■ REVIEW ARTICLE

Artificial Intelligence in Healthcare Industry: A Transformation From Model-Driven to Knowledge-Driven Decision Support Systems

Abdulkadir Hızıroğlu [a], **Ali Pişirgen** [b†], **Mert Özcan** [b], **Halil Kemal İlter** [a]

[a] Department of Management Information Systems, University of Bakırçay, İzmir, Turkey
[b] University of Bakırçay, İzmir, Turkey
† alipisirgen@gmail.com, corresponding author

RECEIVED JANUARY 4, 2022
ACCEPTED APRIL 30, 2022

CITATION Hızıroğlu, A., Pişirgen, A., Özcan, M., & İlter. H. K. (2022). Artificial Intelligence in Healthcare Industry: A Transformation From Model-Driven to Knowledge-Driven Decision Support Systems. *Artificial Intelligence Theory and Applications, 2(*1), p. 41-58

Abstract

Healthcare professionals and inter (or multi) disciplinary academia have been paying more attention to decision support systems (DSS) for improved decision making during their health service processes or management, as well as clinical practices. Although there have been numerous DSS applications in the healthcare industry, it has been intended to provide a categorical snapshot view of current implementations or academic work at specific DSS types for better understanding the application domains by addressing the gap in the literature. To achieve this, it has been focused on DSS applications in healthcare specifically by concentrating on two main types: model-driven and knowledge-driven. In this context, relevant information systems and medical science literatures were reviewed. For health service problems like hospital placement decisions and homecare route planning, model-driven DSS applications are used for optimization and modelling. Both conventional operations research techniques like optimization, decision analysis, simulation, and multi-criteria decision making, as well as contemporary ones like heuristic search, benefit from these applications. In addition, artificial intelligence techniques help health decision makers via knowledge-driven DSS applications, specifically clinical decision support systems (CDSS). Artificial intelligence applications can also assist health professionals in enhancing their decision-making abilities by incorporating complex operational rules and developing such procedures as single-or multi-agent systems. This research focuses on what to emphasis on while designing a DSS in the healthcare setting, such as which programming or modelling languages to employ and how to transform a model-driven DSS into a knowledge-driven DSS, or how to create the DSS more intelligent. Overall, this study indicates a present course for DSS and offers useful knowledge for both scholars and professionals in the healthcare domain.

Keywords: decision support systems, model-driven DSS, knowledge-driven DSS, artificial intelligence in healthcare, intelligent decision support systems.

Artificial Intelligence Theory and Applications, ISSN: 2757-9778. ISBN : 978-605-69730-2-4 © 2022 University of Bakırçay

1. Introduction

Healthcare industry, particularly its decision-making capabilities has recently received significant interest from researchers and practitioners [1]. This increased attention has been observed by healthcare professionals and inter-disciplinary and multi-disciplinary academia on decision support systems (hereafter DSS) [2]. Healthcare service processes or management and clinical practices have then been investigated via numerous DSS applications for enhanced decision-making in the healthcare industry [3]. These applications trigger to develop effective DSS. This continuing interest encouraged both academia, managers, and practitioners to reveal the importance of designing, developing, and implementing functional DSS [4].

DSS in healthcare industry has been evolving since the foundation of DSS has been changing with the increased use of developing technologies such as big data, cloud computing, artificial intelligence (hereafter AI), and machine learning [5]. This evolvement enables DSS to become more intelligent and, therefore, helps decision-makers to retrieve meaningful information and facilitate this information during decision making. Nevertheless, the various applications have demonstrated the necessity to classify DSS in the healthcare industry to provide a holistic perspective while focusing on a particular taxonomy branch [6].

The focus of this study is to understand the transformation of DSS from model-driven and knowledge-driven in the healthcare industry with a categorical concentration of AI applications adopted. In this study, relating articles which examined DSS tools associated with various AI techniques performed in the healthcare industry were reviewed. To summarize, this study provides an overview of conceptual categorization of AI techniques from DSS perspective to highlight the increasing use of AI in the healthcare industry.

The reminder of this paper is organized as follows. Section 2 highlights the decision-making and historical perspective of DSS taxonomy while providing a framework of classification of model-driven and knowledge-driven DSS from the artificial intelligence perspective. The following section presents the model-driven DSS in the healthcare industry and its integration with AI applications. Section 4 explains how knowledge-driven DSS in the healthcare industry and its AI applications that make the DSS more intelligent are addressed. Section 5 focuses on different aspects of developing, implementing and using model-driven DSS or knowledge-driven DSS. Finally, the main conclusion is presented in Section 6.

2. Decision Making and Decision Support Systems

Decision-making is a cognitive process of selecting the best possible choice and taking action amongst several possible alternatives. If there is a need to solve complex problems using mathematical methods, the operations research discipline is often benefited [7]. The techniques that are utilized by operations research are generally classified as deterministic and stochastic techniques; depending the degree of certainty. Whereas linear programming, integer programming, goal programming, analytic hierarchy process, transportation and assignment models, nonlinear programming, deterministic dynamic programming, deterministic inventory models, network analysis are some examples of deterministic models; Markov chains, queueing theory, decision analysis, game theory, simulation, forecasting models, probabilistic inventory models, probabilistic dynamic models are well known stochastic model types [8]. Due to the acceleration in technological developments, AI applications integrate with the operations research discipline; ranging from case-based reasoning, fuzzy logic, knowledge-based systems, genetic algorithms and hybrid techniques [7]. The integration has been illustrated in Figure 1.

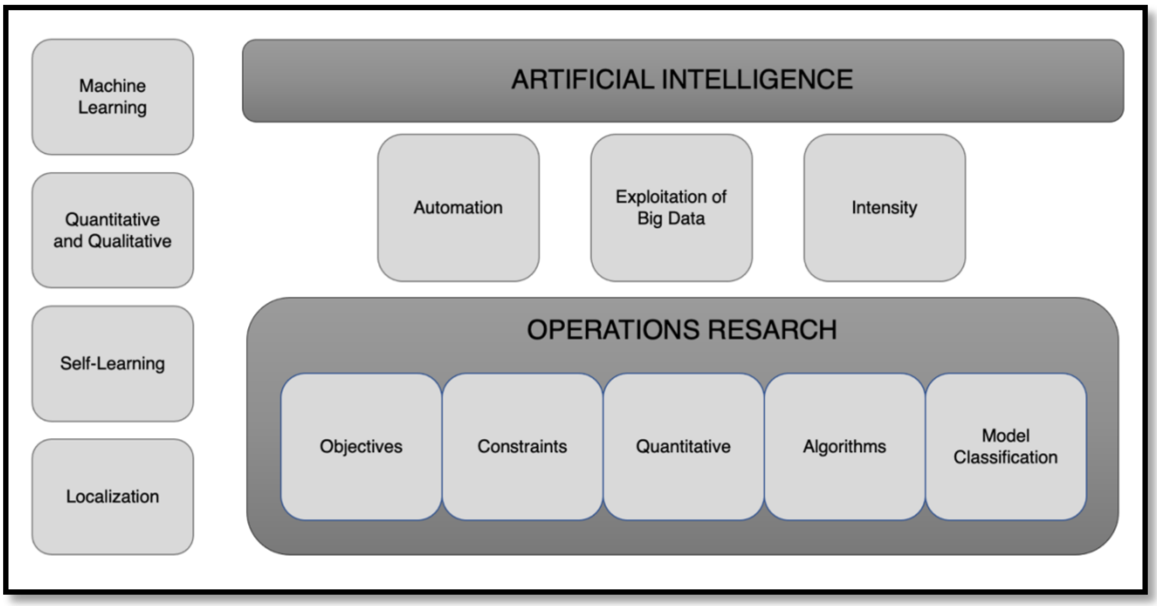

Figure 1. The integration framework between Operations Research and Artificial Intelligence [7].

