS	BDM, Density-Peak-based Clustering Analysis (DPCA) algorithm, association rules, Apriori Algorithm, Apache Spark cloud computing, HDFS, and Protégé		√	√		√			√			
Ali et al. (2018)	Suitable diet plans and drugs for diabetic patients	Type-2 fuzzy logic (T2FL), probabilistic, IoT, wearable sensors, OWL, Protégé, SPARQL, and SWRL			√		√			√			
Bianchini, De Antonellis,De Franceschi, and Melchiori (2017)	Personalized food plans	Brute-force and indigenous algorithm, ranking, similarity matching, OWL, Jena, PREFer algorithm, Java, and MySQL	√				√			√			
Dinata, Dewabharata, and Chou (2015)	Suitable physical activities for health promotion	RDF/XML, W3C semantic sensor network ontology, TF/IDF, and Simi-Huang Similarity Algorithm	√				√				√		
Shi et al. (2015)	Mobile Ambulatory Assessment System for predicting personal alcohol craving or mood status	mAAS, wearable sensor data, ML, and statistical methods to classification		√	√		√						

(Continues)

TABLE 2 (Continued)

			Filtering approaches										
			CB		CL			KB					
REFERENCE	Recommendation topic	Technology used	Heuristic-based	Model-based	Model-based	Memory-based	Hybrid filtering	Case-based	Constraint-based	Rule-based	Context-aware fil.	Social-based fil.	Demographic-based fil.
Ertugrul, Kanmaz, Yüksel, Elçi, and Ertugrul (2016)	A DSS for monitoring fetal heart rate and uterine contractions and detecting urgency	SWRL, OWL, Pellet, Protégé, Java, and mobile app.								√			
Çifçi, Ertugrul, and Elçi (2016)	Suitable mobile applications on right food consumption	BDM, HDFS, MapReduce algorithm, HBase, Hive Sqoop with RDBMS, PHP, Java, and SQL, OWL		√					√				
Sabra, Mahmood, and Alobaidi (2017)	A DSS for identifying risk factors for early diagnosis for a particular disease	SentiWordNet, sentimental analyser, RDF, LOD, SESARF, semantic rules, and ML: any classifier			√		√			√	√		
Ertugrul, Elçi, and Bitirim (2017)	Suitable supportive treatment activities for Acute Respiratory Tract Infection (ARTI) paediatric patients	SWRL, OWL, Pellet, Protégé, Java, and mobile app.								√			
Taçyıldız, Ertuğrul, Bitirim, Akcan, and Elçi (2018)	Suitable treatment and physical activities for paediatric diabetic and obese patients	OWL, SWRL, SQWRL, Pellet, Java, and mobile app.								√			
Rawte and Roy (2015)	A DSS for diagnosing thyroid disease	OWL, SWRL, Protégé, Jena, and JSP Web app.								√			
Chen, Jiang, Huang, and Bau (2017)	Suitable treatment plans for diabetic patients	Fuzzifier, fuzzy rules, fuzzy inference, and de-fuzzier, TOPSIS algorithm, multicriteria decision analysis, OWL, Protégé, and Jena engine			√		√			√			

Abbreviations: BDM, big data mining; CB, content-based filtering; CL, collaborative-based filtering; KB, knowledge-based filtering; ML, machine learning.

factors, and lab tests before suggesting a treatment plan according to the diabetes type of the patient. OWL-DL ontology models the key concepts and relationships in the clinical guidelines to allow clinical knowledge sharing, update, and reuse. Pellet reasoner was used for ontology verification; JESS's SWRL rule-based reasoning engine executes the SWRL rules of the system.

Hu, Elkus, and Kerschberg (2016) proposed an ontology-based clinical DSS for diabetes diagnostic. Their system starts with a person's personal electronic health record (electronic medical records [EMRs]) and augments it by combining crowd-sourced data mined for symptoms, diseases, treatments, and best practices, together with authoritative sources and domain ontologies. The researchers claimed that using anonymized mass-sourced patient data can help determine the best treatment for similar cases. SW services are called to classify the data according to the patient-based or disease-based ontologies created with OWL/RDF by using Protégé. Similarity functions and/or SWRL rules are employed for concept matching.

Geetha and Sivasubramanian (2017) proposed the generation of a personalized ontology utilizing semantic rules for human papilloma virus (HPV) based on treatment schemes. The researchers created a conceptualization of disease-treatment ontology for HPV involving parts on the clinical pathway, quality assurance, details about the virus, cost of treatments, and diet. The system provides an evidence-based recommendation to standardize and optimize the patient care process while also confirming patient safety and quality of care. Evidence-based medical RS consists of intelligent algorithms, such as neural networks, fuzzy theories, support vector machines (SVM), data mining, and hybrid filtering techniques like collaborative filtering, content-based filtering, and knowledge-based filtering (Sodsee & Komkhao, 2013). The collaborative filtering method is applied for the medical history of patients; the content-based filtering is used for experimental studies; the knowledge-based filtering is applied for the case reports and expert opinions. With this description, therefore, the system entails collaborative filtering, content-based filtering, and knowledge-based filtering approaches. SWRL rules are used and integrated into a disease-treatment ontology. The integration provides interaction between rules and ontology leading to the generation of new facts and knowledge.

