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Review Article

Public Health Section

A Scoping Review on the Clinical Decision Support Systems in COVID-19 and the Exigent Need to Develop and Accelerate its Implementation in Long COVID-19

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ABSTRACT

Introduction: The Coronavirus Disease-2019 (COVID-19) pandemic has caused global disruption, putting health experts and healthcare systems at risk. However, the ultimate goal of medical systems to offer precise medical care in a holistic manner for the benefit of patients cannot be compromised. With the massive advancements in digital technology, it is now possible for healthcare systems and medical practitioners to handle and utilise enormous amounts of patient data to provide appropriate medical assistance with minimal error. Integrated with Electronic Health Records (EHR), Clinical Decision Support Systems (CDSS) are digital programs that analyse patient data and assist medical professionals in making decisions and recommendations, thereby enhancing patient care. CDSS have played a critical role in maximising care during the pandemic by helping clinicians offer evidence-based medical care using patient data, paving the way for a more accurate and personalised healthcare delivery. However, their extended usability to manage post-COVID-19 conditions remains unexplored.

Aim: This scoping review seeks to outline the use of these CDSS in the management of COVID-19 and their potential usability in risk assessment, severity prediction, and treatment goals for patients experiencing long COVID-19 symptoms.

Materials and Methods: A thorough literature search was conducted on Google Scholar and PubMed using key search terms to identify relevant articles that support the objective of this study. A total of 3,010 records were available, of which 13 articles were chosen for inclusion in this review after extensive screening in accordance with the eligibility standards set up. The supporting data were meticulously extracted and charted to provide a clear outline of the utility of CDSS. This scoping review also features a conceptual framework for the extended usability of CDSS in long COVID-19 management.

Results: After the methodological search and selection process, data from 13 articles were analysed. Most of the included studies were conducted in the United States. The majority of the CDSS were designed to assess the severity of COVID-19. These CDSS predominantly analysed blood investigations, COVID-19 symptoms, and radiological findings of patients to make appropriate clinical decisions for managing the disease. There was a lack of scientific literature supporting the use of CDSS in long COVID-19 management.

Conclusion: With healthcare systems dealing with massive amounts of patient data, especially during the pandemic and postpandemic crisis, appropriate methods to manage and handle this information are critical to delivering patient-centered medical care. CDSS have been widely utilised in this regard to enhance the health outcomes of patients by guiding health professionals to make the right treatment choices in the most evidence-based manner using patients' health data. Thus, given the future of healthcare systems with Artificial Intelligence (AI), a greater emphasis on expanding the usability of these CDSS beyond the scope of COVID-19 is essential.

Keywords: Artificial intelligence, Digital technologies, Evidence-based medicine, Long-term patient care, Personalised healthcare, Precision medicine, Tracking

INTRODUCTION

Healthcare systems deal with massive quantities of patient health data. This enormous amount of data can be collected, stored, and retrieved using efficient tools such as Electronic Health Records (EHR), Electronic Medical Records (EMR), Personal Health Records (PHR), and Medical Practice Management (MPM) software to improve the data handling process and minimise medical errors [1]. This big data has significant potential to improve the healthcare sector and enable the provision of evidence-based medicine [2]. A CDSS is an information management tool that is integrated with a patient's EHR and computerised physician order entry [3]. CDSS has enabled the health sector to deliver appropriate and higher-quality healthcare to patients by allowing clinicians to make data-driven decisions with precise patient data and helping them make suggestions using digital data analytic tools [4,5].

Recently, the world has experienced a devastating pandemic caused by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), which emerged in Wuhan, China, in December 2019 [6]. The COVID-19 pandemic has caused significant physical and mental suffering for people and professionals in various sectors, including healthcare [7]. To improve patient health and treatment outcomes, the vast amounts of patient data collected during the pandemic should be stored and retrieved with appropriate data-handling tools [8].

These rapid changes in health data utility pose potential challenges to clinical decision-making using patient health records and demand a more flexible decision support system to enhance evidence-based medicine and precise patient care [9]. CDSS will facilitate the appropriate use of this evidence and improve the quality of evidence-based medical care for COVID-19 patients [10]. During the coronavirus pandemic, it has become crucial to make valid decisions regarding diagnosing, monitoring, treating and tracking patients. Thus, CDSSs offer the best assistance to clinicians and patients by reducing the number of medical errors, promoting efficient disease management through reminders about follow-ups and treatments, substantially reducing expenses, providing automated documentation and supporting clinical decisions [11].

Several assessment scores, such as CHA2DS2-VASc, CHA2DS2-VASc-HS, and R2CHA2DS2-VASc-originally used for predicting cardiac dysfunction-have now proven effective in predicting mortality among hospitalised COVID-19 patients [12-14]. Additionally, patients may experience symptoms of COVID-19 weeks or even months after recovering from the disease. This condition is referred to as post-COVID-19 syndrome or Long COVID-19 and is expected to continue affecting the health and quality of life of individuals [15]. Similar to COVID-19, appropriate diagnostic and symptom management protocols should be developed for long COVID-19 [16].

