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Research article

Decision support systems in healthcare: systematic review, meta-analysis and prediction, with example of COVID-19

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Abstract: *Objective:* The objective of this study was to provide an overview of Decision Support Systems (DSS) applied in healthcare used for diagnosis, monitoring, prediction and recommendation in medicine. *Methods:* We conducted a systematic review using PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) guidelines of articles published until September 2022 from PubMed, Cochrane, Scopus and web of science databases. We used KH coder to analyze included research. Then we categorized decision support systems based on their types and medical applications. *Results:* The search strategy provided a total of 1605 articles in the studied period. Of these, 231 articles were included in this qualitative review. This research was classified into 4 categories based on the DSS type used in healthcare: Alert Systems, Monitoring Systems, Recommendation Systems and Prediction Systems. Under each category, domain applications were specified according to the disease the system was applied to. *Conclusion:* In this systematic review, we collected CDSS studies that use ML techniques to provide insights into different CDSS types. We highlighted the importance of ML to support physicians in clinical decision-making and improving healthcare according to their purposes.

Keywords: decision support system; healthcare; clinical decision support system; decision-making support systems

Abbreviations: DMSS = Decision-making support systems, DSS = decision support systems, AI = Artificial Intelligence, i-DSS = Intelligent decision support systems, EHR = electronic health records, ML = machine learning, ANN = artificial neural network, LR = logistic regression, SVM = support vector machines, NB = naive Bayes, kNN = k-nearest neighbors, LDA = linear discriminant analysis, DT = decision trees.

1. Introduction

Decision-Making Support Systems (DMSS), also called Decision Support Systems (DSS), are information systems designed to assist decision-makers and interactively support all phases of a human decision-making process [1]. Intelligent Decision Support Systems (i-DSS) are DSS based on Artificial Intelligence (AI) tools to increase the impact of management support [2]. An i-DSS is a sub-discipline of traditional DSS that incorporates techniques to supply natural intelligence and uses the power of modern computers to support and enhance decision-making through machine learning [2–5]. The i-DSS may, for example, "respond quickly and successfully to new data and information without human intervention, deal with perplexing and complex situations, learn from previous experience, apply knowledge to understand the environment, recognize the relative importance of different elements in the decision, incorporate the knowledge of domain experts, recommend action, and/or act on behalf of the human (by a predefined authorization of the decision-maker)" [1]. In the clinical domain, DSS are denominated Clinical Decision Support Systems (CDSSs). They are defined as any electronic or non-electronic system designed to aid directly the clinical decision-making, in which characteristics of individual patients are used to generate patient-specific assessments or recommendations that are then presented to clinicians for consideration [6]. CDSSs are also defined as computer programs based on evidence-based clinical guidelines with or without AI, and designed to support healthcare providers in identifying problems, resolving them, and reducing errors [7–10]. With the important volume of Electronic Health Records (EHR) data along with the increase in computational power, storage and memory, it represents a great opportunity to apply Machine Learning (ML) methodologies and perform a wide range of complex tasks with impressive accuracy in the healthcare context [11].

CDSSs are based on large amounts of clinical and biological data, and then use algorithms for matching patient conditions and phenotypic patterns to the most relevant recommendations, to provide the most pertinent information and alternative actions, at each step in the clinical decision-making process. It is designed to provide practitioners with optimal, individualized and real-time support, using compiled evidence so that each patient receives efficient, effective, and customized care [12]. These systems are commonly applied in healthcare processes, such as early detection of diseases and predictive medicine providing clinicians with information about individuals at risk, disease onset and how to intervene. CDSS are also used for triage, identification of changes in health symptoms, extraction of patient data from medical records, in-patient support, evaluation of treatment, and monitoring [13]. When planning to implement CDSS, researchers and developers have to focus on the five 'rights' of CDS: the right information, the right person, the right intervention format, the right channel and the right time in workflow [14].

Given the importance of new technologies and data analysis in reducing costs and improving the quality of healthcare, along with the important role of DSS and data mining, it is proposed some AI algorithms, their advantages, challenges and applications in healthcare. Many narrative, systematic and scoping reviews have been realized in CDSS, for diseases, either to focus on the disease like covid-19 [15,16], cancer [17,18], sepsis [19,20], etc. or on the ML techniques applied [21–23]. And generally, researchers studied one or several CDSS purposes, like monitoring, prediction and recommendation systems. However, there is a lack of scientific research with a comprehensive view of the types of CDSS algorithms and techniques in healthcare including monitoring, alert, prediction and recommendation systems.

In this paper, we have conducted a survey of recent state-of-the-art research on CDSS using a systematic review. We used PRISMA to search and select 231 research articles based on our inclusion criteria. We included research that present ML techniques and their applications in clinical systems. We used KH coder to analyze included research, then we outlined and grouped CDSS according to their types, applications and some of their purposes.

2. Methods

2.1. Systematic review

We focused our systematic review on decision support systems used in healthcare. A systematic review is “a review that has been prepared using a systematic approach to minimizing biases and random errors” [24]. It is different from the traditional narrative review by its greater transparency and the reproducibility of the search [25]. In order to emphasize clinical support tools, we used the PRISMA statement [26] which is an evidence-based minimum set of items (27-item check-list) for reporting in systematic reviews and meta-analyses.

2.2. Search strategy

A systematic search of the literature was performed in Mai 2022, and updated in September 2022, using Web of Science, PubMed, Scopus, and Cochrane. The following terms and operators were used for the search: (diagnosis system OR clinical decision support system OR clinical support tool OR computer-aided diagnosis OR health monitoring) AND (life threatening disease OR health) AND ((prediction OR probabilistic OR critical OR decision OR recommendation) AND (system OR model OR approach OR algorithm))

2.3. Study selection criteria

Titles and abstracts were screened for eligibility. Many retained records were not coincident with the request target. So, we included primary research studies that focused on diseases, caregivers, or healthcare professionals; using artificial intelligence-based tools either for diagnosis, monitoring or prediction. We excluded studies made before 2019.

2.4. Data collection process and data items

We extracted data from the selected reports according to the eligibility criteria. Then, we studied them one by one to find the major categories of DSS in healthcare.

3. Results

3.1. Main findings of the review search

The database search retrieved 1605 citations (Figure 1). After title and abstract screening, 837 articles were excluded. We screened the full texts of the remaining 448 articles. After the full-text screening, 286 articles were excluded. Then we kept only studies since 2019, leaving 231 articles. The keywords which were present in most of the selected papers were "clinical decision support system" and "artificial intelligence", which are emphasized in Figure 2.

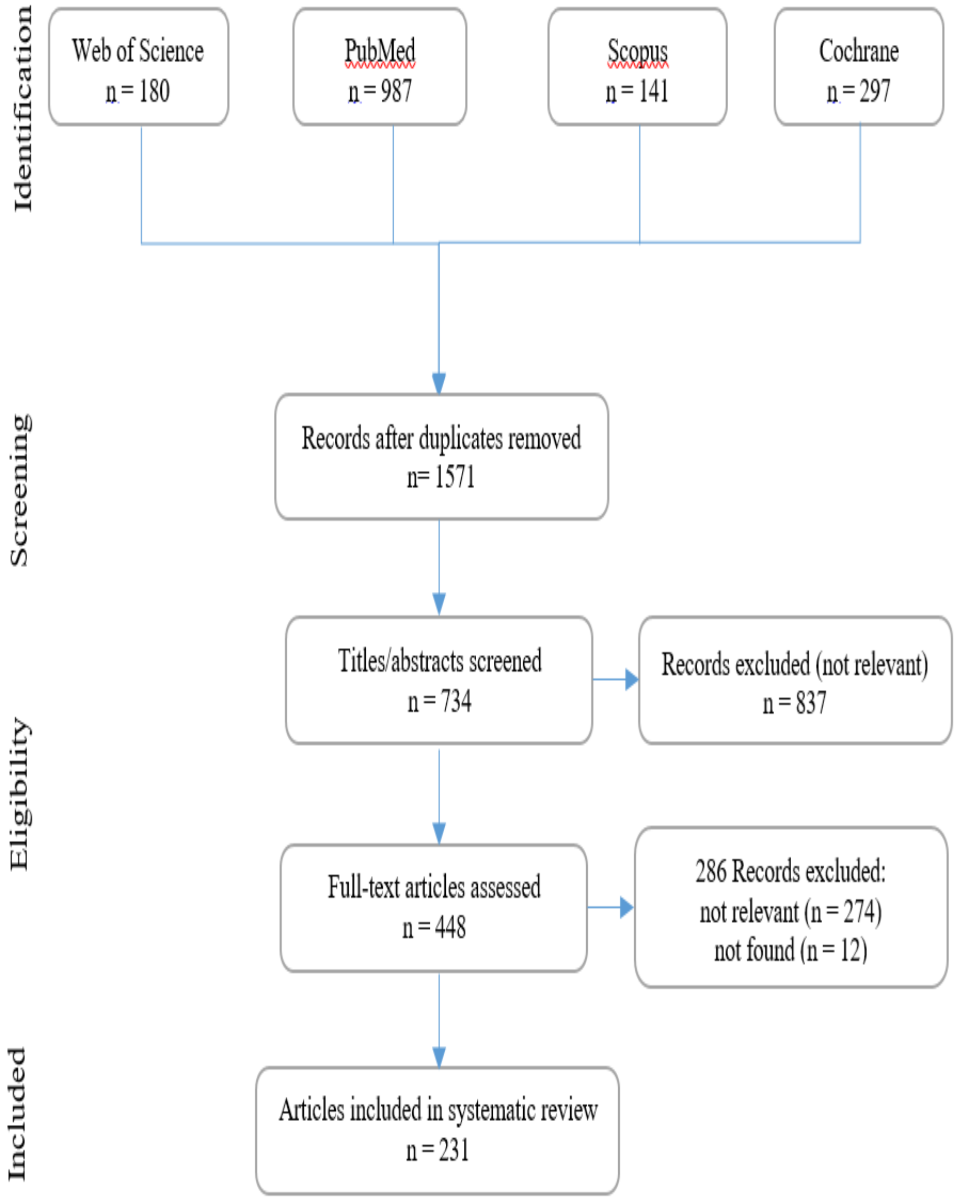

Figure 1. Flow of information through PRISMA review.