Lee and Kim (2015) proposed the eHealth Recommendation Service System (eHeaRSS) as an RS for family doctor role. The health information of eHeaRSS comprises 4-static ontology (4-Ont) and eHealth Service ontology (eHeaRSS-Ont). The 4-Ont contains symptoms, diseases, doctors, and departments to create tailored recommendations, whereas eHeaRSS-Ont is dynamically integrated with the relational parts extracted from 4-Ont according to patient's context. Case-based reasoning (CBR) is applied for the recommendation process on information collected by crowdsourcing in a cloud computing environment. Case selection is processed by a depth-first search to find a case that is the most similar. CBR is an AI technology like rule-based reasoning, neural networks, or genetic algorithms; it may be better defined as a methodology for problem solving, using any suitable technology and any type of RS filtering mechanism. It provides for learning and problem solving based on past experience. CBR combines aspects from the knowledge-based systems and from the machine learning field. Rule-based reasoning and case-based reasoning are two complementary alternatives for building knowledge-based smart DSSs.

Mahmoud and Elbeh (2016) proposed the IRS-T2D, an ontology-and-SWRL-based RS for customizing the treatment of Type 2 diabetes patients. Two OWL ontologies are built: one for patient profiles and another for antidiabetic drugs based on official documents on management of Type 2 diabetes. Protégé is used for modelling the OWL ontologies and SWRL rules. The rules were created based on constraints on Type 2 diabetes medication. OWL/SWRL knowledge base of the system gets converted to JESS reasoning engine using OWL2Jess and SWRL2Jess XSLT tools. Thus, it provides a recommendation for the personalized HbA1c target and antidiabetic drugs with suitable doses.

El-Sappagh, Elmogy, and Riad (2015) proposed the fuzzy KI-CBR, a DSS to diagnose diabetes mellitus. The system is a fuzzy ontology-based CBR framework with a fuzzy semantic retrieval algorithm for a semantic diabetes diagnosis. Compared with the existing CBR systems and a set of five machine learning classifiers (C4.5, k-NN, SVM, Bayesian classifier, and ANN), the system outperformed all achieving 97.67% accuracy.

Dename and Mengistu (2017) focused on an ontology-based DSS to diagnose anaemia, identifying symptoms and signs of anaemia occurrences and preventing anaemia in children. Ontology was created using Protégé ontology editor and open-source ontology-based data access (OBDA; Calvanese et al., 2017) from accounts of personal description, common symptoms, common signs, causes, and diagnosis of anaemia, diseases, and medical recommendation. SPARQL (Sirin & Parsia, 2007) is used to query. An ontology-based GUI generator provides a domain expert to browse the data schema, choose attribute fields according to needs, and prepare a highly customized GUI for users, without requiring programming skills.

Chen, Huang, Bau, and Chen (2012) proposed a diabetes medication RS that uses an ontology knowledge base and the database of the American Association of Clinical Endocrinologists Medical Guidelines for Clinical Practice for the Management of Diabetes Mellitus. The purpose of the system is to analyse the symptoms of diabetes and suggest the most appropriate drug(s). Protégé was used to build the interrelated antidiabetic drugs and patient ontologies. SWRL was used for building antidiabetic drugs association rules; then, XSLT was used to transform SWRL rules for processing in a JESS-based inference engine to generate potential prescriptions.

Thangaraj and Gnanambal (2014) proposed a rule-based DSS to diagnose vitamin D deficiency. The researchers benefited from the NEFCLASS-based decision-making environment supporting SWRL rule construction, execution, and ontology construction. NEFCLASS algorithms and Business Rule Management System (BRMS; Business, 2013; Swennen, 2012) were employed in constructing the rule repository using neuro-fuzzy classifiers from a dataset of food supplements to manage vitamin D deficiency and the rule engine to diagnose vitamin D deficiency. Recommendations are then generated using SWRL rules and JESS.

Khalili and Sedaghati (2013) proposed a tool called Pharmer, an RS for generating semantic prescriptions, to avoid medication errors in the health care domain. Pharmer has a bottom-up style to augment the normal e-prescriptions with semantic annotations via SPARQL queries to a set of predefined datasets of linked open data (LOD; Bauer & Kaltenböck, 2011), such as Schema.org MedicalTherapy and the existing pharmaceutical linked datasets such as DBpedia (Auer et al., 2007), DrugBank (Wishart et al., 2007), DailyMed (De Leon, 2011), and RxNorm (Liu, Ma, Moore, Ganesan, & Nelson, 2005) to automatically detect prescription drugs and collect multidimensional data. Pharmer has three layers that are document layer, semantic layer, and application layer. The document layer consists of drug detection and drug information collector components. The drug detection component uses NLP services to detect the terms referring to a drug in the prescription. Drug information collector component catches all the information about a specific drug from LOD. In addition, Pharmer is an open-source application and accessible for download together with an online demo (at http://code.google.com/p/pharmer/).