Although it is assumed that human beings should have rationality in the best decision-making process, there are also subjective factors that prevent the rationalism of the decision process. Decision-makers may have a lack of knowledge that makes the future uncertain. Therefore, it is possible to define decision analysis as systematic approaches that transform the uncertainty of the future to the most certain one possible.

The need to analyse, evaluate and extract information and desire to systematize decision-making are main catalysers of developing DSS [9]. Another essential factor in implementing DSS is the volume of decisions to be made within a limited time [10]. These challenges trigger managers and practitioners to develop DSS; while academia has played a supporting role during this development [11]. Nevertheless, the fuzziness and proliferation of naming each system for decision making as DSS have increased the importance of classifying existing DSS [12].

The terms “framework”, “taxonomy” and “conceptual model” are interchangeably referred for these classifications based on their mutually exclusive characteristics and often used as misnomer terms [13]. To overcome this problem, classifying DSS enables demonstrating both similarities and differences so that the users have a better understanding of them and therefore adopt relevant DSS that fulfils the need for decision-making. Furthermore, DSS is not a static domain, meaning that DSS’s evolvement is inevitable [14].

In management information system literature, taxonomies of DSS exist; however the “*adaptive*” and “*evolutionary*” nature of DSS requires a revisit of existing taxonomies [13, p. 247]. Starting with Alter’s [15] taxonomy, DSS is categorized under two types: data-oriented and model-oriented, while these two types include a total of seven DSS. These seven categories are file-drawer systems, data analysis systems, analysis information systems, accounting models, representational models, optimization models and suggestion models which summarize the generic operations ranging from data to decision-making.

Further extensions have been included to the taxonomy of Alter [15], such as Bonczek et al. [16], Klein and Methlie [17], and Holsapple and Whinston [18], While these extensions do not concentrate on significant changes and focus adoption of DSS, another important taxonomy evolved (Fig. 2) from Alter [15], is Power's [14] taxonomy which identifies DSS in five categories as data-driven, model-driven, knowledge-driven, document-driven and communication-driven. While this taxonomy provides parallelism with Alter [15], knowledge-driven DSS which prioritises database management, is added. In addition to knowledge-driven DSS, communication-driven DSS and document-driven DSS are included in this taxonomy. Nevertheless, focusing on recent technological developments, including communication and cloud-based document sharing, communication and document-driven DSS are not considered as standalone DSS. At the same time, any business intelligence applications embed them. Therefore, Moreira et. al. [6] narrows DSS groups and presents them into three categories: data-driven, model-driven and knowledge-driven.

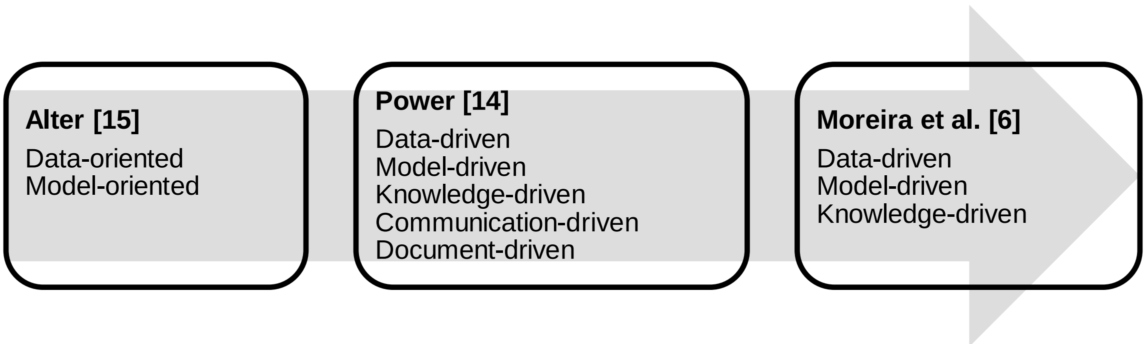

Figure 2 – Transition framework from model-driven to knowledge-driven DSS

Data-driven DSS derive from inductive reasoning that concentrates on "time-series of internal, external, and real-time data" from online analytical processing (OLAP) and data warehouse systems [12]. Alter [15] exemplified the first data-driven DSS as an analytical information system, and further developments in software trigger the evaluation of analytical information systems to executive information systems [19]. On the other hand, model-driven DSS provides an elementary level of functionality to the users and enables them to manipulate model inputs. Nevertheless, large databases are not required for model-driven DSS [4]. Since computerized systems made model-driven DSS easily accessible to managers, manipulation optimization and simulation models with AI applications to overcome more complex problems. The last and the most promising is knowledge-driven DSS which provide suggestions and recommendations via an AI machinery inference [6].

This study enables more precise mapping of the DSS framework to relate this taxonomy with AI applications. This framework addresses how model-driven and knowledge-driven DSS are adopted conventionally and complementarily by concentrating on the healthcare industry. Starting with model-driven DSS, decision analysis and multi-criteria decision making, optimization, mathematical programming, and simulation are conventional methods and enable decision-makers to solve problems based on provided data [6]. These tools are then combined with AI applications such as fuzzy systems, heuristic search, and agent-based systems [20 - 24]. In the healthcare industry, model-driven DSS is adopted to overcome operational problems such as deciding the location of a hospital and providing a route for homecare practitioners. In addition to model-driven DSS, knowledge-driven DSS includes knowledge management systems, learning management systems and knowledge repository as conventional methods and expert systems, automated tools and machine learning as complementary AI-based methods that make knowledge-driven DSS more intelligent [25 - 28].

Figure 3 includes only model-driven and knowledge-driven DSS methods. It excludes data-driven DSS since both conventional and complementary model-driven and knowledge-driven DSS methods facilitate from data and documents as inputs. Furthermore, utilizing large datasets to obtain meaningful information makes DSS more intelligent and helps users by offering predictive models. This inclusion of data encourages focusing on model-driven and knowledge-driven DSS.

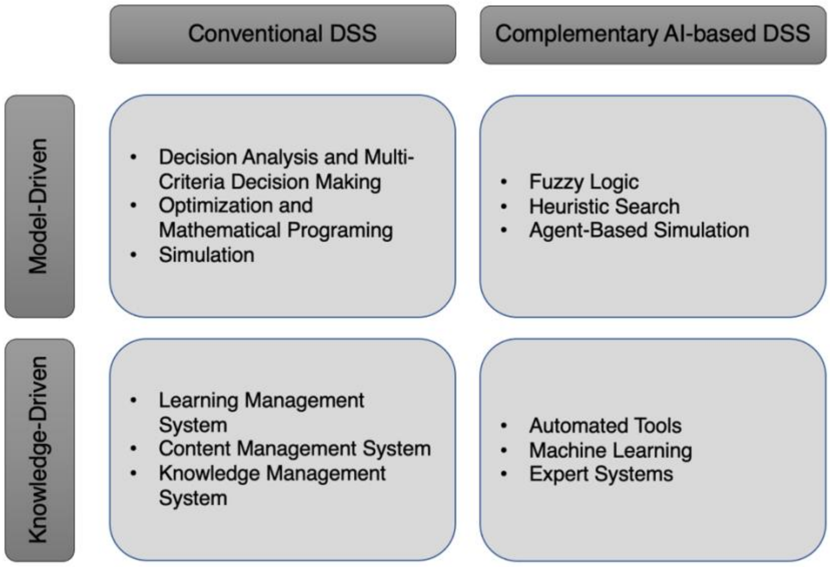

Figure 3 – Transition framework from model-driven to knowledge-driven DSS

3. Model Driven Decision Support Systems in the Healthcare Industry

Model-driven DSS is a tool that decision makers manipulate inputs to analyse the problem while understanding the impact on outputs. The primary understanding behind a model-driven DSS is that a decision-maker who has no skills in designing DSS can facilitate a model-driven DSS. In other words, after a model-driven DSS is developed, there is no further need to amend. Decision-makers benefit from it by changing inputs repeatedly [12]. A model-driven DSS includes decision analysis and multi-criteria decision making, optimization and mathematical programming, and simulation as techniques [4]. Furthermore, the inclusion of AI into these techniques developed advanced methods such as fuzzy systems, heuristic search, and agent-based simulation.

