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Review Article

Clinical Decision Support Systems and Where to Apply Them: A Systematic Review

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Abstract

Background: Clinical decision support systems (CDSSs) provide healthcare providers with suggestions by evaluating the situation and organizing the decision-making process to reduce their mental workload so they can make decisions more effortlessly and safely in emergencies and critical-safety situations. This article reviews the applications of CDSSs and the benefits that these systems bring to healthcare settings.

Method: Scopus, PubMed/Medline, and Web of Science were selected to search high-quality CDSS-related journal articles published in English from 2000 to 2022. Two reviewers, under the supervision of the third reviewer, screened and analyzed the search results based on the inclusion criteria.

Results: The required information was extracted from 78 included articles, and it was found that CDSSs have been exploited for four primary purposes, namely, accurate diagnoses, early prevention of diseases, management of clinical/medical processes, and prescriptions.

Conclusion: CDSS has many benefits for each of the four applications, the most important of which is to improve patient safety. Generally, the results showed that DSSs in healthcare can positively affect medical decisions by reducing possible errors and putting forward specific medical suggestions for each patient.

Keywords: Clinical decision support system, Computer-assisted decision-making, CDSS, Diagnostic errors, Electronic health records

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Introduction

Making safety-and-time-critical decisions in emergency working situations and unpredictable conditions with complexity and uncertainty requires many variables to be taken into account, and the actions must be taken quickly (1). In these situations, decisions are difficult to make and prone to human errors, as these increase the decision-makers' mental workload and stress. Decision support systems (DSSs) evaluate and organize the decision-making process and give suggestions to decision-makers to diminish their mental workload so they can tackle specific problems effortlessly and safely (2). Since the advent of advanced technologies such as databases and visual user interfaces, DSSs have been combined with cutting-edge technologies to better support decisions. Initially, DSSs were mainly applied in business and engineering, but they have now expanded to a broader set of working domains (3). In recent years, because of the high importance of human lives, DSSs have strikingly attracted the attention of healthcare providers. In healthcare systems, these are called clinical decision support systems (CDSS), recognized as diagnostic aid tools for clinicians that can be implemented in medical and public health education, clinical research, management, and health information systems (4).

Today, DSS is extensively utilized in healthcare services, and many well-cited DSSs are clinical systems. Very few studies have analyzed the applications and advantages of CDSSs. These papers are often outdated or have only examined a specific aspect of CDSS applications and technologies. Kaplan reviewed the use cases of these systems in medicine and healthcare, which included education, warning systems, reminder systems, and treatment planning (5). However, having integrated with advanced technologies and medical record systems, CDSSs unfolded their applications; thus, an update is necessary. Shahsavarani et al studied different types of CDSS (6), but they did not offer an explicit classification to guide the readers in designing a CDSS. In another review article, Martínez-Pérez et al explored only the usage of mobile applications of clinical support systems (7). Hooijenga also categorized machine learning (ML) algorithms used in CDSSs (8). This study, however, has attempted to group the CDSSs into distinct categories by comprehensively reviewing the applications of CDSS. It is performed to uncover both the purposes of the use of these systems and the benefits that they have brought in medical contexts. In this way, system developers could more readily realize the intents of the customers or stakeholders in designing a new CDSS for them.

Classifications of Decision Support Systems

Before addressing the query of this study, it is noteworthy to have insight into the types of DSS. DSSs may be classified from different perspectives (9). From the standpoint of the mechanism, they are often grouped into knowledge-based and data-driven systems. There is also a third type of DSS, according to Power (10), constructed based on models. The human-system interaction in CDSS is shown in Figure 1.

Knowledge-based systems present the users with a set of potential solutions by analyzing the prior information gathered from experts and stored as facts, rules, procedures, or relationships of variables (9, 11). The rules are based on the experts' experiences, the results of past studies, clinical practice guidelines (CPG), and information obtained from the practice or the patients (12).

Data-driven systems also require a data source, but instead of being programmed based on expert knowledge, these systems take advantage of artificial intelligence (AI) and ML algorithms (9). The main technological drivers used for developing data-driven DSSs are online analytical processing, cloud computing, the internet of things, executive information/support systems, and geographic information systems (13,14). One of the advantages of such systems is that they can enable diagnosis and advance knowledge even for those who do not have particular knowledge about them. These systems can be suitable for diagnostic purposes in health and treatment wards since they use pattern recognition methods and statistical techniques to detect data changes (11).

