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Review Article

The Impact of AI-Powered Clinical Decision Support Systems on Clinical Decision-Making and Treatment Quality: A Systematic Review

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ABSTRACT

Introduction: Artificial intelligence (AI) is revolutionizing clinical decision-making processes by leveraging vast data generated from health records and delivery systems. This enhances safety and quality of care decisions, making Clinical Decision Support Systems (CDSS) essential tools in healthcare, thereby improving clinicians' decisions and patient outcomes.

Methodology: A systematic review was conducted across PubMed, Google Scholar and Cochrane Library, that assessed the use of AI-powered CDSS. Following title and abstract screening, full-text articles were evaluated for methodological quality and compliance to the inclusion criteria. The data extraction process concentrated on study design, AI technologies used, reported outcomes, and proof of AI-CDSS impact on patient and clinical outcomes. A total of 32 studies were included after the screening of the articles, encompassing various study designs and healthcare applications. The analysis focused on evaluating the type of AI technologies employed, their effects on clinical decision-making and treatment quality, and the challenges faced during implementation.

Results: The review found that ML algorithms, including Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs), were predominant among the included studies. Significant improvements were noted in the diagnostic accuracy (reported in 18 studies) and timely medical interventions (12 studies). Personalized treatment recommendations were facilitated in 10 studies, further optimizing treatment protocols in 08 studies. However, challenges such as data privacy concerns and the need for clinician training were highlighted in 10 studies, while ethical considerations were reported in 05 studies.

Conclusion: This systematic review underscores the potential of AI-powered CDSS to significantly enhance clinical decision-making and treatment quality. While AI technologies improve diagnostic and therapeutic processes, their successful integration into clinical practice requires addressing ethical concerns, clinical training, and data management challenges. Future research should focus on long-term impacts, real-world applications, and strategies for overcoming barriers to AI adoption in healthcare settings.

Key words: Artificial Intelligence, Machine Learning, Clinical Decision Support Systems, CDSS, healthcare.

Authors' Contribution:
All authors contributed equally to the conception, literature search, manuscript drafting, editing and review

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Introduction

The healthcare sector is undergoing a profound transformation, propelled by the exponential growth of complex clinical data and rapid advancements in Artificial Intelligence (AI) and Machine Learning (ML) technologies. These innovations are not merely supplemental tools but are increasingly integrated into Clinical Decision Support Systems (CDSS) to augment human cognitive capabilities and enhance the overall quality and efficiency of medical.[1] The potential applications of AI-powered CDSS span the entire spectrum of healthcare, from expediting early disease detection and refining diagnostic accuracy to optimizing personalized treatment strategies and enabling real-time, remote patient monitoring.[2,3]

Modern medicine is characterized by an overwhelming volume of patient data, intricate disease presentations, and constantly evolving treatment protocols. AI and ML algorithms excel at processing and identifying patterns within these vast datasets that may elude human perception. For instance, in time-sensitive conditions like sepsis, where delays in recognition and treatment directly correlate with increased mortality, AI-CDSS can analyze electronic medical records to predict risk and organ failure even before clinical manifestation, thereby providing crucial lead time for interventions.[4] Similarly, in infectious diseases, AI-CDSS are being developed to assist with diagnosis, outcome prediction, and antimicrobial management across various bacterial and viral pathogens.[5]

Healthcare systems globally face immense pressure to improve efficiency and optimize resource allocation. AI-CDSS offer solutions to streamline administrative costs, improve workflow efficiencies, and reduce avoidable bed-days, as demonstrated by systems that predict safe hospital discharge after major surgery.[6] In specialized fields like orthodontics, AI's ability to automate tasks such as identifying cephalometric landmarks and predicting treatment outcomes can save significant clinical time and improve precision. The paradigm of personalized medicine relies heavily on analyzing individual patient characteristics to tailor interventions. AI-CDSS enable this by sifting through patient-specific data to offer customized treatment recommendations, thereby moving beyond one-size-fits-all approaches. In dementia care, AI-powered systems can aid in early diagnosis and help decrease clinicians' subjectivity, paving the way for more targeted management. [8]