As it is known, health-related videos are very popular on YouTube, but their quality is often a crucial problem. Bocanegra, Ramos, Rizo, Civit, and Fernandez-Luque (2017) discussed the feasibility of building a semantic and content-based RS to complement health videos on YouTube by providing additional educational content, such as website links, to support consumers. The RS connects a health consumer to prestigious health educational websites from MedlinePlus (Miller, Lacroix, & Backus, 2000) for a given health video on YouTube (Davidson et al., 2010). In recommending websites from MedlinePlus, semantic technologies, such as SNOMED-CT (Donnelly, 2006) and bio-ontology, are used. The scheme is tested by health professionals favourably. A collection of health-related videos and their available metadata are used as dataset in this study. Precision at K (Sujatha & Dhavachelvan, 2011) and normalized discounted cumulative gain (Distinguishability, 2013) metrics indicating the relevance of the “top” returned results and Cohen's kappa formula (Cohen, 1968) to determine the level of agreement between two given raters are computed to assess the appropriateness of the recommended links for a given video.

Hors-Fraile et al. (2018) proposed an RS to generate motivational health messages for smoking cessation using m-Health solution integrated with an electronic health record. In this study, researchers developed a m-Health Recommender System (m-HRS) that provides to send tailored motivational health messages selected by a health counsellor based on the current electronic health records and profiles of patients who are participating in a smoking cessation programme. The m-HRS uses a health recommendation system algorithm (HRSA) that is an information filtering algorithm and provides to choose the most relevant motivational messages aimed at smoking cessation for each user based on his or her profile. In addition, HRSA follows a hybrid filtering approach to improve its performance, as suggested by Burke (2000). By using hybrid filtering, HRSA assesses patient's demographic similarity, perceived utility of the message topics, and statement of primary interest of patients. Concisely, the overall system was designed to perform two main principles by the researchers which are (a) customizing messages and (b) predicting the best time to send the tailored motivational messages to patients through the app.

Gómez, Oviedo, and Zhuma (2016) proposed an ontology-based patient monitoring RS along with the Internet of Things (IoT) paradigm. The idea is to monitor the health and workout routine of patients with chronic diseases and rendering recommendations. The architecture of the RS is modelled as a context-aware integrated IoT system with the context in three categories: Context computer (network connectivity, communication costs, communication bandwidth, resources, etc.), background user (user profile, location, nearby people, etc.), and physical context (power, traffic conditions, temperature, etc.). Additionally, the ontology involves the knowledge of personal profile, location in GPS coordinates, date and time, and type of exercises, which provide inferences on the system behaviour according to the type of context. Web services of the system are consumed naturally by the mobile device of the patient. The reasoning is performed through OWL and SWRL.

Chi, Chen, and Tsai (2015) proposed an ontology- and rule-based chronic disease dietary consultation system. The researchers evolved domain and task ontologies, and semantic rules using OWL and Protégé tool in collaboration with a dietician, a physician, and a knowledge engineer. Twenty-nine semantic rules among the concepts of personal profile, personal dietary, and personal nutrient count were developed using SWRL and SQWRL (O'Connor & Das, 2009) in order to infer the dietary consultation results, that is, recommending suitable food and serving quantities from different food groups for balanced key nutrient ingestion.

Shen et al. (2018) proposed IDDAP, an ontology-based clinical DSS for infectious disease diagnosis and antibiotic prescription. A hierarchical conceptual schema was constructed by collating existing ontologies related to infectious diseases, patterns, bacteria, and drugs. The IDDAP detects possible infectious diseases based on the information entered by the patient, such as temperature, former/recent observed symptoms, then, suggesting customized antibiotic usage through a weighted Naïve Bayes classifier identifying possible infectious diseases by detecting a certain level of dependency between symptoms. Instead of using OWL, the researchers preferred to adopt the Neo4j graph database to store their IDDAP ontology. Neo4j is used to store their ontology in a graph data structure effectively and represent ontological relations and rules accurately.

Chang, Fan, Lo, Hung, and Yuan (2015) implemented a cloud-based mobile diagnosis system detecting depression through inferencing based on own developed depression ontology model (DOM) and Bayesian network approach to deduce the possibility of becoming depressed. The researchers used multiagents to run on the Android platform of the proposed system. The rules used for inferring ontologies were constructed with the GeNNe and SMILE reasoning engine (Druzdzel, 1999), which is a semantic Web framework for Java that supports semantics for defining rules. The results of the research study indicated that the system may be useful in helping diagnose depression.

Bucci, Sandrucci, and Vicario (2011) proposed an approach using disease domain knowledge ontology and Bayesian network (BN) in medical diagnosis. The approach involves a heuristic of several steps: (1) Insert the observations of the patient as asserted data to ontology; (2) run the system's reasoner to discover further possible observations, according to semantic rules; (3) for all observation types (asserted and inferred), find out all proper pathology types and then build its BN; (4) annotate the nodes of the BN by the a priori probabilities contained in the knowledgebase; and (5) modify the probability of nodes according to the asserted and inferred observations (e.g., findings) and compute a posteriori probabilities. As a case study on flu disease, the off-the-shelf library Hugin Expert (Brochure, 1998) was employed to generate and evaluate BN and decision networks.