Model-based DSSs, on the other hand, help decision-makers using the analytical software, such as fuzzy programming and simulation, that optimize or simulate the results of decisions based on available data (15). One could manipulate the input factors and their interrelationships in the model and examine the outcomes to analyze the situation. This type of CDSS integrates various mathematical and analytical models to simulate and predict future trends (16). Therefore, the ability to solve the problem of these simulation models makes it possible to avoid the limitations created by approximate optimization methods.

Methods

Search Strategy and Inclusion Criteria

Three online databases, namely, Scopus, PubMed, and Web of Science, were selected to search for high-quality CDSS-related articles with a timeframe from 2000 to 2022. The keywords used for searching desired papers in Scopus and Web of Science were "Clinical decision support systems", "Computerized decision support systems", "healthcare", "diagnosis", and "disease" in the titles, abstracts, and keywords of searched articles. To search the publications in the PubMed depository, several mesh terms were applied, including (Diagnostic errors), (Decision support systems, clinical), (Decision-making, computer-assisted), (Clinical decision-making), (Health records, personal), and (Electronic health records). Eligibility criteria for inclusion/exclusion were open access or available free articles that our institute accesses, studies published as journal articles, full texts published in English, and most importantly, papers focusing on the application of DSS in healthcare settings.

Data Extraction Process

Two reviewers screened out the search results by initially reading the titles and abstracts. The articles were excluded

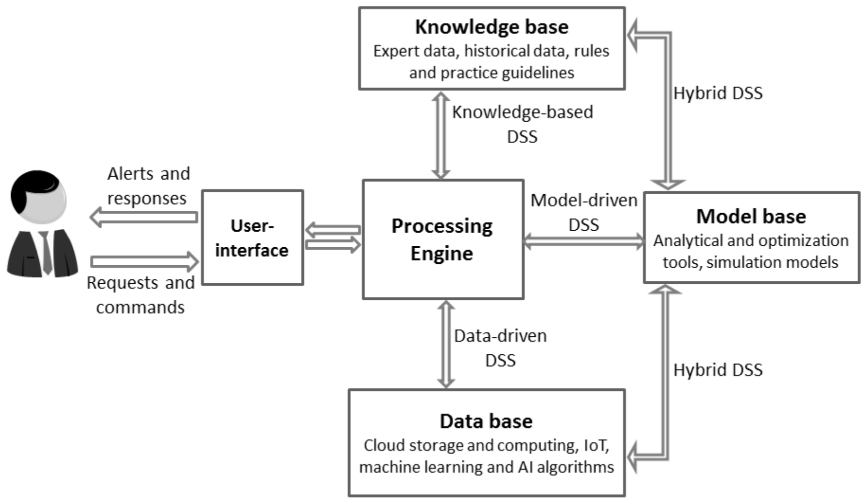

Figure 1. Human-system Interaction in DSS Design. Note. DSS: Clinical decision support systems. The user gives his request or command to the system through the user interface. The system's reasoning engine retrieves the data related to the request from the database, analyzes them, and presents the result to the user as warnings or suggestions. The database may store the information as rules and simulated models of real situations or collect them from the environment online. A combination of these methods is also feasible

from the process if their abstracts provided irrelevant information or did not meet the inclusion criteria. In addition to the accepted papers searched, those with unclear details in the abstract were included for reading the full text. The most relevant information analyzed by the reviewers included the purpose of developing a CDSS and its benefits in clinical settings. The third reviewer intervened in the process when the two reviewers did not reach a consensus on the eligibility of an article. The extracted data were recorded on a sheet for further analysis and concurrence. The data were the journal's name and metrics the papers published in, the paper's title, year of publication, authors' names, the country the CDSS was developed in, the study's primary objective, the domain of application, the advantage of using CDSS if available, and the DSS design approach. Having completed the reading of all the full texts, only those with the above-mentioned information remained for the final analysis and synthesis. The qualitative verbal explanations of the reviewers regarding the application and type of CDSSs were integrated according to the classification terms used in Power's taxonomy (10) and Hak et al (17).

