A Comprehensive Review on Smart Decision Support Systems for Health Care

Mário W. L. Moreira, *Student Member, IEEE*, Joel J. P. C. Rodrigues, *Senior Member, IEEE*, Valery Korotaev, Jalal Al-Muhtadi, and Neeraj Kumar, *Senior Member, IEEE*

***Abstract*— Medical activity requires responsibility not only based on knowledge and clinical skills, but also in managing a vast amount of information related to patient care. It is through the appropriate treatment of information that experts can consistently build a strong policy of welfare. The primary goal of decision support systems (DSSs) is to give information to the experts where and when it is needed. These systems provide knowledge, models, and data processing tools to help the experts make better decisions in several situations. They aim to resolve several problems in health services to help patients and their families manage their health care by providing better access to these services. This paper presents a deep review of the state of the art of smart DSSs. It also elaborates on the latest developments in intelligent systems to support decision-makers in health care. The most promising findings brought in literature are analyzed and summarized according to their taxonomy, application area, year of publication, and the approaches and technologies used. Smart systems can assist decision-makers to improve the effectiveness of their decisions using the integration of data mining techniques and model-based systems. It significantly improves the current approaches, enabling the combination of knowledge from experts and knowledge extracted from data.**

***Index Terms*—Applications, data mining (DM), decision-making, health care, smart decision support systems (DSSs) technologies.**

Manuscript received June 26, 2018; revised November 17, 2018; accepted December 24, 2018. This work was supported in part by National Funding from the FCT - Fundação para a Ciência e a Tecnologia through the Project UID/EEA/50008/2013, in part by the Government of the Russian Federation under Grant 08-08, in part by Finep, with resources from Funttel, under Grant 01.14.0231.00, under the Centro de Referência em Radiocomunicações - CRR project of the Instituto Nacional de Telecomunicações (Inatel), Brazil, in part by the Brazilian National Council for Scientific and Technological Development (CNPq) via Grant 309335/2017-5, in part by the Ciência sem Fronteiras of CNPq, Brazil, through the Process 207706/2014-0, and in part by the International Scientific Partnership Program ISPP at King Saud University through ISPP #0129. *(Corresponding author: Joel J. P. C. Rodrigues.)*

M. W. L. Moreira is with the Instituto Federal de Educação, Ciência e Tecnologia do Ceará, Aracati, CE 62800-000, Brazil, and also with the Instituto de Telecomunicações, Universidade da Beira Interior, Covilhã 6200-161, Portugal (e-mail: mario.moreira@ieee.org).

J. J. P. C. Rodrigues is with the National Institute of Telecommunications, Santa Rita do Sapucaí, MG 37540-000, Brazil, with the Instituto de Telecomunicações, Universidade da Beira Interior, Covilhã 6200-161, Portugal, with ITMO University, Saint Petersburg 197101, Russia, and also with the College of Computer and Information Sciences, King Saud University, Riyadh 12372, Saudi Arabia (e-mail: joeljr@ieee.org).

V. Korotaev is with ITMO University, Saint Petersburg 197101, Russia (e-mail: korotaev@grv.ifmo.ru).

J. Al-Muhtadi is with the College of Computer and Information Sciences, King Saud University, Riyadh 12372, Saudi Arabia (e-mail: jalal@ccis.edu.sa).

N. Kumar is with the Department of Computer Science and Engineering, Thapar University, Patiala 147003, India (e-mail: neeraj.kumar@thapar.edu).

Digital Object Identifier 10.1109/JSYST.2018.2890121

I. Introduction

IN THE last decade, decision support systems (DSSs) have presented numerous reliable health services. These services have offered affordable health care solutions. Nowadays, people can use information and communication technologies that favor the interaction between patients and their physicians, improving the patient's quality of life. Physicians can have easy access to patients' medical records, lab results, images, and information about medication, anytime and anywhere [1]. In the same way, patients can have access to their diagnostic situation as well as information about how to have a healthy life. Medical diagnosis is one of the most important research topics in information technology and medical informatics. Smart systems present several challenging issues and limitations. In this sense, computer-based techniques are proposed as a solution to overcome such barriers, concentrating on enhancing the patients' quality of life.

Schummers *et al.* discuss risk prediction models in development by evaluating their performance under various predictive characteristics [2]. This study shows that the state of the art on such systems offers little insight for researchers looking to assess whether a predictive model works well for a particular research question. Thus, Yoo *et al.* present data mining (DM) techniques as an essential solution that has been growing in recent decades [3]. These inference mechanisms for intelligent systems can help decision-makers obtain meaningful information, facilitating the understanding of large health datasets. Besides this, there are several approaches to the validation of DM solutions, giving support to all phases of DM testing. These assessment techniques provide objective measures that can be used to evaluate the computer-assisted method's reliability for predictive analysis. Feinleib suggests that DM methods are an excellent way to transform health care through decision-making assistive instruments [4]. Health-care experts make several decisions during a day. These can have important effects on their patients' health and their well-being. Although medical care is improving, the escalating amount of data and consequently, the way in which that data can relate to patients, is making these decisions more and more complicated. Rubiano and Garcia analyze the results obtained at each iteration in a DM process [5]. Each obtained result is evaluated as to the expected results, the characterization of the data input and output, and the model pertinence achieved regarding its prediction accuracy. The results show that, depending on the strategies implemented during the DM process, a careful preprocessing could have a significant impact on the mining results. Decisions such as the elimination

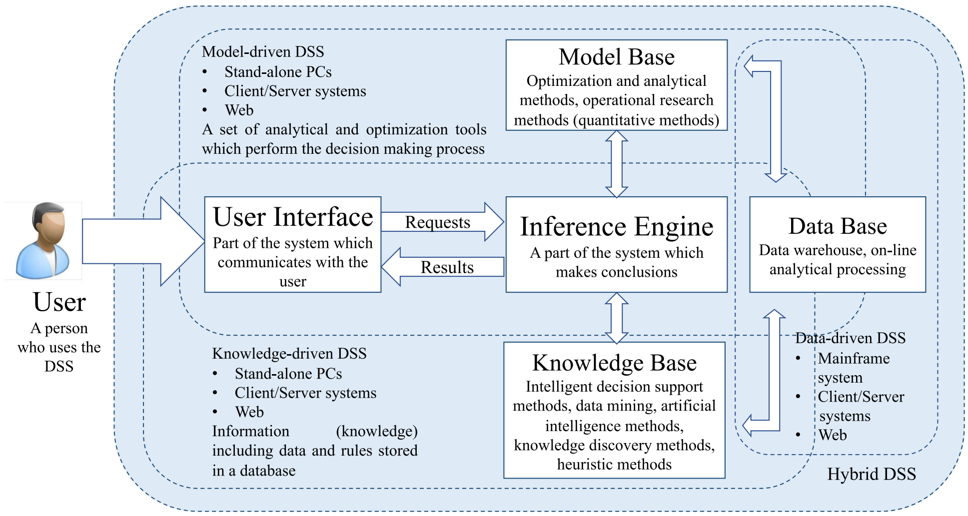

Fig. 1. Overall architecture scheme of a DSS. Source: Authors' elaboration.

of attributes or the discretization of data should not be taken without due consideration. Besides, a careful evaluation of the removal of ignored and misclassified instances can substantially improve accuracy rates in the predictive model development.