Hu et al. (2010) proposed an ontology-based ubiquitous monitoring and treatment framework against depression. The approach involved steps of (1) development of a context ontology of mental disorders for gathering, formalizing, and manipulating patient data; (2) implementing an online cognitive behaviour therapy (CBT) application for treating depression. The application provides the talk, chat, and messaging services to help in retrieving neurofeedback and supporting collaborative diagnosis when necessary. (3) An online statistics report generation is available in the system. The system was compared against relevant research in the field. C# and NET programming were used for mobile client development whereas Java Micro Edition for the server implementation.

Abbas, Bilal, Zhang, and Khan (2015) proposed an ontology- and cloud-based RS to select health insurance plans according to user criteria and preferences. The RS provides to compare various health insurance plans according to the fulfilment of user criteria and preferences. Health insurance providers save their plans in ontology format and maintain repositories. The RS's requirement engine is used for collecting user requirements and preferences, and then transforming them into XML schemas. An ontology schema provides grounds for standardized representation of all plans on which the data as a service (DaaS) (Mokadem, Morvan, Guegan, & Benslimane, 2014) runs catering for retrieving proper plan data from among a large number of insurance plans supplied by insurance providers. A tree-based matching algorithm is used in discovering structural similarities between user requirements and insurance plans. A ranking algorithm based on the multi-attribute utility theory (MAUT; Sarin, 2013) was implemented to rank health insurance plans based on user preferences or importance criteria. The RS implemented as software as a service (SaaS) was tested on a locally administered Ubuntu cloud computing set-up.

Chen et al. (2018) proposed a disease diagnosis and treatment recommendation system (DDTRS) based on big data mining and cloud computing. The researchers used massive historical medical inspection datasets to derive disease-symptom clusters aiming to discover association relationships among diseases, diagnoses, and treatments. A Density-Peak-based Clustering Analysis (DPCA) algorithm was used for disease-symptom clustering. The DPCA algorithm provided to classify more precise disease-symptom relations particularly for the diseases with multiple treatment phases and multipathogenesis efficiently. Disease diagnosis (D-D) and disease-treatment (D-T) association rules are derived from the treatment knowledge of experienced doctors and hospitals through analysis by the Apriori Algorithm in data mining. This algorithm serves for frequent item set mining and association rule learning. An interactive recommendation interface of DDTRS serves recommendations. Aiming to achieve high performance and low latency response, DDTRS was implemented by a Resilient Distributed Dataset (RDD) programming concept parallel solution on Apache Spark cloud computing platform with the enormous medical data stored in a Hadoop Distributed File System (HDFS).

Ali et al. (2018) proposed a type-2 fuzzy ontology and IoT-based diabetes-specific health care RS to effectively track a patient and recommend diet plans of particular foods and drugs. The RS monitors risk factors through wearable sensors predicts the patient's health and recommends diabetes-specific prescriptions for a smart medicine box and food for a smart refrigerator. The combination of type-2 fuzzy logic (T2FL) and the fuzzy ontology improves the prediction accuracy of a patient's condition and the precision rate for drugs and food recommendations. System ontology developed in OWL using Protégé involves the knowledge of patient disease history, food consumption, and drugs used. Description logic (DL) and SPARQL queries were used to assess and validate the system ontology; SWRL rules and fuzzy logic were used in the inferencing mechanism. The experimental results indicated that the system is effective for the extraction of patient risk factors and recommending diabetes prescriptions.

Bianchini, De Antonellis, De Franceschi, and Melchiori (2017) proposed the Prescriptions for REcommending Food (PREFer) system, which recommends personalized healthy menus considering a user's short-/long-term preferences and medical prescriptions. The researchers considered the recommendation of menus in three steps. First, recipes are selected by content-based filtering, based on comparisons among features used to annotate both user profile and recipes. Second, candidate menus are generated by brute-force and indigenous algorithm from the selected recipes. Third, menus are refined and ranked taking into account also prescriptions. The filtering algorithm of PREFer is based on semantics with ontology; the recommendation algorithm is the concept-based similarity of a recipe and the request. Ontology is modelled on OWL and reasoning is made by using Jena. PREFer offers education to improve users' nutrition habits in time. PREFer was developed as a J2EE Web application of Java and MySQL for DBMS. The researchers applied two algorithms in the menu generation task of PREFer: (a) the algorithm that establishes the optimal solution (because it generates all the menus before sorting them based on the relevance with the user's request) and (b) the PREFer algorithm.

Dinata, Dewabharata, and Chou (2015) proposed an Ontology-enabled Service Discovery for Supporting Health Promotion System. A conceptual model of context-aware service metadata ontology was developed to provide a better service description. Service discovery based on semantic similarity and relatedness measures the interrelations among the user's context and the service context. Simi-Huang Similarity Algorithm (Dapeng, Qianhui, & Jingmin, 2009) which is best in the computation of accuracy, especially with sparse data, is used to resolve the service discovery issues. The researchers applied context-aware reasoning to determine the proper physical activity for a recommendation from physical activity recommendation services. Context-aware reasoning and CBR can be used to develop intelligent environment (IE) systems. Khan, Alegre, Kramer, and Augusto (2017) emphasized that context-awareness reasoning and CBR are unequal but complementary methodologies for solving a domain-specific problem. The researchers defended the IE development paradigm must build cooperation between these two approaches to overwhelm the individual drawbacks and to maximize the achievement of the IE systems.

