Ann Mil Health Sci Res. 2023 March; 21(1):e134440. https://doi.org/10.5812/amh-134440.

Published online 2023 August 9. **Review Article**

Clinical Reasoning and Artificial Intelligence

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Received 2022 December 26; **Revised** 2023 June 27; **Accepted** 2023 July 10.

Abstract

Context: Artificial intelligence refers to a set of systems that are capable of performing functions similar to human intelligent functions. Today, artificial intelligence has been successfully incorporated into clinical decision support systems (CDSS).
Evidence Acquisition: The current study aimed to briefly present a narrative mini-review on clinical reasoning and artificial intelligence. Data were gathered from Google Scholar, ScienceDirect, and PubMed databases using the "clinical decision support system, artificial intelligence, and clinical reasoning" keywords.
Results: Clinical decision support systems are divided into two categories: Knowledge-based and data-driven. The first category is called the rule-based expert system, and the second category is also named the machine-learning system. The usefulness of the mentioned systems and artificial intelligence in interpreting algorithmic and statistical information, where the human element can easily make a mistake, is that they are much more efficient and work with fewer errors. However, when it comes to dealing with a patient and his complaints and symptoms, because of the requirement for clinical judgment, the human element works much better in obtaining a mental image of the patient's condition. Artificial intelligence is specifically used in scenarios such as the diagnosis of electrolyte disorders, interpreting ECG findings, and recognizing the causes of myocardial hypertrophy. Nonetheless, artificial intelligence has challenges, such as a lack of responsibility for medical decisions and treatment errors.
Conclusions: Referring to the above-mentioned benefits and challenges of artificial intelligence, artificial and human intelligence cannot be superior to each other, and both have an irreplaceable role in clinical decision-making. The new view is that the goal of CDSS is to help the physician make better decisions by processing vast pieces of information as a whole entity rather than individually.

Keywords: Clinical Decision Support System, Artificial Intelligence, Clinical Reasoning

1. Context

In today's world, due to the expansion of science and the complexity of decision-making, the use of information systems, especially artificial intelligence systems, has become more valuable in supporting decision-making. Artificial intelligence refers to a set of systems that are capable of performing functions similar to human intelligent functions (such as analyzing complex problems, simulating the stages of thinking and reasoning, learning science, and the ability to reason to find answers to problems) (1). Introducing artificial intelligence systems to medicine is one of the aspects of the digitalization of society. According to developers, policymakers, and medical professionals, artificial intelligence can make great contributions to health care and is expected to improve health care by reducing the workload of health staff and increasing the quality of clinical decision-making. Therefore, this type of intelligence is often proposed as a solution to face complex healthcare challenges in the future (2). Artificial intelligence has the potential to make use of vast amounts of genomic, biomarker, and phenotypic information. Enormous health data, from birth information to health records, exist throughout the health system and can be used to increase the safety and quality of clinical care decisions. Today, artificial intelligence has been successfully incorporated into clinical decision support systems (CDSS) with great potential to change almost all aspects of medicine (3, 4). These systems are created to improve healthcare services by facilitating targeted medical decision-making based on available knowledge, patient information, and health information (5). Due to an exponential increase in the amount of available data, the diversity of therapeutic options, and the rapid development of medical technologies, there is an immediate need for designing CDSS, which can be a valuable tool for providing medical care according to patients' preferences and their biological characteristics. One of the important needs of today's societies is to personalize medicine in order to improve treatment outcomes, save money, and prevent unnecessary therapeutic measures. Therefore, patients can reap benefits from the pile of human knowledge, clinical expertise, diagnostic guidance, treatment modalities, and supervision (6).

Clinical decision support systems are classified based on the underlying technology (rules, deep learning, probabilistic models, genetic algorithms, and reinforcement learning). Also, in terms of functionality, there are different types of CDSSs that support different clinical decisions, including warning and reminder systems (such as patient monitors), monitoring the execution of orders during patient care, identifying drug interactions, controlling chronic diseases, diagnostic support, suggesting clinical diagnoses, and scheduling therapeutic plans. In addition to diagnosis and treatment, CDSS can play a role in predicting a specific disease, interpreting radiology images and pathology findings, optimizing therapeutic doses, and performing screening and preventive care (2). The rapid growth of artificial intelligence, machine learning, and computerized CDSS, along with the increase in the amount of clinical data, has increased interest in their potential applications in providing comprehensive healthcare services. Computerized CDSS refers to any software aiming to help doctors and patients make a specific decision based on dynamic knowledge in clinical decision-making and patient information (6).