3.1. Decision Analysis and Multi-Criteria Decision Making: The Role of Fuzzy Logic

Decision analysis is a systematic analysis approach that provides better decision support for decision-makers by using various quantitative methods [29]. These methods are chosen depending on the conditions such as under certainty and uncertainty.

DSS in the healthcare industry also uses multi-criteria decision-making methods. Multi-criteria decision-making methods are systematic decision-making approaches, which enable to reach the best option among the alternatives and criteria. In addition, fuzzy multi-criteria decision-making methods are used in cases where there are incomplete and vague data in defining alternatives and criteria. They provide analysis and solutions to complex problems.

There are various examples where decision analysis and multi-criteria decision-making approaches are used in the healthcare industry. There has been a remarkable increase in the implementation of model-driven DSS in the field of health recently. Zarkogianni et al. [30] examined the management process of diabetes from a preventive healthcare perspective. Thanks to the clinical decision support systems (hereafter CDSS) integrating electronic health records, substantial gains have been provided to both patients and physicians regarding preventive care and clinic management of diabetes.

By developing wearable technologies, information obtained from smart sensors is applied in the remote management of diseases. In parallel with developments in mobile communication technologies, it is observed that model-driven DSS applications have emerged in emergency healthcare services. Andriopoulou and Dagiuklas [31] developed a system with real-time data that monitors patients' vital signs. This system was integrated with the decision tree model; thus, they proposed a model-driven DSS converted into automatic emergency calls when needed.

Nair et al. [32] proposed a real-time and model-driven DSS in which anaesthesia procedures were developed in surgical processes. DSS, integrated with the anaesthesia information management system, was modelled based on logical decision rules and created significant improvements in patient care, billing, and material management in the healthcare facility.

It is observed that there is an increasing number of studies on DSS in which multi-criteria decision making methods are applied in the healthcare industry.

Ağaç and Baki [33] conducted a review about the usage of multi-criteria decision-making techniques in healthcare. They stated that Analytical Hierarchy Process (AHP) and Analytical Network Process (ANP) were preferable methods. According to their study; these techniques were addressed to solve problems such as selecting hospital and medical waste location, evaluating service quality, risk assessment, supplier selection, providing decision support for medical treatments, and selecting medical waste disposal method.

Broekhuizen et al. [34] studied the multi-criteria decision making methods when facing an uncertain situation. They stated that DSS using fuzzy sets were benefited in areas such as environmental health and diagnosis.

Mardani et al. [24] investigated the development of multi-criteria decision making and fuzzy set applications in the field of health for the last 30 years. According to the findings, AHP and hybrid techniques were the most commonly used methods. The other methods were Fuzzy AHP, TOPSIS, Fuzzy TOPSIS, ANP, Fuzzy ANP, VIKOR, Fuzzy VIKOR, PROMETHEE, and ELECTRE. They also stated that these methods were applied in environmental sustainability, medical waste management, medical service quality, risk management, medical equipment and material selection, and hospital services.

Nazari et al. [35] developed a hybrid DSS integrating with Fuzzy AHP and Fuzzy Inference Methods to assess heart attack risk. They discussed the implementation results of the study. They also emphasized that significant improvements were achieved in evaluating the possibility of developing heart disease in a patient, providing early diagnosis, and decreasing the clinical costs.

Due to the clinical complexities and pathological differences of many diseases, it is thought that many statistical methods sometimes do not meet the expectations in medical diagnosis processes adequately. This situation may cause various errors and uncertainties in the diagnosis stages. In such cases, AI-based fuzzy DSS provides essential support to decision-makers in diagnosing various diseases like malaria related infectious diseases, cardiovascular diseases, cancer, asthma, flu, influenza, hepatitis, bone marrow diseases, and meningitis [36]. AI and model-driven DSS will also have an impact on the diagnosis and treatment of different diseases.

3.2. Optimization and Mathematical Programming: The Role of Meta-Heuristic Search

In addition to decision analysis and multi-criteria decision making, optimization and mathematical programming methods which are amongst the operations research techniques have been applied for model-driven DSS in the healthcare industry. The primary purpose of applying optimization and mathematical models is to solve the problem related to the operations of the business. Furthermore, these methods constitute a model-driven DSS to visualize a model via data presentation, graphic display, and statistics [37].

Like other industries, optimization and mathematical programming are used to optimize the operations of healthcare organizations. Determining the location of a hospital and a unit inside the hospital, shift planning, and logistical needs such as blood supply chain are main operational issues solved via optimization and mathematical programming [38]. In their study, Geçici and Güler [39] modelled the problem of shift scheduling of nurses working in a hospital's cardiovascular surgery clinic by using mixed integer programming model. They transformed this model into an Excel-based decision support application.

With the inference of AI-based methods, optimization and mathematical programming facilitate from meta-heuristic search, a method chosen to provide an optimal solution in an acceptable time. Speed, quality, and cost are the parameters that target achieving optimality, while extensive mathematical modelling and the power to calculate are required. Studies, which started developing meta-heuristic algorithms on the calculation of the optimum travel route for the sales representative, are used today in making optimal operational decisions in the healthcare industry [40]

Determining the location of the hospital is of great importance for healthcare investments. Model-driven DSS using heuristic algorithms is used to determine this hospital’s location, which is an operational decision. In Korea, Kim and Kim [23] tried to determine the optimal location to serve the maximum number of patients, considering the patient diversity, from the determination of the locations where the health institutions would be built within the budget by heuristic search. Developed on the LaGrange heuristic algorithm, they created a model-based DSS for patients in various income groups who would prefer private or public hospitals to make the optimal decision with computer-based experiments. This model was intended to be used by health authorities in the future to select the most appropriate hospital location in Korea.

Dios et al. [20] carried out a similar scheduling study in planning surgical operating rooms in the largest hospital in Spain. It was stated that the model had 98% consistency in short term schedules. A time saving of approximately 30 hours per month was achieved by transferring the manual schedules to the digital system. Kuo et al. [41] handled the optimization approach with a mixed integer linear programming model. They proposed a solution approach modelled with real-time data for the distribution of emergency medical resources after disasters. They also discussed how the proposed decision support tool could be adapted to this model.

In another study conducted in the healthcare industry, different distribution methods were compared to optimize the transportation activities performed during the planning phase of home care services (Laesanklang & Landa-Silva, 2017) [42]. After intensive mathematical programming, the study revealed that the heuristic approach was the system that proposed the fastest transportation route among these methods. Furthermore, Fathollahi-Fard et al. [43]. compared different heuristic algorithms and presented various models according to priorities to optimize home health services.

These studies reveal that optimization and mathematical programming methods are used in model-driven DSS, particularly planning. At the same time, heuristic approach is one of the preferred tool for decision making, particularly operational decisions in healthcare [38].