Figure 2. Keywords cloud.

3.2. KH coder

KH Coder is an open source software for computer assisted qualitative data analysis, quantitative content analysis and text mining. It can be also used for computational linguistics, and for factual examination co-event system hub structure, computerized arranging guide, multidimensional scaling, and comparative calculations. Coder allows to identify themes in large unstructured datasets, and supports several kinds of searches with frequency tables indicating what kind of words appeared frequently [27]. In order to investigate included records themes, we analyze the 231 articles using the KH Coder text mining tool. Table 1 shows frequently occurring words. The most frequent word was "support". Frequent keywords related to our research were "support", "decision", "clinical", "use", "health", "machine", "care", "learning", "base", and "monitoring".

Figure 3a,b show network diagrams of words and word connections. In Figure 3a, looking at the word arrangement, "study", "health", "decision", and "support" were almost in the center. In Figure 3b, "support" is a keyword because it is the center of strong co-occurrences. As for "support", the connection of decision systems was seen mainly from "clinical", and "decision" that co-occurred with "support". In the co-occurrence network, knowledge extraction was classified into four groups. From the set of extracted words, group 1 was interpreted as "support", group 2 as "decision", group 3 as "monitoring" and group 4 as "prediction".

Hierarchical cluster analysis (Figure 4) was performed with the minimum number of occurrences limited to 9 or more. "clinical", "decision", and "support" were included in the same cluster, and other terms concerning decision support systems regarding "machine", "health" and "prediction" were also convincing. In the cluster analysis, knowledge extraction was classified into five clusters. From the clustering of knowledge extraction, cluster 1 was interpreted as "support", cluster 2 as "monitoring", cluster 3 as "learning", cluster 4 as "prediction", and cluster 5 as "diagnosis".

Table 1. Word Frequency F.

Word	F	Word	F	Word	F
support	106	intelligence	7	develop	4
decision	60	Intelligence	7	Diabetes	4
clinical	56	intervention	7	Factors	4
Decision	53	Model	7	Feasibility	4
Clinical	50	Network	7	Hospital	4
use	41	Patients	7	Human	4
Health	32	tool	7	impact	4
machine	26	cancer	6	IoT	4
care	25	detection	6	manage	4
Learning	22	Disease	6	Management	4
base	21	disorder	6	medical	4
monitoring	19	Evaluation	6	Medical	4
Data	18	Framework	6	medication	4
prediction	18	framework	6	Mobile	4
Study	18	Implementation	6	modeling	4
primary	16	learn	6	Neural	4
Systems	16	Methods	6	Novel	4
Development	15	Mixed	6	Observational	4
study	15	neural	6	Prediction	4
diagnosis	13	Patient	6	quality	4
review	13	predict	6	Retrospective	4
artificial	12	adult	5	risk	4
Artificial	12	algorithm	5	Services	4

Continued on next page

Word	F	Word	F	Word	F
deep	12	approach	5	shock	4
health	12	Assessment	5	signal	4
Review	12	Big	5	support	4
Care	11	controlled	5	technique	4
COVID-19	11	Deep	5	Techniques	4
improve	10	Detection	5	thing	4
design	9	diabetes	5	Treatment	4
disease	9	effect	5	treatment	4
Electronic	9	electronic	5	type	4
evaluation	9	emergency	5	Adolescent	3
implementation	9	image	5	Analytics	3
learning	9	Integrated	5	Antibiotic	3
management	9	method	5	Area	3
model	9	randomize	5	barrier	3
network	9	scoping	5	cardiac	3
patient	9	sepsis	5	Cardiovascular	3
trial	9	Trial	5	case	3
analysis	8	Algorithm	4	Control	3
Analysis	8	arrhythmium	4	covid-19	3
Approach	8	assess	4	Decision-Making	3
Risk	8	automate	4	department	3
systematic	8	chronic	4	Diagnostic	3
Tool	8	classification	4	Diseases	3
use	8	cluster	4	Effects	3
application	7	computer-aided	4	Emergency	3
Cancer	7	convolutional	4	factor	3
datum	7	Design	4	feasibility	3

Figure 3 shows a diagram where similar words are clustered and classified in a hierarchical structure, in order to hierarchically capture combinations of words having similar appearance patterns from the extracted words.

Figure 4 is focusing on the word “support” in the cluster represented in the self-organizing map of Figure 5, and “decision”, “evaluation”, and “implementation” were formed in the same cluster.

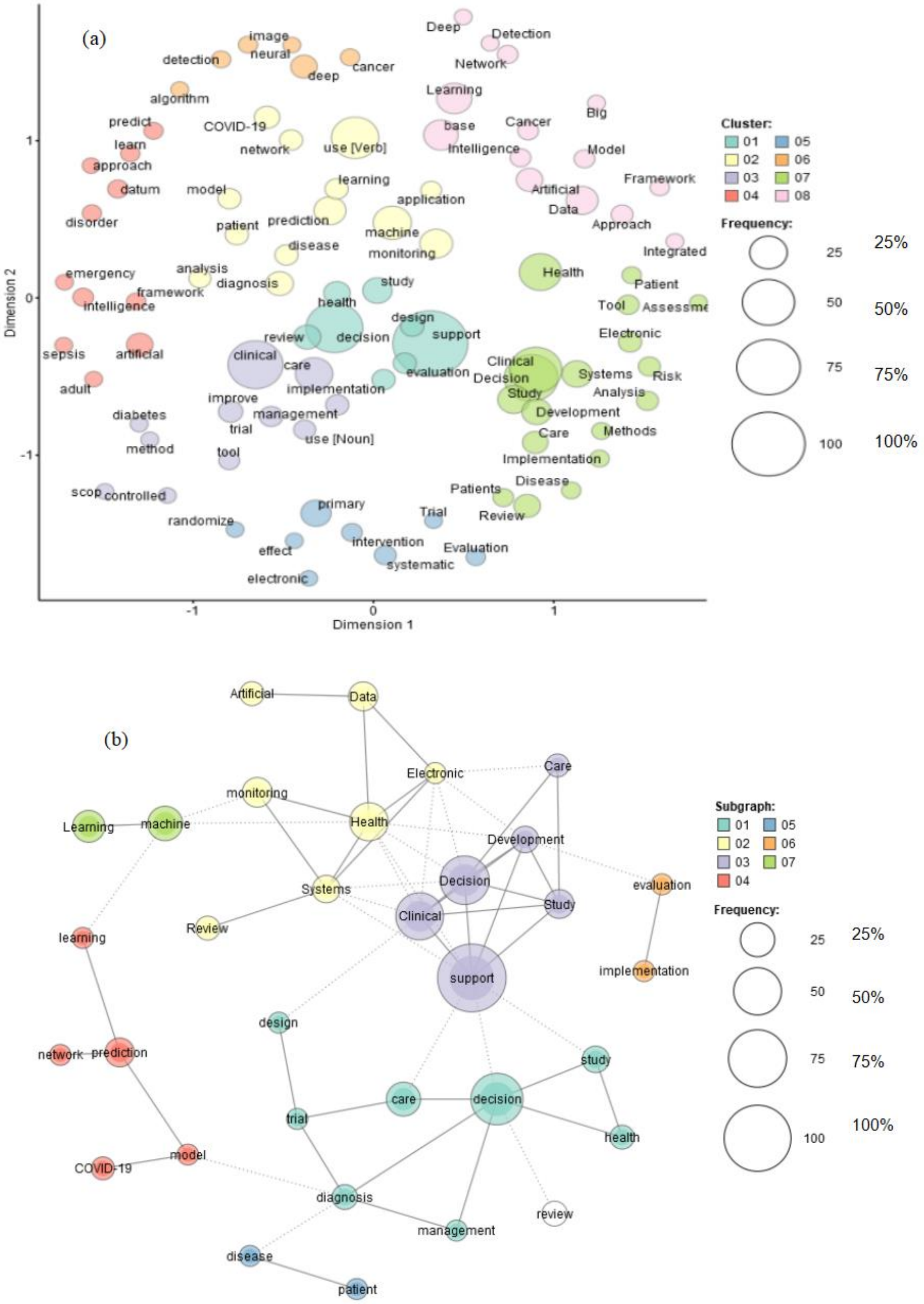

Figure 3. (a) Diagram of words, where the words “study”, “health”, “decision” and “support” are almost in the center. (b) Co-occurrence network of words, where “support” is a keyword, as center of strong co-occurrences.