Although such CDSSs are in use to manage COVID-19, their application to long COVID-19 remains unexplored. Hence, comprehensive knowledge about existing CDSSs in COVID-19 care and their extended utility for long COVID-19 is needed to assist physicians and healthcare providers in improving patient health outcomes and delivering high-quality evidence-based medicine. Thus, the scope of this review was to provide a deep understanding of the current CDSSs in COVID-19 and the need to enhance CDSSs for long COVID-19.

Objectives

This scoping review intends to:

1. Conduct a thorough literature search on CDSSs in COVID-19.
2. Analyse the utility of CDSSs in diagnosing and monitoring COVID-19.
3. Identify the challenges in the implementation of CDSSs for the management of a disease like COVID-19.
4. Recommend strengthening the use of CDSSs for patients with long COVID-19 syndrome.
5. Propose a conceptual framework for the extended utilisation of CDSS to manage long COVID-19.

MATERIALS AND METHODS

This scoping review was conducted systematically, from the search for relevant articles to the analysis and reporting of the study's findings. The five-stage methodological framework of Arksey and O'Malley [17] was adhered to, while carrying out this scoping review. Additionally, the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) extension for Scoping Reviews (PRISMA-ScR) were followed in structuring the manuscript [18].

Research Question

This scoping review aims to address the following research questions:

What are CDSSs and how effective are they in managing COVID-19 using the data collected from patients at the time of diagnosis?

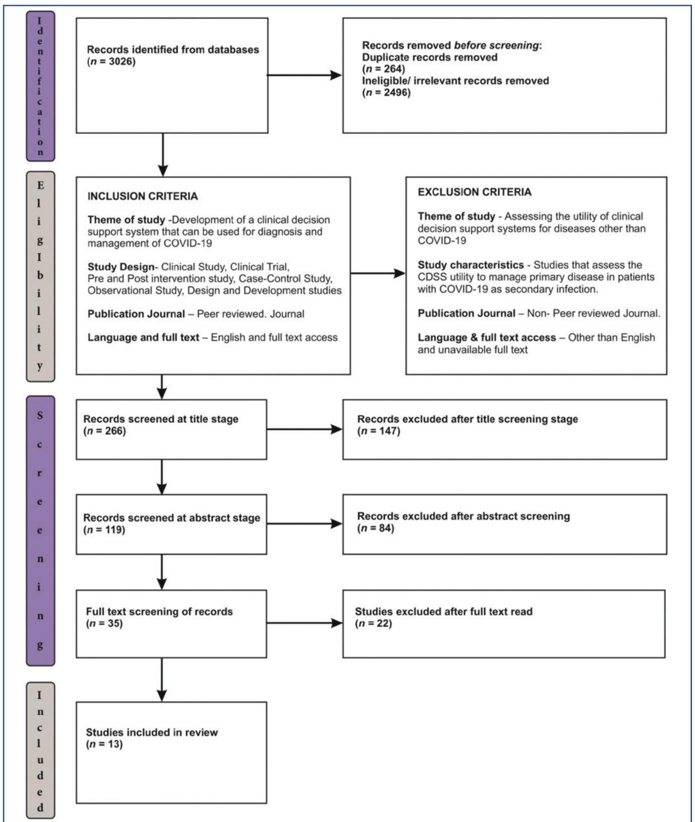
How can these CDSSs be used to track and improve the health outcomes of patients suffering from Long COVID?

Identification of Relevant Studies

The study aimed to identify the available scientific literature that could be used for this review using an evidence-based method. Electronic databases such as Google Scholar, PubMed, SCOPUS, and EMBASE were utilised to identify relevant studies. The key search terms and Medical Subject Headings (MeSH) used were: 'CDSS' OR 'COVID-19' OR 'AI' OR 'Machine Learning' OR 'Deep Learning' OR 'Algorithms' OR 'Early Diagnosis' OR 'Severity Prediction' OR 'Disease Management' OR 'Mortality Assessment' OR 'Long COVID-19'. An extensive literature search on the development and utility of CDSSs in COVID-19 care and their extended usability for long COVID-19 was performed. Original articles that assessed the utility of CDSSs in COVID-19 care, published from 2020 to the present, were selected from the Google Scholar and PubMed databases. The literature search and data extraction were conducted in November and December 2022.

Selection of Studies

The primary search yielded 3,026 full-text articles from Google Scholar and PubMed published in 2020, 2021, and 2022, excluding books, documents, and reviews. Inclusion and exclusion criteria were established for this study. A total of 266 articles were eligible for title screening. A total of 2,760 articles were excluded using an Excel spreadsheet by identifying duplicate authors and those irrelevant to the objectives of present study. For abstract screening, 119 articles were included, while the rest were excluded as they did not meet the inclusion criteria. For further full-text screening, 35 articles were included, from which 13 articles were finally incorporated into the review. The entire selection process, along with the inclusion and exclusion criteria, is described in [Table/Fig-1].



[Table/Fig-1]: PRISMA flowchart for identification and selection of articles.

Charting the Data

The selected articles were meticulously analysed by the reviewers, and the extracted data was charted for further analysis. The titles and abstracts of all screened studies were evaluated by one reviewer and then cross-checked by other reviewers. The reviewers independently analysed the entire content of the articles included in the first round of analysis, which was later verified by other reviewers in the second round. Any differences in data extraction or charting were resolved through consultation and discussion among the reviewers.