The main contributions of this research include the review of the state of the art, analysis, discussion, and identification of open issues in each type of DSS for health care. Related technologies, approaches, and applications will be described to provide insights into the primary trends, implications, and future research directions for novel theoretical developments. The results of this research will show the potential of further studies, showing that this topic is a hot topic for the research community and will have a significant impact on most readers. This study will enable a more precise mapping of the advances in health care research, implying the development of its primary activity sectors. In this perspective, this research seeks to improve the entire health care field through an appropriate research development, indicating trends, recurrences, and gaps.

The layout of the paper is organized as follows. Section II overviews the works related to smart DSSs for health care. Then, the third section provides an analysis of the novel smart systems solutions for health care. In Section IV, the open issues are illustrated, and the suggested further research is presented. Finally, the main conclusions will be presented in Section V.

II. Smart DSSs in Health Care

The previous section addressed the applications of DSSs in several areas of knowledge. This section will discuss the use of three primary types of smart DSSs in health care. It categorizes these systems by their leading dimensions as well as three secondary aspects (the users, degree of generality, and technology). The main differences among these three categories within the taxonomy proposed by Power [6] are as follows, while model-based intelligent systems provide decision support with the use of analytical tools such as algebraic analysis and simulation, data-based systems enable the management, retrieval, and manipulation of unstructured information in various storage formats. Knowledge-based systems, however, provide a set of solutions or suggestions of the problem through knowledge stored as a form of facts, rules, procedures or similar structures. Fig. 1 presents an overall framework illustrating the main categories of DSSs.

A. *Data-Driven DSSs*

A data-driven DSS allows the "access and manipulation of time series of internal, external, and real-time data" [7]. In more recent years, data-driven DSSs with on-line analytical processing, data warehouse systems, executive information systems, also referred to as executive support systems, and geographic information systems are considered the main approaches to decision support.

In the last decade, research has been conducted in systems designed to support people's daily activities. The use of smart systems is needed to support emergency medical services. Xu *et al.* discuss "a semantic data model to store and interpret Internet of Things (IoT) data" [8]. This approach is designed to collect and treat ubiquitous data to enhance the feasibility of data storage. It can access universal data in real time on a cloud, using a mobile platform. This IoT-based system for emergency medical services provides support for emergency medical services. The results of the research show that this process is efficient in a diversified and distributed data environment. Sunyaev and Chornyi create a prototype of a system of self-management in health that assists patients with diabetes to track their blood glucose levels [9]. The results show that this system is an important instrument in an integrated diabetes treatment that encompasses hospital care, rehabilitation, and self-care.

Recently, health care organizations have adopted electronic health records (EHRs) as a reference on medical registries, and this suggests a high potential for clinical DSSs (CDSSs) that directly use data collected by such an organization [10]. Cheng *et al.* have developed a CDSS for intensive care units to improve outcomes for critically ill patients [11]. That system provides real-time decision support, decreasing the errors in medical decisions. An interactive and easy-to-use user interface was developed that enables decision-makers to use the DM for decision-making in real time. To help people with Parkinson's disease who suffer from mobility problems, Blake and Kerr investigate environments in which physicians diagnose patients with sleep disorders [12]. The study develops an online support system that gathers patients' historical data. It improves the effectiveness of the consultations, medical diagnosis, and patient treatment plans. Puppala *et al.* propose the design of an analytics platform for the health care industry [13]. The research develops an integrated clinical informatics environment for improving research. This framework considers an enterprise data warehouse and intelligent and analytical software for enabling a broad range of CDSS to facilitate data access. The results show that this system could aid significant research in clinical informatics, providing a means for data synthesis and adequate access in promoting medical research. Goldberg *et al.* test the effectiveness of performing brain trauma prognostication rules for children with minor blunt head injury [14]. The study integrates EHRs and a web-based CDSS for emergency departments to assess the performance features of the combined model and the source of the recommendations generated by experts. The results show that a remote clinical decision support system decreases time-to-trial in the decision support to clinical interventions.

The increasing number of wearable systems for collecting data provides a better opportunity for an early diagnosis. Mazilu *et al.* present a wearable system designed for independent use [15]. This system uses a smartphone application to allow careful and long-term monitoring of the patient's medical condition by sending sensing data and statistical information to an e-health service. The statistical results show a positive effect on participants' mobility when using the wearable support system [16].

Data-driven systems can be crafted to enable diagnostics and prognostics even without system-specific knowledge. Data-driven approaches that use pattern recognition and statistical techniques to detect changes in the system can be suitable for diagnostic purposes. There are some limitations to data-driven systems. Their approaches depend on historical data to determine correspondences, establish patterns, and assess data. In most cases, there will not be sufficient data to achieve health evaluations. Therefore, this requirement of historical data to make decisions is one of the restrictions of data-driven methods.

B. *Knowledge-Driven DSSs*

In the 1990s, the DSSs began to use artificial intelligence (AI) techniques. Expert systems are modeled using reasoning to solve problems on a machine by way of inference engines. The knowledge domain may be classified in three levels—contextual, content, and structured or unstructured knowledge. Moreover, there are two types of technologies for knowledge modeling—clustering and ontology. Clustering techniques classify the knowledge into different classes whereas ontology captures the consensual experience.

Ontologies are commonly used for the integration of knowledge, as well as for performing inferences about this knowledge. This approach promotes the representation of information through terms, real-world concept definitions, and the description of semantic relations. Thus, this approach does more than describing the syntactic relationships among data. The clustering analysis, which is present in the domain ontology, corresponds to the unsupervised learning most used in data analysis and mining, focused on the discovery and interpretation of groups of objects presenting similar properties and/or behaviors.

Tawfik *et al.* review clinical applications in three different geographical regions. This research reveals that ontological practices play a fundamental purpose in adapting information for decision support [17]. It proposes an advanced web-based framework for effective clinical practices in decision support. The conceptual design of this system uses a comprehensive-based analysis of health care into ontological methods. Khan *et al.* present a medical DSS that uses an approach based on the probabilistic reasoning for time-critical decision scenarios [18]. This hybrid system uses an ontology to support decision-making about patient treatment. This research combines semantic, ontology, and probabilistic reasoning to give decision-makers an effective treatment to offer to the patients. This approach can be applied in other decision-making situations where several restrictions limit the application of conventional processes. Zhang *et al.* present a semantic-based method for the combined description of health care field knowledge and patient data for decision-making in clinical employment [19]. The study performs a learning engineering sequence to generate a semantic base, including an ontology to represent the information and the patient data. An expression repository is used to codify clinical decision-making standards and consultations. A case study was performed using inpatient management data of diabetes mellitus patients to assess this approach. The proposed method provides a high accuracy rate.