3.3. Simulation Techniques: The Role of Agent-Based Systems

Simulation is defined as “imitating the behaviour of an actual or anticipated human or physical system” [4, p. 1047]. A model-driven DSS using simulation techniques such as Monte Carlo simulation, discrete-event simulation, system dynamics are used in the healthcare industry to assess health risk and cost-benefit evaluation of a medical treatment; to plan healthcare services and health economic models; and to evaluate public health policy and infrastructure [44]. In their study, Huang et al. [45] intended to evaluate the cost-effectiveness of diabetes care using Monte Carlo simulation and concluded that some level of improvements were observed during simulation, and cost-effectiveness is gained for diabetes treatment. Another study by Roze et al. [46] presented a study adopting a computer simulation to evaluate a health economic model focused on the relation of the lifetime of dyslipidaemia patients and cost outcomes of lipid-modifying therapy. The simulation results revealed the successful application of a model for dyslipidaemia therapy and highlighted that the model was incrementally helpful for the evaluation of new and existing therapy options.

With ongoing developments in information technology and inference of AI in the healthcare industry, agent-based simulation technique received significant attention from researchers [21]. Agent-based simulation enables researchers to understand the agent and artificial world, which provides constructive opportunities to recreate the artificial world when necessary. This artificial world of an agent is a very likely representation of the actual situation [47]. This simulation method is widely used in the healthcare domain for clinical treatments. In their research, Abbott et al. [48] simulated the hallmarks of cancer by facilitating an agent-based simulation model known as CancerSim to understand the population dynamics of cancer cells and define their characteristics of these hallmarks. This study highlights the importance of adopting agent-based simulation and demonstrates how AI opens new venues for model-driven DSS with a conclusion of relevance to the possible therapies and artificial life phenomena.

In addition to clinical treatments, agent-based simulation is implemented to understand the potential scenarios of an epidemic. Liu et al. [49] conducted a study that aimed to imitate the transmission of measles among individuals in various locations such as houses, schools, kindergartens, workplaces, and neighbourhoods. The results of the study demonstrated the importance of vaccination and immunity coverage and provide opportunity to develop a model of vaccination. Furthermore, the managers of healthcare emergency departments applied agent-based simulation to create dedicated strategies for emergency units, so this provides them an opportunity to design a model-driven DSS [50].

To achieve the optimal staff configuration, including doctors, nurses, and admission personnel; and to minimize waiting time of the patients, agent-based simulation was conducted. The results present a better understanding of the problem and help emergency department managers to set up a model-driven DSS. Additionally, Kalton et al. [22] used the multi-factor simulation method to analyse the complex structure of mental health systems. The developed model-based system provides information to decision-makers to be used in planning, performance, and various other healthcare services received by patients with mental illness. In another study, a model-driven DSS was created by simulating the operating room. An operation process was evaluated as preliminary, activity, and post-operative, and the simulation technique was used to define the problem and improve the service [51].

4. Knowledge-Driven DSS in the Healthcare Industry

Knowledge-driven DSS, which reflect intelligent human behaviour, are known as computer-based reasoning systems. Decision makers facilitate these DSS to solve specialized problems and are therefore referred to as "person-computer systems" [12, p. 131]. Nevertheless, knowledge-driven DSS, before the inclusion of AI methods, include some tools such as knowledge management systems (KMS), learning management systems (LMS), and content management systems (CMS). Lee and Hong [52] refer to knowledge management systems as centralized applications that enable strategic and tactical decision-making. In addition to KMS, considered the technological infrastructure of DSS, organizations utilize LMS to construct an organizational learning culture that is inevitable for achieving a competitive advantage in a knowledge-based economy [53]. Furthermore, organizations utilize from CMS while dealing with increasing complexity and volute of information. Decision-makers then acknowledge the strategical role of CMS for decision support, and CMS positively impacts decision support activities [54].

Nevertheless, these systems lack AI interference, and with the inclusion of AI, automated tools, machine learning and expert systems become preferable methods for knowledge-driven DSS [55].

4.1. Automated Tools

Increasing demand for health services regarding limited time and personnel cause decision-makers to gain efficiency [27]. AI, in this manner, serves as a method to enhance decision-making and analytical processing while imitating human cognitive functions. Automated tools are referred to as automated AI-based healthcare tools that not only assist patients in being diagnosed but also promote their wellbeing. Starting with automated conversational agents, Laranjo et al. [56] reviewed the literature and highlighted that advancement in voice recognition, natural language processing, and AI trigger the implementation. Nevertheless, although automated tools are considered as primitive stage of expert systems, the results provided that the use of automated tools in the healthcare industry was relatively limited. After Covid-19 pandemic, to lower the transmission of the virus, the increasing need for telemedicine leads to the prevalence of automated conversation agents [57]. This application provides an opportunity for remote intelligent consultancy and timely and quality treatment. In addition to conversational agents, the healthcare industry benefits from automated healthcare kiosk to manage chronic diseases. Patients with these diseases regularly visit the kiosk instead of practitioners when the outcomes are within range of expectable conditions extracted from the knowledge database. Nevertheless, after certain visits to the kiosks, patients are expected to visit practitioners. This study reveals that the healthcare kiosk presents an alternative way to support patients for stable chronic diseases [58].

Nevertheless, automated tools in the healthcare industry have the potential the improve the service quality, the importance of AI with large datasets of patients' information plays significant role particular to expert systems. These datasets are also inputs for machine learning applications which will then be useful for developing comprehensive expert systems.

4.2. Machine Learning

Machine learning is a learning method from existing data via algorithms to predict the results of future tests of new data [59]. Based on supervised, unsupervised, semi-supervised and reinforcement techniques, the experiences obtained from historical data are processed by the machine to extract insights or useful knowledge to help decision-making process, as illustrated in Figure 4.

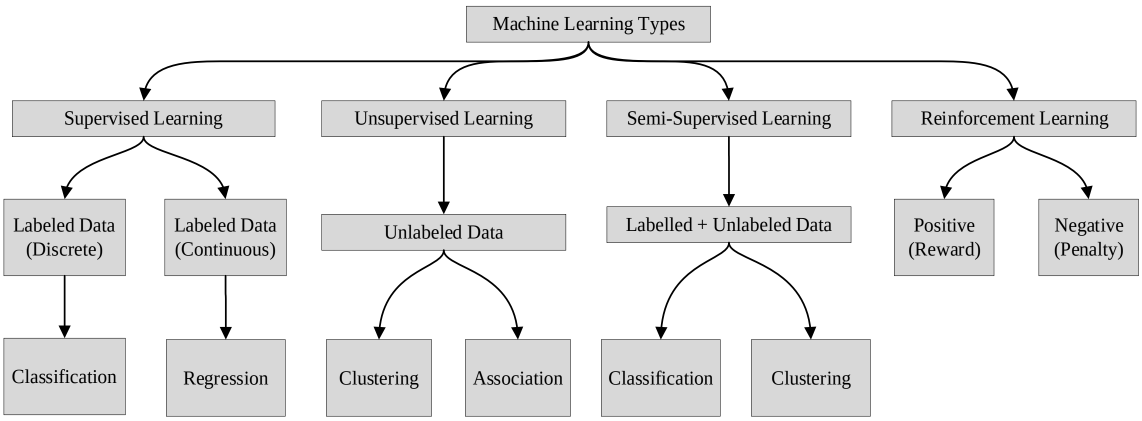

Figure 4. Taxonomy of Machine Learning [60].

The application of machine learning in the healthcare industry offers an opportunity for analysing a large volume of data so that patients' risk scores are categorized, diseases are diagnosed, and healthcare operations are improved.