Collating, Reporting, and Summarising the Findings

All papers that were screened had their titles and abstracts examined by one reviewer KMS, who then cross-checked the work of the other reviewers (MS and AJ). In the first round of analysis, the reviewers independently examined the entire content of each article (MS and KMS). In the second round of analysis, the results were confirmed by another reviewer (AJ). The other reviewers were consulted to resolve any discrepancies in data extraction or charting (MS and KMS).

RESULTS

Data Extraction and Charting

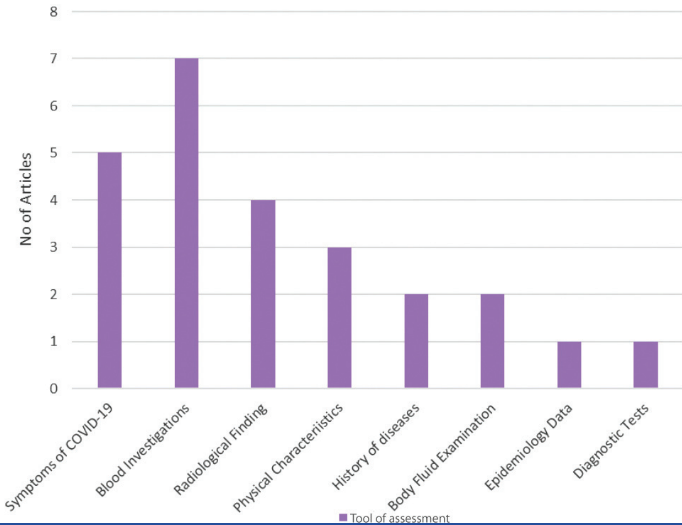
The extracted data, after two rounds of verification, is represented in [Table/Fig-2,3]. Data variables identified from the full text of the articles were grouped into the following categories: name of the first author, year of study, study objectives, study design, country of study, study population, tool of assessment, parameters measured, and the main area of focus of the CDSS. A study ID was assigned to each article. The extensive process of data extraction and charting was conducted comprehensively, and the results are tabulated in [Table/Fig-2] [19-31].

Summary of the Characteristics of Extracted Data

CDSS: Tool of assessment: The CDSSs designed and developed in the studies analysed for this review use various patient health indicators and laboratory findings to manage COVID-19 and aid evidence-based decisions by clinicians. Most of the CDSSs focused on blood investigations to assess the severity and management options for patients with COVID-19 (n=7). This was followed by CDSSs that analyse the COVID-19 symptoms of patients to support decision-making (n=5). Other tools used for assessment included radiological findings (n=4), the physical characteristics of patients (n=3), history of any illness (n=2), body fluid examination (n=2), epidemiological data (n=1), and diagnostic tests (n=1). [Table/Fig-3] shows a diagrammatic illustration of the tool of assessment.

Study ID	Authors and year	Country	Type of study	Number of COVID-19 patients	Tool of assessment	Parameters measured	Area of focus of CDSS
1.	Saegerman C et al., (2021) [19]	Belgium	Prospective cohort study	Not mentioned	Symptoms of COVID-19	Dyspnoea, chest pain, rhinorrhoea, sore throat, dry cough, wet cough, diarrhoea, headache, myalgia, fever and anosmia	Diagnosis confirmation
2.	Wu G et al., (2020) [20]	China	Retrospective cohort study	725	Symptoms of COVID-19 and body fluid examination	Fever, dry and wet cough, sputum, weakness, diarrhoea, vomiting, chest tightness, dyspnoea, myalgia, chill, conjunctival congestion, headache, or dizziness	Severity assessment
3.	Karthikeyan A et al., (2021) [21]	India	Design and development Study	375	Blood investigation and physical characteristics	Neutrophil, lymphocytes, Lactate Dehydrogenase (LDH), high sensitivity C-Reactive Protein (hs-CRP) and age	Mortality prediction
4.	McRae MP et al., (2020) [22]	China	Design and development study	160	Blood investigation	C-Reactive Protein (CRP), N-terminus pro B type Natriuretic Peptide (NT-proBNP), myoglobin (MYO), D-dimer, procalcitonin (PCT), Creatine Kinase-myocardial band (CK-MB), and cardiac troponin I (cTnI)	Severity assessment
5.	Qjidaa M et al., (2020) [23]	Morocco	Case control study	A total of 100 COVID-19 patients, A total of 100 typical viral pneumonia patients, A total of 100 normal subjects	Radiographical findings	One hundred chest X-rays of COVID-19 patients One hundred chest X-rays of patients with typical viral pneumonia One hundred chest X-rays of normal study subjects	Early detection
6.	Onari MA et al., (2021) [24]	Iran	Design and development study	Not mentioned	Symptoms of COVID-19	Symptoms: fever, fatigue, dry cough, dyspnoea, sore throat, no symptom Experiencing symptom: pains, nasal congestion, rhinorrhoea, diarrhoea	Severity assessment
7.	Vepa A et al., (2021) [25]	United Kingdom	Case-control study	335	Radiographical findings, blood investigations, physical characteristics	Chest CT images, CRP level in blood, oxygen saturation level	Mortality prediction, treatment assistance
8.	McRae MP et al., (2020) [26]	United States	Design and development study	701	Tier 1: Physical characteristics and symptoms Tier 2: Blood investigations	Tier 1: Age, sex, BMI, blood pressure, temperature, dry and wet cough, fever, shortness of breath, co-morbidities Tier 2: C-Reactive Protein (CRP), N-terminus pro B type Natriuretic Peptide (NT-proBNP), D-dimer, procalcitonin (PCT), and cardiac troponin I (cTnI)	Severity assessment additionally, treatment assistance
9.	Alakus TB and Turkoglu I (2020) [27]	Brazil	Design and development study	600	Blood investigations	Haematocrit, haemoglobin, platelets, red blood cells, lymphocytes, basophils, eosinophils, monocytes, serum glucose, neutrophils, urea, CRP, creatinine, potassium, sodium, alanine transaminase, aspartate transaminase	Prediction of infection
10.	Dugdale CM et al., (2021) [28]	United States	Pre-post intervention study	Not mentioned	Epidemiological factors, symptoms, blood investigations, radiological findings, body fluid examination, diagnostic tests	Contact history, disease prevalence, shortness of breath, dry and wet cough, fever, chills, headache, sore throat, muscle ache, loss of taste, loss of smell, chest radiographic findings, chest CT, sputum examination, nucleic acid amplification test, tracheal aspirate	Risk assessment
11.	Mayya V et al., (2021) [29]	India	Descriptive study	150	Radiological findings	Chest X-rays	Diagnosis confirmation
12.	Suraj V et al., (2022) [30]	United States	Design and development study	Not mentioned	History of diseases	Patients Electronic Health Records (EHR), history of any illness, cancer	Treatment assistance
13.	Ahmed F et al., (2021) [31]	Bangladesh	Design and development study	485	Blood investigations	LDH, lymphocytes, hs-CRP	Severity assessment