2. Evidence Acquisition

Due to the rapid increase in the amount of available health data, the diversity of therapeutic options, and the fast development of medical technologies, there is a great need for designing CDSSs. The current study aimed to briefly present a narrative mini-review on clinical reasoning and artificial intelligence. Data were gathered from Google Scholar, ScienceDirect, and PubMed databases, using the "clinical decision support system, artificial intelligence, and clinical reasoning" keywords.

3. Results

3.1. Benefits and Challenges

Clinical decision support systems are divided into two categories: knowledge-based and data-driven. The first category is also called the rule-based expert system, and the second category is known as the machine-learning system. An example of the first category includes online guidelines such as the Up-to-date (7). Systems in the second category are based on enormous input information enabling them to identify a specific pattern and help diagnose a disease (for example, Isabel's online diagnosis database). These systems mostly work in the field of visual information and the stored data obtained from a large number of clinical cases (2, 7). The usefulness of the mentioned systems and artificial intelligence in interpreting algorithmic and statistical information, where the human element can easily make a mistake, is that they work much more efficiently and with fewer errors. However, when it comes to dealing with a patient and his complaints and symptoms (such as when there is a need for clinical judgment), the human element works much better in obtaining a mental image of the patient's conditions (7).

One of the benefits of CDSS is a reduction in the incidence of prescription errors and drug side effects. Of course, in relation to this topic, one of the weaknesses of CDSS is the high rate of unimportant warnings. These systems can help provide less expensive treatments and reduce the use of paraclinical tests and the workload of health care staff. However, the costs of purchasing and operating such systems in the long term should be balanced against their usefulness. In fact, one of the challenges of artificial intelligence systems is their considerable costs (5).

Collecting, interpreting, and matching a patient's health information can be conducted by humans because artificial intelligence delivers weaker performance in collecting such information compared to a doctor. Nevertheless, artificial intelligence systems can be used to gather disease-related information (2).

In a study conducted in 2014 by Zuccotti and his colleagues, the role of CDSS systems such as Isabel, Up-to-date, DX plain, and Visual Dx was investigated in reducing clinical risks and errors, noting that about half of the clinical errors that imposed additional costs of over 40 millions of dollars on the healthcare system could be potentially prevented using these systems (8).

Another point of concern is the issue of responsibility. The doctor is accountable when dealing with a patient, concluding on a clinical diagnosis, and prescribing treatments. Making a decision about a patient using an evidence-based medical process can fundamentally affect the decision-making process about a patient, but it cannot in any way reduce the burden of the doctor's responsibility. Evidence-based medicine is a part of knowledge-based CDSSs, including the scientific information stored in an artificial intelligence system (such as existing physical scientific references). Now, when a doctor uses data-driven CDSSs (e.g., the Isabel database) to determine differential diagnoses, this decision can change all subsequent orders for patient management. As a result, when using artificial intelligence, the doctor should know that these systems are ultimately not responsible, and the doctor is the one who makes the decision and must accept the responsibility for that decision (9). Furthermore, when a diagnostic or treatment error is committed by artificial intelligence, it is not clear to what extent the physician is responsible. This situation is one of the cases that should be explicitly foreseen in the law, and since the role of the doctor in the decisions offered by artificial intelligence varies in different clinical conditions, it takes a long time to set specific legal provisions for each individual condition. Therefore, from a legal point of view, artificial intelligence-related issues require novel measures to be resolved (10).

Another point that can be mentioned about CDSS systems is the role of the clinical expert in asking relevant and understandable questions about the clinical case. The CDSS cannot interpret the patient's symptoms as the patient expresses them, while the clinical specialist should make the patient's clinical complaints and symptoms understandable to the system. One of the challenges of CDSS is the ability of the system to perform this function, similar to a doctor (2).

In traditional decision-making, the doctor makes a differential diagnosis in his mind based on clinical signs and symptoms and then tries to reach a definitive diagnosis based on complementary investigations (laboratory or imaging studies) or even after starting an experimental treatment. This method is limited to the knowledge and intelligence of the doctor, who should act far from error in a limited time (11, 12). In addition, in surgery fields, the doctor may be biased due to the need for emergency actions for a possible provisional diagnosis and consider surgical treatment necessary for the patient (13). Of course, the risk of bias is not limited to surgeons; many physicians may suffer from recall bias (i.e., considering a specific diagnosis that has recently been encountered more frequently or a therapeutic plan used a lot in the past for a new patient) (14). With the help of artificial intelligence modeling and based on the data that is always being updated, a definitive diagnosis and treatment can be achieved for patients without time, emotional, knowledge, and skill limitations (15, 16).