Shi et al. (2015) proposed a mobile Ambulatory Assessment System (mAAS) for psychology research, especially for alcohol craving studies, to improve current methods and provide real-time data monitoring and collection. mAAS involves a wearable sensor, an Equivital EQ2 sensor, for measuring physiological data, an Android smartphone, and a Web server. The user's smartphone is responsible for gathering physiological data via the wireless wearable sensor, recording the data, interacting with the user to perform several surveys, and uploading the data to the system's Web server. The system also collects accelerometer, light sensor, and GPS data from the smartphone. The system server is responsible for data processing, computation, and visualization. The sensor and survey data are used by machine learning methods to build models to predict alcohol or other substance cravings and emotion dysregulation caused by various psychological disorders. The primary aim of mAAS is to predict personal alcohol craving or mood status.

Ertugrul, Kanmaz, Yüksel, Elçi, and Ertugrul (2016) proposed a DSS called Fetal Heart Rate Monitoring System (FHRMS) via a mobile integrated Doppler device (mDoppler) with an attached Toco Probe for gathering fetal heart rate (FHR) and uterus contraction (UC) signals, respectively. The system is designed to assess the FHR values of an unborn baby at certain intervals, by considering instant baseline FHR, baseline FHR variability, and any periodic and/or nonperiodic FHR changes, including acceleration and deceleration signals. FHRMS is able to determine the current fetus status via its inferencing mechanism coded as green, yellow, and red indicating normal, atypical/warning, and abnormal/alarm status, respectively. In the case of the latter, the ambulance service is also informed. SW rule knowledge base of FHRMS is constituted from various medical SWRL rules by using the SWRL tab of Protegé. To run the SWRL rules via Web services, Pellet API (Pellet) is used. By importing OWL API (Horridge & Bechhofer, 2011) and Pellet API libraries in the Java environment, the inference engine of FHRMS is developed on Web service modules of the system.

Çifçi, Ertugrul, and Elçi (2016) proposed an ontology-based RS called mobile search service (MSS) to search and find mobile applications on proper food consumption. The MSS utilizes many tools for the development of search engine components, such as Hadoop, MapReduce, HBase, Hive Sqoop with RDBMS, PHP, Java, and SQL. The Redlink Solr plugin (Redlink) is used for semantic search on Hadoop. MSS uses content-based filtering to recommend a list of appropriate food consumption mobile services.

Sabra, Mahmood, and Alobaidi (2017) proposed a clinical decision support tool entitled Semantic Extraction and Sentimental Assessment of Risk Factors (SESARF). SESARF provides an early diagnosis by analysing the clinical notes of electronic health records (EHR) in order to detect hidden risk factors. SESARF is a semantic extractor to identify hidden risk factors in clinical notes and a sentimental analyser, which uses SentiWordNet for assessing positivity or negativity of an adjective or adverb, to assess the severity levels associated with the identified risk factors, thus providing early diagnosis. The identified risk factors are mapped to ontologies to find their correlation in pinpointing the top three diseases for further testing to confirm a diagnosis; semantic rules help filter certain characteristics that apply to some risk factors to enhance accuracy. Linked open data (LOD) sources such as Diseasome, DBpedia, and Bio2RDF are used while creating risk factors disease-focused dictionary vocabulary. This tool can be customized to any disease using LOD by selecting a specific disease and collecting its risk factors list from medical ontologies.

Ertugrul, Elçi, and Bitirim (2017) proposed an RS named Intelligent Tracking System: Application to Acute Respiratory Tract Infection (TrackARTI). The TrackARTI system has two main parts: TrackARTI Mobile Application and TrackARTI Inferencing Mechanism. The system provides to track disease term of 0–6 age group child patients remotely (e.g., home and clinics). The aim of the system is to help to diagnose and recommending appropriate supportive medical emergency intervention through its own inferencing mechanism. TrackARTI includes its own OWL 2.0-based TrackARTI ontology and SWRL rules to determine a set of supportive medical suggestions for parents and medical staff alike. Pellet reasoner is used for executing the SWRL rules to drive inferencing in Java Web services. Certain add-on mobile medical apparatuses (e.g., add-on camera lens, mobile-enabled otoscope, and infrared mobile temperature sensor) were also employed in this research study.

Taçyıldız, Ertuğrul, Bitirim, Akcan, and Elçi (2018) proposed an ontology-based Obesity Tracking System for Children and Adolescents as an RS. The system involves four primary modules: health expert module (HeM), parent module (PaM), child/adolescent module (ChM), and rule-based expert module (RbEM). Obesity patient data are collected by health experts through HeM during their consultations and by the parents through PaM at home via a mobile application. The profile and medical data of the patient such as present age, latest weight, latest height, head circumference (HC), and waist circumference (WC) are collected during consultation. Some metrics such as body mass index (BMI), BMI percentile, weight percentile, and height percentile are calculated for assessing the progress of obesity risk as well as recommending subsequent proper treatment, daily physical activities, and required nutritional habits for the patient. The system produces various notifications (e.g., pill reminders, a reward for an accomplishment) and suggestions (e.g., TV/ iPad/smartphone screen activity period). The system supports experts as a smart expert health care system through its built-in Obesity Tracking Ontology (OTO), SWRL and SQWRL rules, and inference engine.