[Table/Fig-2]: Extracted data from scientific literature reviewed [19-31].



[Table/Fig-3]: Tool of assessment.

Parameters measured by CDSS: Under each tool of assessment, the various parameters measured are explained in [Table/Fig-4-6] along with the study ID. A total of 18 parameters were included under symptoms of COVID-19, 25 blood investigations, and six parameters for the physical characteristics of patients. Furthermore, there were two parameters for radiological findings, epidemiological data, history of disease, and body fluid examination, followed by one measurable parameter for diagnostic tests.

Study ID	Symptoms of COVID-19 measured	Assessment of severity	Reported in COVID-19-19 patients	Level of severity reported
1, 2, 6, 8 10	Dyspnoea or shortness of breath	Not seen, mild, moderate, severe	Yes	Mild to moderate
1, 2	Chest pain or chest tightness	Not seen, mild, moderate, severe	Yes	Mild to severe
1, 2, 6, 8, 10	Fever	Not seen, mild, moderate, severe	Yes	Moderate to severe
1, 6	Rhinorrhoea	Not seen, mild, moderate, severe	Yes	Mild
1, 6, 10	Sore throat	Not seen, mild, moderate, severe	Yes	Mild to moderate
1, 2, 6, 8, 10	Dry cough	Not seen, mild, moderate, severe	Yes	Moderate to severe
1, 2, 8, 10	Wet cough	Not seen, mild, moderate, severe	Yes	Mild to moderate
1, 2, 6	Diarrhoea	Not seen, mild, moderate, severe	Yes	Mild
1,2, 10	Headache and dizziness	Not seen, mild, moderate, severe	Yes	Moderate to severe
1, 2, 6, 10	Myalgia	Not seen, mild, moderate, severe	Yes	Moderate to severe
2, 10	Chills	Not seen, mild, moderate, severe	Yes	Mild to moderate
1, 10	Anosmia	Not seen, mild, moderate, severe	Yes	Moderate to severe
10	Ageusia	Not seen, mild, moderate, severe	Yes	Moderate to severe
2, 6	Weakness or fatigue	Not seen, mild, moderate, severe	Yes	Moderate to severe
2	Vomiting	Not seen, mild, moderate, severe	Yes	Mild to moderate
2	Conjunctival congestion	Not seen, mild, moderate, severe	Yes	Mild
6	Nasal congestion	Not seen, mild, moderate, severe	Yes	Mild to moderate
6	No symptoms	-	Yes	-

[Table/Fig-4]: Disease severity assessment by CDSS using symptoms.