Results

Search Results

In this study, the authors searched for high-quality studies that utilized CDSS in clinical settings. A total of 6027 scientific articles were found in our search results, which decreased to 4319 records after removing the duplicates. The records were screened by checking the titles and abstracts, and 225 articles remained. Having read the full texts, only 78 eligible papers finally remained for our review study. This process is diagrammatically demonstrated in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow chart in Figure 2.

The articles were classified into four domains based on CDSS applications during the review of the titles and abstracts. Table 1 summarizes the number of papers included in each application domain and the metrics of journals in which the articles were published.

Applications and Benefits of Clinical Decision Support Systems

In medical and healthcare contexts, CDSSs are applied for different purposes as they bring many advantages to each. The most frequent intentions of CDSSs can be categorized into diagnosis, prevention, management and planning, and drug prescription groups (3). The noteworthy benefits of CDSS with respect to its applications are summarized in Table 2.

It might be worth mentioning that the US had the most field research in CDSS with 22 articles out of 78, followed by the UK and Spain with 8 and 7 papers, respectively. China and Germany rank next, each with 5 research papers. More than 42% of the research works used already-designed DSSs for diagnostic purposes, of which about 10% were performed by 2010, and 32% were conducted after 2011. Around one-third of the studies utilized CDSSs for supporting prescription-related issues, of which 13% were conducted by 2010, and 20% were performed since 2011, demonstrating a growing trend toward using DSS in medical sciences.

Diagnostic Decision Support Systems

Diagnostic CDSSs support specialists in establishing an early diagnosis by analyzing clinical evidence, examination

Table 1. Summary of Papers Included in the Review and the Journal Metrics

Application Domain	Number of Papers	Journals Quartile			
		Q1	Q2	Q3	Q4
Diagnostics	33	25	3	2	3
Prevention	6	6	-	-	-
Management	13	7	5	1	-
Prescription	26	25	1	-	-
Total	78	63	9	3	3

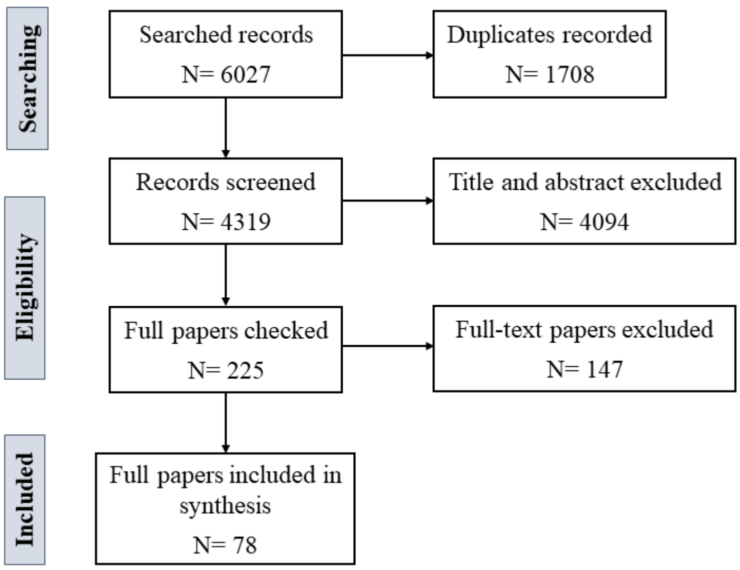

Figure 2. PRISMA Flow Chart of Study Selection for a Systematic Review. *Note*. PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses

Table 2. Potential Advantages of Using CDSS With Respect to Each Functionality

Diagnosing
• Providing diagnostic suggestions based on patient information • Avoiding human errors • Preventing late diagnoses • Automating outputs according to test results • Assisting practitioners in interpreting medical images • Providing helpful information on the results of pathological and laboratory tests
Prevention
• Increasing the percentage of screening • Establishing an early diagnosis • Preventing the severity of diseases
Management
• Facilitating the management of the clinical process • Speeding up the therapeutic workflow • Improving administrative documentation and automation • Guiding patients to make good decisions • Scheduling the hospital's resources, such as equipment, beds, and surgery rooms • Managing human resources • Administering drugs and blood banks better • Assisting nurses in doing their tasks and making decisions in patient care
Prescription
• Improving patient safety • Preventing human errors in prescribing inappropriate medicines • Monitoring and managing the doses of medications • Mitigating the medication side effects • Preventing the dire consequences of drug-drug interactions • Controlling medication costs • Helping in replacing rare drugs with other homogeneous drugs • Preventing the repetition of tests and medical prescriptions