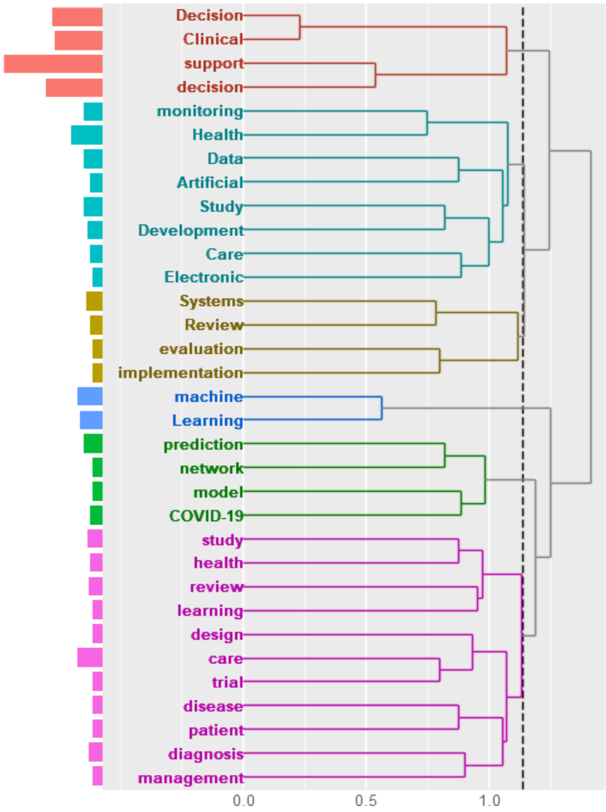

Figure 4. Hierarchical cluster analysis.

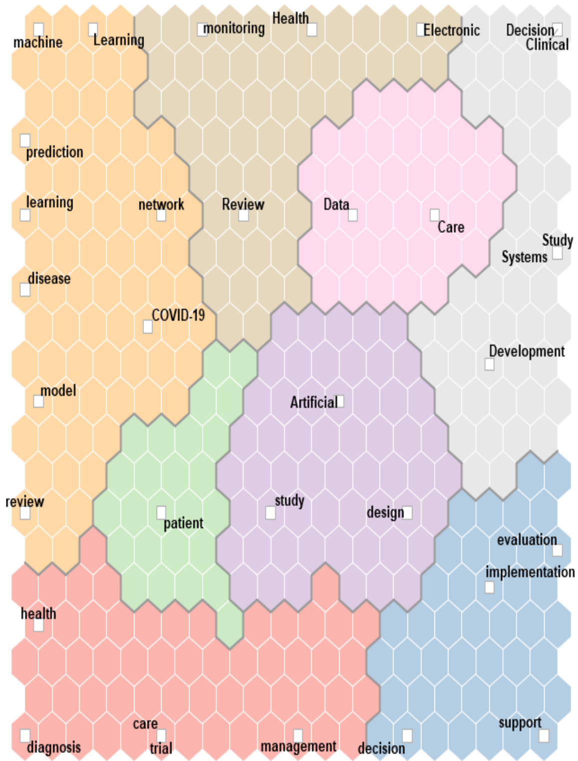

Figure 5. Self-organizing map.

3.3. CDSS

The CDSSs are based on the five "right" concepts representing the right information, the right person, the right intervention format, the right channel and the right time in workflow [14] (Figure 6).

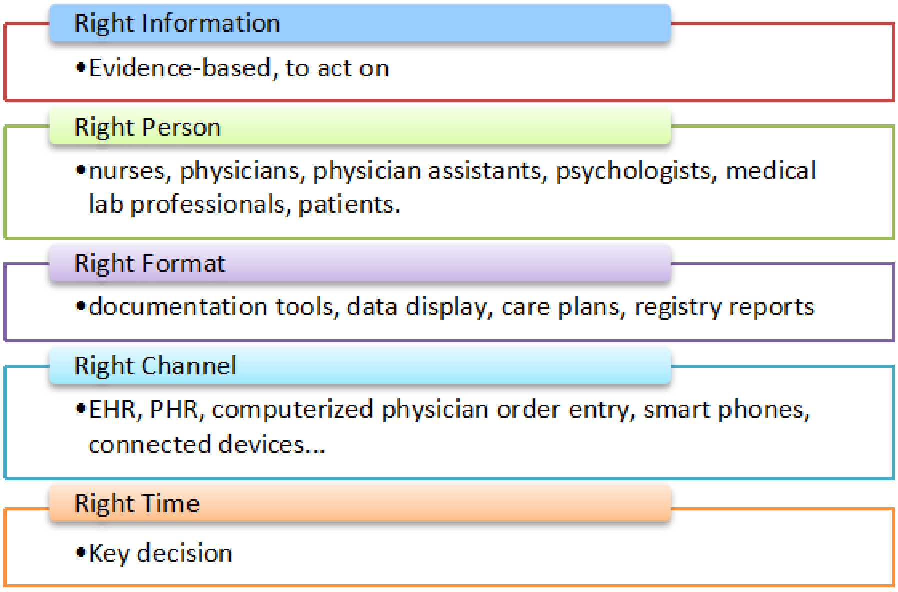

Figure 6. Five "right" CDS basis.

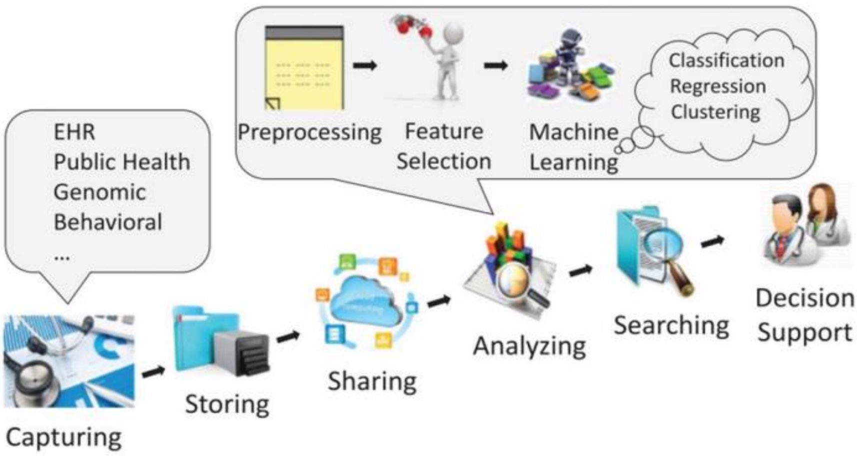

Figure 7. Health informatic processing pipeline [18].

CDSSs intervene in health informatics processing pipeline (Figure 7) and provide several modes of decision support, including alerts, reminders, advice, critiques, and suggestions for improved care. They are intended to assist physicians and other medical professionals in making informed decisions about a patient's care, based on electronic health records, medical literature, and clinical guidelines.

We classified CDSSs retrieved from our review according to the type of the system. We sort them into alert systems; monitoring systems; recommendation systems and prediction systems.

3.3.1. Alert systems

Computerized alert systems are widely used in clinical medicine for different specialties such as oncology [28], neurology [29], endocrinology [30], acute medical care [31,32], etc. These systems can be categorized as simple alert systems, and alert systems combined with monitoring, recommendation or early detection systems according to the physician's needs. Simple alert systems were used for various diseases like covid-19 [33], cancer [28], diabetes [30], and influenza [34]. Some of them were used in intensive care [31] and polypharmacy [35] to improve process efficiency. Other more complex alert systems, used for dual purposes, like combined with monitoring systems in polypharmacy [36], or with recommendation systems for drug prescription [37,38] or early detection systems for brain [29] and kidney [39] injuries or seasonal allergic rhinoconjunctivitis [40] (Table 2).

Table 2. Clinical alert systems.

Type of CDSS	Sub-category	Application	Purpose
		Healthcare	to realize a bibliometric Review and Content Analysis of alerts in clinical decision systems [41]
		Diabetes	to manage diabetes in secondary mental healthcare through record retrieval and alerting with CogStack [30]
		covid-19	for covid-19 detection using convolution neural network, deep learning neural network, feature selection, optimized artificial immune network, SVM [33]
		Cancer	to evaluate breast Cancer Risk using machine learning [28]
		Population health management	to targeted individuals who meet criteria for preventive measures or treatment [42]
		Emergency department (ED)	to describe alert override patterns with a commercial medication CDSS in an academic, using rule-based, alert type–specific logic; logistic regression model for assessing the risk of the alert override ED [31]
		Pediatry	to improve influenza vaccine uptake using best practice alert (BPA) [34]
Alert systems		Polypharmacy	to support targeting high-alert medications using machine learning [35]
	Monitoring	Polypharmacy	to improve naloxone distribution and coprescription within Military Health System pharmacies in the US, using data mining technics [36]
	Recommendation	pharmacy	to evaluate the clinical validity of the dose range checking (DRC) tool and compare it to the institutional Formulary and Drug Therapy Guide [37]
		Healthcare	to provide a Review of Drug–drug interactions [38]
		Critical care	to figure out factors associated with critical care decision making (cognitive biases, environmental, patient and personal factors) [32]
		Healthcare	to improve quality of care in primary healthcare settings using mobile devices [43]
	Early detection	Kidney Injury	to evaluate acute Kidney Injury Events [39]
		Brain Injury	to detect mild traumatic brain injury from Human sleep electroencephalogram [29]
		Seasonal allergic rhinoconjunctivitis	to improve Allergen immunotherapy prescription decision [40]

3.3.2. Monitoring systems

Medical monitoring systems are devices or software applications that are used to track and record various physiological parameters of a patient. They are involved in several specialties like cardiolody [44], geriatry [45,46], to help clinicians to screen patients' vitals both in hospitals [47] and remote health either to improve hospital-homecare transition [48], or simply to track patients vitals and preventive healthcare [49–51] (Table 3).