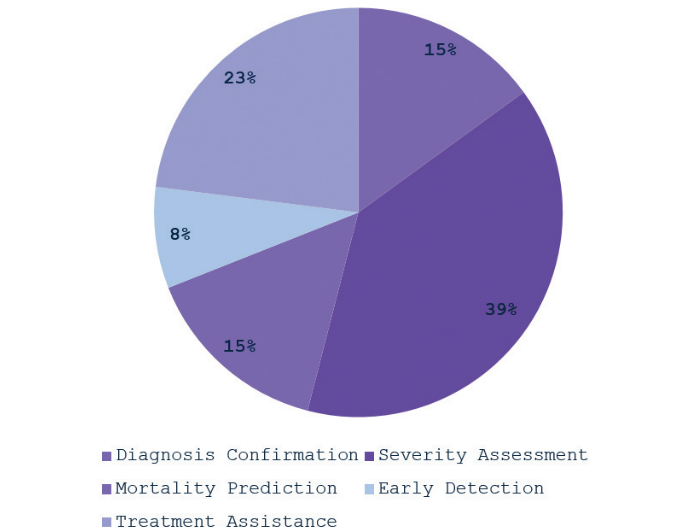
Study ID	Blood investigations assessment	Pattern of change	Indicates
3, 13	Lactate Dehydrogenase (LDH)	Increased	Increased severity
4, 7, 8, 9	C-Reactive Protein (CRP)	Increased	Independent of severity
3, 13	high sensitivity C-Reactive Protein (hs-CRP)	Increased	Increased severity
4, 8	N-terminus pro B type Natriuretic Peptide (NT-proBNP)	Increased	Increased severity
4	Myoglobin (MYO)	Increased	Increased severity
4, 8	D-dimer	Increased	Increased severity
4, 8	Procalcitonin (PCT)	Increased	Increased mortality
4	Creatine Kinase- Myocardial Band (CK-MB)	Increased	Increased mortality
4, 8	Cardiac Troponin I (cTnI)	Increased	Increased mortality
9	Haematocrit	Decreased	Increased severity
9	Haemoglobin	Decreased	Increased severity
9	Red cell Distribution Width (RDW)	Increased	Increased mortality
9	Platelets	Decreased	Increased severity
3, 9, 13	Lymphocytes	Decreased	Increased severity
3, 9	Neutrophils	Increased	Increased severity
9	Basophils	Decreased	Increased severity
9	Monocytes	Increased	Mild to moderate
9	Serum urea	Increased	Increased severity
9	Serum glucose	Increased	Increased severity and mortality
9	Serum creatinine	Increased	Increased severity and mortality
9	Potassium	Decreased	Increased severity
9	Sodium	Decreased	Increased mortality
9	Alanine Transaminase (ALT)	Increased	Increased severity
9	Aspartate Transaminase (AST)	Increased	Increased severity
12	Erythrocyte Sedimentation Rate (ESR)	Increased	Independent of severity

[Table/Fig-5]: Disease severity assessment by CDSS using blood investigations.

Parameters measured	Study ID
Radiological finding	
Chest X-ray	5, 10, 11
Chest CT	7, 10
Epidemiology data	
Contact history	10
Prevalence of disease	10
History of disease	
Co-morbidities	8, 12
Cancer	12
Physical characteristics	
Age	3,8
Gender	8
Body Mass Index (BMI)	8
Blood pressure	8
Temperature	8
Oxygen saturation	7
Body fluid examination	
Sputum	2, 10
Tracheal aspirate	10
Diagnostic test	
Nucleic Acid Amplification Test (NAAT)	10

[Table/Fig-6]: Disease severity assessment by CDSS using other parameters.

Area of focus of CDSS: The CDSSs measure different health variables and assist clinicians in making appropriate decisions based on evidence. CDSSs can be used for assessing various conditions, and the area of focus varies based on the analysis and interpretation of measured variables. In view of this, the main areas of focus of the CDSS in COVID-19 can be categorised into six domains: CDSSs that focus on confirming the diagnosis (n=2), severity assessment (n=5), mortality prediction (n=2), early detection (n=1), and treatment assistance (n=3). [Table/Fig-7] depicts the area of focus of the CDSSs.



[Table/Fig-7]: Area of focus of CDSS.

Significance of CDSS: From the analysis of the studies, it is evident that CDSSs have the potential to predict the severity, mortality, and treatment of long COVID-19 by analysing several health parameters. Compared to the manual and tedious collection of data to analyse potential health outcomes, digital interventions such as CDSSs that are integrated with patients' EHRs are effective and feasible in monitoring and evaluating patients' health data for better prognosis. These CDSSs are helpful in estimating the severity of COVID-19 symptoms and associated treatment outcomes. Patients can be assessed for the severity of symptoms such as dyspnoea, chest pain, fever, rhinorrhoea, sore throat, dry cough, wet cough, diarrhoea, headache, dizziness, myalgia, chills, anosmia, ageusia, weakness, vomiting, fatigue, conjunctival congestion, nasal congestion, or even without any symptoms, to predict the likely outcome of treatment and aid medical practitioners in making decisions that are relative to the clinical condition of the patient [1,2,6,8,10].

Compared to expensive diagnostic procedures and time-consuming methods of interpretation, reports of simple blood investigations can be analysed by the CDSS to evaluate the condition of COVID-19 patients and recommend effective treatment options to improve patient health outcomes. The CDSS software can simplify complex radiological reports that are hard to interpret by extracting key information related to COVID-19 patients' co-morbidities and organ damage from chest X-rays and Computed Tomography (CT) scans. This simplification enables healthcare providers to quickly grasp essential details without the need to interpret lengthy and intricate reports, facilitating prompt decision-making and treatment planning. Simple investigations, such as the estimation of haematocrit, haemoglobin, Red Blood Cells (RBC), White Blood Cells (WBC), and platelets, can reveal a substantial amount of information regarding disease progression. Serum markers such as Lactate Dehydrogenase (LDH), C-Reactive Protein (CRP), high sensitivity C-Reactive Protein (hs-CRP), cardiac troponins, creatine kinase, myoglobin, etc., can be used to predict adverse effects in hospitalised COVID-19 patients, which will help clinicians and healthcare providers in making precautionary plans to avoid any unfortunate events [3,4,7,8,9,13].