Note. CDSS: Clinical Decision Support Systems.

results, and previous records and reviewing the rules and guidelines. The main goal of this type of support system is to consider all aspects to prevent human errors in making a diagnosis. The advantages of these systems could be offering diagnostic suggestions according to patient information, automating outputs based on test results, and presenting additional information for interpreting the results of medical examinations and images. Studies that developed such systems worked mainly on detecting diseases in primary care, evaluating and diagnosing various cancers, cognitive/psychological disorders, cardiovascular diseases, malaria, typhoid fever, dengue fever, pulmonary disease, and Parkinson's, and managing and diagnosing osteoporosis. Studies that used CDSS for diagnostic purposes are presented in Table 3.

Clinical Decision Support Systems for Prevention Purposes

The goal of the systems designed for prevention is to increase the percentage of screening, reach a diagnosis at early stages, and prevent the severity of diseases. Alaa et al designed a case-specific CDSS to screen breast cancer using an ML algorithm linked with electronic health records. The system classifies the women based on their conditions and produces 31% fewer false positives (51). Paydar et al established a preventive system that prognosticates pregnancy consequences in women with systemic lupus erythematosus (52). Romero-Aroca et al in Spain built an intelligent system for screening diabetic retinopathy using fuzzy random forest with 80.1% accuracy (53). Durieux et al developed a CDSS based on CPG in France for preventing venous thromboembolism in surgical patients. They found that the number of errors in prescribing declined from 191 to 44 errors using the CDSS, and practitioners followed the guidelines 12% more than when there was no DSS (54). Steele et al proposed a web-based CDSS that helps physicians screen and prevent tuberculosis infection. They programmed the practice guidelines so the physicians could follow these instructions in diagnosing and screening the disease. The proposed tool accurately detected 99.7% of the infected cases and showed a 16% performance improvement (55). DeJesus et al designed an osteoporosis screening tool in the Netherlands. The system works using a rule-based module already made and checks the results of bone density tests on aged women. Compared to non-CDSS screening, 67% improvement was achieved with this tool (56).

Management and Planning Decision Support Systems

The goal of designing this type of CDSS is to plan and manage hospital processes, especially the planning of hospital resources such as beds, surgical rooms, and equipment, human resource management, including doctors, technicians, and nurses, as well as the management and logistics of drugs and blood banks in hospitals. Such CDSSs could be of assistance in better managing the treatment process by following the clinical instructions and tracking and reminding the treatment process. They also make it feasible to accelerate the treatment workflow and improve documentation and administrative automation by selecting the diagnosis codes, documenting and completing the notes automatically, and retrieving information from electronic medical records (EMRs). Finally, by directly extracting information from personal health records (PHRs), CDSS facilitates decision-making for patients.

Regarding planning management decisions in medical settings, a large body of literature has mainly covered issues related to clinical processes, hospital beds, and medical equipment. In a study performed by Collin et al (57), to increase the quality of medical services, reduce care time, and facilitate the process of patient care by nurses, a CDSS was designed that offered treatment suggestions by integrating the computerized physician order entry (CPOE) system with the electronic picture archiving and communication systems. Cheng et al designed a CDSS to promote the quality and precision of medical decisions made in the intensive care unit. This system collects required data from various sources and uses a rule-mining technique to shape relationships and make rules (58). Schmidt et al (59) and Cudney et al (60) developed CDSSs for hospital bed management to predict the length of stay of patients and the resources shared with them. Ghandforoush and Sen (2010) proposed a CDSS to manage the supply chain of blood platelets in the hospital