DSS based on machine learning techniques is also used in various applications in the healthcare industry. The combination of machine learning techniques and DSS makes essential contributions to the early diagnosis of cancer diseases. One of the features of machine learning that distinguish cancer from other diseases is the low success rates in early diagnosis. Bashiri et al. [25] highlighted the importance of approaches including machine learning techniques based on gene expressions data. According to the narrative review, thanks to developing CDSS based on machine learning methods, decreasing the prediction errors and developing proper and more individualized treatments are possible. Choy et al. [61] reviewed and discussed the applications of knowledge-driven DSS via

AI approaches in radiological practices. This study highlighted the significance of machine learning and underlies the potential in radiology for the future.

Data that are gathered from intensive care units are potential inputs of DSS. Studies regarding machine learning techniques in intensive care units also support the potential mentioned above. Shillan et al. [28] investigated the preferable usage of machine learning techniques in intensive care units in this context. The study indicated that the most common aims were predicting complications, predicting mortality, and classifying sub-populations in intensive care units. According to the study, the most preferred machine learning approaches were neural networks, support vector machines, and classification/decision trees, respectively. In addition to these diagnosis-oriented machine learning applications, Gartner and Padman [62] addressed an operational behavioural problem in the healthcare industry. In their study, the waiting time perception of emergency care patients was analysed using machine learning classification. The results pointed out that when staff shifts were changed, the overestimation of waiting time by patients lowers, assuming that this potentially improved patients' satisfaction.

4.3. Expert systems: The Role of AI

Expert system as a branch of AI reflect individual or organizational behaviour with expert knowledge for specific problems. These systems are computer programs and require a knowledge base that refers to agreed facts general to the knowledge, a strategy to represent and diversify knowledge, and an inference engine as a problem-solving tool [63].

As a method of knowledge-driven DSS, expert systems are benefited for specific problems to be solved in the healthcare industry and serve as intelligent assistants to diagnose a disease, analyse laboratory test results, develop treatment protocol, and so on [64]. In addition to clinical applications of expert systems, Kunz and Schaaf [65] integrated a clinical balance scorecard into the expert system software to assess the performance and concluded that the expert systems with a clinical balance scorecard application served effectively as a performance measurement tool. In another study conducted by Abu Nasser [66], how expert systems can benefit from the healthcare industry was analysed via a survey. According to the analysis of the results, expert system-based computer programs supported many diagnosis and treatment processes such as back pain, hepatobiliary, urinations problems, breast cancer, hypertension, endocrine, rheumatic, and genital diseases. In their study, Hamedan et al. [26] developed a fuzzy logic expert system for chronic kidney disease by identifying diagnostic parameters and risk factors. This knowledge-driven DSS supported by the expert system indicates the usefulness of prediction of chronic kidney disease successfully.

Another contribution highlighted by Saibene et al. [26] is related to the applications of expert systems in the healthcare domain within the last decade. According to their investigation; when developed countries are examined, it is seen that there is a need of monitoring of chronic diseases integrating with real time automated tools. To take the pressure of the health-related problems, they reported that medical expert systems which are applied in various sub-practises including heart related issues, fall detection and elderly problems, neurology and chronic pains, pulmonary, urinary system represent subsidiary decision support systems particularly in daily clinical practices. In Table 1, some studies are listed to demonstrate examples of expert systems used for diagnostic purposes.

Table 1. Examples of Experts Systems for diagnostic purposes

Studies	Disease	Accuracy Rate
Neshat et al.[68]	Hepatitis	86,35% – 94,58%
Subanya et al.[69]	Heart Disease	81,50% – 86,4%
Dheeba et al.[70]	Breast cancer	89,87% – 93,67%
Vijay et al. [71]	Brain Tumour	92% – 95%
Sawhney et al. [72]	Cervical Cancer	94,92% – 97,36%
Rashid et al. [73]	Diabetic Mellitus	89,99% – 97,32%

All these studies highlight the intelligence capability of expert systems in the healthcare industry while recognizing the importance of AI. AI also enables decision-makers to develop automated tools.

5. Consideration for Developing Model-driven or Knowledge-driven DSS in Healthcare Industry

DSS requires specific infrastructural considerations: a language system, a presentation system, and a knowledge system. While programming language is considered as the technical focus of a language system, a presentation system refers to the user interface. Moreover, a knowledge system includes any input such as data, document and datasets [74]

Starting with the language system, studies in the healthcare industry present various programming languages such as C #, Visual Basic, and Phyton and database management systems such as MySQL. Dios et al. [20] presented a linear programming model for hospital management as an administrative decision support application. C # programming language and MySQL database management system were used during the development of DSS. Geçici and Güler [39] proposed DSS for users who require technical capabilities of use Python programming language. Nair et al.'s [32] server-client application called Smart Anesthesia Manager (SAM) was developed using Labview and coded using Visual Basic programming language. Andriopoulou et al. [31] benefited from the C++ multithreading programming model and open sources technologies such as InfluxD and Grafana. Hamedan et al. [26] developed a CDSS using Matlab programming platform to predict chronic kidney disease.

As a language system represent technical infrastructure of DSS, a user interface fulfils the basic characteristics. This refers to a non-tech user's capability to create and modify various DSS by only changing input parameters. Therefore, a user interface is considered as one of the foundation of DSS [4]. Regarding the healthcare industry, the user interface has significant importance since, in the US, user interface of a DSS is considered one of the key requirements [75]. Shojania et al. [76] addressed an essential feature of DSS as alerts, and in their study, recommendations as alerts were over-ruled by nurses. These workarounds were important factors that lower the effectiveness of DSS. In another study, Yuan et al. [77] focused on the design process of a user interface based on the needs of practitioners and nurses and explained the need to include recommendations based on treatment protocols. Furthermore, the study revealed that the checklist-based design helped healthcare users to follow the work process. After a training program and participatory adoption of DSS, this user interface design was implemented in other facilities.

The last but the most infrastructural element of DSS is a knowledge system that representing all the inputs such as data, documents, and datasets that DSS access and store, while generating knowledge from these inputs. In the context of the healthcare industry, patients' history such as diagnosis and prescriptions, medical and clinical data such as imaging and laboratory test results, and personal medical data of patients are the main inputs for decision-makers [78] These data constitute a large volume of healthcare repository, then used for data mining purposes to construct DSS. Furthermore, sharing dataset is nowadays considered as a significant academic contribution. In this regard, Johnson et al. [79] shared a large dataset of patients in critical care units in a journal dedicated to dataset sharing, named ScientificData.

Overall, DSS require certain infrastructural elements as a language system, a presentation system, and a knowledge system similar to other industries. Nevertheless, specific issues related to DSS infrastructure arise in the healthcare industry, such as requirements of DSS user interfaces and ethical responsibilities of healthcare data. These problems remain unsolved and take significant attention from various stakeholders [80-81].

6. Conclusion

Decision making is defined as a cognitive process that enables humans to collect information and choose alternatives while the human brain endeavour to decide. Therefore, systematic decision-making approaches are required to help humans during evaluation. DSS is a tool that enables decision-makers to solve complicated problems by presenting specific methods. However, DSS is often used as a misnomer phrase and needs to be scrutinized both terminologically and systematically since the evolution of information systems is inevitable.

This study particularly adopts the categorization of DSS in two groups as model-driven and knowledge-driven; however, these groups are not defined before, particularly after recent developments in information technology such as big data, AI, machine learning. This study contributes a framework to the literature that provides the transition from conventional methods, which enables model-driven and knowledge-driven DSS to become more intelligent. Furthermore, this framework enables future researchers and users of DSS to understand what actually they intend to develop and which methods are used in the relevant section of the framework.