Dong *et al.* propose the use of a CDSS "to improve the accuracy of the diagnosis of headache disorders" [20]. The methodology applied in this proposal for the construction of an ontology makes use of a computerized clinical model for guidelines and a medical knowledge base. The results show that this knowledge-based model had "high diagnostic precision for most of the primary headaches and some categories of secondary headaches." It could help experts at first attendance hospitals "improve the diagnostic accuracy and reduce headache disorders."

Basilakis *et al.* describe a telehealth system that uses a combination of obtained clinical measurement parameters of a DSS [21]. This model combines "a rules mechanism and statistical analysis instruments to analyze the collected data searching for trends and patterns in parameter values". It influences the changes in targeting clinical resources to patients with the most need. This research shows the potential benefits of integrating telehealth and decision-making support in the management of chronic diseases. Bi and Abraham introduce a web-based CDSS "that integrates intelligent technology, complex guidelines, and knowledge to improve decision-making in asthma care" [22]. The system uses a model-view-controller approach. It uses three tiers—"a web-server, reasoning algorithms, and a database."

The recent development of technologies and application domains of knowledge-based DSSs, such as ontology engineering, and contextual knowledge in medical systems, has elicited a strong link showing a broader picture and provided a synergistic view of these systems. Future research will focus on the development of these systems in general and, in particular, clinical systems to support decision-making groups.

C. Model-Driven DSSs

The model-driven DSS optimizes or simulates the outcomes of decisions based on provided data. In these systems, the decision-maker manipulates the model to analyze a situation. The mathematical model is a plausible representation of the real process. In these systems, the statistical data input is limited, and the computational methods and evaluation of uncertainty are essential. Nowadays, there are three techniques used to create a model-driven system—decision analysis, mathematical programming, and simulation. This section focuses on the recent applications of these technologies in the construction of a model-driven system.

Zarkogianni *et al.* present the latest studies in sensors for glucose and lifestyle monitoring [23]. This study discusses a CDSS that facilitates the self-management of diseases and gives support to health care professionals in the decision-making process. The results show that the integration of sensor data and EHR combined with intelligent data analytics methods and user-based approaches enable necessary changes in diabetes care. Nair *et al.* have developed a smart system for managing anesthesia that works in conjunction with an information management system to provide clinical decision support [24]. This system uses logical rules and notification strategies. This real-time approach can be extended to identify medical problems and inform the health care providers in other fields [25], [26]. Such systems can also interact with various data systems and tools to improve the range of decision support.

Laskowski *et al.* present an agent-based modeling system to simulate the propagation of influenza virus contamination [27]. This research uses mathematical modeling techniques for disease spread. It uses ordinary least squares regression to analyze data. The results suggest that this DSS could assess the impact of infection control strategies. Hudson and Cohen describe a DSS that combines several methodologies for trend analysis in cardiology [28]. This system uses a general algorithm that uses a variety of techniques. This system needs "changes in the structure of the EHR to form a comprehensive record" of the patient lifetime. Emanet *et al.* develop predictive models that use machine learning (ML) methods to diagnose an asthma patient [29]. These models use sounds obtained from the thorax of the patient in a clinical laboratory. The performance evaluation of these models compares the accuracy of ensemble models, such as random forest (RF) and artificial neural network (ANN) models. The results show that this approach could help health practitioners make faster and reliable diagnostic decisions in conditions constrained by limited resources. Temko *et al.* present different approaches for visualizing the output information in a neonatal convulsion detection system [30]. This method is based on a binary output, probabilistic evidence, and a spatiotemporal map. This research evaluates the accuracy of a support vector machine (SVM) classifier, comparing its results with clinical expert knowledge using conventional metrics. This study also establishes an association among information visualization and the different techniques to determine these evaluation metrics. The results show that the aggregation of binary output and a probabilistic evidence method is a better technique to visualize the output in neonatal illness prediction systems.

Tekin *et al.* propose an expert system that learns online and suggests to the patient the best health expert, depending on the context [31]. A novel class of algorithms, aimed at discovering the most relevant patient circumstances, as well as the best clinics and specialists, is developed. The performance evaluation uses a real breast cancer dataset. The results show that this model-based approach could be applied in other environments. Champaign *et al.* present a framework for the care of children with autism [32]. The main focus of this system is for patients selecting objects from a web repository giving the caregivers the children's condition. This approach uses a method of simulated learning through a user survey. The results show its effectiveness at acquiring knowledge.

Bashir *et al.* propose a "multi-layer classifier ensemble model based on the association of different classifiers" [33]. A performance evaluation of several well-known classifiers uses datasets of heart, breast cancer, diabetes, liver disease, Parkinson's disease, and hepatitis, acquired from public repositories. This comparison shows that the proposed framework has achieved high diagnostic accuracy.

Model-based DSSs integrate different kinds of mathematical and analytical models for simulation and prediction of trends [34]. Therefore, the problem resolution capability of these simulation models contributes to avoiding the limitations of the approximations often used for optimization. The critical issue is the choice of the proper models and software, and the definition of the data format.

III. Classification Based on Power's Taxonomy

This section presents the critical aspects and objectives of the most vital smart DSSs for healthcare. Table I provides a summary and offers a comparative analysis of the most meaningful solutions for intelligent systems on health care. Moreover, this table highlights the classification of each solution into specific categories and approaches. The first column presents the references for the leading works in current literature. The second column (Power's taxonomy [6]/approach) considers the technologies for each type of approach, for example, the techniques for reasoning and inference. The third column discusses the contribution of each research as well as the methodologies used to reach these objectives. The critical aspects of each approach are presented in the fourth column. This point of view is essential for identifying future research directions. In the last column, future research suggestions are considered. This analysis is important for understanding the different types of approaches used in recent studies that will support and justify