Table 3. Studies Conducted on Diagnostic CDSS

Authors and Year	Study's Goal	Inference Engine	Country
Emery et al, 2000 (18)	Diagnosis of breast and ovarian cancer by interpreting family history	Model-based	England
Razzouk et al, 2006 (19)	Early diagnosis of schizophrenia disorder	Knowledge-based	Brazil
Patkar et al, 2006 (20)	Assessment and diagnosis of breast cancer	Knowledge-based	England
Roukema et al, 2008 (21)	Diagnosis and treatment of children with fever without apparent symptoms	Knowledge-based (Rule-based module)	Netherlands
Dubenske et al, 2008 (22)	Diagnosis of advanced cancers	Knowledge-based	USA
Gan et al, 2008 (23)	Intestinal lesions in the capsule endoscopy	Algorithmic thinking	China
Saxton et al, 2009 (24)	Detection of mild cognitive impairment in elderly individuals	Knowledge-based (Variable-based and CPG)	USA
Chi et al, 2010 (25)	Cost-effective diagnosis of thyroid, diabetes, hepatitis, and heart diseases	Data-driven (ML)	USA
Uzoka et al, 2011 (26)	Development of a diagnostic support system using the AHP method for malaria diagnosis	Knowledge-based	Canada
Lin et al, 2011 (27)	Diagnosis and treatment of prostate cancer	Model-based	China
Bhande and Raut 2014 (28)	Diagnosis of Parkinson's disease using ANN	Data-driven (AI)	India
Blake and Kerr, 2014 (29)	Enhancement of the accuracy and quality of sleep disorder diagnosis and self-management	Knowledge-based	Australia
Rammazzo et al, 2016 (30)	Diagnosis and management of balance disorders	Model-based	European countries
Marcelin et al, 2016 (31)	Improving HIV diagnosis and screening in primary care	Knowledge-based	USA
Harber et al, 2017 (32)	Diagnosis of work-related asthma	Knowledge-based	USA
Martinez-de-Lizarduy et al, 2017 (33)	Diagnosis of Alzheimer's disease based on speech pathologies	Algorithmic thinking and ML	Spain
Halldorsson et al, 2017 (34)	Diagnosis and treatment of osteoporosis	Knowledge-based	Iceland
Masood et al, 2018 (35)	Diagnosis and stage classification of lung cancer using AI algorithms	Data-driven (AI)	China
Tuncer and Alkan, 2018 (36)	Early diagnosis of kidney cancer by detecting malignant renal cells	Data-driven (ML)	Turkey
Nazari et al, 2018 (37)	Diagnosis of heart disease using a fuzzy inference system	Hybrid	Iran
Lim et al, 2019 (38)	Diagnosis of benign paroxysmal positional vertigo in primary care	Data-driven (Deep learning)	South Korea
Masood et al, 2019 (39)	Detection of lung cancer using the cloud system	Hybrid	China
Langarizadeh et al, 2019 (40)	Diagnosis of osteoporosis with the help of ANN	Hybrid	Iran
Sahu et al, 2020 (41)	Detection of cancers using the biomarker gene identification technique	Data-driven (ML)	India
Shoaip et al, 2020 (42)	Diagnosis of Alzheimer's disease based on fuzzy ontology	Knowledge-based	Egypt
Carvalho et al, 2020 (43)	Diagnosis of dementia, Alzheimer's disease, and MCI	Data-driven (ML)	Brazil
Mohapatro et al, 2021 (44)	An accurate diagnosis of dengue fever	Knowledge-based	India
Suárez-Araujo et al, 2021 (45)	Diagnosis of MCI	Variable-based and ANN	Spain
Bamiou et al, 2022 (46)	Diagnosis of vestibular balance problems in primary care	Hybrid (model-based and data mining)	European countries
Hoyos et al, 2022 (47)	Diagnosis of dengue fever using a fuzzy cognitive map	Hybrid	Colombia and Venezuela
Ragab et al, 2022 (48)	Diagnosis and categorization of breast cancer based on ultrasound scan images	Data-driven (Deep-learning)	Saudi Arabia
Newaz et al, 2022 (49)	Diagnosis of cervical cancer	Data-driven (AI/ML algorithms)	Bangladesh
Adekunle et al, 2022 (50)	Diagnosis of malaria disease	Data-driven (ML)	Nigeria

Note. AI: Artificial intelligence; ML: Machine learning; ANN: Artificial neural network: MCI: Mild cognitive impairment; CPG: Clinical practice guidelines; CDSS: Clinical decision support systems; AHP: *Analytical hierarchy* process; HIV: Human immunodeficiency virus.

and optimize the delivery of platelets from the production centers to the blood centers of the hospitals (61). There are also other support systems developed and validated for different purposes, such as operating room planning designed by Dios et al (62), taking care of depressed patients conducted by Fortney et al (63), and acute illness management and its impact on the patient care process performed by Sahota et al (64). Tang et al combined the case-based reasoning technique, medical records, and cloud computing to develop a CDSS, enabling home nurses to formulate care planning and strategies for the elderly (65). Likewise, Eigner and Bodendorf developed an intelligent system using multiple risk prediction models that enabled healthcare providers to manage unplanned patient readmissions (66).

