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REVIEW ARTICLE

Effectiveness of AI-assisted clinical decision support tools for chronic disease management: a systematic review

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ABSTRACT

Clinical decision support systems (CDSSs) help physicians in several aspects, including diagnosis and management of diseases. The integration of artificial intelligence (AI) has pushed CDSS into a new era of effectiveness by revolutionizing CDSS capabilities, which enable the processing and interpretation of large amounts of healthcare data with unprecedented speed and precision. Chronic diseases require continuous and accurate management. Therefore, managing chronic diseases might benefit from the integration of AI in CDSS. This study aimed to assess the effectiveness of AI-assisted clinical decision support in the management of chronic diseases by reviewing the previous studies conducted on this subject. Relevant articles were searched through electronic databases using relevant keywords. The inclusion criteria were articles published from 2021 to the present, reporting AI implementation in decision support for chronic conditions, providing original findings, written in English, and available in full text. A total of seven articles were included, of which three were trial designs. Each of the included studies concerned a different chronic condition. One study enrolled 117 patients with hypertension medications, and the remaining studies included 7,545 patients. Various models were used in the studies, with Random Forest being the most used tool, as reported in three studies. AI-assisted CDSS was effective in the management of chronic disease by performing several tasks. The tasks were performed by different models and across different chronic diseases, which indicated the effectiveness of AI-assisted CDSS in the management of chronic diseases regardless of the disease and the model used.

Keywords: AI, chronic diseases, management, effectiveness, systematic review.

Introduction

Clinical decision support systems (CDSSs) help physicians in diagnosis and management of diseases, prescribing, and drug control, and they are often implemented through alarm systems [1,2]. CDSSs have been especially effective in increasing adherence to clinical guidelines, public health strategies, and applying prevention and improving patient safety [3,4]. Furthermore, the integration of CDSS into electronic health records (EHRs) has led to a reduction in the incidence of pharmacological adverse events with personalization of recommendations and alerts [4,5].

In recent years, the integration of artificial intelligence (AI) has pushed CDSS into a new era of effectiveness and sophistication. AI technologies have revolutionized CDSS capabilities, enabling it to process and interpret large amounts of healthcare data with unprecedented speed and precision [6]. AI can mimic human behavior and handle the increasing amount of medical data within healthcare systems. Machine learning (ML) is the most common AI technique used [7].

ML acts as the cornerstone of modern CDSS, empowering healthcare providers with decision-making support and predictive analytics capabilities. ML enables CDSS to process and analyze huge volumes of data, including

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EHRs, medical imaging, and genomic information, to extract meaningful insights and inform clinical decisions [6]. Distinct classes of ML algorithms include decision tree algorithms, neural networks, support vector machines (SVMs), Bayesian networks, and Ensemble Learning Methods [6].

The burden of chronic diseases has increased globally; therefore, proper management is crucial [8]. Physicians spend 25% of their time on direct care of patients, whereas 31% of their time is spent on documentation of work [9]. Previous literature revealed that AI outperformed the average level of clinicians in most clinical situations except for treatment suggestions [10,11]. So, this systematic review was performed to identify the effectiveness of AI-assisted clinical decision support in the management of chronic diseases.

Subjects and Methods

Search strategy

The PRISMA checklist [12] was the guidance for writing this systematic review. Searching for relevant articles was performed through electronic databases of PubMed, ScienceDirect, and Google Scholar. The search procedure was restricted to all studies published from 2020 to the present. Several relevant terms were implemented as keywords in the search process, and they were used in different combinations to obtain all possible articles. The keywords used included "AI, Decision support, Chronic disease, Chronic Conditions, Management, Effectiveness, and Outcomes." All the produced titles were examined thoroughly to prevent missing potential studies.