TABLE I
COMPARISON ANALYSIS BETWEEN THE MOST VITAL SMART DSSS ON HEALTH CARE

Authors' name	Proposal approach	Main goals	Main technical aspects	Future work
Chalmers *et al.* [36]	Model-driven	· Specify a system that constitutes a prediction model.	· Use a conditional fuzzy c-means clustering with a custom distance to identify patterns in patient's data. · Need several simulations and tests.	· Improve the indicators of treatment outcomes.
Yao and Azam [37]	Model-driven (Web-based)	· Extend the game-theoretic rough set mode.	· Use a three-way decision-making strategy as well as the Markovian approach. · There is the occurrence possibility of inconsistencies among predictions performed by different classifiers.	· Analyze diverse decision-making perspectives.
Valenza *et al.* [38]	Model-driven	· Use a wearable system able to monitoring physiological parameters.	· Use a stochastic process based on the Markov chain to mood recognition. · Present a low storage and processing capacity. Need for a bridge device for data collection of the embedded devices.	· Develop a monitoring system for health care.
Kothari *et al.* [39]	Hybrid (computer-aided)	· Develop an image-based prediction model.	· Use a multiclass SVM algorithm. · High computational complexity and processing time.	· Increase the expanse of data repositories.
Taati *et al.* [40]	Model-driven	· Compare several DM techniques to recognize patients with the best survival chances.	· Use binary classifiers, such as logistic regression, SVM, and RF to achieve excellent classification results. · Lack of capacity of traditional tools to handle a large volume of data.	· Improvement in algorithms based on binary matrix operations.
Maggio *et al.* [41]	Hybrid (computer-aided)	· Describe an efficient approach to perform a computer-aided detection scheme.	· Use a nonlinear multi-characteristic algorithm for the classification task. · The unequal distribution of examples in the classes remains an issue to be addressed.	· Improvements regarding Performance evaluation related to prediction significance of the proposed technique.
Niaf *et al.* [42]	Hybrid (computer-aided)	· Address the pattern classification problem that is resulting from uncertainty caused by lack of information.	· Use a hybrid approach based on the classic SVM algorithm and fuzzy logic. · There is no precise mathematical definition.	· Investigate other multitask approaches.
Sukor *et al.* [43]	Data-driven	· Performance assessment of algorithms for measuring the quality of acquired signals.	· Use a novel noise detection algorithm based on waveform morphology analysis to identify noise artifacts in contaminated waveforms. · Necessity more investigation regarding the impact of data quality on model precision.	· Investigate the impact of data quality on system precision.
Mattila *et al.* [44]	Data-driven	· Classification assessment and computational performance using medical datasets.	· Use probability density functions for determining the resulting fitness function and the optimal classification threshold. · The implementations considered use more computational resources than other recent models.	· Algorithm precision enhancements to reach better performance results.
Mougiakakou *et al.* [45]	Data-driven	· Present a platform to assist the monitoring, administration, and treatment of patients with chronic diseases.	· Use a hybrid algorithm based on the combination of a compartmental model and a real-time ANN. · Issues related to standardization and interoperability need to be addressed to universalize the access to telemedicine.	· Investigate the quality of the service and the experience of telemonitoring systems.

the best technology for the development of further research on the topic. The use of DM appears in most of these research. This concept has been increasingly used in information management to reveal important knowledge structures for decision-making [35].

IV. OPEN ISSUES AND SUGGESTIONS FOR FURTHER DSS APPLICATIONS RESEARCH

After a detailed analysis of the above-presented approaches used in DSSs (in several areas of knowledge), the design of a smart system to give support to decision-makers still presents

TABLE I
(CONTINUED.)

Authors' name	Proposal approach	Main goals	Main technical aspects	Future work
Billis *et al.* [46]	Knowledge-driven	· Propose a decision support framework that can accurately evaluate the progression of the depression symptoms.	· Use Hebbian learning for fuzzy cognitive map-based algorithms for data classification. · Algorithms based on logic fuzzy do not learn quickly. · Difficulty setting rules correctly.	· Development of applications for monitoring daily living activities and identification of diseases.
Zięba [47]	Hybrid (service-oriented)	· Proposes a service-oriented DSS for diagnostic problems. · Applies several ML solutions in different distributed Web services.	· An ensemble SVM algorithm together with the repeated incremental pruning to produce error reduction algorithm presents the best performance. · Needs large volumes of clinical data to learn and reach high accuracy.	· Use ensemble learning classifiers for decision-making in diagnostic problems.
Exarchos *et al.* [48]	Hybrid	· Propose a DSS for integrate heterogeneous data.	· The best performing classification method involves a Bayesian network joint with a correlation-based feature subset selection algorithm. · Ensure shared information remains with the same context and meaning for all actors involved.	· Further evaluation to enhance the generalization capability of the proposed approach.
Guidi *et al.* [49]	Knowledge-driven	· Present a CDSS for the examination of heart failure cases. · Adopts classifiers based on decision trees to reach satisfactory results.	· The classification and regression tree algorithm is the most adequate to provide reliable outputs regarding the severity and type of heart failure. · Decision Trees do not extract patterns from the examples, only memorize observations. Thus, it is not expected that their capability can extrapolate to unforeseen cases.	· Generalize the findings to other approaches to improve the classification performance.
Soguero-Ruiz *et al.* [50]	Knowledge-driven	· Propose ontologies for cardiovascular risk recognition.	· Use ontologies for developing a cardiovascular risk stratification standardization framework. · Requires the presence of domain specialists for the construction of ontologies.	· Integrate several techniques to provide evidence-based decision support.
Lee and Wang [51]	Knowledge-driven	· Integrate new tools based on DM techniques with evidence-based decision support.	· Present a fuzzy ontology generation for semantic decision-making. · New assertion additions alter possible interpretations, which is improper for some domains.	· Refine the fuzzy ontology for a better complex illness prediction.

several challenges. A plethora of approaches and technologies have been identified in this survey. These technologies have influenced the development of novel systems significantly [52]. Moreover, it is possible to guarantee that these systems can support health professionals to cope with problems of uncertainty and complexity, increasing the efficiency and reliability of their decisions [53]. Based on the contributions collected from related literature, the most significant open issues can be classified into three main groups: 1) big data analytics; 2) DM; and 3) IoT. These issues are discussed and analyzed in the following sections.

A. *Big Data Analytics*

Big data analytics has great potentiality to modify the manner that health care professionals use modern technologies to gain knowledge from their medical and other data repositories [54]. "Big Data Analytics applications in healthcare are at the beginning stage of development, but fast advances in platforms and tools" are accelerating its development process [55]. Analyzing disease patterns, outbreak tracking, and data transmission to improve surveillance and give a more rapid response in emergencies, need more improvement. Transforming large amounts of evidence into significant information is very useful to identify needs in providing services. In the same way, this information can help predict and prevent risk situations. The next points address the major research fields on big data in health care.

- Hardware improvements. Development of necessary hardware components in the big data analytics in the health care field. For example, the development of cheaper solid-state drive technology with faster reading/recording time.
- Development of big data platforms and languages. Conventional tools are inefficient at handling big data. Big data-based platforms are very useful because most of the standard platforms have datasets that are too large for database management applications. Research on this trend could better the execution of enormous datasets to reduce costs and processing time.
- Development of role-specific database solutions. A significant problem in this research topic is predicting the

potential relationships between the existent nodes in the graph network. The composition of this network is frequently changing and continuously morphs with the inclusion, removal, and modification of existing nodes or borders. Comprehending the network organization might permit a better prediction of the dynamics or development of the network [56].
- Improvements in data visualization. To visualize essential information from a poorly understood and complex data, the development of complex algorithms is decisive for an accurate result. The accelerated development of knowledge visualization, visual analytics, and health informatics has produced substantial benefits in personal health monitoring [57], [58], medical treatment decisions, and general welfare policy [59]. These three domains have benefited from new relevant trends in several health application areas. The extraordinary affluence of the potential for knowledge visualization methods to improve health care will induce profound changes in many of these fields.

B. Data Mining

Knowledge discovery, as one of the DM techniques, affords a new way to extract valuable data information. It consists of the extraction of potentially useful information from data using ML [60], statistical [61], and “visualization techniques to discover and to present knowledge” that is easily comprehensible [62]. This method allows finding useful correlations, patterns, and trends, by filtering vast amounts of data using statistical and mathematical techniques. The directions of research in DM can be presented in terms of three main topics.