Table 3. Medical monitoring systems.

Type of CDSS	Application	Purpose
Monitoring Systems	Geriatrics	to monitor multi parameters to categorize and determine the abnormal patient details present in the dataset [45]
		to review the effects of CDSS interventions in older hospitalized patients [47]
		to explore the impact of glaucoma screening of elders in remote areas with artificial intelligence (AI) automated diagnosis from a budgetary standpoint [46]
	Remote health	conceptual framework of Remote Health Monitoring in Clinical Trial using Machine Learning Techniques [49]
		to propose an AI-enabled IoT-CPS (Cyber-Physical Systems) doctors can use to discover diseases in patients [51]
		to Improve Patient Prioritization During Hospital-Homecare Transition [48]
		to track patient's activities and their vitals during those activities [50]
	Emergency	to identify fall-risk of elders in emergency department (design and implementation) [52]
	Sepsis	to analyze the impact of display on risk perception of sepsis-induced health deterioration [53]
	Cardiology	To identify whether CDSS would improve the primary care provided to patients with Atrial fibrillation [44]
	Image processing	to automate crack detection in image processing [54]
	Diagnostic strategy	to improve diagnostic thinking process and dual-process theory [55]
	Healthcare	to Monitor patient health during Autonomous Hospital Bed Transport using Wrist-Wearable Sensor [56]
		to help physicians analyze athletes' conditions and offer the proper medications to them, even if the doctors are away [57]
	Trial monitoring	To evaluate the advantages and disadvantages of different monitoring strategies for clinical intervention studies [58]
		to formulate a new conceptual framework for monitoring clinical trial using Support Vector Machine and Artifcial Neural Network classifiers with physiological datasets from a wearable device [49]
	Non-communicable diseases	to provide a protocol to screen and monitor non-communicable diseases in resource-poor settings [59]

3.3.3. Recommendation systems

Recommendation systems are particularly used for drug prescription [60,61], laboratory tests [62] and polypharmacy management [21,63], besides diseases like diabetes [64], rare diseases [65], blood pressure, thyroid [66], etc. (Table 4).

Table 4. Clinical recommendation systems.

Type of CDSS	Application	Purpose
Recommendation systems	Healthcare	to realize a review that offers a definition of PHI (participatory healthcare informatics) considering themes and technologies that make healthcare participatory [67]
		to achieve computer-aided syndrome differentiation and prescription recommendation through deep learning and reinforcement learning technics [68]
		to recommend patients suffering from Diabetes or Blood pressure or Thyroid healthier diet and exercise plans by analyzing and monitoring health parameters and the values from their latest reports related to their disease [66]
	Rare diseases	to present Opportunities and Challenges for Machine Learning in Rare Diseases [65]
	Polypharmacy	to improve Antibiotic Prescription Recommendations in Primary Care [60]
		to improve medication and polypharmacy management [21,63]
		to improve decision-making by clinicians as well as drug safety namely concerning drug-drug interactions [61]
	Laboratory	to Recommend Laboratory Tests [62]
	Urinary tract infections	to assess the impact of CDSS on treatment success and change in antibiotic prescription behavior of the physician [69]
	Diabetes	to identify people with Diabetes Treatment through Lipids Profile [64]
	Cancer	to Assist Breast Cancer Patients with Lifestyle Modifications during the COVID-19 Pandemic [70]
		to evaluate efficacy of digital tools supporting cancer survivors [71]

3.3.4. Prediction systems

The prediction systems are particularly used for complex diseases with high mortality rates like cancer [72–74], sepsis, typhoid, etc. or diseases having a lot of ambiguity in their diagnosis, that need a good expertise to be well treated. They are used for diagnosis, and particularly for early detection of diseases. Moreover, they are used to predict the outcome of some treatment and mortality rate given some conditions [75]. During the covid-19 epidemic, these systems were used for early detection [76–78], vaccination [79,80] and mortality prediction [75] (Table 5).

Table 5. Clinical prediction systems.

Type of CDSS	Application	Purpose
Prediction systems	Covid-19	to classify priorities for COVID-19 vaccination campaign [79]
		to Predict Post-Vaccination Adverse Effects Based on Predisposing Factors [80]
		to realize self-pre-diagnosis system and predict Covid-19 in smartphone users using personal data and observed symptoms [81]
		to detect covid-19 disease [76–78]
		for Early COVID-19 Mortality Prediction [75]
	Cancer	to diagnose colorectal cancer in elderlies via internet of medical things [72]
		to improve Lung Cancer Diagnosis through Deep Learning applied on Computed Tomography (CT) images [82]
		to diagnose breast cancer studying histopathological Images [83]
		to diagnose liver cancer using multimodal deep learning techniques [9]
	Human activity recognition	Literature Review of the risks and sources of uncertainty in IoT decision-making systems [84]
	Emergency	to personalize care levels among emergency room patients for hospital admission [85]
	Sepsis	for early Detection of Septic Shock Onset Using Interpretable Machine Learners [86]
	Chronic diseases	to develop and apply methods for enhancing chronic disease care using AI [87]
	Obstetrics	to predict the mode of delivery according to three categories: caesarean section, euthocic vaginal delivery and, instrumental vaginal delivery [88]
	Cardiology	to study the continuous measurement of the Arterial blood pressure (ABP) through a cufess, non-intrusive approach and use deep learning technics to infer ABP [89]
	Osteoarthritis knee	to Predict Knee Osteoarthritis Based on Nonimage Longitudinal Medical Record [90]
	Opioid use disorder	to predict which patients will discontinue opioid use disorder treatment within less than a year [91]
	Healthcare	to detect diseases at early stage before laboratory tests reducing the unlimited waiting time and cost expenditure [92]
	Typhoid fever	To diagnose typhoid fever disease [93]

3.4. CDSS algorithms

We can define two categories of CDSS, Knowledge-Based and Non-Knowledge-Based. The Knowledge-Based category uses knowledge-bases to infer the results. A knowledge base represents rules (“if-then”) and queries inside an inference engine. While Non-Knowledge-Based CDSSs depend on Machine Learning (ML) to analyze patient data. ML uses a wide number of techniques from simple data analysis and pattern recognition to fuzzy logic and inference. In this section, we are focusing on the last category and its algorithms. The most popular classification algorithms are logistic regression (LR), support vector machines (SVM), naive Bayes (NB), k-nearest neighbors (kNN), linear discriminant analysis (LDA), artificial neural networks (ANN) with deep learning techniques, decision trees (DT), ensembles like random forests and gradient boosting [94]. Besides these techniques, there are several other algorithms used in CDSS, that will not be detailed in this paper like Bayesian networks [95,96] used in various diseases studies like covid-19 [97] and sepsis diagnosis [98].

3.4.1. Logistic regression

Logistic regression (LR) is a statistical method for binary classification that can be generalized to multiclass classification. It has a very good performance and gives linearly separable classes [99]. LR is commonly used in healthcare due to its easy interpretability, having been used for several diseases like diabetes [64], covid-19 mortality prediction [75], septic shock early detection [86] and admission management at emergency department [100]. The probability p of an event to occur given the value x of an observable variable is calculated from the logistic function:

$$p = \frac{1}{1+e^{-y}}, \text{ where } y = b_0 + b_1 x \tag{1}$$

The quantity $log[p/(1-p)]$ is the logarithm of the odd ratio, also known as log-odd or logit. The odd ratio of an event is the likelihood that this event will occur. It can be seen as the ratio of "successes" to "non-successes". Technically, odd ratio represents the probability of an event divided by the probability that this event will not occur [101]. This probability can be calculated from the odd ratio odd as $p = \frac{Odd}{1+Odd}$.

3.4.2. Support vector machines (SVM)

SVMs are considered as accurate and highly robust. The objective of SVMs is to find the most suitable function of classification to separate the classes in the training data when undertaking the two-class learning task. Namely, finding the most extreme margin of hyperplanes with the best use of generalization is the motivation that drives investigating SVMs [99]. SVM algorithm is widely used in CDSS, such as for covid-19 [33] and ECG arrhythmia detection [102], and remote health [45,49], since it permits the most appropriate classification performance on training data, perfectly classifies future data, and thereby offers the best generalization ability [103]. The function to maximize, in order to actually find the maximum margin is:

$$L_p = \frac{1}{2} \|\vec{w}\| - \sum_{i=1}^{t} \alpha_i \gamma_i (\vec{w}.\vec{x_i} + b) + \sum_{i=1}^{t} \alpha_i, \tag{2}$$

where t is the number of training examples, and $\alpha_i, i = 1, \dots, t$, are non-negative numbers such that the derivatives of L_p with respect to α_i are zero. α_i are the Lagrange multipliers and L_p is called the Lagrangian operator. In this equation, the vectors $\vec{w}$ and constant b define the hyperplane.