Eligibility criteria

The findings were examined in stages to refine the articles based on the determined inclusion criteria. First, all articles published before 2021 and/or duplicate articles were excluded, as this review focused on articles published between 2021 and the present and to avoid duplication of extracted data, respectively. Then, examination of the disease and condition involved in each study was conducted simultaneously with examination of AI incorporation to exclude all articles focused on non-chronic diseases and those that did not implement AI-assisted systems and used other CDSSs. The remaining findings were again examined for their type and language to include only the original articles written in English and exclude other types of articles and/ or those written in other languages. Finally, all articles that were available as abstracts only were excluded, and only those available in full text were considered eligible and included (Figure 1).

Data review and analysis

The abstracts of all the eligible studies were examined to determine the data of interest for further data extraction. Each article was then reviewed for data extraction

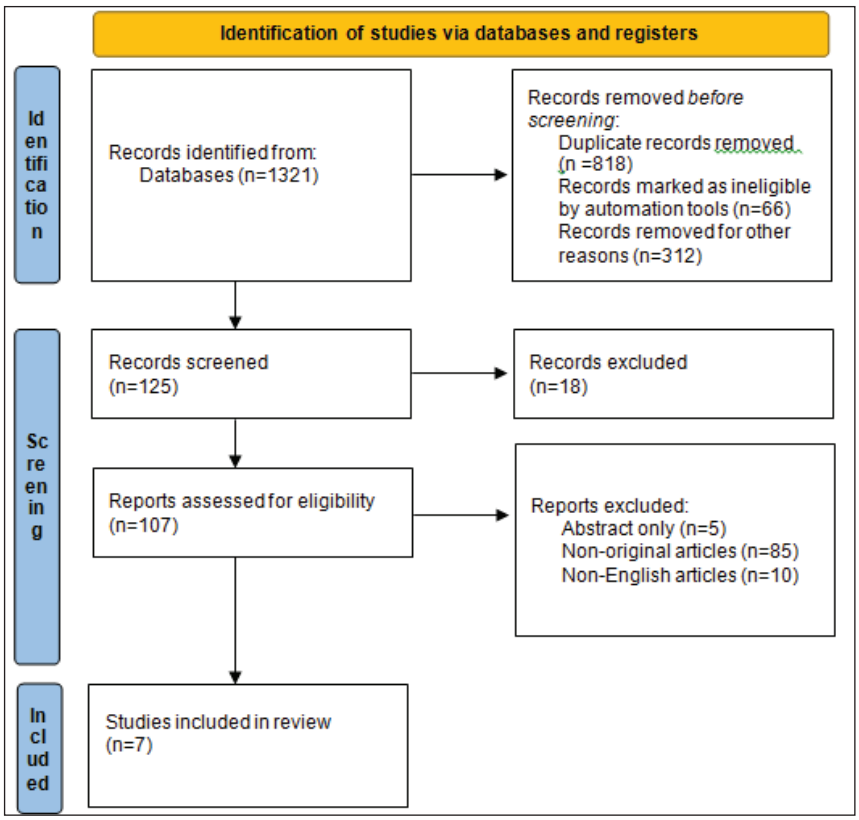


Figure 1. *Eligibility criteria.*

using an Excel sheet for data extraction and saving. The extracted data were then revised and transferred to a pre-designed table to be summarized under major titles.

Results

This systematic review included seven studies that met the defined criteria [13–19]. One study did not report the design [14], whereas the remaining designs included retrospective [13], trials [15,18,19], prospective [16], and pilot [17]. The studies involved assessment of AI tools in various chronic diseases and conditions, including obstructive sleep apnea (OSA) [13], hypertension [14], type 2 diabetes mellitus (T2DM) [15], suspected sleep apnea (SA) [16], rheumatoid arthritis (RA) [17], suspected coronary heart disease (CHD) [18], and asthma [19]. One study included medications and enrolled 117 hypertension medications [14], whereas the remaining six studies enrolled a total of 7,545 patients; of that number, there were 184 children, as the study enrolled pediatric asthmatic patients [19]. Additionally, four studies categorized the subjects into two groups [13,15,18,19]; one study categorized subjects into training and test [13], and another study categorized subjects based on the method of insulin titration into a physician group and a group that depended on AI for insulin titration (iNCDSS group) [15]. A third study categorized patients into training and validation sets [18], and the final study categorized patients into control and intervention based on the care received, either usual care or usual care and AI-based care [19]. There were various AI and machine learning models used in the included studies, where two studies adopted more than one model [13,18], whereas five studies adopted only one model [14–19]. However, Random forest was the most used model in the studies [13,16,18] (Table 1).