Artificial intelligence has limitations; for example, the optimal interpretation may not be obtained when comparing patient data due to variations in algorithms and the design of the database. This issue highlights the need for artificial intelligence to consider a standard information model among various available standard algorithms (in general, the doctor himself routinely chooses one of them) (17). Among other issues, one can note the risk of bias resulting from defects in data collection, leading artificial intelligence to make mistakes in predicting or detecting a disease (18, 19). In addition, artificial intelligence still needs a complete set of data to reach, sometimes, a simple diagnosis, while a doctor could easily and without the need for data, which sometimes can be expensive to gather (e.g., a series of tests), to reach the right diagnosis (20).

3.2. Dedicated Applications

In a study, Knackstedt et al. showed how to obtain the volume of the left cardiac ventricle and measure its function with the help of machine learning during echocardiography (21). One of the main causes of ventricular hypertrophy is exercise, which is a completely physiological entity. However, sometimes it becomes difficult to distinguish "athlete's heart" from hypertrophic cardiomyopathy, which is a very dangerous condition. Narula et al. designed models in which machine learning could reliably distinguish between two causes of hypertrophy (i.e., physiological vs. pathological) (22). Zhang et al. went much further and distinguished other causes of myocardial hypertrophy, such as amyloids and pulmonary arterial hypertension, with the help of artificial intelligence (23).

Artificial intelligence can also be used to diagnose electrolyte disorders. Among the most important of these are potassium disorders, which can cause arrhythmia and, ultimately, cardiac arrest. Hypokalemia and hyperkalemia create certain patterns in ECG, which sometimes are difficult to be differentiated by the doctor, increasing the possibility of diagnostic errors (24). Recently, artificial intelligence has entered this field, and some of its models have been able to identify ECG patterns created by moderate to severe hypokalemia and hyperkalemia (25). This ability does not end here, and with the help of deep learning, it is possible to identify ECG patterns resulting from calcium and even sodium irregularities (26).

Tison et al. (27) proposed an interesting application of deep neural networks (DNNs) for detecting atrial fibrillation (AF) using smartwatch data, such as the heart rate and step count. The DNN was trained using a heuristic pretraining method that approximated representations of the R-R interval without manual labeling of the training data. The model was validated against 12-lead electrocardiography in a separate cohort of patients undergoing cardioversion, smartwatch data from ambulatory, and self-reported persistent AF patients. According to the researchers, the combination of smartwatch photoplethysmography and DNN could provide a passive method for detecting AF; however, a slight reduction was noticed in sensitivity and specificity compared to standard ECG (28).

It is worth noting that the scope of EKG interpretation by artificial intelligence is not limited only to electrolyte disturbances. Koulaouzidis et al. designed indicators that could be used to early detect tachycardia or ventricular fibrillation (29). Attia et al. showed new dimensions of EKG interpretation with the help of pattern programming in order to diagnose ventricular dysfunction (defined as a cardiac output of less than 35%) only through the patient's EKG (30). By combining the findings of EKG and echocardiography using the cardio-HARTTM technology, artificial intelligence was able to obtain comprehensive information on the cardiac rhythm and its structural and functional changes, revolutionizing the diagnosis, treatment, and follow-up of heart failure patients (31). One of the great challenges of artificial intelligence is related to the interpretation of radiology images (such as a mammogram) by this technology. In this field, a false negative report by artificial intelligence will probably lead to a diagnostic error at a much higher rate than when an expert personally inspects the image (32).

3.3. Clinical Examples

According to the explanations provided, we will further examine the challenges of CDSSs by exploring the case of a real patient using a data-driven CDSS (the Isabel site). By presenting this example, we aimed to check whether artificial intelligence and CDSS in the field of clinical reasoning could deliver a diagnostic accuracy close to or equal to the human element.