3.4.3. Naive Bayes.

Naive Bayes (NB) classification method is based on simple probability using independent class assumption. The advantage of such approach is that error value would be minimum with high speed of process if number of data is big. The probability *P(x)* of data with unknown class is:

$$P(c|x) = \frac{P(X|C)P(c)}{P(x)} \tag{3}$$

where c is a specific class hypothesis data; $P(c|x)$ represents the probability hypothesis C based on x condition (posteriori probability); $P(c)$ is the probability hypothesis c (prior probability) and $P(x|c)$ represents the probability x based on hypothesis c condition [93].

3.4.4. K-Nearest neighbors (kNN)

KNN is a classification algorithm based on proximity data. It uses a memory-based technique and samples of trial have to be kept during run time in this memory [93]. Considering the first sample and the second sample, then distance between the data would be calculated based on their proximity. To do so, Euclidean Distance formula is used:

$$dist(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{4}$$

where x represents testing data and y training data. dist *(x,y)* is the distance between data training and testing and n is the dimension of the free variable data. This classification algorithm is also used in several CDSS particularly for heart disease detection [102,104,105].

3.4.5. Linear discriminant analysis (LDA)

LDA is a generalization of Fisher's linear discriminant analysis, generally used to find a linear combination of features, which separates two or more classes of data. Linear classifiers are supervised learning models used to make prediction decisions for a given observation based on a linear predictor function combining a set of weights with the components of the observation feature vector [106]. LDA is widely used for early detection of diseases using EHR data [106–108].

3.4.6. Decision trees (DTs)

DTs are used in several CDSS research like diabetes [64] and covid-19 detection [75], urinary infections studies [69], and septic shock early detection [86]. They have a structured hierarchy like a tree, with internal nodes having exactly two outgoing edges. The splits are selected using towing criteria and the tree obtained is pruned by cost-complexity pruning [109]. Classification trees have target variables taking a discrete set of values while regression trees target variables use continuous values. DTs are inefficient if they learn from incomplete data, however contrarily to ANN, they are not black-box models and provide an easy interpretation of the classification system [110].

3.4.7. Random Forest (RF)

RF used also in various disease studies like diabetes [64] and covid-19 detection [75], septic shock early detection [86] and heart disease detection [102], is based on DT as the main classifier, and on the use of ensemble learning technique to characterize information. The ensemble technique combines indicators from multiple trained classifiers to classify new instances. A random forest is a type of classifier that consists of tree-organized classifiers. Each tree makes a unit vote for the most well-known class. A random vector is independent of the former random vectors with the same distribution, and the training test is employed to create a tree [99].

3.4.8. Fuzzy logic classifier

Fuzzy systems are used to describe uncertain phenomena, since real world is a complex system with a lot of interacting elements at different levels. The use of fuzzy expert systems based on fuzzy logic to handle uncertainties generated by imprecise, incomplete and/or vague information, can transform information gathered by experts into knowledge, which can be used later for early diagnosis of diseases or for developing treatment plans for elders [111] and patients suffering from diabetes [112] and chronic kidney disease [113]. The fuzzy classifier has the advantage of interpretability compared with other techniques like ANN.

3.4.9. Artificial neural networks (ANNs)

ANNs are used in CDSS for prediction, diagnosis, classification and regression problems. They are based on a nonlinear approach to solve a given problem where the relationships between inputs and outputs are known. ANNs are inspired by the human brain. They present a set of processing units that work in the same way as the human brain performs its functions [114]. Data are divided into a training dataset and testing dataset, and ANN acquires knowledge through the training process and learns specific patterns from the inputs provided in the training dataset. When the network is trained, we test the obtained model on the testing dataset and evaluate its performance. Since nowadays, the processing speeds of computer systems have increased immensely, ANNs have been widely used in CDSS in many clinical studies [114] related to covid-19 detection [76], diabetes glycemic control [115], heart diseases [116,117], liver disorder [118] and suicide attempt prediction [119]

4. Discussion

AI is currently widely used in CDSS to improve the diagnosis, prognosis and treatment of a particular pathology. It predicts the risk for a certain disease or the probability of a medical outcome, based on various data types, from different data sources like HER, research papers, etc. Our study showed that according to medical professionals needs, several CDSS algorithms can be used for the same purpose. To predict if a patient has some disease, different classification tools can be applied, such as SVM, decision tree, random forest, etc, and data scientists have to choose the right tool with the highest accuracy and the lowest error rate. Therefore, several studies in our review were based on different algorithms for covid-19 early detection. [76] used deep learning method to analyze X-ray images and detect covid-19, while [77] proposed an ANN-based CDSS based on EHR of previous patients to help doctors in their diagnosis and [78] used linear and logistic regression to develop a covid risk calculator. All these proposed techniques aim to enhance diagnostic accuracy and assist physicians to make better-informed decisions and thereby improving patients' outcomes and increasing their satisfaction. Moreover, we found that some AI techniques like SVM, can be involved in different CDSS types. It has been used in the alert systems for covid-19 detection [33], in prediction system to help obstetricians to make more informed decisions about delivery mode [88], as well as in remote health monitoring in clinical trials [49].

5. Conclusion

In the medical domain, in most countries, particularly in developing ones, diagnosis and treatment are based on the experience of medical staff, particularly of physicians, rather than on exploiting all the knowledge acquired in EHR data. However, recently, AI has been introduced in biomedical applications such as clinical decision support systems, diagnosis, prediction and monitoring systems. These systems have been applied in several specialties like infectious diseases, chronic diseases, and cardiovascular diseases, as well as in oncology and psychiatry. This paper presents through a systematic review using the PRISMA statement, the state of the art of CDSS and their various applications. The goal of this paper is to provide an overview of how the DSS can benefit healthcare and biomedical applications, what challenges have been faced, what methods have been proposed on the algorithm design level, and what future trends are. As a result of our study, we got a systematic review with a large sample of studies that are high quality. However, PRISMA is primarily focused on the reporting of systematic reviews and meta-analyses. So, it cannot deal with missing data, handle studies with a high risk of bias, or assess the overall quality of the evidence.

And even if CDSSs have generally a lot of benefits, risks also exist. Therefore, there are many challenges related to data safety and availability, requiring ethical clearance and data access approval, particularly with the reuse of clinical information within the system [120]. There are also challenges relative to the five 'rights', since the CDSS must be value-added for the right target, user-friendly and useful, according to individual needs, purposes and culture. Thereby, in order to develop a good CDSS, practicing clinicians should be involved in all the CDSS phases. And further research needs to be done to improve AI explainability since medical professionals can become skeptical if they do not understand the data processing, algorithms and their outcomes [121].

Conflict of interest

The authors declare no conflict of interest.

Author contributions

Contributions of all authors are the same.

References

1. Gupta JN, Forgionne GA, Mora M (2007) *Intelligent decision-making support systems: foundations, applications and challenges,* Germany: Springer Science & Business Media.
2. Merkert J, Mueller M, Hubl M (2015) *A Survey of the Application of Machine Learning in Decision Support Systems.*
3. Proudlove NC, Vadera S, Kobbacy KAH (1998) Intelligent management systems in operations: A review. *J Oper Res Soc* 49: 682–699. https://doi.org/10.1057/palgrave.jors.2600519
4. Gottinger HW and Weimann P (1992) Intelligent decision support systems. *Decis Support Syst* 8: 317–332. https://doi.org/10.1016/0167-9236(92)90053-R