Due to variations in the models used in each study, disease, and objective of each study, the results varied among the included studies. Regarding OSA, the study implemented

Table 1. *Summary of the extracted data.*

Author and Publication year	Design	Characteristics	Results and main findings	AI final impact
Lopez-Prado et al. 2026 [13]	Retrospective	*OSA -*N* = 200 patients *Training = 160 *Test = 40 *Scenario A included pre-treatment variables *Scenario B included pre-treatment variables and early adherence metrics -4 models used; RF, LR, SVM-RBF &GB	*RF had the highest AUC for scenario A (AUC = 0.72) and scenario B (AUC = 0.88) *The application of the RF model in the test group for scenario A resulted in an AUC of 0.71, sensitivity of 0.83, and specificity of 0.45 * The application of the RF model in the test group for scenario A resulted in an AUC of 0.91, sensitivity of 0.90, and specificity of 0.82 *The high AUC of A&B in testing confirmed that early adherence is a highly relevant predictor of one-year adherence.	Early prediction of treatment adherence using machine learning is feasible. Treatment adherence would help in improving patient outcomes.
Lee et al. 2025 [14]	---------	*Hypertension -*N* = 117 hypertension medications - MEDSReM system	* The safe window for taking missed/overdue medication was programmed into the MEDSReM app for each medication and dosing frequency. * The MEDSReM© decision support algorithm provided a safe window of time for each hypertension medication for older adults when they need to take their medication after the intended target time has passed.	The MEDSReM decision support system provided a safe window of time for hypertension medication, which would help improve medication adherence.
Ying et al. 2025 [15]	Randomized trial	*T2DM -*N* = 149 patients *Physician group = 74 *iNCDSS group = 75 -iNCDSS	*There were no significant differences between the two groups regarding time spent with glucose levels within range, glucose level, and capillary glucose concentration ($p > 0.05$). *There were no significant differences in adverse events between the two groups. *Most physicians were satisfied with the iNCDSS for its clear, time-saving, effective, and safe clinical support.	The AI-CDSS displayed similarity to endocrinology physicians in insulin titration and glucose level control.
Mosteiro-Añón et al. 2025 [16]	Prospective	*Suspected SA -*N* = 5385 suspected individuals -Random forest-based intelligent CDSS	*Using the intelligent CDSS helped in accurately diagnosing patients suspected of SA based on clinical variables, with an AUC of 0.87–0.95.	AI helped in early and precise diagnosis of SA among suspected patients, which would lead to precise therapeutic management using only clinical variables.

(*Continued*)