Rawte and Roy (2015) proposed an ontology-based expert system for thyroid disease diagnosis. The ontology involves the domain concepts and properties of thyroid diseases and their symptoms. The system consists of three parts: (a) an ontology knowledge base and logic rules, (b) an inference engine, and (c) a user interface. The main role of the ontology in the study is to keep domain knowledge and rules used to infer the thyroid disease-related diagnosis. Protégé and SWRL are used in creating the system ontology and semantic rules, respectively. Jena reasoner is used to deducing diagnosis based on the ontology knowledge and the SWRL rules. MySQL database keeps the data in the back end. A JSP Web application provides the user interface. In order to compare approaches, the researchers also applied a neural network trained on thyroid hormone levels (i.e., TSH, T3, and T4) in the blood; it is found that the ontology-based expert system gives more accurate results with lesser complexity.

Chen, Jiang, Huang, and Bau (2017) proposed a DSS for diabetes based on ontology reasoning and TOPSIS analysis. There are four modules in the system: (1) the patient consultation management module, (2) the patient perfect HbA1c target inference module, (3) the drug knowledge ontology and reasoning module, and (4) the antidiabetic medication ranking module. Through Module 1, a clinical doctor can input patient data. Module 2 uses some fuzzy approaches (fuzzifier, fuzzy rules, fuzzy inference, and de-fuzzier) to infer the patient's personalized HbA1c target. Module 3 recommends antidiabetic drugs for the patient. Module 4 uses technique for order of preference by similarity to ideal solution (TOPSIS) algorithm (Hwang & Yoon, 1981), which is a multicriteria decision analysis method, to calculate the relative closeness to the ideal solution, thus determining the ranking of antidiabetic drugs. A drug ontology knowledge base for diabetes disease was created using Web-based Protégé; Jena is used as well to evaluate the antidiabetic medication reasoning module.

6 | DISCUSSION AND OPEN ISSUES

In this study, we compared the proposed RSs in the literature in terms of the techniques and filtering used. As a result of literature research, the candidate RSs are assembled under seven main groups in terms of filtering features: content-based filtering, collaborative-based filtering, hybrid filtering, knowledge-based filtering, context-aware based filtering, social-based filtering, and demographic-based filtering. Furthermore, the techniques and methods commonly used under these seven main groups, such as clustering, classifying and regression, graph theory, knowledge-based, context-aware based, probabilistic, and matrix factorization, are discussed and compared. Some concerns and corresponding critical questions popped up during the studies discussed in this research, and these are: (a) Which filtering is seen as a better approach? (b) How do we accurately evaluate the recommendations generated by an RS as an indication of the system performance? (c) Can user satisfaction from an RS be measured and somehow integrated into RSs? We shall briefly consider these concerns below.

6.1 | Which filtering is a better approach?

According to the idea obtained from the research studies discussed in this article, the systems proposed offering hybrid filtering and OWL ontology knowledge base have shown good results in producing better predictions for the users. However, considering all approaches in perspective, the performance values of such systems are still not comparable clearly for want of correct metrics that can express the goodness of an RS. Nevertheless, we can say from our own perspective; hybrid systems, especially blending of machine learning and knowledge-based approaches, produce better recommendations thanks to explicit annotation of customer and product properties, constraints on the properties of customer and product, filtering conditions (relationship between customer and product), instantiations of customers and products, and machine-understandable format. Such hybrid solutions achieve accurate problem-solving reasoning (case-based reasoning, constraint-based reasoning, and rule-based reasoning approaches are highly used) while maintaining knowledge base shareability and extensibility. As a result, neither other filtering recommenders nor stand-alone knowledge-based recommenders are efficient and successful systems on their own; but they are highly complementary to other types of RSs.

6.2 | How can we evaluate the recommendations generated?

RSs have been extensively studied in the last decade and have shown to suit many economic sectors. Recently gaining preeminence due to easy and ubiquitous Internet access, e-commerce companies seek RSs to increase their sales (e.g., Netflix, YouTube, Tinder, and Amazon). Through algorithms used, RSs provide predictions of items that the user may find interesting to purchase or, at the least, attract user attention to provided recommendations matching user's preferences. RS studies in the literature proposed how to evaluate RSs generally used machine learning metrics for offline cases; these are *accuracy*, *root mean square error*, *mean average error*, *precision*, and *recall* performance metrics, which have been widely applied for measuring system performance. These metrics are necessary for the offline performance of RSs; however, they are not enough to give an idea of how well an RS satisfies users' requirements. To evaluate the goodness of an RS, Silveira, Zhang, Lin, Liu, and Ma (2019) identified a *totally 25 major state-of-art performance metrics* discussed and summarized in six concept groups: *utility*, *novelty*, *diversity*, *unexpectedness*, *serendipity*, and *coverage*. These are briefly introduced below.

Utility is defined as an order of favourite of consumption. This metric is suggested to assess *utility* in the recommendation focusing on how the user might react to the predictions generated by a recommender. They also stated that the use of utility could be measured by evaluating the rating that the user gives to predicted items after consuming. For instance, users' ratings of movies on a 1–5 scale, with 5 being the highest rating.