5. Elam JJ and Konsynski B (1987) Using artificial intelligence techniques to enhance the capabilities of model management systems. *Decision Sci* 18: 487–502. https://doi.org/10.1111/j.1540-5915.1987.tb01537.x
6. Kawamoto K, Houlihan CA, Balas EA, et al. (2005) Improving clinical practice using clinical decision support systems: a systematic review of trials to identify features critical to success. *BMJ* 330: 765. https://doi.org/10.1136/bmj.38398.500764.8F
7. Islam MdM, Haque MdR, Iqbal H, et al. (2020) Breast cancer prediction: A comparative study using machine learning techniques. *SN Computer Science* 1: 290. https://doi.org/10.1007/s42979-020-00305-w
8. Islam Ayon S and Milon Islam Md (2019) Diabetes prediction: a deep learning approach. *IJIEEB* 11: 21–27. https://doi.org/10.5815/ijieeb.2019.02.03
9. Akter L and Islam MM (2021) Hepatocellular carcinoma patient's survival prediction using oversampling and machine learning techniques, *2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST)*, IEEE, 2021: 445–450.
10. Akter L, Al Islam F, Islam M, et al. (2021) Prediction of cervical cancer from behavior risk using machine learning techniques. *SN Computer Science* 2: 177. https://doi.org/10.1007/s42979-021-00551-6
11. Wiens J and Shenoy ES (2018) Machine learning for healthcare: on the verge of a major shift in healthcare epidemiology. *Clin Infect Dis* 66: 149–153. https://doi.org/10.1093/cid/cix731
12. Clausen CE, Leventhal BL, Nytrø Ø, et al. (2021) Clinical decision support systems: An innovative approach to enhancing child and adolescent mental health services. *J Am Acad Child Adolesc Psychiatry* 60: 562–565. https://doi.org/10.1016/j.jaac.2020.09.018
13. Pombo N, Araújo P, Viana J (2014) Knowledge discovery in clinical decision support systems for pain management: a systematic review. *Artif Intell Med* 60: 1–11. https://doi.org/10.1016/j.artmed.2013.11.005
14. Campbell RJ (2013) The five rights of clinical decision support: CDS tools helpful for meeting meaningful use (web version updated February 2016). *J AHIMA* 84: 42–47.
15. Chadaga K, Prabhu S, Vivekananda BK, et al. (2021) Battling COVID-19 using machine learning: A review. *Cogent Eng* 8: 1958666. https://doi.org/10.1080/23311916.2021.1958666
16. Syeda HB, Syed M, Sexton KW, et al. (2021) Role of machine learning techniques to tackle the COVID-19 crisis: systematic review. *JMIR Med Inf* 9: e23811. https://doi.org/10.2196/23811
17. Kaur B, Goyal B, Daniel E (2022) A survey on machine learning based medical assistive systems in current oncological sciences. *Curr Med Imaging* 18: 445–459. https://doi.org/10.2174/1573405617666210217154446
18. Kreuzberger N, Damen JA, Trivella M, et al. (2020) Prognostic models for newly-diagnosed chronic lymphocytic leukaemia in adults: a systematic review and meta-analysis. https://doi.org/10.1002/14651858.CD012022.pub2
19. Hassan N, Slight R, Weiand D, et al. (2021) Preventing sepsis; how can artificial intelligence inform the clinical decision-making process? A systematic review. *Int J Med Inform* 150: 104457. https://doi.org/10.1016/j.ijmedinf.2021.104457
20. Wulff A, Montag S, Marschollek M, et al. (2019) Clinical decision-support systems for detection of systemic inflammatory response syndrome, sepsis, and septic shock in critically ill patients: a systematic review. *Methods Inf Med* 58: e43–e57. https://doi.org/10.1055/s-0039-1695717

21. Mouazer A, Tsopra R, Sedki K, et al. (2022) Decision-support systems for managing polypharmacy in the elderly: A scoping review. *J Biomedl Inform* 130: 104074. https://doi.org/10.1016/j.jbi.2022.104074
22. Nazari E, Biviji R, Roshandel D, et al. (2022) Decision fusion in healthcare and medicine: a narrative review. *Mhealth* 8: 8. https://doi.org/10.21037/mhealth-21-15
23. Wei Y, Zhou J, Wang Y, et al. (2020) A review of algorithm & hardware design for AI-based biomedical applications. *IEEE T Biomed Circ S* 14: 145–163. https://doi.org/10.1109/TBCAS.2020.2974154
24. Chalmers I and Altman DG (1995) *Systematic Reviews*. London: BMJ Publications.
25. Needleman I, Moles DR, Worthington H (2005) Evidence-based periodontology, systematic reviews and research quality. *Periodontology 2000* 37: 12–28. https://doi.org/10.1111/j.1600-0757.2004.37100.x
26. Moher D, Liberati A, Tetzlaff J, et al. (2009) Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *Ann Intern Med* 151: 264–269. https://doi.org/10.7326/0003-4819-151-4-200908180-00135
27. Higuchi K (2016) KH Coder 3 reference manual. Kioto (Japan): Ritsumeikan University.
28. Casal-Guisande M, Comesaña-Campos A, Dutra I, et al. (2022) Design and development of an intelligent clinical decision support system applied to the evaluation of breast cancer risk. *J Pers Med* 12: 169. https://doi.org/10.3390/jpm12020169
29. Vishwanath M, Jafarlou S, Shin I, et al. (2021) Investigation of machine learning and deep learning approaches for detection of mild traumatic brain injury from human sleep electroencephalogram, *43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, 2021: 6134–6137. https://doi.org/10.1109/EMBC46164.2021.9630423
30. Patel D, Msosa YJ, Wang T, et al. (2022) An implementation framework and a feasibility evaluation of a clinical decision support system for diabetes management in secondary mental healthcare using CogStack. *BMC Med Inform Decis Mak* 22: 100. https://doi.org/10.1186/s12911-022-01842-5
31. Yoo J, Lee J, Rhee P-L, et al. (2020) Alert override patterns with a medication clinical decision support system in an academic emergency department: retrospective descriptive study. *JMIR Med Inf* 8: e23351. https://doi.org/10.2196/23351
32. Beldhuis IE, Marapin RS, Jiang YY, et al. (2021) Cognitive biases, environmental, patient and personal factors associated with critical care decision making: a scoping review. *J Crit Care* 64: 144–153. https://doi.org/10.1016/j.jcrc.2021.04.012
33. Kanwal S, Khan F, Alamri S, et al. (2022) COVID-opt-aiNet: A clinical decision support system for COVID-19 detection. *Int J Imag Syst Tech* 32: 444–461. https://doi.org/10.1002/ima.22695
34. Bratic JS, Cunningham RM, Belleza-Bascon B, et al. (2019) Longitudinal evaluation of clinical decision support to improve influenza vaccine uptake in an integrated pediatric health care delivery system, Houston, Texas. *Appl Clin Inform* 10: 944–951. https://doi.org/10.1055/s-0039-3400748
35. Potier A, Dufay E, Dony A, et al. (2022) Pharmaceutical algorithms set in a real time clinical decision support targeting high-alert medications applied to pharmaceutical analysis. *Int J Med Inf* 160: 104708. https://doi.org/10.1016/j.ijmedinf.2022.104708
36. Rittel AG, Highland KB, Maneval MS, et al. (2022) Development, implementation, and evaluation of a clinical decision support tool to improve naloxone coprescription within Military Health System pharmacies. *Am J Health-Syst Ph* 79: e58–e64. https://doi.org/10.1093/ajhp/zxab206

37. Al-Jazairi A, AlQadheeb E, Alshammari L, et al. (2019) Clinical validity assessment of integrated dose range checking tool in a tertiary care hospital using an electronic health information system. *Hosp Pharm* 56: 95-101. https://doi.org/10.1177/0018578719867663
38. Hammar T, Hamqvist S, Zetterholm M, et al. (2021) Current knowledge about providing drug-drug interaction services for patients—a scoping review. *Pharmacy* 9: 69. https://doi.org/10.3390/pharmacy9020069
39. Robert L, Rousseliere C, Beuscart J-B, et al. (2021) Integration of explicit criteria in a clinical decision support system through evaluation of acute kidney injury events. *Pub Health Inform* 281: 640–644. https://doi.org/10.3233/SHTI210249
40. Arasi S, Castelli S, Di Fraia M, et al. (2021) @IT2020: An innovative algorithm for allergen immunotherapy prescription in seasonal allergic rhinitis. *Clin Exp Allergy* 51: 821–828. https://doi.org/10.1111/cea.13867
41. Chien S-C, Chen Y-L, Chien C-H, et al. (2022) Alerts in clinical decision support systems (CDSS): a bibliometric review and content analysis. *Healthcare* 10: 601. https://doi.org/10.3390/healthcare10040601
42. Bradshaw RL, Kawamoto K, Kaphingst KA, et al. (2022) GARDE: a standards-based clinical decision support platform for identifying population health management cohorts. *J Am Med Inform Assn* 29: 928–936. https://doi.org/10.1093/jamia/ocac028
43. Agarwal S, Glenton C, Tamrat T, et al. (2021) Decision-support tools via mobile devices to improve quality of care in primary healthcare settings. *Cochrane DB Syst Rev* 7: CD012944. https://doi.org/10.1002/14651858.CD012944.pub2
44. Ru X, Zhu L, Ma Y, et al. (2022) Effect of an artificial intelligence-assisted tool on non-valvular atrial fibrillation anticoagulation management in primary care: protocol for a cluster randomized controlled trial. *Trials* 23: 1–12. https://doi.org/10.1186/s13063-022-06250-8
45. Premalatha G and Bai VT (2022) Wireless IoT and cyber-physical system for health monitoring using honey badger optimized least-squares support-vector machine. *Wireless Pers Commun* 124: 3013–3034. https://doi.org/10.1007/s11277-022-09500-9
46. Xiao X, Xue L, Ye L, et al. (2021) Health care cost and benefits of artificial intelligence-assisted population-based glaucoma screening for the elderly in remote areas of China: a cost-offset analysis. *BMC Public Health* 21: 1065. https://doi.org/10.1186/s12889-021-11097-w
47. Damoiseaux-Volman BA, van der Velde N, Ruige SG, et al. (2021) Effect of interventions with a clinical decision support system for hospitalized older patients: systematic review mapping implementation and design factors. *JMIR Med Inform* 9: e28023. https://doi.org/10.2196/28023
48. Zolnoori M, McDonald MV, Barrón Y, et al. (2021) Improving patient prioritization during hospital-homecare transition: protocol for a mixed methods study of a clinical decision support tool implementation. *JMIR Res Protoc* 10: e20184. https://doi.org/10.2196/20184
49. Abiodun TN, Okunbor D, Osamor VC (2022) Remote health monitoring in clinical trial using machine learning techniques: a conceptual framework. *Health Technol* 12: 359–364. https://doi.org/10.1007/s12553-022-00652-z
50. Malche T, Tharewal S, Tiwari PK, et al. (2022) Artificial intelligence of things- (AIoT-) based patient activity tracking system for remote patient monitoring. *J Healthc Eng* 2022: 8732213. https://doi.org/10.1155/2022/8732213