Nevertheless, the border between the sections of framework will become more ambiguous since DSS includes a single method and combination of methods to overcome problems that make it more problematic to identify the categorization of DSS. On the other hand, this inclusion of multiple methods will lead to DSS's evolution from monadic operation to multi-task operations.

In the healthcare industry, CDSS with the interference of big data and AI, becomes hypervisible; however, CDSS has the limitations of focusing on single operations such as image recognition to diagnose. We believe that the DSS research will follow the direction of focusing on multi-task CDSS in the future. Furthermore, healthcare data will gain more significance, providing considerable opportunities to the researchers who develop DSS that facilitate AI-based methods. Finally, genetic algorithms have the potential to improve the preventive healthcare services.

References

[1] Rong, G., Mendez, A., Bou Assi, E., Zhao, B., & Sawan, M. (2020). Artificial Intelligence in Healthcare: Review and Prediction Case Studies. In *Engineering* (Vol. 6, Issue 3, pp. 291–301). Elsevier Ltd. https://doi.org/10.1016/j.eng.2019.08.015

[2] Eldabi, T., Jun, G. T., Clarkson, J., Connell, C., & Klein, J. H. (2010). Model driven healthcare: Disconnected practices. Proceedings of the 2010 Winter Simulation Conference, 2271–2282. https://doi.org/10.1109/WSC.2010.5678925

[3] Shahmoradi, L., Safdari, R., Ahmadi, H., & Zahmatkeshan, M. (2021). Clinical decision support systems-based interventions to improve medication outcomes: A systematic literature review on features and effects. *Medical Journal of The Islamic Republic of Iran*, *35*(27). https://doi.org/10.47176/mjiri.35.27Ansen, David (1986). "Tall Tale: Lord of the Mosquitoes." (Mosquito Coast) Newsweek 106 (Dec 1).

[4] Power, D. J., & Sharda, R. (2007). Model-driven decision support systems: Concepts and research directions. Decision Support Systems, 43(3), 1044–1061. /https://doi.org/10.1016/j.dss.2005.05.030

[5] Kavitha, P. T., & Sasipraba, T. (2012). Knowledge Driven HealthCare Decision Support System using Distributed Data Mining. Asian Journal of Computer Science and Technology (AJCST), 1(2), 24–27.

[6] Moreira, M. W. L., Rodrigues, J. J. P. C., Korotaev, V., Al-Muhtadi, J., & Kumar, N. (2019). A Comprehensive Review on Smart Decision Support Systems for Health Care. IEEE Systems Journal, 13(3), 3536–3545. https://doi.org/10.1109/JSYST.2018.2890121

[7] Gupta, S., Modgil, S., Bhattacharyya, S., & Bose, I. (2022). Artificial intelligence for decision support systems in the field of operations research: review and future scope of research. Annals of Operations Research, 308(1–2), 215–274.https://doi.org/10.1007/s10479-020-03856-6

[8] Demirer Ö., Alkan R.M., "The Usage of Operational Research for Engineering Applications as an Interdisciplinary Approach" Electronic Journal of Map Technologies, 2015, 7(1), 37-46, doi: 10.15659/hartek.15.04.88

[9] Hall, D. J. (2008). Decision Makers and Their Need for Support Dianne. In P. Bernus, J. Blazewicz, G. Schmidt, & M. Shaw (Eds.), International Handbook on Information Systems (pp. 83–103). Springer-Verlag Berlin Heidelberg.

[10] Camacho, J., Zanoletti-Mannello, M., Landis-Lewis, Z., Kane-Gill, S. L., & Boyce, R. D. (2020). A Conceptual Framework to Study the Implementation of Clinical Decision Support Systems (BEAR): Literature Review and Concept Mapping. *J Med Internet Res*, *22*(8), e18388. https://doi.org/10.2196/18388

[11] El Morr, C., & Ali-Hassan, H. (2019). Analytics in Healthcare: A Practical Introduction. Springer.

[12] Power, D. J. (2008). Decision Support Systems: A Historical Overview. In P. Bernus, J. Blazewicz, G. Schmidt, & M. Shaw (Eds.), International Handbook on Information Systems (pp. 121–140). Springer-Verlag Berlin Heidelberg. https://doi.org/10.1007/978-3-540-48713-5

[13] Arnott, D. (2004). Decision support systems evolution: framework, case study and research agenda. European Journal of Information Systems, 13(4), 247–259.

[14] Power, D. J. (2004). Specifying An Expanded Framework for Classifying and DescribingDecision Support Systems. Communications of the Association for Information Systems, 13(1), 13.

[15] Alter, S. L. (1980). Decision Support Systems: Current Practice and Continuing Challenges. Addison-Wesley Publishing Co.

[16] Bonczek, R. H., Holsapple, C. W., & Whinston, A. B. (1981). A Generalized Decision Support System Using Predicate Calculus and Network Data Base Management. Operations Research, 29(2), 263–281. https://doi.org/10.1287/opre.29.2.263

[17] Klein, M. R., & Methlie, L. B. (1995). Knowledge-Based Decision Support Systems With Applications in Business. Wiley.

[18] Holsapple, C. W., & Andrew B., W. (1996). Decision Support Systems: A Knowledge Based Approach. West Group.

[19] Power, D. J. (2002). A Brief History of Decision Support Systems. http://dssresources.com/history/dsshistoryv28.html

[20] Dios, M., Molina-Pariente, J. M., Fernandez-Viagas, V., Andrade-Pineda, J. L., & Framinan, J. M. (2015). A Decision Support System for Operating Room scheduling. Computers & Industrial Engineering, 88, 430–443. https://doi.org/https://doi.org/10.1016/j.cie.2015.08.001

[21] Djitog, I., Aliyu, H. O., & Traoré, M. K. (2018). A model-driven framework for multi-paradigm modeling and holistic simulation of healthcare systems. SIMULATION, 94(3), 235–257. https://doi.org/10.1177/0037549717744888

[22] Kalton, A., Falconer, E., Docherty, J., Alevras, D., Brann, D., & Johnson, K. (2015). Multi-Agent-Based Simulation of a Complex Ecosystem of Mental Health Care. Journal of Medical Systems, 40(2), 39. https://doi.org/10.1007/s10916-015-0374-4

[23] Kim, D.-G., & Kim, Y.-D. (2013). A Lagrangian heuristic algorithm for a public healthcare facility location problem. Annals of Operations Research, 206(1), 221–240. https://doi.org/10.1007/s10479-013-1378-4

[24] Mardani, A., Hooker, R. E., Ozkul, S., Yifan, S., Nilashi, M., Sabzi, H. Z., & Fei, G. C. (2019). Application of decision making and fuzzy sets theory to evaluate the healthcare and medical problems: A review of three decades of research with recent developments. Expert Systems with Applications, 137, 202–231. https://doi.org/https://doi.org/10.1016/j.eswa.2019.07.002

[25] Bashiri, A., Ghazisaeedi, M., Safdari, R., Shahmoradi, L., & Ehtesham, H. (2017). Improving the prediction of survival in cancer patients by using machine learning techniques: experience of gene expression data: a narrative review. Iranian Journal of Public Health, 46(2), 165.