In addition to physical characteristics and blood investigations, radiological findings also have a broader scope in CDSS assessment for severity prediction. Reports of chest X-rays and chest CT scans of COVID-19 patients help accurately detect any co-morbidities and the extent of damage to vital organs such as the heart and lungs. Analysing this information is crucial, as hospitalised COVID-19 patients who have been severely infected have a higher chance of developing cardiac and pulmonary failure, which can lead to the patient's death. When this can be analysed earlier using digital tools such as CDSS, it undoubtedly offers a chance for good prognosis and effective treatment options. CDSS, through the analysis of radiological findings like chest X-rays and CT scans in COVID-19 patients, aids in the early detection of co-morbidities and organ damage, particularly to the heart and lungs. This early assessment enables prompt intervention, leading to better prognoses and more effective treatment, which is crucial in preventing cardiac and pulmonary failure and ultimately reducing mortality rates [5,7,10,11].

Additionally, CDSSs can be used to track and improve the health outcomes of patients by analysing epidemiological data. Details about contact history and the prevalence of disease in a locality can be used to assess the rate of infection spread, the likelihood of becoming infected, and potential adverse outcomes. As CDSSs are integrated with EHRs, patients' previous exposure to any disease or the prevalence of other conditions, such as diabetes, cancer, or other diseases that can potentially impact severity and recovery during COVID-19 infection, can also be evaluated to improve treatment efficacy. Thus, CDSSs offer a wide range of benefits in terms of diagnosis, predicting risk factors, severity assessment, and mortality prediction among COVID-19 patients and those at risk, by integrating and analysing their health data [8,10,12].

DISCUSSION

The purpose of this scoping review was to thoroughly examine the published literature on the development of CDSSs for the management of COVID-19 and their potential application for long COVID-19. Present study conducted a comprehensive electronic search of databases to retrieve and scrutinise 13 relevant articles that align with the objectives of this study. Most of the articles were published in 2021 and were predominantly from the United States, India, and China. The majority of the included studies were design and development type studies that elaborated on the process of developing CDSSs for COVID-19 management. The variables extracted from the articles were grouped into assessment tools, parameters measured, and areas of focus of the CDSS in order to study the effectiveness and decision-making processes of these digital tools.

CDSS for COVID-19 management: CDSSs help clinicians make evidence-based decisions at the point of care. These computerised systems are capable of handling large volumes of data and can minimise errors in data reporting and management [32]. In the context of COVID-19, simple and efficient CDSSs can be utilised in the emergency departments of hospitals to immediately report patients' symptoms, assist in severity assessment, and allocate resources for those who are at higher risk [18]. A web-based CDSS known as CADNN is an efficient and economical tool that can be used for the early detection of COVID-19 using chest X-rays and chest CT scans of patients. This interactive CDSS can send and receive feedback from clinicians, which helps generate verified and reliable reports on patients [29].

Most of the studies included in this review focused on analysing the blood investigations of COVID-19 patients in assessing the severity of the disease [22,26,31]. There was a significant association between co-morbid conditions and an elevation in serum biomarkers. For hypertensive patients, cardiac biomarkers had a greater influence when assessing the severity of COVID-19 illness. Other biomarkers, such as CRP, D-dimers, and procalcitonin, indicated other pathophysiological conditions, such as infections, inflammation, thrombosis, and bacterial sepsis [22]. These CDSSs that use blood investigations to report findings offer easier and faster methods of disease prediction and are feasible tools to reduce the overload of patients and investigations in hospital laboratories [31].

These machine-learning algorithms are also capable of combining various reports of blood tests, radiological findings, and physical characteristics such as age and gender to accurately diagnose diseases and predict mortality in severely ill COVID-19 patients [21,33]. These automated models, which act as diagnostic and predictive tools, offer point-of-care solutions to patients and can help categorise low- and high-risk individuals in order to improve health outcomes by facilitating appropriate treatment through evidence-based decisions in highly demanding situations [34,35]. These CDSSs are not just for the use of clinicians and healthcare providers; they can also be employed as self-assessment tools by the public to check their COVID-19 symptoms, thereby obtaining decisions from digital tools for further medical assistance. This approach will reduce the harmful impacts of self-medication and negligence in treatment. Such feasible CDSSs can also be made available in primary health centres to assist the rural population in combating the pandemic and preventing morbidity or mortality due to delays in treatment [36]. Thus, these CDSS tools and applications comprehensively analyse the health status of patients and help both clinicians and patients decide on appropriate treatment options to improve health outcomes in an evidence-based manner during the COVID-19 pandemic [37].