Despite the evident promise, the widespread adoption of AI-based CDSS in clinical practice has been slower than in other industries.[9] Significant barriers persist, including the critical need to build trust among healthcare professionals, which often requires a deeper understanding of AI model explainability and transparency.[10] Clinicians' hesitation to embrace these technologies is frequently linked to the perceived "black box" nature of complex algorithms and a lack of clear regulatory.[4] Furthermore, concerns regarding data privacy, the necessity for diverse and robust datasets for generalizable model building, and ethical considerations surrounding AI's impact on human empathy and the doctor-patient relationship must be meticulously addressed.[3]

Given this complex landscape of immense potential intertwined with significant practical and ethical challenges, a comprehensive synthesis of the current evidence is imperative. This systematic review aims to systematically identify, evaluate, and synthesize studies on AI-powered CDSS in clinical decision-making. By doing so, we intend to explore the specific benefits realized, delineate the range of AI methodologies employed, and articulate the critical challenges that must be overcome. Ultimately, this review seeks to provide a consolidated understanding for clinicians, researchers, and policymakers, guiding future research, development, and strategic implementation efforts to maximize the positive impact of AI in healthcare and improve patient outcomes globally.

Methodology

A systematic review was rigorously conducted following established guidelines to identify relevant studies. The search encompassed three major electronic databases: PubMed, Google Scholar, and Cochrane Library. The search strategy utilized a comprehensive combination of keywords, including but not limited to "Artificial Intelligence," "Machine

Learning," "Clinical Decision Support Systems," "CDSS," "healthcare," "diagnosis," "treatment," and specific medical domains. The search was focused on article published between January 1, 1990, and January 31, 2024, to capture a broad range of developments in this rapidly evolving field.

The initial database search yielded a total of 420 records. These records were then meticulously screened for duplicates, resulting in the removal of 400 redundant entries. The remaining 400 unique records underwent an initial screening based on their titles and abstracts to assess their preliminary relevance to the review's objectives. This stage led to the exclusion of 250 records that did not meet the basic criteria.

Subsequently, 150 full-text articles were sought for retrieval. Of these, 118 could not be successfully retrieved due to various reasons, such as unavailability or access restrictions. The remaining 150 full-text articles were then rigorously assessed for eligibility against predefined inclusion and exclusion criteria. Studies were included if they focused on AI-powered CDSS, reported clinical outcomes, and were published in English. Exclusion criteria included studies with ineligible designs (e.g., non-clinical studies, purely theoretical papers), those that did not meet specific inclusion criteria, articles deemed to have insufficient methodological quality, or those that did not report outcomes relevant to clinical decision-making or treatment quality. Following this detailed assessment, a final set of 32 studies was deemed eligible and included in the systematic review. The PRISMA flow diagram (Figure 1) illustrates the study selection process.

Data were extracted from the included studies focusing on the following aspects: study design, AI technologies employed, reported outcomes, and evidence of AI-CDSS impact on patient and clinical outcomes. This included details on diagnostic accuracy, timely interventions, personalized treatment recommendations, optimization of treatment protocols, and challenges encountered during implementation.