[26] Hamedan, F., Orooji, A., Sanadgol, H., & Sheikhtaheri, A. (2020). Clinical decision support system to predict chronic kidney disease: A fuzzy expert system approach. International Journal of Medical Informatics, 138, 104134. https://doi.org/https://doi.org/10.1016/j.ijmedinf.2020.104134

[27] Nadarzynski, T., Miles, O., Cowie, A., & Ridge, D. (2019). Acceptability of artificial intelligence (AI)-led chatbot services in healthcare: A mixed-methods study. DIGITAL HEALTH, 5, 2055207619871808. https://doi.org/10.1177/2055207619871808

[28] Shillan, D., Sterne, J. A. C., Champneys, A., & Gibbison, B. (2019). Use of machine learning to analyse routinely collected intensive care unit data: A systematic review. Critical Care, 23(1), 1–11. https://doi.org/10.1186/s13054-019-2564-9

[29] Keefer, D. L., Kirkwood, C. W., & Corner, J. L. (2004). Perspective on Decision Analysis Applications, 1990–2001. Decision Analysis, 1(1), 4–22. https://doi.org/10.1287/deca.1030.0004

[30] Zarkogianni, K., Litsa, E., Mitsis, K., Wu, P. Y., Kaddi, C. D., Cheng, C. W., Wang, M. D., & Nikita, K. S. (2015). A Review of Emerging Technologies for the Management of Diabetes Mellitus. IEEE Transactions on Biomedical Engineering, 62(12), 2735–2749. https://doi.org/10.1109/TBME.2015.2470521

[31] Andriopoulou, F., Orphanoudakis, T., & Dagiuklas, T. (2017). IoTA: IoT automated SIP-based emergency call triggering system for general eHealth purposes. International Conference on Wireless and Mobile Computing, Networking and Communications, 2017-Octob, 362–369. https://doi.org/10.1109/WiMOB.2017.8115830

[32] Nair, B. G., Newman, S. F., Peterson, G. N., & Schwid, H. A. (2013). Smart anesthesia managerTM (SAM)-a real-time decision support system for anesthesia care during surgery. IEEE Transactions on Biomedical Engineering, 60(1), 207–210. https://doi.org/10.1109/TBME.2012.2205384

[33] Ağaç, G., & Baki, B. (2016). Application of Multi-Criteria Decision Making in Health Care Field: A Literature Review. Hacettepe Journal of Health Administration, 19(3), 343–363.

[34] Broekhuizen, H., Groothuis-Oudshoorn, C. G. M., van Til, J. A., Hummel, J. M., & IJzerman, M. J. (2015). A review and classification of approaches for dealing with uncertainty in multi-criteria decision analysis for healthcare decisions. Pharmacoeconomics, 33(5), 445–455.

[35] Nazari, S., Fallah, M., Kazemipoor, H., & Salehipour, A. (2018). A fuzzy inference- fuzzy analytic hierarchy process-based clinical decision support system for diagnosis of heart diseases. Expert Systems with Applications, 95, 261–271. https://doi.org/https://doi.org/10.1016/j.eswa.2017.11.001

[36] Thomas, L. L., Goni, I., & Emeje, G. D. (2019). Fuzzy Models Applied to Medical Diagnosis: A Systematic Review. Advances in Networks, 7(2), 45.

[37] Chang, N.-B., & Wang, S. F. (1996). The development of an environmental Decision Support System for municipal solid waste management. Computers, Environment and Urban Systems, 20(3), 201–212. https://doi.org/https://doi.org/10.1016/S0198-9715(96)00015-4

[38] Batur, G. D., & Erol, S. (2018). Operations research in healthcare systems: literature review of years 2007-2017. Pamukkale University Journal of Engineering Sciences, 24(1), 153–166. https://doi.org/10.5505/pajes.2017.44389

[39] Geçici, E., & Güler, M. G. (2020). A decision support system for nurse scheduling problem. Pamukkale University Journal of Engineering Sciences, 26(4), 749–757. https://doi.org/10.5505/pajes.2019.86402

[40] Lin, S., & Kernighan, B. W. (1973). An Effective Heuristic Algorithm for the Traveling-Salesman Problem. Operations Research, 21(2), 498–516. https://doi.org/10.1287/opre.21.2.498

[41] Kuo, Y. H., Leung, J. M. Y., Meng, H. M., & Tsoi, K. K. F. (2015). A Real-Time Decision Support Tool for Disaster Response: A Mathematical Programming Approach. Proceedings - 2015 IEEE International Congress on Big Data, BigData Congress 2015, 639–642. https://doi.org/10.1109/BigDataCongress.2015.98

[42] Laesanklang, W., & Landa-Silva, D. (2017). Decomposition techniques with mixed integer programming and heuristics for home healthcare planning. Annals of Operations Research, 256(1), 93–127. https://doi.org/10.1007/s10479-016-2352-8

[43] Fathollahi-Fard, A. M., Hajiaghaei-Keshteli, M., & Mirjalili, S. (2020). A set of efficient heuristics for a home healthcare problem. Neural Computing and Applications, 32(10), 6185–6205. https://doi.org/10.1007/s00521-019-04126-8

[44] Katsaliaki, K., & Mustafee, N. (2011). Applications of simulation within the healthcare context. Journal of the Operational Research Society, 62(8), 1431–1451. https://doi.org/10.1057/jors.2010.20

[45] Huang, E. S., Zhang, Q., Brown, S. E. S., Drum, M. L., Meltzer, D. O., & Chin, M. H. (2007). The Cost-Effectiveness of Improving Diabetes Care in U.S. Federally Qualified Community Health Centers. Health Services Research, 42(6p1), 2174–2193. https://doi.org/https://doi.org/10.1111/j.1475-6773.2007.00734.x

[46] Roze, S., Liens, D., Palmer, A., Berger, W., Tucker, D., & Renaudin, C. (2006). A health economic model to determine the long-term costs and clinical outcomes of raising low HDL-cholesterol in the prevention of coronary heart disease. Current Medical Research and Opinion, 22(12), 2549–2556. https://doi.org/10.1185/030079906X148490

[47] Bagni, R., Berchi, R., & Cariello, P. (2002). A comparison of simulation models applied to epidemics. Journal of Artificial Societies and Social Simulation, 5(3).

[48] Abbott, R. G., Forrest, S., & Pienta, K. J. (2006). Simulating the Hallmarks of Cancer. Artificial Life, 12(4), 617–634. https://doi.org/10.1162/artl.2006.12.4.617

[49] Liu, F., Enanoria, W. T. A., Zipprich, J., Blumberg, S., Harriman, K., Ackley, S. F., Wheaton, W. D., Allpress, J. L., & Porco, T. C. (2015). The role of vaccination coverage, individual behaviors, and the public health response in the control of measles epidemics: an agent-based simulation for California. BMC Public Health, 15(1), 447. https://doi.org/10.1186/s12889-015-1766-6

[50] Cabrera, E., Taboada, M., Iglesias, M. L., Epelde, F., & Luque, E. (2011). Optimization of Healthcare Emergency Departments by Agent-Based Simulation. Procedia Computer Science, 4, 1880–1889. https://doi.org/https://doi.org/10.1016/j.procs.2011.04.204

[51] Peng, Q., Niu, Q., Xie, Y., & Elmekkawy, T. (2009). Operating Room Simulation and Agent-Based Optimization Improvement. In Multi-Agent Systems for Healthcare Simulation and Modeling: Applications for System Improvement (pp. 69–89). IGI Global.