51. Ramasamy LK, Khan F, Shah M, et al. (2022) Secure smart wearable computing through artificial intelligence-enabled internet of things and cyber-physical systems for health monitoring. *Sensors* 22: 1076. https://doi.org/10.3390/s22031076
52. Jacobsohn GC, Leaf M, Liao F, et al. (2022) Collaborative design and implementation of a clinical decision support system for automated fall-risk identification and referrals in emergency departments. *Healthcare* 10: 100598. https://doi.org/10.1016/j.hjdsi.2021.100598
53. Capan M, Schubel LC, Pradhan I, et al. (2022) Display and perception of risk: Analysis of decision support system display and its impact on perceived clinical risk of sepsis-induced health deterioration. https://doi.org/10.1177/14604582211073075
54. Parente L, Falvo E, Castagnetti C, et al. (2022) Image-based monitoring of cracks: Effectiveness analysis of an open-source machine learning-assisted procedure. *J Imaging* 8: 22. https://doi.org/10.3390/jimaging8020022
55. Shimizu T (2022) System 2 diagnostic process for the next generation of physicians: “inside” and “outside” brain—the interplay between human and machine. *Diagnostics* 12: 356. https://doi.org/10.3390/diagnostics12020356
56. Tan YH, Liao Y, Tan Z, et al. (2021) Application of a machine learning algorithms in a wrist-wearable sensor for patient health monitoring during autonomous hospital bed transport. *Sensors* 21: 5711. https://doi.org/10.3390/s21175711
57. Wu X, Liu C, Wang L, et al. (2021) Internet of things-enabled real-time health monitoring system using deep learning. https://doi.org/10.1007/s00521-021-06440-6
58. Klatte K, Pauli-Magnus C, Love SB, et al. (2021) Monitoring strategies for clinical intervention studies. *Cochrane DB Syst Rev* 12: MR000051. https://doi.org/10.1002/14651858.MR000051.pub2
59. Zaman SB, Evans RG, Singh R, et al. (2021) Feasibility of community health workers using a clinical decision support system to screen and monitor non-communicable diseases in resource-poor settings: study protocol. *Mhealth* 7: 15. https://doi.org/10.21037/mhealth-19-258
60. Madar R, Ugon A, Ivanković D, et al. (2021) A web interface for antibiotic prescription recommendations in primary care: user-centered design approach. *J Med Internet Res* 23: e25741. https://doi.org/10.2196/25741
61. Lau L, Bagri H, Legal M, et al. (2021) Comparison of clinical importance of drug interactions identified by hospital pharmacists and a local clinical decision support system. *Can J Hosp Pharm* 74: 203–210. https://doi.org/10.4212/cjhp.v74i3.3147
62. Islam MdM, Poly TN, Yang H-C, et al. (2021) Deep into laboratory: An artificial intelligence approach to recommend laboratory tests. *Diagnostics* 11: 990. https://doi.org/10.3390/diagnostics11060990
63. Mouazer A, Leguillon R, Leroy B, et al. (2022) ABiMed: towards an innovative clinical decision support system for medication reviews and polypharmacy management. *Inform Technol Clin Care Pub Heal* 289: 61–64. https://doi.org/10.3233/SHTI210859
64. Alcalá-Rmz V, Galván-Tejada CE, García-Hernández A, et al. (2021) Identification of people with diabetes treatment through lipids profile using machine learning algorithms. *Healthcare* 9: 422. https://doi.org/10.3390/healthcare9040422
65. Decherchi S, Pedrini E, Mordenti M, et al. (2021) Opportunities and challenges for machine learning in rare diseases. *Front Med* 8: 747612. https://doi.org/10.3389/fmed.2021.747612

66. Mogaveera D, Mathur V, Waghela S (2021) e-Health monitoring system with diet and fitness recommendation using machine learning. *6th International Conference on Inventive Computation Technologies (ICICT)*, 2021: 694–700. https://doi.org/10.1109/ICICT50816.2021.9358605
67. Denecke K, Gabarron E, Petersen C, et al. (2021) Defining participatory health informatics-a scoping review. *Inform Health Soc Ca* 46: 234–243. https://doi.org/10.1080/17538157.2021.1883028
68. Zhang Q, Bai C, Yang LT, et al. (2021) A unified smart chinese medicine framework for healthcare and medical services. *IEEE/ACM Trans Comput Biol Bioinf* 18: 882–890. https://doi.org/10.1109/TCBB.2019.2914447
69. Herter WE, Khuc J, Cinà G, et al. (2022) Impact of a machine learning-based decision support system for urinary tract infections: prospective observational study in 36 primary care practices. *JMIR Med Inform* 10: e27795. https://doi.org/10.2196/27795
70. Papandreou P, Gioxari A, Nimee F, et al. (2021) Application of clinical decision support system to assist breast cancer patients with lifestyle modifications during the COVID-19 pandemic: a randomised controlled trial. *Nutrients* 13: 2115. https://doi.org/10.3390/nu13062115
71. Mlakar I, Lin S, Aleksandraviča I, et al. (2021) Patients-centered survivorShIp care plan after cancer treatments based on big data and artificial intelligence technologies (PERSIST): a multicenter study protocol to evaluate efficacy of digital tools supporting cancer survivors. *BMC Med Inform Decis Making* 21: 243. https://doi.org/10.1186/s12911-021-01603-w
72. Asghari P (2021) A diagnostic prediction model for colorectal cancer in elderlies via internet of medical things. *Int J Inf Tech* 13: 1423–1429. https://doi.org/10.1007/s41870-021-00663-5
73. Emani S, Rui A, Rocha HAL, et al. (2022) Physicians' perceptions of and satisfaction with artificial intelligence in cancer treatment: A clinical decision support system experience and implications for low-middle-income countries. *JMIR Cancer* 8: e31461. https://doi.org/10.2196/31461
74. Haddad T, Helgeson JM, Pomerleau KE, et al. (2021) Accuracy of an artificial intelligence system for cancer clinical trial eligibility screening: retrospective pilot study. *JMIR Med Inform* 9: e27767. https://doi.org/10.2196/27767
75. Karthikeyan A, Garg A, Vinod PK, et al. (2021) Machine learning based clinical decision support system for early COVID-19 mortality rediction. *Front Public Health* 9: 626697. https://doi.org/10.3389/fpubh.2021.626697
76. Nayak SR, Nayak DR, Sinha U, et al. (2021) Application of deep learning techniques for detection of COVID-19 cases using chest X-ray images: a comprehensive study. *Biomed Signal Process Control* 64: 102365. https://doi.org/10.1016/j.bspc.2020.102365
77. Shanbehzadeh M, Nopour R, Kazemi-Arpanahi H (2022) Developing an artificial neural network for detecting COVID-19 disease. *J Educ Health Promot* 11: 153. https://doi.org/10.4103/jehp.jehp_1017_21
78. Dugdale CM, Rubins DM, Lee H, et al. (2021) Coronavirus disease 2019 (COVID-19) diagnostic clinical decision support: A pre-post implementation study of CORAL (COvid Risk cALculator). *Clin Infect Dis* 73: 2248–2256. https://doi.org/10.1093/cid/ciab111
79. Romeo L and Frontoni E (2022) A unified hierarchical XGBoost model for classifying priorities for COVID-19 vaccination campaign. *Pattern Recogn* 121: 108197. https://doi.org/10.1016/j.patcog.2021.108197