Sometimes, these are built to make clinical processes easier for nurses, known as the advanced nursing process. For example, Beeckman et al designed a system to prevent bedsores in nursing care at home (67). Another system proposed by Rood et al allowed the nurses to have precise control of patients' blood sugar, contributing to enhancing the accuracy of the nurses in adjusting the insulin dose, adhering strictly to the treatment protocol, increasing the patient's trust in the nurses, and increasing their compliance with the nurses of the special care department (68).

Decision Support Systems for Prescriptions and Orders

DSSs in prescriptions have also been developed for several reasons. The first and most important reason is that inappropriate prescriptions or doses of medications have harmful side effects, sometimes followed by serious consequences. Thus, reducing the incidence of medicine side effects by reducing human errors in prescribing is one of the greatest merits of these systems, leading to higher patient safety. Moreover, some drugs are rare, and the correct decision in prescribing these drugs is highly vital in terms of drug-drug interaction effects and cost control for both the patient and the hospital. Therefore, these CDSSs control the costs by suggesting relatively affordable drugs or treatment options. Indeed, they can avoid repeating tests and medical orders. The studies with these objectives have been performed to avoid human errors while improving safety in prescriptions under different conditions, monitor and manage pharmacotherapy and the recommended doses, and lower the prescription of extremely expensive medicines and the cost of prescriptions. Table 4 presents the studies that used CDSSs for prescribing purposes.

Discussion

This systematic review aimed to determine the applications and classifications of CDSSs, along with the advantages of these tools for healthcare providers. According to the findings, four roles were found that CDSSs take in the healthcare context. Diagnostic CDSS aims to assist physicians in the correct and timely diagnosis of the disease. While some of these systems were limited only to the diagnosis of illnesses, others also pointed out how to treat them and what medications to prescribe. Bamiou et al used a CDSS to detect vestibular balance problems in primary care. They made a comparison between CDSS-aided diagnosis and a golden standard through objective measurements, demonstrating a 14% improvement in correct diagnosis by the CDSS (46). Chi et al developed a smart CDSS to optimize the costs, efficiency, and accuracy of disease diagnosis. They established four datasets corresponding to thyroid, heart disease, hepatitis, and diabetes to be applied in ML algorithms. This system saved the diagnosis time and costs up to 73% and 57%, respectively (25). Adekunle et al presented an ML-based CDSS to detect malarial disease. The algorithm discovered the pattern of the infected cells by analyzing a vast number of medical images to compare infected cells with non-infected ones. They found their system successfully predicted 98% of the cases (50). Hoyos et al designed a DSS based on a fuzzy cognitive map to detect dengue fever in Latin America. The CDSS demonstrated the relationships and interdependencies between the symptoms and the examinations to create the model, resulting in a diagnostic accuracy of 89.4% (47). For drug prescription, the reviewed systems pursued several goals, such as managing the cost of medicines, managing the dosage of certain drugs, reducing redundant medications, managing the quality of prescriptions, and reducing the risks of drug-drug interactions and medication side effects. As its fourth role, CDSS supported the managers in planning the clinical process and managing the resources. The objective of using most of these systems was to facilitate decision-making and effective planning of hospital equipment and resources, including planning surgical rooms, improving the quality of medical services, saving care time and costs, optimizing the use of equipment and resources, and admitting patients on time. The management of the clinical process was addressed in less than 17% of the papers. The most influential advantages that DSSs have for clinical wards are accurate and quick disease diagnosis, case-based diagnosis, prevention of mental fatigue and workload of physicians, prevention of inappropriate prescriptions, shortening of the time of hospitalization, and management of clinical processes and resources. Sutton et al (95) and Castillo and Kelemen (96) also found similar benefits for CDSSs in their studies.