- Classical statistics. Conventional statistics adopt such concepts as “regression analysis, standard distribution, deviation and variance, cluster analysis” [63], and confidence intervals, used essentially to study data and data relationships [64]. Health care practitioners and researchers have been encouraged to investigate together further medical and public health applications using classical statistics. These have the opportunity to make some significant additional contributions to the theory using conventional statistical methods for the improvement of clinical diagnosis.
- AI. The primary objective of the development of AI is to understand the human intelligence at all levels. In another way, it represents a valuable technological development based on knowledge. AI has been used to create novel paths in addressing and solving very complex and math-based problems. Nowadays, the health care field is facing new challenges. These could be solved with the use of AI techniques. For example, the treatment of new diseases, cost reductions, and quick decisions during moments of emergency [65]. In the collection, treatment, processing, and presentation of patients’ data, these techniques perform a significant role in decision making [66]. AI could be useful to test and simulate novel treatments, scenarios, and devices [67].
- ML. The new trends of DM are the ML techniques, more accurately described as the union of statistics and AI. First, AI methods were used as research tools. Then, ML adopted these methods. This technique is an evolution from AI because it blends AI heuristics with statistical analysis. For the health care field, an important research topic is the development of algorithms that learn to recognize complex patterns using a large amount of data to make smart decisions. The primary focus is on developing techniques for an array of different challenging problems, such as clinical analysis [68], planning CDSS, and real world review evidence.

C. Internet of Things

There are, at least, five significant research trends on IoT.

- Extracting insights from remote monitoring data. IoT is one of the actual major research topics alongside patient remote monitoring and treatment [69]–[71]. The increase of patient records brings a new complexity for data treatment by the care provider and health experts. The development of IoT platforms helps extract insights from large datasets, solving several issues of these molds.
- Patient-centered analytics. This trend focuses on employing advanced analytics, visualizations, and decision support tools to improve diagnostic accuracy [72]. Research on this topic could improve treatments, making it more accurate, efficient, and personalized [73].
- Semantic interoperability and data integration. The semantic interoperability of health systems will allow managing the EHR of patients distributed on several heterogeneous systems. It has an important role in describing essential factors to improve patient care quality, public health services, and medical investigation.
- IoT solutions for health management. Each day, users are taking more responsibility for their health. Research on this topic could yield better access to data and improved health technology solutions. Besides, it could also allow consumers to manage their health care.
- Sharing of patient data with security and privacy. It is important to establish a novel set of protection policies focused on the IoT, mainly for wearable and implantable technologies [74].

V. Conclusion

Smart systems are intended to support experts in identifying and solving problems of decision-making. Systems that combine both statistical models and data are projected to assist the decision-makers better. The primary goal of intelligent systems is to improve the effectiveness of decision-making. This work stresses that DM integration approaches can significantly improve the available approaches, enabling the union of knowledge from experts with information obtained from data. This research is based on a deep analysis of the state of the art and identifies the approaches and technologies employed in DSSs in several areas of knowledge. The objective of this chronological survey contributes in making a comprehensive analysis of the state of the art, identifying open research issues in smart DSSs in health care. For this purpose, this paper presented a broad discussion, identifying the open topics of several research studies, discussing the primary challenges, qualities, and weaknesses in the development of smart solutions for decision support. The limitations of this research are related to the difficulty in enclosing the recent studies in a given category, considering that the development of new approaches is dynamic and discusses several aspects found in each of these categories. Another limitation is the rapid development of methods and technologies, which precludes a complete view of the whole state of the art.

References

[1] J. Horsky, J. Aarts, L. Verheul, D. L. Seger, H. van der Sijs, and D. W. Bates, "Clinical reasoning in the context of active decision support during medication prescribing," *Int. J. Med. Inform.*, vol. 97, pp. 1–11, Jan. 2017.

[2] L. Schummers, K. P. Himes, L. M. Bodnar, and J. A. Hutcheon, "Predictor characteristics necessary for building a clinically useful risk prediction model: A simulation study," *BMC Med. Res. Methodology*, vol. 16, no. 1, Dec. 2016, Art. no. 123.

[3] I. Yoo *et al.*, "Data mining in healthcare and biomedicine: A survey of the literature," *J. Med. Syst.*, vol. 36, no. 4, pp. 2431–2448, Aug. 2012.

[4] D. Feinleib, "Big data," in *Big Data Bootcamp: What Managers Need to Know to Profit From the Big Data Revolution*. Berkeley, CA, USA: Apress, 2014, pp. 1–14.

[5] S. M. M. Rubiano and J. A. D. Garcia, "Analysis of data mining techniques for constructing a predictive model for academic performance," *IEEE Latin Amer. Trans.*, vol. 14, no. 6, pp. 2783–2788, Jun. 2016.

[6] D. J. Power, "Decision support systems: A historical overview," in *Handbook on Decision Support Systems 1*. Berlin, Germany: Springer, 2008, pp. 121–140.

[7] D. J. Power, "Understanding data-driven decision support systems," *Inf. Syst. Manage.*, vol. 25, no. 2, pp. 149–154, Mar. 2008.

[8] B. Xu, L. D. Xu, H. Cai, C. Xie, J. Hu, and F. Bu, "Ubiquitous data accessing method in IoT-based information system for emergency medical services," *IEEE Trans. Ind. Inform.*, vol. 10, no. 2, pp. 1578–1586, May 2014.

[9] A. Sunyaev and D. Chornyi, "Supporting chronic disease care quality: Design and implementation of a health service and its integration with electronic health records," *J. Data Inf. Qual.*, vol. 3, no. 2, May 2012, Art. no. 3.

[10] E. Kilsdonk, L. Peute, and M. W. Jaspers, "Factors influencing implementation success of guideline-based clinical decision support systems: A systematic review and gaps analysis," *Int. J. Med. Inform.*, vol. 98, pp. 56–64, Feb. 2017.

[11] C.-W. Cheng, N. Chanani, J. Venugopalan, K. Maher, and M. D. Wang, "icuARM-An ICU clinical decision support system using association rule mining," *IEEE J. Transl. Eng. Health Med.*, vol. 1, 2013, Art. no. 4400110.

[12] J. Blake and D. Kerr, "Sleep disorder diagnosis: The design and implications of online tools," *Decis. Analytics*, vol. 1, no. 1, pp. 1–18, Dec. 2014.

[13] M. Puppala *et al.*, "METEOR: An enterprise health informatics environment to support evidence-based medicine," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 12, pp. 2776–2786, Dec. 2015.

[14] H. S. Goldberg *et al.*, "Use of a remote clinical decision support service for a multicenter trial to implement prediction rules for children with minor blunt head trauma," *Int. J. Med. Inform.*, vol. 87, pp. 101–110, Mar. 2016.