[52] Lee, S. M., & Hong, S. (2002). An enterprise-wide knowledge management system infrastructure. Industrial Management & Data Systems, 102(1), 17–25. https://doi.org/10.1108/02635570210414622

[53] Hall, D. J., & Paradice, D. (2005). Philosophical foundations for a learning-oriented knowledge management system for decision support. Decision Support Systems, 39(3), 445–461. https://doi.org/https://doi.org/10.1016/j.dss.2004.01.005

[54] Alalwan, J. A., Thomas, M. A., & Weistroffer, H. R. (2014). Decision support capabilities of enterprise content management systems: An empirical investigation. Decision Support Systems, 68, 39–48. https://doi.org/https://doi.org/10.1016/j.dss.2014.09.002

[55] Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. Future Healthcare Journal, 6(2), 94–98. https://doi.org/10.7861/futurehosp.6-2-94

[56] Laranjo, L., Dunn, A. G., Tong, H. L., Kocaballi, A. B., Chen, J., Bashir, R., Surian, D., Gallego, B., Magrabi, F., Lau, A. Y. S., & Coiera, E. (2018). Conversational agents in healthcare: a systematic review. Journal of the American Medical Informatics Association, 25(9), 1248–1258. https://doi.org/10.1093/jamia/ocy072

[57] Bharti, U., Bajaj, D., Batra, H., Lalit, S., Lalit, S., & Gangwani, A. (2020). Medbot: Conversational Artificial Intelligence Powered Chatbot for Delivering Tele-Health after COVID-19. 2020 5th International Conference on Communication and Electronics Systems (ICCES), 870–875. https://doi.org/10.1109/ICCES48766.2020.9137944

[58] Ng, G., Tan, N., Bahadin, J., Shum, E., & Tan, S. W. (2016). Development of an Automated Healthcare Kiosk for the Management of Chronic Disease Patients in the Primary Care Setting. Journal of Medical Systems, 40(7), 169. https://doi.org/10.1007/s10916-016-0529-y

[59] Callahan, A., & Shah, N. H. (2017). Machine Learning in Healthcare. In A. Sheikh, K. M. Cresswell, A. Wright, & D. W. B. T.-K. A. in C. I. Bates (Eds.), Key Advances in Clinical Informatics : Transforming Health Care Through Health Information Technology (pp. 279–291). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-12-809523-2.00019-4

[60] Sarker, I. H. (2021). Machine Learning: Algorithms, Real-World Applications and Research Directions. SN Computer Science, 2(3), 1–21. https://doi.org/10.1007/s42979-021-00592-x

[61] Choy, G., Khalilzadeh, O., Michalski, M., Do, S., Samir, A. E., Pianykh, O. S., Geis, J. R., Pandharipande, P. V, Brink, J. A., & Dreyer, K. J. (2018). Current Applications and Future Impact of Machine Learning in Radiology. Radiology, 288(2), 318–328. https://doi.org/10.1148/radiol.2018171820

[62] Gartner, D., & Padman, R. (2020). Machine learning for healthcare behavioural OR: Addressing waiting time perceptions in emergency care. Journal of the Operational Research Society, 71(7), 1087–1101. https://doi.org/10.1080/01605682.2019.1571005

[63] McCauley, N., & Ala, M. (1992). The use of expert systems in the healthcare industry. Information & Management, 22(4), 227–235. https://doi.org/https://doi.org/10.1016/0378-7206(92)90025-B

[64] Samarghitean, C., & Vihinen, M. (2008). Medical expert systems. Current Bioinformatics, 3(1), 56–65.

[65] Kunz, H., & Schaaf, T. (2011). General and specific formalization approach for a Balanced Scorecard: An expert system with application in health care. Expert Systems with Applications, 38(3), 1947–1955. https://doi.org/https://doi.org/10.1016/j.eswa.2010.07.127

[66] Abu-Nasser, B. (2017). Medical expert systems survey. International Journal of Engineering and Information Systems (IJEAIS), 1(7), 218–224.

[67] Saibene, A., Assale, M., & Giltri, M. (2021). Expert systems: Definitions, advantages and issues in medical field applications. Expert Systems with Applications, 177. https://doi.org/10.1016/j.eswa.2021.114900

[68] Neshat, M., Sargolzaei, M., Nadjaran Toosi, A., & Masoumi, A. (2012).Hepatitis disease diagnosis using hybrid case based reasoning and particle swarm optimization. ISRN Artificial Intelligence, 2012.

[69] Subanya, B., & Rajalaxmi, R. R. (2014). Artificial bee colony based feature selection for effective cardiovascular disease diagnosis. International Journal of Scientific & Engineering Research, 5(5), 606-612.

[70] Dheeba, J., Singh, N. A., & Selvi, S. T. (2014). Computer-aided detection of breast cancer on mammograms: A swarm intelligence optimized wavelet neural network approach. Journal of biomedical informatics, 49, 45-52.

[71] Vijay, V., Kavitha, A. R., & Rebecca, S. R. (2016). Automated brain tumor segmentation and detection in MRI using enhanced Darwinian particle swarm optimization (EDPSO). Procedia Computer Science, 92, 475-480.

[72] Sawhney, R., Mathur, P., & Shankar, R. (2018, May). A firefly algorithm based wrapper-penalty feature selection method for cancer diagnosis. In International Conference on Computational Science and Its Applications (pp. 438-449).

[73] Rashid, T., & Abdullah, S. (2018). A Hybrid of Artificial Bee Colony, Genetic Algorithm, and Neural Network for Diabetic Mellitus Diagnosing. ARO-The Scientific Journal of Koya University, 6(1), 55-64.

[74] Holsapple, C. W. (2008). DSS Architecture and Types. In P. Bernus, J. Blazewicz, G. Schmidt, & M. Shaw (Eds.), *International Handbook on Information Systems* (pp. 163–180). Springer-Verlag Berlin Heidelberg.

[75] Bolton, L. B., Gassert, C. A., & Cipriano, P. F. (2008). Technology solutions can make nursing care safer and more efficient. *Journal of Healthcare Information Management: JHIM*, *22*(4), 24–30.

[76] Shojania, K. G., Jennings, A., Mayhew, A., Ramsay, C., Eccles, M., & Grimshaw, J. (2010). Effect of point-of-care computer reminders on physician behaviour: a systematic review. *Canadian Medical Association Journal*, *182*(5), E216 LP-E225. https://doi.org/10.1503/cmaj.090578

[77] Yuan, M. J., Finley, G. M., Long, J., Mills, C., & Johnson, R. K. (2013). Evaluation of User Interface and Workflow Design of a Bedside Nursing Clinical Decision Support System. *Interact J Med Res*, *2*(1), e4. https://doi.org/10.2196/ijmr.2402

[78] Dash, S., Shakyawar, S. K., Sharma, M., & Kaushik, S. (2019). Big data in healthcare: management, analysis and future prospects. *Journal of Big Data*, *6*(1), 54. https://doi.org/10.1186/s40537-019-0217-0

[79] Johnson, A. E. W., Pollard, T. J., Shen, L., Lehman, L. H., Feng, M., Ghassemi, M., Moody, B., Szolovits, P., Anthony Celi, L., & Mark, R. G. (2016). MIMIC-III, a freely accessible critical care database. *Scientific Data*, *3*(1), 160035. https://doi.org/10.1038/sdata.2016.35

[80] Abouelmehdi, K., Beni-Hssane, A., Khaloufi, H., & Saadi, M. (2017). Big data security and privacy in healthcare: A Review. *Procedia Computer Science*, *113*, 73–80. https://doi.org/https://doi.org/10.1016/j.procs.2017.08.292

[81] Miller, K., Mosby, D., Capan, M., Kowalski, R., Ratwani, R., Noaiseh, Y., Kraft, R., Schwartz, S., Weintraub, W. S., & Arnold, R. (2018). Interface, information, interaction: a narrative review of design and functional requirements for clinical decision support. *Journal of the American Medical Informatics Association*, *25*(5), 585–592. https://doi.org/10.1093/jamia/ocx118