Novelty is a concept which usually comprises the idea of having original items in the recommendation. In fact, novelty concept is considered "to be at first" simply however, it has various definitions in the literature. Therefore, the researchers categorize the novelty definitions and metrics into three levels, which are a life-level novelty, system-level novelty, and recommendation list-level novelty. The first, life-level novelty means that an item is novel in the life of the user, that is, the user has never heard of the item in his/her life (e.g., launching a new alternative product in the market and offering it to users for the first time). The system-level novelty comprises that an item is unknown for the user according to the user's consumption history (e.g., video content provider Netflix analyses past movies watched by a user to help the user decide which movie to choose). The recommendation list-level novelty is concerned with nonredundant items in the recommendation list. For instance, system does not show extra items or repeated recommendations in the recommendation list generated (e.g., a book retailer system does not show the books previously read by a user or recommended three times in the past).

Diversity is a concept concerned with the diversity of items in the recommendation list. It is a required and essential concept in recommendation systems due to users' wish and need for some variety in the recommendation. The metric calculates diversity as a dissimilarity between the items; therefore, it can be calculated through measuring distance between items *i* and *j* in the recommendation results (e.g., a book retailer system would recommend books from the same genre to the user in the recommendation list). If the diversity value in the recommendation results is low, that means the items in the recommendation results are similar to one another. In the other case, one is considered the opposite.

Unexpectedness is another concept that defines the idea of surprise in recommendation results. In the research, study unexpectedness is defined as a deviation from the expected recommendations. For this concept, researchers proposed two sets of metrics. The first set is metrics based on a primitive recommender. Second, principles-based metrics that do not involve a primitive recommender. According to researchers, a primitive recommender usually indicates what items the user expects to consume. The problem in primitive recommenders based on metrics extends in the selection of an appropriate primitive recommender. The choice must be made taking into account the context of recommendation. For example, there may be different expectations for movies and songs. Moreover, different primitive recommender will lead to different unexpected values. Principles-based metrics do not involve a primitive recommender; they provide to compare the recommended items and the user's history and then check to see if the user is likely to know the predictions.

RSs typically recommend items that users are already familiar with. Therefore, the recommended items attract little attention for them. For example, in a shopping system, it can offer products such as milk and bread to their customers. Although the system actually predicts that the customer can buy these two products, such recommendations will not be surprising or intriguing to the customer. Because it is clear that those two products will be purchased without prompting. The goal of the *unexpectedness* metric is to increase the diversity of recommended items in such systems and to surprise users by offering unexpected items.

Serendipity is defined as another concept that means a lucky finding or a satisfying surprise (e.g., user finds something good or useful while not specifically searching for it). Metrics have been proposed to measure serendipity in recommendation lists. In general, it means preventing and avoiding users' expectations. In addition, the criteria for measuring serendipity in the lists of recommendations have some relationship with the concepts in which serendipity is included: novelty, unexpectedness, and utility.

Coverage is another concept that evaluates the whole RS instead to evaluate recommendation results. In addition, the concept is categorized by item space coverage, userspace coverage, and genre space coverage. Item space coverage refers to the extent of items that an RS is able to make predictions. An RS with lower item coverage bounds the recommendations for the user. Low coverage stops them from discovering suitable items to consume, effecting the users' satisfaction and in the overall system. Userspace coverage indicates the proportion of users that an RS can predict items for. For some types of recommendation problems, the predictor may not have high sureness in the accuracy of the prediction for users. Therefore, this coverage type would measure the proportion of users receiving effective recommendations. The last coverage type, genre space coverage, is defined by the researchers as the number of distinct genres of items that are recommended to users effectually. Eventually, the genre of space coverage is more relevant to the diversity of suggestion lists.

6.3 | Can user satisfaction be measured by and integrated into RSs?

The concept groups introduced above have been put forward with the goal to satisfy customer requirements. The researchers presented the detailed definition of each metric underlying each concept aimed to evaluate recommendations, also displaying differences and usages of them. The metrics are clustered according to their user dependency characteristics. The concepts in evaluations of generated recommendations are concerned for user satisfaction so that the predictions can provide more worth for users. For this reason, the performance of an RS should be measured by the value it can generate for the customer. As a result, the offline performance measurement of an RS is essential, but it is not enough alone for user satisfaction. There are many useful concepts as composite metrics to evaluate recommendations by an RS in online mode as introduced above. Future research in PHRSs could evaluate the generated recommendations and used algorithms by taking into account all the discussed concepts. As a result, user satisfaction on recommendations and their impacts (e.g., *utility*, *novelty*, *diversity*, *unexpectedness*, *serendipity*, *and coverage of the recommendations*) and using ontology knowledge bases in terms of shareability and extensibility in RSs should be considered when modelling new RSs.

This review provides a compendium of resources regarding filtering approaches and methodologies applied in PHRSs, clear problems in system performance, customer satisfaction metrics, and concepts, and how to structure the architecture of future PHRSs. After evaluations, we identified the important and valuable aspects of the main directions of open issues for future study in the field of PHRSs as discussed above.