[15] S. Mazilu *et al.*, "A wearable assistant for gait training for Parkinson's disease with freezing of gait in out-of-the-lab environments," *ACM Trans. Interact. Intell. Syst.*, vol. 5, no. 1, Mar. 2015, Art. no. 5.

[16] A. Hess, K. A. Hummel, W. N. Gansterer, and G. Haring, "Data-driven human mobility modeling: A survey and engineering guidance for mobile networking," *ACM Comput. Surv.*, vol. 48, no. 3, Dec. 2016, Art. no. 38.

[17] H. Tawfik, O. Anya, and A. K. Nagar, "Understanding clinical work practices for cross-boundary decision support in e-health," *IEEE Trans. Inf. Technol. Biomed.*, vol. 16, no. 4, pp. 530–541, Jul. 2012.

[18] A. Khan, J. A. Doucette, and R. Cohen, "Validation of an ontological medical decision support system for patient treatment using a repository of patient data: Insights into the value of machine learning," *ACM Trans. Intell. Syst. Technol.*, vol. 4, no. 4, Sep. 2013, Art. no. 68.

[19] Y.-F. Zhang, Y. Tian, T.-S. Zhou, K. Araki, and J.-S. Li, "Integrating HL7 RIM and ontology for unified knowledge and data representation in clinical decision support systems," *Comput. Methods Programs Biomed.*, vol. 123, pp. 94–108, Jan. 2016.

[20] Z. Dong, Z. Yin, M. He, X. Chen, X. Lv, and S. Yu, "Validation of a guideline-based decision support system for the diagnosis of primary headache disorders based on ICHD-3 beta," *J. Headache Pain*, vol. 15, no. 1, Dec. 2014, Art. no. 40.

[21] J. Basilakis, N. H. Lovell, S. J. Redmond, and B. G. Celler, "Design of a decision-support architecture for management of remotely monitored patients," *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 5, pp. 1216–1226, Sep. 2010.

[22] J. Bi and A. Abraham, "An intelligent web-based decision support tool for enhancing asthma guideline adherence," in *Proc. 2nd ACM SIGHIT Int. Health Inform. Symp.*, Miami, FL, USA, 2012, pp. 51–60.

[23] K. Zarkogianni *et al.*, "A review of emerging technologies for the management of diabetes mellitus," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 12, pp. 2735–2749, Dec. 2015.

[24] B. G. Nair, S.-F. Newman, G. N. Peterson, and H. A. Schwid, "Smart anesthesia manager (SAM)—A real-time decision support system for anesthesia care during surgery," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 1, pp. 207–210, Jan. 2013.

[25] N. Li, M. Sun, Z. Bi, Z. Su, and C. Wang, "A new methodology to support group decision-making for IoT-based emergency response systems," *Inf. Syst. Frontiers*, vol. 16, no. 5, pp. 953–977, Nov. 2014.

[26] F. Andriopoulou, T. Orphanoudakis, and T. Dagiuklas, "IoTA: IoT automated SIP-based emergency call triggering system for general eHealth purposes," in *Proc. 13th IEEE Int. Conf. Wireless Mobile Comput., Netw. Commun.*, Rome, Italy, 2017, pp. 362–369.

[27] M. Laskowski, B. C. Demianyk, J. Witt, S. N. Mukhi, M. R. Friesen, and R. D. McLeod, "Agent-based modeling of the spread of influenza-like illness in an emergency department: A simulation study," *IEEE Trans. Inf. Technol. Biomed.*, vol. 15, no. 6, pp. 877–889, Nov. 2011.

[28] D. L. Hudson and M. E. Cohen, "Diagnostic models based on personalized analysis of trends (PAT)," *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 4, pp. 941–948, Jul. 2010.

[29] N. Emanet, H. R. Öz, N. Bayram, and D. Delen, "A comparative analysis of machine learning methods for classification type decision problems in healthcare," *Decis. Analytics*, vol. 1, no. 1, pp. 1–20, Dec. 2014.

[30] A. Temko, W. Marnane, G. Boylan, and G. Lightbody, "Clinical implementation of a neonatal seizure detection algorithm," *Decis. Support Syst.*, vol. 70, pp. 86–96, Feb. 2015.

[31] C. Tekin, O. Atan, and M. van der Schaar, "Discover the expert: Context-adaptive expert selection for medical diagnosis," *IEEE Trans. Emerg. Topics Comput.*, vol. 3, no. 2, pp. 220–234, Jun. 2015.

[32] J. Champaign, R. Cohen, and D. Y. Lam, "Empowering patients and caregivers to manage healthcare via streamlined presentation of web objects selected by modeling learning benefits obtained by similar peers," *ACM Trans. Intell. Syst. Technol.*, vol. 6, no. 4, Jul. 2015, Art. no. 54.

[33] S. Bashir, U. Qamar, F. H. Khan, and L. Naseem, "HMV: A medical decision support framework using multi-layer classifiers for disease prediction," *J. Comput. Sci.*, vol. 13, pp. 10–25, Mar. 2016.

[34] A. R. Al Taleb, M. Hoque, A. Hasanat, and M. B. Khan, "Application of data mining techniques to predict length of stay of stroke patients," in *Proc. Int. Conf. Inform., Health Technol.*, Riyadh, Ar Riyad, Saudi Arabia, 2017, pp. 1–5.

[35] S. C. Misra, S. Bisui, and K. Fantazy, "Identifying critical changes in adoption of personalized medicine (PM) in healthcare management," *Int. J. E-Health Med. Commun.*, vol. 7, no. 3, pp. 1–15, Jul. 2016.

[36] E. Chalmers, W. Pedrycz, and E. Lou, "Human experts' and a fuzzy model's predictions of outcomes of scoliosis treatment: A comparative analysis," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 3, pp. 1001–1007, Mar. 2015.

[37] J. Yao and N. Azam, "Web-based medical decision support systems for three-way medical decision making with game-theoretic rough sets," *IEEE Trans. Fuzzy Syst.*, vol. 23, no. 1, pp. 3–15, Feb. 2015.

[38] G. Valenza *et al.*, "Wearable monitoring for mood recognition in bipolar disorder based on history-dependent long-term heart rate variability analysis," *IEEE J. Biomed. Health Inform.*, vol. 18, no. 5, pp. 1625–1635, Sep. 2014.

[39] S. Kothari, J. H. Phan, T. H. Stokes, A. O. Osunkoya, A. N. Young, and M. D. Wang, "Removing batch effects from histopathological images for enhanced cancer diagnosis," *IEEE J. Biomed. Health Inform.*, vol. 18, no. 3, pp. 765–772, May 2014.

[40] B. Taati, J. Snoek, D. Aleman, and A. Ghavamzadeh, "Data mining in bone marrow transplant records to identify patients with high odds of survival," *IEEE J. Biomed. Health Inform.*, vol. 18, no. 1, pp. 21–27, Jan. 2014.

[41] S. Maggio, A. Palladini, L. de Marchi, M. Alessandrini, N. Speciale, and G. Masetti, "Predictive deconvolution and hybrid feature selection for computer-aided detection of prostate cancer," *IEEE Trans. Med. Imag.*, vol. 29, no. 2, pp. 455–464, Feb. 2010.