CDSS for long COVID-19: As a sequela of the novel coronavirus pandemic, patients who were exposed to the SARS-CoV-2 virus experience an unusual prolongation or sudden onset of new symptoms around three months after the viral infection, which last for at least two months without any underlying disease condition. This is known as the ‘post-COVID-19 condition’ or more commonly as ‘Long COVID-19’ [38]. Patients are affected by a wide range of physiological and psychological symptoms that disrupt their normal lifestyle and wellbeing. The uncertainty in diagnostic and treatment modalities to manage long COVID-19 leads to errors in detection and ineffective management of symptoms, resulting in a worsening of health conditions [39].

The CDSSs designed to assist the medical decisions of healthcare providers by combining patient-specific data and scientific evidence can serve as useful information tools for the early prediction and effective management of long COVID-19 [40]. These CDSSs are reliable and transfer research-based information that is verified by experienced healthcare professionals. These digital systems also maintain a database to provide accurate information regarding the treatment and management of diseases. Accelerating the implementation of CDSSs in the management of long COVID-19 will help clinicians support patients with personalised treatment in an organised and economical manner. In addition, these computerised systems save time, eliminate unnecessary laboratory investigations, and reduce the manual effort required to compute and analyse the enormous amount of patient data generated during a crisis [41].

Thus, due to public health concerns regarding post-COVID-19 conditions, there is an urgent need to develop CDSSs for the management of long COVID-19 to improve the quality of health and lifestyle for patients. However, despite the advantages that these automated technological tools offer, many ethical and legal challenges hinder the successful implementation of CDSSs. Issues related to validity, trust, privacy, data handling, patient security, and reliability are potential challenges faced while designing, developing, and implementing such automated tools for human health management [42,43]. Hence, these impediments should be meticulously addressed by software developers, policymakers, and healthcare providers when developing CDSSs for disease management.

Role of AI in CDSS: AI holds immense promise for transforming global healthcare systems, particularly through AI-based CDSS. These systems leverage machine learning to analyse vast datasets, offer treatment recommendations, and enhance efficiency for healthcare professionals [44]. Developments in medical image analysis and data computing have bolstered our understanding of disease processes and treatment options, making AI and machine learning invaluable tools for improving health outcomes [45]. While traditional CDSSs have been in use, AI-powered solutions surpass them significantly, providing doctors with highly intelligent assistants for accurate diagnosis [46]. However, factors such as clinical utility, usability, patient safety, and institutional goals can influence AI adoption in healthcare [47]. To address these challenges and ensure adequate reporting of AI and machine learning findings, it is crucial to present digital methods and analysis results in a concise, understandable format. This approach promotes expert assessment, reproducibility, and broader application of AI and machine learning in medical science. Ensuring transparency and reproducibility through access to software specifications and analysis code further enhances openness and advances the field [48].

Assessing the quality and accuracy of CDSS: A complex technology such as a digital CDSS cannot yet be guaranteed to be safe; the best one can realistically hope for is to make a fair attempt to achieve acceptable quality and safety. Two factors need to be taken into account when evaluating a decision support system’s quality: the quality of the software system and/or the informational material. It is impossible to confirm that a CDSS’s medical knowledge base is of the highest accuracy. Medical knowledge is always evolving, and studies frequently reveal that outdated treatment procedures can be harmful or ineffective. Additionally, the quality of information will often be determined by a professional assessment made by an individual or a team of experts, and safety and effectiveness considerations are not always supported by scientific data. Even when there is evidence, it may be sparse, open to multiple interpretations, and subject to modification as scientific knowledge expands. It is also vital that the software used is reliable, safe, and transparent to the user and operator to ensure safety, privacy, and secure data handling [49-52]. Thus, for the quality and accuracy assessment of CDSSs, the medical knowledge base of the digital tool and software should be critically evaluated and approved to avoid bias and misinformation, while promoting long-term usability instead of temporary diagnosis and management [53,54].

A conceptual framework to understand how CDSSs can be integrated with COVID-19 patient data to monitor and manage Long COVID-19 symptoms is illustrated in [Table/Fig-8].

The framework outlines the flow of patient information and clinical decision-making processes, starting from the reporting of a COVID-19 patient to a healthcare setting and leading to evidence-based clinical decisions for managing Long COVID-19:

1. COVID-19 patient reporting to healthcare setting: This is the first step where a patient with COVID-19 symptoms or diagnosis enters the healthcare system.