Author and Publication year	Design	Characteristics	Results and main findings	AI final impact
Labinsky et al. 2023 [17]	Pilot	*RA -*N* = 50 -AI-based RCM	*The flare prediction tool achieved an AUC of 0.8 with a sensitivity of 72% and a specificity of 76%. *Perceived flare risk and treatment decisions varied largely between physicians, but having access to the flare risk prediction feature numerically increased decision confidence, reduced deviations between physicians, and resulted in more treatment reductions. *RCM usability was rated as good (82/100) and was well accepted (7/10).	AI could support physicians by reducing assessment deviations and increasing treatment decision confidence.
Yan et al. 2022 [18]	Clinical trial	*Suspected CHD -*N* = 1577 patients underwent angiography due to suspected CHD *Training set = 1083 *Validation set = 494 -XGBoost, LightGBM, Random Forest, NGBoost, Logistic model & MLP (DL)	*5.14% had normal coronary arteries. *The overall classification performance of XGBoost was the highest (accuracy of0.844) compared to Random Forest (0.791), NGBoost (0.723), Logistic (0.532), and MLP (0.502), but with comparable performance to LightGBM (0.840). *The system distinguished coronary artery stenosis well in suspected CHD patients. *Personalized probability curves provide individualized intervention guidance.	The AI system had good differentiation ability in the diagnosis of stenosis in suspected CHD patients, which can reduce the number of unnecessary invasive examinations and help in targeted intervention guidance for patients.
Seol et al. 2021 [19]	Randomized trial	*Childhood asthma -*N* = 184 children *Control = 94 received usual asthma care *Intervention = 90 received usual asthma care+A-GPS -A-GPS	*The proportion of children with AE in both groups decreased from baseline (p = 0.042), but there was no difference in exacerbation frequency between the two groups (p = 0.626) during the study period. *A-GPS intervention significantly reduced time for reviewing EHRs for asthma management for each participant compared to usual care without A-GPS (p < 0.001).	A-GPS-based system resulted in a similar reduction in asthma exacerbation events to usual care, but it might reduce clinicians' burden for EHR review, resulting in efficient asthma management and saving time.

OSA = Obstructive sleep apnea, RF = Random forest, LR = Logestic regression, SVM-RBF = Support vector machine with radial kernel, GB = Gradient Boosting, AUC = Area under cureve, MEDSReM = Medication Education, Decision Support, Reminding, and Monitoring, T2DM = Type 2 diabetes mellitus, iNCDSS = intelligence–based insulin clinical decision support system, SA = Sleep apnea, CDSS = Clinical decision support system, RA = Rheumatoid arthritis, RCM = Rheuma-care manager, CHD = Coronary heart disease, A-GPD = Asthma-Guidance and Prediction System, EHRs = Electronic health records.

different AI models for predicting adherence to treatment using two scenarios based on the inclusion of adherence metrics, and it was found that Random Forest achieved the highest performance based on AUC values in both scenarios, with the highest AUC in the scenario involving early adherence metrics [13]. Regarding suspected SA, the study implemented one model to identify the role of AI in early and accurate classification of suspected SA. It was found that the incorporation of routine patient data into the AI system resulted in accurate diagnosis of SA in suspected cases, with high AUC performance of 0.87–0.95 [16]. Regarding hypertension, one model was implemented to identify the effectiveness of AI in guiding patients regarding missed doses of hypertension medications. The implemented tool provided the safe window duration for taking the missed dose to support patients in making their decision [14].

Another study implemented an AI tool to assess the effectiveness of AI in adjusting insulin dose for T2DM. The findings revealed that there were no significant variations between physicians and the iNCDSS tool regarding glucose levels, times when glucose levels were within the range, and adverse events. The iNCDSS was clear, timesaving, effective, and safe clinical support [15]. One study assessed the effectiveness of AI in the prediction of flare risk among RA patients to support the management of the patients. It was found that the tool was effective in predicting flare risk, with an AUC of 0.8. Despite the great variations in management decisions of physicians regarding flare management, the tool provided access to a prediction feature, which increased decision confidence, reduced deviations between physicians, and reduced the number of treatments used [17]. Regarding heart disease, one study implemented several models to diagnose coronary artery stenosis among CHD suspected cases. It was revealed that 5.14% of patients suspected of CHD who underwent angiography were normal and did not need intervention. The overall performance regarding classification of cases was the highest for XGBoost, with an accuracy of 0.844, which was comparable to LightGBM, which provided an accuracy of 0.840. The system was effective in distinguishing stenosis well in CHD-suspected patients [18]. Finally, the implementation of AI to assess its optimization in childhood asthma management revealed similar outcomes when compared to those who received usual care alone in terms of the number of asthma exacerbations. The sole effectiveness

of the tool was discovered regarding reducing the time for reviewing EHRs for asthma management of each participant compared to usual care without A-GPS ($p < 0.001$) [19].