[42] E. Niaf, R. Flamary, O. Rouviere, C. Lartizien, and S. Canu, "Kernel-based learning from both qualitative and quantitative labels: Application to prostate cancer diagnosis based on multiparametric MR imaging," *IEEE Trans. Image Process.*, vol. 23, no. 3, pp. 979–991, Mar. 2014.

[43] J. A. Sukor, M. S. Mohktar, S. J. Redmond, and N. H. Lovell, "Signal quality measures on pulse oximetry and blood pressure signals acquired from self-measurement in a home environment," *IEEE J. Biomed. Health Inform.*, vol. 19, no. 1, pp. 102–108, Jan. 2015.

[44] J. Mattila, J. Koikkalainen, A. Virkki, M. van Gils, and J. Lötjönen, "Design and application of a generic clinical decision support system for multiscale data," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 1, pp. 234–240, Jan. 2012.

[45] S. G. Mougiakakou *et al.*, "SMARTDIAB: A communication and information technology approach for the intelligent monitoring, management and follow-up of type 1 diabetes patients," *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 3, pp. 622–633, May 2010.

[46] A. S. Billis, E. I. Papageorgiou, C. A. Frantzidis, M. S. Tsatali, A. C. Tsolaki, and P. D. Bamidis, "A decision-support framework for promoting independent living and ageing well," *IEEE J. Biomed. Health Inform.*, vol. 19, no. 1, pp. 199–209, Jan. 2015.

[47] M. Zięba, "Service-oriented medical system for supporting decisions with missing and imbalanced data," *IEEE J. Biomed. Health Inform.*, vol. 18, no. 5, pp. 1533–1540, Sep. 2014.

[48] K. P. Exarchos, Y. Goletsis, and D. I. Fotiadis, "Multiparametric decision support system for the prediction of oral cancer reoccurrence," *IEEE Trans. Inf. Technol. Biomed.*, vol. 16, no. 6, pp. 1127–1134, Nov. 2012.

[49] G. Guidi, M. C. Pettenati, P. Melillo, and E. Iadanza, "A machine learning system to improve heart failure patient assistance," *IEEE J. Biomed. Health Inform.*, vol. 18, no. 6, pp. 1750–1756, Nov. 2014.

[50] C. Soguero-Ruiz *et al.*, "Ontology for heart rate turbulence domain from the conceptual model of SNOMED-CT," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 7, pp. 1825–1833, Jul. 2013.

[51] C.-S. Lee and M.-H. Wang, "A fuzzy expert system for diabetes decision support application," *IEEE Trans. Syst. Man, Cybern. Part B*, vol. 41, no. 1, pp. 139–153, Feb. 2011.

[52] R. Toor and I. Chana, "Application of it in healthcare: A systematic review," *ACM SIGBioinform. Rec.*, vol. 6, no. 2, pp. 1–8, Aug. 2016.

[53] S. Sankaranarayanan and S. Ganesan, "Applications of intelligent agents in health sector – review," *Int. J. E-Health Med. Commun.*, vol. 7, no. 1, pp. 1–30, Jan. 2016.

[54] C. Yang, Q. Huang, Z. Li, K. Liu, and F. Hu, "Big data and cloud computing: Innovation opportunities and challenges," *Int. J. Digit. Earth*, vol. 10, no. 1, pp. 13–53, Jan. 2017.

[55] R. Fang, S. Pouyanfar, Y. Yang, S.-C. Chen, and S. Iyengar, "Computational health informatics in the big data age: A survey," *ACM Comput. Surv.*, vol. 49, no. 1, Jun. 2016, Art. no. 12.

[56] I. D. Dinov, "Methodological challenges and analytic opportunities for modeling and interpreting big healthcare data," *Gigascience*, vol. 5, no. 1, pp. 1–15, Feb. 2016.

[57] A. Manirabona, L. C. Fourati, and S. Boudjit, "Investigation on healthcare monitoring systems: Innovative services and applications," *Int. J. E-Health Med. Commun.*, vol. 8, no. 1, pp. 1–18, Jan. 2017.

[58] L. Raffaeli, S. Spinsante, and E. Gambi, "Integrated smart TV-based personal e-health system," *Int. J. E-Health Med. Commun.*, vol. 7, no. 1, pp. 48–64, Jan. 2016.

[59] A. M. Alaa, K. H. Moon, W. Hsu, and M. van der Schaar, "Confidentcare: A clinical decision support system for personalized breast cancer screening," *IEEE Trans. Multimedia*, vol. 18, no. 10, pp. 1942–1955, Oct. 2016.

[60] P. H. Abreu, M. S. Santos, M. H. Abreu, B. Andrade, and D. C. Silva, "Predicting breast cancer recurrence using machine learning techniques: A systematic review," *ACM Comput. Surv.*, vol. 49, no. 3, Oct. 2016, Art. no. 52.

[61] J. Jiang, J. Zheng, C. Zhao, J. Su, Y. Guan, and Q. Yu, "Clinical-decision support based on medical literature: A complex network approach," *Phys. A Statist. Mech. Appl.*, vol. 459, pp. 42–54, Oct. 2016.

[62] M. Keshtkaran, L. Churilov, J. Hearne, B. Abbasi, and A. Meretoja, "Validation of a decision support model for investigation and improvement in stroke thrombolysis," *Eur. J. Oper. Res.*, vol. 253, no. 1, pp. 154–169, Aug. 2016.

[63] D. Anand, B. Pandey, and D. K. Pandey, "Facioscapulohumeral muscular dystrophy diagnosis using hierarchical clustering algorithm and K-nearest neighbor based methodology," *Int. J. E-Health Med. Commun.*, vol. 8, no. 2, pp. 33–46, Apr. 2017.

[64] M. Feldman, A. Even, and Y. Parmet, "A methodology for quantifying the effect of missing data on decision quality in classification problems," *Commun. Statist.-Theory Methods*, vol. 47, no. 11, pp. 2643–2663, 2018.

[65] S. B. Othman, H. Zgaya, M. Dotoli, and S. Hammadi, "An agent-based decision support system for resources' scheduling in emergency supply chains," *Control Eng. Pract.*, vol. 59, pp. 27–43, Feb. 2017.

[66] Y. Siegert, X. Jiang, V. Krieg, and S. Bartholomäus, "Classification-based record linkage with pseudonymized data for epidemiological cancer registries," *IEEE Trans. Multimedia*, vol. 18, no. 10, pp. 1929–1941, Oct. 2016.

[67] N. Beerlage-de Jong, J. Wentzel, R. Hendrix, and L. van Gemert-Pijnen, "The value of participatory development to support antimicrobial stewardship with a clinical decision support system," *Amer. J. Infection Control*, vol. 45, no. 4, pp. 365–371, Apr. 2017.

[68] P. Bountris, E. Topaka, A. Pouliakis, M. Haritou, P. Karakitsos, and D. Koutsouris, "Development of a clinical decision support system using genetic algorithms and Bayesian classification for improving the personalised management of women attending a colposcopy room," *Healthcare Technol. Lett.*, vol. 3, no. 2, pp. 143–149, Jun. 2016.