7 | CONCLUSION

This paper contributes to the current state of research by discussing major concepts and practices applied in PHRSs. As a result of the literature review of recent research studies, RSs were slotted under the following seven main groups in terms of their filtering features, namely, content-based, collaborative-based, hybrid, knowledge-based, context-aware based, social-based, and demographic-based filtering. Various machine learning, data mining, information retrieval, graph theory, heuristics, and probabilistic approaches used in PHRSs were collated under these main groups as well. Numerous PHRSs were reviewed, discussed, and compared in the case study section; they were also modelled on clustering, classifying and regression, graph theory, knowledge-based, context-aware based, similarity matching, and matrix factorization. In addition, the three critical questions derived from the research studies were discussed in the evaluation and open issues section which are: (a) Which filtering is seen as a better approach? (b) How do we accurately evaluate the recommendations generated by an RS that indicates the performance of the system? (c) Can user satisfaction be integrated into and measured by RSs? As a result, the performance of PHRSs should be measured both offline and online by considering user satisfaction and the quality of recommendations generated. In addition, some open points in PHRSs should be discussed in future RS studies, and plausible answers to the following four questions should be researched: (a) What concepts and their metrics should be considered in PHRSs to satisfy user requirements? (b) What factors are crucial for the hybrid PHRSs with an ontology knowledge-based filtering approach? (c) What methodology of online evaluation to employ in the PHRSs? (d) What online evaluation metrics and their relationships with offline performance metrics are crucial in the PHRSs? These four aspects are important and valuable for future studies regarding PHRSs.

The concern for treatment quality in the health sector has been on the increase lately. The main challenge is to personalize treatment while improving treatment quality. The provision of similar treatment recommendations to every patient reduces the quality of treatment. Therefore, personalization of treatment is a necessity because each patient is a different case, plausibly exhibiting special conditions. Over the next decade, field experts have considered increasingly digitalized life and the well-being of individuals. Sara Kiesler, professor emerita and National Science Foundation program director, stated, "There will be winners and losers, as occurs now, and for individuals, some aspects of life will be better, and some will be worse" (Anderson & Rainie, 2018). Whereas Sara Kiesler described the winners as "entrepreneurs who invent new services or products and successfully reach new customers; …," the losers were described as "people without the resources to take advantage of online health, education or financial services; people who use the internet as a substitute for in-person social interactions; people who believe everything they read, hear, or see online and never question these opinions." Clearly, it is important for online health care users to benefit from PHRSs, make themselves aware of their use, monitor positive and negative impacts on them, and seek measurable online/offline performance of systems in terms of their satisfaction.

Besides the complexity of filtering techniques and algorithms used in PHRSs, making sense of complex and unstructured health data pause another important challenge. Hybrid PHRS may execute machine learning models and training on available data before serving health care providers with results. Google has submitted a comprehensive patent covering deep learning and EHR analytical foundations in the health care industry (Bresnick, 2019). To create comprehensive PHRSs working on EHR big data, researchers are performing many scientific studies and working hard to identify variables, normalize data, and overcome missing parts in real-time EHR data. Therefore, Google stated that PHRSs with machine learning and deep learning could be used for detecting abnormal lab variables, predicting unplanned transfers to intensive care, and alerting providers to conditions like acute kidney injury. The idea is that their application goes on to describe nearly every permutation of predictive analytics using deep learning on EHR data and includes the idea of aggregating EHR data from multiple sources into a single and standardized format.

Wiesner and Pfeifer (2014) argued that "a recommendation process must be able to cope with: (a) imprecise terms (e.g., Hepatitis ⇔ chronic viral Hepatitis), (b) colloquial terms (e.g., Period ⇔ Menstruation) and (c) misspellings (e.g., Diabedes or Diabedis ⇔ Diabetes mellitus)." According to the researchers, a good PHRS should cope with expert vocabulary primarily used by doctors and other health professionals as well as layman's description of symptoms. In addition, the PHRS may need to determine whether the clinical conditions specified in the clinical reports are unfavourable (e.g., "Autoimmune retinopathy in the absence of cancer" ⇔ excluded term "cancer"). It also stated that finding relevant information can be a challenging task, especially for health-related information by individuals (Wiesner & Pfeifer, 2014). A health consumer can access the Internet, but it can be difficult to determine which resource is relevant to his or her health problem. Often, the user cannot even find appropriate key terms to narrow down the search for specific medical problems. Another problem is that, even if the person finds the information necessary for the medical problem as a result of the search, he/she cannot understand the semantics of the relevant medical terms. Medical terminology, which is used online in many sources, is often misunderstood and misinterpreted by individuals without a medical background. Another issue is context-awareness. Data on a medical problem should be given or interpreted in a particular medical as well as personal context, usually in connection with a case or medical condition. Using a search engine or encyclopaedia holds the risk of missing this kind of context, leading to incorrect results and inadequate decisions.

In short, in advanced PHRS systems, we think that health information content should be pinned to a relevant general structure such as a domain upper ontology, be standardized, shareable and extensible, expanded by systems, enabling reasoning, and inferences in case reviews. In addition, in measuring the performance of a PHRS, it is obvious that more accurate results could be obtained with a large number of users in training a PHRS, either offline or online, which is costly. To that end, new performance measurement models may be required to achieve more accurate assessments with fewer user data.

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How to cite this article: Çelik Ertuğrul D, Elçi A. A survey on semanticized and personalized health recommender systems. *Expert Systems*. 2020;37:e12519. https://doi.org/10.1111/exsy.12519