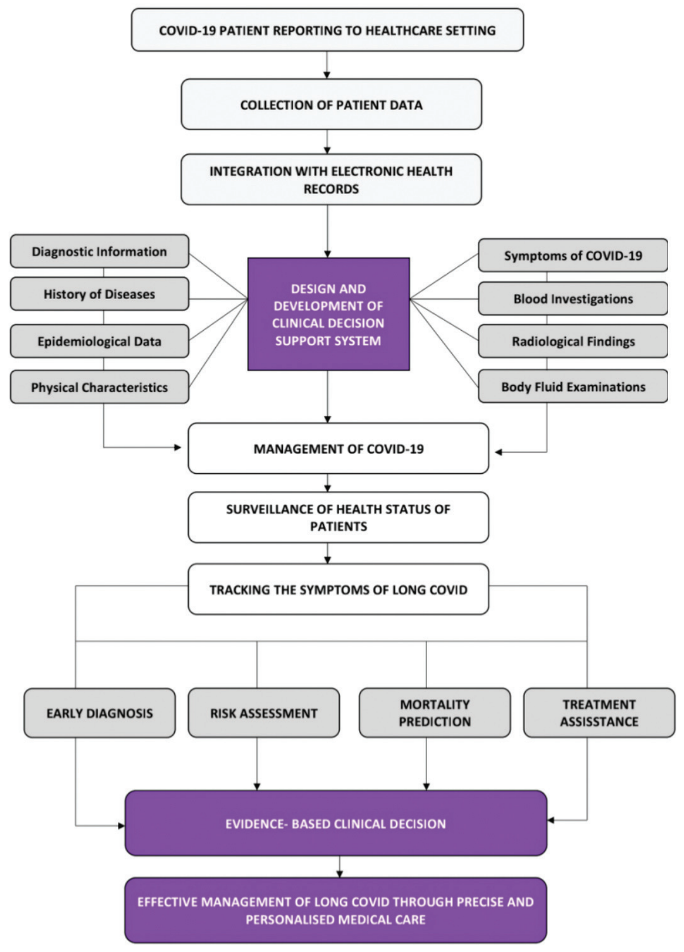
2. Collection of patient data: The collection of comprehensive patient data is the next step.

3. Integration with EHRs: The collected patient data is then integrated into the EHR system for better accessibility and analysis.

4. The diagram branches into two paths:

- **Diagnostic information:** This includes the history of the disease, epidemiological data, and physical characteristics.
- **Symptoms of COVID-19:** This includes conducting blood investigations, radiological findings, and body fluid examinations.

5. Management of COVID-19: The information from the diagnostic and symptoms branches is used to manage the patient’s COVID-19 condition.



[Table/Fig-8]: Conceptual framework for Clinical Decision Support Systems (CDSS) in the management of Long COVID-19.

6. Surveillance of health status of patients: Ongoing surveillance is conducted to monitor the health status of patients.

7. Tracking the symptoms of long COVID-19: Special attention is given to tracking any persistent symptoms that could indicate Long COVID-19.

8. This leads to early diagnosis, risk assessment, mortality prediction, and treatment assistance. These are critical steps for effectively managing the patient.

9. Evidence-based clinical decision making: All the collected information and tracking lead to evidence-based clinical decisions.

10. Effective management of long COVID-19 through process and personalised medical care: The ultimate goal of the framework is to provide effective management of Long COVID-19 through a structured process and personalised care tailored to the individual patient's needs.

Implications of the Study

According to the results of present study, CDSSs can be more beneficial when used to evaluate the likelihood and severity of long-lasting COVID-19 symptoms in patients who have recovered from a SARS-CoV-2 virus infection. In order to track patient data and help physicians provide individualised medical care for the planning, prevention, management, and recovery from Long COVID-19, EHR that preserve patients' information can be combined with various digital supporting tools.

In a similar way to how CDSSs use symptoms, blood investigations, radiological findings, epidemiological data, physical characteristics, and other health-related information to diagnose, predict, and assess severity and mortality among COVID-19 patients, such data can be integrated into patients' health records and combined with CDSSs for long-term monitoring.

Patients who have recovered from COVID-19 can keep track of their health status and report any concerning symptoms for early diagnosis. This CDSS will analyse the existing clinical condition, assess the patient's health based on previous health data, and provide clinicians with accurate, evidence-based information for effective and personalised decision-making.

Knowledge Gaps and Directions for Future Research

Present study identified and substantiated the advantages of AI and deep-learning algorithms in the creation of CDSSs for diagnosing, assessing severity, predicting mortality and managing COVID-19 illness among patients. Although healthcare systems worldwide have effectively tackled the COVID-19 pandemic, Long COVID-19 syndrome remains a risk for patients. While CDSS tools have been well established for managing COVID-19, their potential usability in the treatment of Long COVID-19 has not been extensively explored. Present study identified a lack of scientific literature supporting the use of CDSS in managing long COVID-19 and therefore necessitate the development of such digital support systems. These systems would assist clinicians and other healthcare providers in making evidence-based decisions and offering precise medical care to patients who are at risk of developing long COVID-19 symptoms and to those who are living with long COVID-19 symptoms.

Limitation(s)

As the world has experienced an unprecedented surge in COVID-19 cases, the number of research studies and technological advancements aimed at improving health outcomes and patient satisfaction has also increased. Although this review has thoroughly analysed the utility of CDSSs in COVID-19 care and their extended application in long COVID-19, this scoping review does not guarantee the inclusion of all articles published up to date. Therefore, information extracted from articles published in languages other than English, updated versions of preprints, and unpublished or under-review CDSS models currently in practice were not included in this study.

CONCLUSION(S)

This review emphasises the pivotal role of CDSS in addressing the challenges of COVID-19. While CDSS show promise in diagnosing and monitoring the disease, challenges in implementation exist, including data integration and user interface design. To effectively manage long COVID-19 syndrome, there is a need to extend the utilisation of CDSS. It is recommended to strengthen the use of CDSS for long COVID-19 patients and propose a framework for their enhanced application in symptom management and treatment. By leveraging CDSS, one can improve healthcare delivery amidst the pandemic and in future health crises.

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