A 55-year-old male patient diagnosed with hypothyroidism and treated with levothyroxine visited a doctor with the main complaints of headache and chest pain starting 6 months ago. Four months before the appearance of these symptoms, while walking, he felt pain and cramping in the lower part of his legs with more intensity on the right side. Also, he had discomfort in the epigastric area after consuming food, which led to a slight decrease in appetite and weight loss of 3 kg in the last 6 months. During the last 6 months, the patient also developed a speech disorder and partial paralysis of the face, which was transient and lasted less than 24 hours. During the first visit to the doctor, regarding the blood pressure of 190/110 in the right upper limb and 160/90 in the left upper limb, he was examined by CT angiography and treated with Valzomix at a dose of 80/5 on a daily basis. In angiography, evidence of a saccular aneurysm in the left subclavian artery and thickening of the subclavian and carotid arteries were seen on both sides. During the second visit to a cardiologist due to the swelling of the right hand and pain in the left hemithorax, further investigations revealed thrombosis in the internal carotid artery and popliteal artery, as well as an increase in the thickness of the wall of the superior mesenteric artery. Arterial thrombosis was also identified in CT angiography and ultrasound examination. Carotid artery Doppler was reported. Considering vascular involvement, the cardiologist examined the patient for rheumatological diseases, specifically vasculitis, and the tests revealed an increase in p-ANCA and a decrease in C4 levels. Also, according to the suspicious history of thrombosis, the levels of homocysteine, C, and S proteins and coagulation factors were checked, revealing an increase in the serum levels of homocysteine and a decrease in C and S proteins. Finally, with the possible diagnosis of Takayasu's arthritis, protein C and S deficiency, and hyperhomocysteinemia, the patient was treated with corticosteroids and azathioprine and underwent long-term treatment with oral anticoagulants.

In this review, Isabel was used as an example of a CDSS for approaching a clinical case. Relevant data, including age, gender, vacancy, and the patient's symptoms, including abdominal pain after meals, hypertension, hand swelling, headache, lameness, and shoulder pain, were entered into the system, and more than 30 differential diagnoses were proposed. Takayasu's arthritis was not mentioned among any of the differential diagnoses. Of course, Isabel raised Giant cell arteritis as one of the main differential diagnoses, which ironically was also one of the main differential diagnoses raised by the cardiologist. If we assume that the specialist using this system in the approach to the above patient could become closer to his differential diagnosis, an important question that arises is whether the mere approach to differential diagnoses can be considered a benefit. Could it be an example of the benefits mentioned at the beginning of the discussion? Another problem with this clinical example and the applicability of the Isabel site was that hypercoagulability, i.e., proteins C and S deficiencies and hyperhomocysteinemia, was not mentioned among the differential diagnoses proposed. In fact, the performance of the Isabel site, an example of CDSS, was poor in terms of the diagnosis of accompanying underlying diseases. Regarding the management and treatment of the above-mentioned patient, another question raised was what the best treatment could be for the patient. What dose of the medicine should be administered? What is the duration of treatment and prognosis of the disease? It seems that Up-to-date as a knowledge-based CDSS can help clinicians make more accurate and better decisions with lower errors within a shorter time than the human element in these cases.

4. Conclusions

According to the clinical case presented, data-driven CDSS seems to lack adequate power and needs more input information for reaching a diagnosis. Referring to the notions raised about their benefits and challenges, artificial intelligence and human intelligence cannot be superior to each other; both have an irreplaceable role in clinical decision-making, and ongoing research efforts have been conducted on their combination as dual intelligence (2). Dual intelligence systems cover the weaknesses of artificial intelligence by combining the capabilities of human and machine intelligence. Unlike artificial intelligence, human intelligence is dynamic and can perform more diverse tasks (33). The performance and scope of artificial intelligence are limited to the information received from humans as input. The future of medical sciences and clinical decision-making without artificial intelligence seems unimaginable, error-prone, and time-consuming. It is also impossible to eliminate human intelligence. More research is needed to approach dual intelligence. Clinical professionals should keep up with the progress of artificial intelligence and CDSS and learn how to use these networks. The optimal use of artificial intelligence requires accurate knowledge of its components, types, weaknesses, and strengths, as well as knowledge of more complete and efficient examples of artificial intelligence applications. Systematic studies have shown that the effective use of CDSS reduces the risk of inappropriate actions and the risk of work overload, and job burnout in the healthcare system and increases the quality of healthcare. It also cuts healthcare costs, improves diagnostic accuracy, patient safety, and adherence to preventive and therapeutic guidelines, and reduces medication errors (6, 8). In the past, it was thought that CDSS could replace the doctor, but the new view is that the goal of CDSS is to help the doctor make better decisions by processing a large amount of information, a task that may be beyond the capabilities of either of them alone (6).

Footnotes

Authors' Contribution: Ali Ghasemi and Mahdi Naeimaeyi Aali conceived and designed the study, drafted the manuscript, and collected the clinical data.

Conflict of Interests: The authors declared no conflict of interest.

Funding/Support: There was no financial or material support for this work, and the study was personally funded by the main author.

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