[69] P. Lambin *et al.*, "Decision support systems for personalized and participative radiation oncology," *Adv. Drug Deliv. Rev.*, vol. 109, pp. 131–153, Jan. 2017.

[70] M. A. Ferradji and A. Zidani, "Collaborative environment for remote clinical reasoning learning," *Int. J. E-Health Med. Commun.*, vol. 7, no. 4, pp. 62–81, Oct. 2016.

[71] H. Mushcab, W. G. Kernohan, J. Wallace, R. Harper, and S. Martin, "Self-management of diabetes mellitus with remote monitoring: A retrospective review of 214 cases," *Int. J. E-Health Med. Commun.*, vol. 8, no. 1, pp. 52–61, Jan. 2017.

[72] A. Menychtas, P. Tsanakas, and I. Maglogiannis, "Automated integration of wireless biosignal collection devices for patient-centred decision-making in point-of-care systems," *Healthcare Technol. Lett.*, vol. 3, no. 1, pp. 34–40, Mar. 2016.

[73] J. C. Zgibor, F. X. Solano, and L. Siminerio, "A primary health-care system approach to improving quality of care and outcomes in people with diabetes: The University of Pittsburgh Medical Center experience," in *Integrated Diabetes Care: A Multidisciplinary Approach*, D. Simmons, H. Wenzel, and J. C. Zgibor, Eds., Cham, Switzerland: Springer, 2017, pp. 51–64.

[74] S. Bhartiya, D. Mehrotra, and A. Girdhar, "Hierarchy similarity analyser-an approach to securely share electronic health records," *Int. J. E-Health Med. Commun.*, vol. 7, no. 2, pp. 14–29, Apr. 2016.

Mário W. L. Moreira (S'17) received the M.Sc. degree in mathematics from the State University of Ceará, Fortaleza, Brazil, in 2012. He is currently working toward the Ph.D. degree on informatics engineering at the Instituto de Telecomunicações, University of Beira Interior, Covilhã, Portugal.

He is a Professor with the Department of Education, Federal Institute of Ceará, Aracati, Brazil. He is a Member of the Next Generation Networks and Applications Group supervised by Prof. Joel J. P. C. Rodrigues. His research interests include DSSs, e-health and m-health systems.

Joel J. P. C. Rodrigues (S'01–M'06–SM'06) received the five-year B.Sc. degree (licentiate) in informatics engineering from the University of Coimbra, Coimbra, Portugal, the M.Sc. degree and the Ph.D. degree in informatics engineering from the University of Beira Interior (UBI), Covilhã, Portugal.

He received the academic title of Aggregated Professor of informatics engineering from UBI, and the Habilitation in computer science and engineering from the University of Haute Alsace, Alsace, France. He has been a Professor with the UBI and a Visiting Professor with the University of Fortaleza, Fortaleza, Brazil. He is currently a Professor with the National Institute of Telecommunications (Inatel), Santa Rita do Sapuca, Brazil and Senior Researcher with the Instituto de Telecomunicações, Aveiro, Portugal. He has authored or coauthored more than 650 papers in refereed international journals and conferences, three books, and holds two patents.

Prof. Rodrigues is the Leader of the Internet of Things Research Group, Director for Conference Development—IEEE ComSoc Board of Governors, IEEE Distinguished Lecturer, Technical Activities Committee Chair of the IEEE ComSoc Latin America Region Board, the President of the scientific council at ParkUrbis Covilh Science and Technology Park, the Past-Chair of the IEEE ComSoc Technical Committee on eHealth, the Past-chair of the IEEE ComSoc Technical Committee on Communications Software, Steering Committee Member of the IEEE Life Sciences Technical Community and Publications Co-Chair, and Member Representative of the IEEE Communications Society on the IEEE Biometrics Council. He is the Editor-in-Chief for the *International Journal on E-Health and Medical Communications* and Editorial Board Member of several high-reputed journals. He has been General Chair and technical program committee (TPC) Chair of many international conferences, including IEEE International Conference on Communications, IEEE Global Telecommunications Conference, and HEALTHCOM. He is a member of many international TPCs and has participated in several international conferences' organization. He had been awarded several Outstanding Leadership and Outstanding Service Awards by IEEE Communications Society and several Best Papers Awards. He is a Licensed Professional Engineer (as Senior Member), member of the Internet Society, and a Senior Member of the Association for Computing Machinery.

Valeriy Korotaev received the honorary Doctor of Engineering, Ph.D. degree in optical engineering, Specialist degree in optical-electronic systems from the Institute of Fine Mechanics and Optics (now ITMO University), St. Petersburg, Russia.

He is a Head of the Department of Optical-Electronic Devices and Systems, ITMO University. He has authored over 200 papers in refereed international and domestic journals and conferences and holds 21 patents. His main research interests include optical-electronic measuring devices and systems, linear and angular measurements, the polarization properties of optical systems and their components, nondestructive testing and fault detection, and inspection of large-scale objects.

Dr. Korotaev is the Leader of the International Laboratory "Technosphere Safety" (http://irc.ifmo.ru/en/87809/), Honorary Worker of Higher Professional Education of the Russian Federation, Corresponding Member of the Prokhorov Academy of Engineering Sciences, Member of the Rozhdestvensky Optical Society (part of Electrical Optical Systems Inc.), Member of the Educational Council for the direction "optical engineering," and Member of the Educational Association of Russian Universities for Instrumentation Technology and Optical Engineering.

Jalal Al-Muhtadi received the Ph.D. degree from the University of Illinois at Urbana-Champaign, Champaign, IL, USA, where he was a member with the Systems Research Group and Gaia.

He is currently an Assistant Professor with the College of Computer and Information Sciences and the Director of the Center of Excellence in Information Assurance, King Saud University, Saudi Arabia. His research interests include ubiquitous and pervasive computing, middleware, and information security and privacy.

Neeraj Kumar (SM'18) received the M.Tech. degree from Kurukshetra University, Kurukshetra, India, and the Ph.D. degree from Shri Mata Vaishno Devi University, Katra, India, both in computer science engineering.

He is currently working as an Associate Professor with the Department of Computer Science and Engineering, Thapar University, Patiala, India. He has received a Postdoctoral Fellowship from Coventry University, Coventry, U.K. He is a Reviewer for various leading journals/conferences. He has supervised many Ph.D. and M.E. students. He has more than 13 years of experience in teaching and research both at UG/PG levels. His research is supported by research grants from University Grants Commission and Tata Consultancy Services. He has visited Australia, Hungary, Poland, and U.K. mainly for academic purposes. He has research collaborations with top-level universities in Asia, Australia, Europe, and USA. He has more than 100 technical research papers in leading journals and conferences of repute from IEEE, Elsevier, Springer, and Wiley. His research is focused on routing and security issues in wired/wireless networks.

Dr. Kumar is a member of the Association for Computing Machinery.