There exist three CDSS mechanisms, namely, knowledge-based, model-based, and data-driven systems. Most of the studies developed a subgroup of knowledge-based systems using the practice guidelines, the rules made by the experts, and ontology. The effectiveness and usefulness of such systems were much higher when they were linked to the hospital's information systems, such as CPOE, EMR, HER, and PHR. However, a closer look at these studies makes it clear that the use of data-driven DSSs (i.e., AI and ML algorithms integrated with the internet of things and cloud computing technologies) has been more extensive in recent years. It is found that a hybrid system, combining data-driven technologies with specialists' knowledge, is more effective than when an approach is utilized alone. This is because each approach has its advantages and disadvantages. Rule-based expert systems, for instance, have poor performance in reducing human errors due to activating too many false alarms. On the other hand, despite the greater accuracy and easier modeling of data-driven systems, they are less flexible in dealing with unknown situations. Thus, it can be alleviated by combining them with the knowledge of experts.

Conclusion

This study provided a comprehensive overview of the goals of using DSSs and the benefits these systems have brought

Table 4. Studies That Used CDSS for Prescription Purposes

Authors	Study Goal	Inference Engine	Country	Effectiveness
Fitzmaurice et al, 2000 (69)	Managing and monitoring anticoagulant medicines by nurses	Knowledge-based	England	CDSS improved the quality of clinical care led by nurses.
McMullin et al, 2004 (70)	Cutting the costs of prescriptions by suggesting alternative drugs	Knowledge-based (Evidence-based)	USA	On average, the cost of a prescription decreased by almost $5.
Berner et al, 2006 (71)	Decreasing the prescribing errors on non-steroidal anti-inflammatory drugs in outpatient departments	Knowledge-based (Rule-based module)	England	A 50% reduction was found in prescribing errors.
McGregor et al, 2006 (72)	Improving the management of antimicrobial therapy	Knowledge-based	USA	A reduction of about 1% was observed in the side effects, length of stay, and mortality.
Raebel et al, 2007 (73)	Filling safer prescriptions for pregnant women	Knowledge-based (CPG)	USA	Harmful prescriptions decreased during 4 months.
Field et al, 2009 (74)	Enhancing the quality of prescriptions in terms of dosage, frequency of use, and inappropriateness of the medications for renal insufficiency	Knowledge-based (CPG)	Canada	The relative risks became significantly lower, except for dosage alerts.
Fortuna et al, 2009 (75)	Managing the prescription of highly used hypnotic medicines	Hybrid	USA	The risk ratio of the CDSS was significantly (26%) less than the usual method.
Seidling et al, 2010 (76)	Controlling the doses of drugs according to each patient's condition	Knowledge-based (Rule-based and algorithmic logic)	Germany	The excessive dose of prescribed medicines decreased by 20%.
Trafton et al, 2010 (77)	Reducing the adverse side effects of opioid drugs prescribed for patients with chronic pain	Knowledge-based (Rule-based module and CPG)	USA	A developed model was more effective than stand-alone EMR systems.
Helmons et al, 2010 (78)	Controlling and managing the dose of antimicrobial medications prescribed for renal problems	Knowledge-based (Rule-based module)	Netherlands and USA	A cost of almost $19000 would be saved annually.
Kazemi et al, 2011 (79)	Reducing prescription errors regarding anticonvulsant and antibiotic medicine dosage in neonatal care units	Knowledge-based (CPG)	Iran	The error rate had a significant 20% reduction.
Lee et al, 2014 (80)	Diminishing medication errors in safety-critical prescriptions	Knowledge-based	Korea	The drugs' exceeded dose decreased significantly, and 4137 errors out of 18100 cases were prevented.
Chow et al, 2016 (81)	Decreasing the number of antibiotic prescriptions	Knowledge-based (CPG)	Singapore	On average, only 11% of the antibiotics ordered by physicians were accepted.
Niehoff et al, 2016 (82)	Making multi-criteria decisions on medication regimen, dosage, and appropriateness integrated with the HER system	Knowledge-based (Rule-based module)	USA	The CDSS found 98%, 25%, and 58% of prescription problems among the factors, respectively.
Miller and Mansingh, 2017 (83)	Prescribing optimal medications in terms of safety using a mobile application	Knowledge-based (Variable-based expert system)	Jamaica	The mental workload of doctors in multi-criteria prescribing decisions was reduced.
Baypinar et al, 2017 (84)	Minimizing the medication errors and drug-drug interaction in prescriptions via three different pop-up notification algorithms	Knowledge-based	Netherlands	The algorithms enhanced patient safety by 47%, 29%, and 11%.
Robinson et al, 2018 (85)	Comparing computerized and manual DSSs to find out the more effective one in reducing psychotropic drugs' adverse consequences within 2 years	Knowledge-based	USA	The computerized system showed that better support resulted in significantly lower perceived consequences.
Shen et al, 2018 (86)	Helping patients to take antibiotics safely in primary care without a physician's prescription	Hybrid (Anthology-based system and AI/ML algorithms)	China and the USA	The hybrid system showed about 90% accuracy compared to the single-approach systems with 84% and 74%, respectively.
Desmedt et al, 2018 (87)	Increasing prescription accuracy and suitability with renal insufficiency	Knowledge-based (CPG)	Belgium	The dosage suitability improved insignificantly, from 14.9% to 16.6%.
Prasert et al, 2019 (88)	Decreasing unsuitable drug prescriptions filled for the elderly	Knowledge-based	Thailand	A 13% reduction was observed in the rate of improper prescriptions.
Segal et al, 2019 (89)	Reducing prescription errors and medication side effects using the outlier detection system and EMR	Hybrid	Israel	The system was found clinically helpful, with 85% valid notifications.
Ibáñez-Garcia et al, 2019 (90)	Reducing prescription errors and drugs' side effects via real-time notifications	Knowledge-based	Spain	A 66% improvement was observed in making decisions, leading to higher patient safety.