80. Hatmal MM, Al-Hatamleh MAI, Olaimat AN, et al. (2022) Reported adverse effects and attitudes among Arab populations following COVID-19 vaccination: A large-scale multinational study implementing machine learning tools in predicting post-vaccination adverse effects based on predisposing factors. *Vaccines* 10: 366. https://doi.org/10.3390/vaccines10030366
81. Çelik Ertuğrul D and Çelik Ulusoy D (2022) A knowledge-based self-pre-diagnosis system to predict Covid-19 in smartphone users using personal data and observed symptoms. *Expert Syst* 39: e12716. https://doi.org/10.1111/exsy.12716
82. Jiang W, Zeng G, Wang S, et al. (2022) Application of deep learning in lung cancer imaging diagnosis. *J Healthc Eng* 2022: 6107940. https://doi.org/10.1155/2022/6107940
83. Agaba A, Abdullahi M, Junaidu S, et al. (2022) Improved multi-classification of breast cancer histopathological images using handcrafted features and deep neural network (dense layer). *Intelligent Syst Appl* 14: 200066. https://doi.org/10.1016/j.iswa.2022.200066
84. Hussain T, Nugent C, Moore A, et al. (2021) A risk-based IoT decision-making framework based on literature review with human activity recognition case studies. *Sensors* 21: 4504. https://doi.org/10.3390/s21134504
85. Nguyen M, Corbin CK, Eulalio T, et al. (2021) Developing machine learning models to personalize care levels among emergency room patients for hospital admission. *J Am Med Inform Assoc* 28: 2423–2432. https://doi.org/10.1093/jamia/ocab118
86. Misra D, Avula V, Wolk DM, et al. (2021) Early detection of septic shock onset using interpretable machine learners. *JCM* 10: 301. https://doi.org/10.3390/jcm10020301
87. Tarumi S, Takeuchi W, Chalkidis G, et al. (2021) Leveraging artificial intelligence to improve chronic disease care: Methods and application to pharmacotherapy decision support for type-2 diabetes mellitus. *Methods Inf Med* 60: e32–e43. https://doi.org/10.1055/s-0041-1728757
88. De Ramón Fernández A, Ruiz Fernández D, Prieto Sánchez MT (2022) Prediction of the mode of delivery using artificial intelligence algorithms. *Comput Meth Prog Biomed* 219: 106740. https://doi.org/10.1016/j.cmpb.2022.106740
89. Paviglianiti A, Randazzo V, Villata S, et al. (2022) A comparison of deep learning techniques for arterial blood pressure prediction. *Cogn Comput* 14: 1689–1710. https://doi.org/10.1007/s12559-021-09910-0
90. Ningrum DNA, Kung W-M, Tzeng I-S, et al. (2021) A deep learning model to predict knee osteoarthritis based on nonimage longitudinal medical record. *J Multidiscip Healthc* 14: 2477–2485. https://doi.org/10.2147/JMDH.S325179
91. Hasan MM, Young GJ, Shi J, et al. (2021) A machine learning based two-stage clinical decision support system for predicting patients' discontinuation from opioid use disorder treatment: retrospective observational study. *BMC Med Inform Decis Mak* 21: 331. https://doi.org/10.1186/s12911-021-01692-7
92. Zohra FT (2020) Prediction of different diseases and development of a clinical decision support system using naïve bayes classifier. *IJRASET* 8: 8–13. https://doi.org/10.22214/ijraset.2020.5002
93. Andrianto B, Suprapto YK, Pratomo I, et al. (2019) Clinical decision support system for typhoid fever disease using classification techniques. *International Seminar on Intelligent Technology and Its Applications (ISITIA)*, IEEE, 2019: 248–252. https://doi.org/10.1109/ISITIA.2019.8937286
94. Sarkar D, Bali R, Sharma T (2018) *Practical Machine Learning with Python*, CA: Apress Berkeley. https://doi.org/10.1007/978-1-4842-3207-1

95. Cypko MA and Stoehr M (2019) Digital patient models based on Bayesian networks for clinical treatment decision support. *Minim Invasiv Ther* 28: 105–119. https://doi.org/10.1080/13645706.2019.1584572
96. Laxmi P, Gupta D, Gopalapillai R, et al. (2021) A scalable multi-disease modeled CDSS based on Bayesian network approach for commonly occurring diseases with a NLP-Based GUI, *Intelligent Systems, Technologies and Applications: Proceedings of Sixth ISTA 2020, India,* Singapor: Springer, 161–171. https://doi.org/10.1007/978-981-16-0730-1_11
97. Edye EO, Kurucz JF, Lois L, et al. (2021) Applying Bayesian networks to help physicians diagnose respiratory diseases in the context of COVID-19 pandemic, *IEEE URUCON*, IEEE, 2021: 368–371. https://doi.org/10.1109/URUCON53396.2021.9647280
98. Gupta A, Liu T, Shepherd S (2020) Clinical decision support system to assess the risk of sepsis using tree augmented Bayesian networks and electronic medical record data. *Health Inform J* 26: 841–861. https://doi.org/10.1177/1460458219852872
99. Subasi A (2020) Machine learning techniques, *Practical Machine Learning for Data Analysis Using Python*, Elsevier: Academic Press, 91–202. https://doi.org/10.1016/B978-0-12-821379-7.00003-5
100. Araz OM, Olson D, Ramirez-Nafarrate A (2019) Predictive analytics for hospital admissions from the emergency department using triage information. *Int J Prod Econ* 208: 199–207. https://doi.org/10.1016/j.ijpe.2018.11.024
101. Bruce P, Bruce A, Gedeck P (2020) *Practical statistics for data scientists: 50+ essential concepts using R and Python*, USA: O'Reilly Media.
102. Sraitih M, Jabrane Y, Hajjam El Hassani A (2021) An automated system for ECG arrhythmia detection using machine learning techniques. *J Clin Med* 10: 5450. https://doi.org/10.3390/jcm10225450
103. Wu X, Kumar V, Ross Quinlan J, et al. (2008) Top 10 algorithms in data mining. *Knowl Inf Syst* 14: 1–37. https://doi.org/10.1007/s10115-007-0114-2
104. Mukherjee R, Sadhu S, Kundu A (2022) Heart disease detection using feature selection based KNN classifier, *Proceedings of Data Analytics and Management*, Singapore, Springer: 577–585. https://doi.org/10.1007/978-981-16-6289-8_48
105. Kannan S (2022) An automated clinical decision support system for predicting cardiovascular disease using ensemble learning approach. *Concurrency Comput Pract Exp* 34: e7007. https://doi.org/10.1002/cpe.7007
106. Sharma SK, Vijayakumar K, Kadam VJ, et al. (2022) Breast cancer prediction from microRNA profiling using random subspace ensemble of LDA classifiers via Bayesian optimization. *Multimed Tools Appl* 81: 41785–41805. https://doi.org/10.1007/s11042-021-11653-x
107. Yang S, Bian J, Sun Z, et al. (2018) Early detection of disease using electronic health records and Fisher's Wishart discriminant analysis. *Procedia Comput Sci* 140: 393–402. https://doi.org/10.1016/j.procs.2018.10.299
108. De Andres J, Ten-Esteve A, Harutyunyan A, et al. (2021) Predictive clinical decision support system using machine learning and imaging biomarkers in patients with neurostimulation therapy: a pilot study. *Pain Physician* 24: E1279–E1290.
109. Fernandes M, Vieira SM, Leite F, et al. (2020) Clinical decision support systems for triage in the emergency department using intelligent systems: a review. *Artif Intell Med* 102: 101762. https://doi.org/10.1016/j.artmed.2019.101762

110.Dreiseitl S and Ohno-Machado L (2002) Logistic regression and artificial neural network classification models: a methodology review. *J Biomed Inform* 35: 352–359. https://doi.org/10.1016/S1532-0464(03)00034-0
111.Ehn M, Derneborg M, Revenäs Å, et al. (2021) User-centered requirements engineering to manage the fuzzy front-end of open innovation in e-health: A study on support systems for seniors' physical activity. *Int J Med Inform* 154: 104547. https://doi.org/10.1016/j.ijmedinf.2021.104547
112.Ylenia C, Chiara DL, Giovanni I, et al. (2021) A clinical decision support system based on fuzzy rules and classification algorithms for monitoring the physiological parameters of type-2 diabetic patients. *MBE* 18: 2654–2674. https://doi.org/10.3934/mbe.2021135
113.Hamedan F, Orooji A, Sanadgol H, et al. (2020) Clinical decision support system to predict chronic kidney disease: A fuzzy expert system approach. *Int J Med Inform* 138: 104134. https://doi.org/10.1016/j.ijmedinf.2020.104134
114.Shafi I, Ansari S, Din S, et al. (2021) Artificial neural networks as clinical decision support systems. *Concurrency Comput Pract Exp* 33: e6342. https://doi.org/10.1002/cpe.6342
115.Pappada SM, Owais MH, Cameron BD, et al. (2020) An artificial neural network-based predictive model to support optimization of inpatient glycemic control. *Diabetes Technol Ther* 22: 383–394. https://doi.org/10.1089/dia.2019.0252
116.Jin Y, Qin C, Huang Y, et al. (2020) Multi-domain modeling of atrial fibrillation detection with twin attentional convolutional long short-term memory neural networks. *Knowl-Based Syst* 193: 105460. https://doi.org/10.1016/j.knosys.2019.105460
117.Faust O and Acharya UR (2021) Automated classification of five arrhythmias and normal sinus rhythm based on RR interval signals. *Expert Syst Appl* 181: 115031. https://doi.org/10.1016/j.eswa.2021.115031
118.Haque MdR, Islam MdM, Iqbal H, et al. (2018) Performance evaluation of random forests and artificial neural networks for the classification of liver disorder, *International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2)*, Rajshahi, IEEE, 2018: 1–5. https://doi.org/10.1109/IC4ME2.2018.8465658
119.Lyu J and Zhang J (2019) BP neural network prediction model for suicide attempt among Chinese rural residents. *J Affect Disorders* 246: 465–473. https://doi.org/10.1016/j.jad.2018.12.111
120.Sutton RT, Pincock D, Baumgart DC, et al. (2020) An overview of clinical decision support systems: benefits, risks, and strategies for success. *Npj Digital Medicine* 3: 17. https://doi.org/10.1038/s41746-020-0221-y
121.Antoniadi AM, Du Y, Guendouz Y, et al. (2021) Current challenges and future opportunities for XAI in machine learning-based clinical decision support systems: a systematic review. *Appl Sci* 11: 5088. https://doi.org/10.3390/app11115088