Discussion

This systematic review was conducted to identify the effectiveness of AI-associated CDSS in the management of chronic diseases. ML algorithms, which are a branch of AI, teach computers to learn from data and improve their performance over time without being explicitly programmed [20]. Massive training datasets were used as input to train ML algorithms to make precise predictions, allowing computers to learn without explicit programming [7]. Such algorithms continuously learn from new data inputs, refining their predictive capabilities and adapting to evolving clinical scenarios. Hence, CDSS powered by ML can provide personalized recommendations tailored to individual patient needs, consequently enhancing clinical decision-making and patient outcomes [21].

In the current analysis, there were two studies reporting models trained for the prediction of adherence to OSA treatment [13] and models trained for the diagnosis of stenosis among suspected CHD [18]. It was found that, regarding adherence prediction, the RF model was the best, especially in scenario B, which involved adherence metrics. The high AUC of both scenarios, especially scenario B in testing, confirmed that early adherence is a highly relevant predictor of one-year adherence. Therefore, AI revealed effectiveness in early prediction of treatment adherence among patients, which would help improve patient management and outcomes [13]. Also, regarding diagnosis and detection of stenosis among suspected CHD, the system was effective in distinguishing stenosis well in CHD-suspected patients, and this indicated effectiveness of differentiation ability in diagnosing stenosis among CHD-suspected cases, which can reduce the number of unnecessary invasive examinations and help in personalized intervention, consequently improving the management and outcomes of the patients [18].

SVMs are among the diverse repertoire of ML algorithms utilized in CDSS to address several clinical challenges, including disease diagnosis, risk stratification, and treatment optimization [22]. The study that adopted SVM-RBF applied this model for prediction of adherence; however, the RF model was superior in performance to SVM [13].

ML algorithms empowered CDSS to analyze patient data and make predictions, helping in diagnosis and therapeutic planning [6]. It was previously reported that ML algorithms were effective in adherence prediction [13] and in the detection and diagnosis of stenosis in suspected CHD cases. However, none of the studies investigated the effectiveness of AI in therapeutic planning, but its effectiveness in adjusting insulin dose was reported to be similar to physicians, leading to glycemic control and good management of the disease [15].

Providing diagnostic support is one of the most impactful applications of AI-driven CDSS. It was stated that AI is effective in enhancing diagnostic accuracy and improving patient outcomes [6]. This application was discovered regarding stenosis in suspected CHD patients, as the study revealed that the algorithm used was able to detect normal subjects at a rate of 5.14%, and this proportion, with the help of AI-assisted CDSS, can avoid invasive examination, whereas the confirmed cases can undergo the examination to implement the proper management and consequently improve patient outcomes. Additionally, AI displayed high diagnostic performance, with an AUC of 0.87-0.95 among SA-suspected patients, as it could early and accurately identify and classify suspected SA patients. This, in turn, can guide differential diagnosis and personalize treatment strategies. This indicates the effectiveness of AI in the early diagnosis and management of SA among suspected SA cases using only clinical variables [16].

AI-driven CDSS can also be applied for risk prediction and early intervention, facilitating clinicians in foreseeing and addressing considerable health threats before they progress into severe conditions. The AI systems can stratify patients based on their risk profiles, allowing for targeted intervention and resource allocation [6]. This function of AI was found in one of the included studies in this review; one study reported the effectiveness of AI in the prediction of flare risk among RA patients to support the management of patients. AI could support the physician by reducing assessment deviations and increasing treatment decision confidence, which would help in effective management of patients and avoiding expected flares [17].

Also, AI has the potential for personalized treatment recommendations tailored to individual patient characteristics. This, in turn, revolutionizes conventional approaches to healthcare delivery by leveraging a holistic view of each patient. AI tools can identify the optimal treatment strategies that optimize efficacy and reduce risks [6]. In the current review, it was found that AI was effective in adjusting insulin doses, which reflects individualization of treatment based on each case [15]. Also, personalized treatment with the help of AI could be deduced from one of the included studies, where AI displayed high performance in classifying SA among suspected patients, which helps in personalized treatment [16].