Table 4. Continued.

Authors	Study Goal	Inference Engine	Country	Effectiveness
Corny et al, 2020 (91)	Increasing patient safety and reducing prescription errors through a hybrid approach	Hybrid (ML-rule-based approach)	France	The accuracy of a hybrid system was 20% higher than that of a knowledge-based one.
Hashemi et al, 2021 (92)	Reducing different error types of prescriptions in the pediatric care unit by a CPOE-integrated DSS	Knowledge-based (CPG)	Netherlands	The CDSS cut the number of errors by half.
Wickström et al, 2022 (93)	Managing antibiotic prescriptions in ulcer infection treatment	Knowledge-based	Sweden	Prescribing antibiotics decreased significantly, from 26% to 8%.
Calvo-Cidoncha et al, 2022 (94)	Reducing prescription errors using CPOE integrated with electronic health records	Knowledge-based (Ontology-driven module)	Spain	The acceptance rates of the warnings were around 46% for drug dosage and drug-drug interaction, and 100% for allergies.

Note. CDSS: Clinical decision support systems; EMR: Electronic medical records; CPOE: Computerized physician order entry; CPG: Clinical practice guidelines; AI: Artificial intelligence; ML: Machine learning.

in medical contexts. To this end, 78 journal articles out of others were analyzed in this field of study by three authors. Generally, the results demonstrated that CDSSs could positively affect medical decisions by reducing possible errors and putting forward specific medical suggestions and reminders for each patient. In the healthcare system, DSSs have four practical applications, including clinical diagnosis, prevention, management/planning, and prescription. They also bring financial, logistical, time, safety, task facilitation, and mental workload reduction benefits to healthcare settings. Researchers and system developers would benefit from the findings of this review article to realize the applications and functions of CDSSs and the various diseases that have been addressed so far.

Finally, it should be kept in mind that in the design of CDSSs, the nature of the work (the need for fast and critical responses in emergency cases versus the need for effective and comprehensive actions), the purpose of creating a CDSS, and access to the required technology and data should be taken into account to select the design approaches accordingly.

A limitation of this research study was categorizing DSSs into one or two classifications due to the unclear information provided by some studies. We highly recommend that the papers studying DSS explain what approach they adopted to develop the system's inference engine. Another challenge was related to achieving a consensus among the reviewers on whether or not a paper contains useful methodology and outcomes.

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Competing Interests

The contributing authors have no potential conflict of interests.

Disclaimers

All authors provided critical feedback and approved the final submitted version of the manuscript.

Ethical Approval

This study was approved by the Ethics Committee of Hamadan University of Medical Sciences (No. IR.UMSHA.REC.1402.609).

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