Previous literature revealed that the achievements of AI were comparable to those of human experts, with a high accuracy of 90%–100% in predefined diagnostic decisions [10,11]. This could be found in adjusting insulin doses, where the model used (iNCDSS) was similar to physicians in effectiveness regarding adjusting doses [15].

Furthermore, this review found that AI was effective in decision support and adherence to medication for hypertensive patients, where, in case of a missed hypertension medication dose, the decision support system provided a safe window of time for medication, which would help in improving adherence to medication

and consequently management of the disease [14]. However, AI, when combined with usual care, displayed no superiority to usual care alone for children with asthma in reducing the number of asthma exacerbations. Nonetheless, it might be helpful in time-saving, as it reduced clinicians' burden for EHR review, which might result in efficient asthma management [19]

Another systematic review included 123 studies and categorized AI contributions into three functions, including disease detection, COVID-19, and oncology. It was found that AI-driven CDSS exhibited strong diagnostic and prognostic accuracy in imaging and laboratory settings [23]. A systematic review was conducted to identify the role of AI in the management of chronic conditions and included ten studies. It was found that AI was valuable in various aspects related to administration, physician burden, and patient adherence [8]. A previous scoping review included six studies to identify AI-based CDSs in primary care, but did not focus on chronic disease, and found that AI-CDSSs had various tasks, including diagnosis support, management and treatment recommendations, and complication prediction. Additionally, it was discovered that the AI-CDSS had a potential role in improving clinical management, patient satisfaction, and safety while reducing physician workload [7]. Similarly, it was found that AI-assisted CDSS was effective in the management of chronic disease by performing various tasks, including early and accurate diagnosis, prediction of adherence, adjusting medication dose, providing a safe window for medication administration, and prediction of risk of complications.

The limitations of this review include the small number of included studies and the heterogeneity found between the studies due to variations in population, study designs, tools used, and objectives of implementing AI. However, this review has strengths, including the identification of AI-assisted CDSs across different chronic conditions and diseases. Therefore, further studies are highly recommended to perform comparisons between the effectiveness of each AI model across different chronic conditions.

Conclusion

AI-assisted CDSS was effective in the management of chronic disease by performing several tasks, including prediction of medication adherence, prediction of risk of complications, providing a safe window for missed doses of medication, adjusting medication doses, and, in turn, individualizing therapy for the patients, early and accurate classification and diagnosis of conditions among suspected cases, and saving physicians' time. Additionally, such tasks were performed by different models and across different chronic diseases, which indicates the effectiveness of AI-assisted CDSS in the management of chronic diseases regardless of the disease and the model used. However, selection of the model is necessary, as some models displayed superior performance to others.

List of Abbreviations

AI	Artificial Intelligence
CDSS	Clinical decision support system
CDS	Clinical decision support
A-GPS	Asthma-guidance and prediction system
AUC	Area under the curve
CHD	Coronary heart disease
EHR	Electronic health record
GB	Gradient boosting
iNCDSS	Intelligence-based insulin clinical decision support system
LightGBM	Light gradient boosting machine
LR	Logistic regression
ML	Machine learning
MLP	Multilayer perceptron
NGBoost	Natural gradient boosting
OSA	obstructive sleep apnea
PRISMA	Preferred reporting Items for systematic reviews and meta-analyses
RA	Rheumatoid arthritis
RCM	Rheuma-care manager
RF	Random forest
SA	Sleep Apnea
SVM	Support vector machine
SVM-RBF	Support vector machine with radial basis function Kernel
T2DM	Type 2 diabetes mellitus
XGBoost	Extreme gradient boosting

Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this article.

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Consent for publication

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Ethical Approval

Not applicable.

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