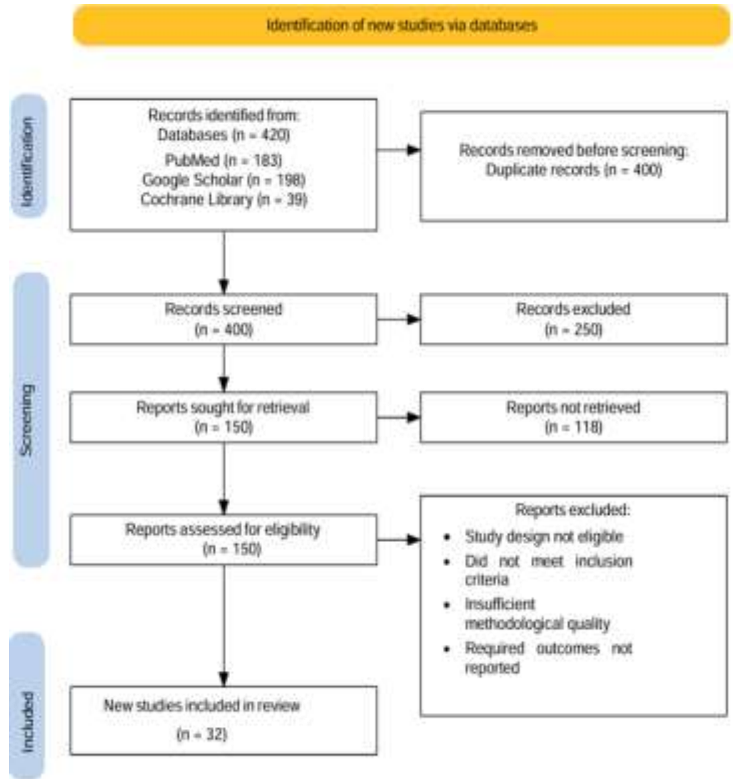

Figure 1:PRISMA Flow diagram of study selection.

The risk of bias for each included study was assessed using criteria adapted from Cochrane's risk of bias domains. Five domains were evaluated: D1 (Bias arising from the randomization process), D2 (Bias due to deviations from intended intervention), D3 (Bias due to missing outcome data), D4 (Bias in measurement of the outcome), and D5 (Bias in selection of the reported result). Each domain was rated as "Low risk" (+), "High risk" (X), or "Some concerns" (–). An overall judgment for the risk of bias was assigned to each study based on these individual domain assessments.

Results

This systematic review included 32 studies examining the application and impact of AI-powered CDSS across diverse medical disciplines. The studies encompassed a wide range of designs, including systematic reviews, retrospective cohort studies, randomized controlled trials, and qualitative investigations. The breadth of clinical areas covered highlights the broad applicability of AI in healthcare, from infectious disease diagnosis and treatment to oncology, cardiovascular monitoring, diabetes management, dental diagnostics, and emergency department triage.

AI Technologies Employed	
Convolutional Neural Networks (CNNs) and Artificial Neural Networks (ANNs)	These models were frequently employed, particularly for tasks involving image recognition and analysis. Examples include identifying cephalometric landmarks and predicting facial attractiveness in orthodontics (Sanjeev B. Khanagar et al., 2021), diagnosing dental caries and assessing dental conditions from radiographs (Carlo Bulletti et al., 2024), and mapping infarct core in acute ischemic stroke (Ela Marie Z. Akay et al., 2023).
Support Vector Machines (SVMs)	SVMs were commonly used for classification and regression tasks, demonstrating effectiveness, especially with smaller datasets and high-dimensional data, as seen in identifying drug targets and classifying tumors (Khajamoinuddin Syed et al., 2020) and in dementia care (Amirhossein Eslami Andargoli et al., 2024).
Natural Language Processing (NLP)	NLP techniques were critical for extracting and analyzing unstructured information from clinical notes (Khajamoinuddin Syed et al., 2020) and understanding clinician sentiments regarding AI usage (Hyeyoung Hah et al., 2021).
Other ML and Deep Learning Approaches	Genetic Algorithms (GAs) were used for optimization problems, while Decision Trees, k-Nearest Neighbors (kNN), and k-Means clustering provided interpretative models for patient outcomes and groupings (Khajamoinuddin Syed et al., 2020). Deep learning models, including Long Short-Term Memory (LSTM) and Transformers (BERT), were also noted for prognosis and real-time clinical decision support (Robert Oehring et al., 2023).

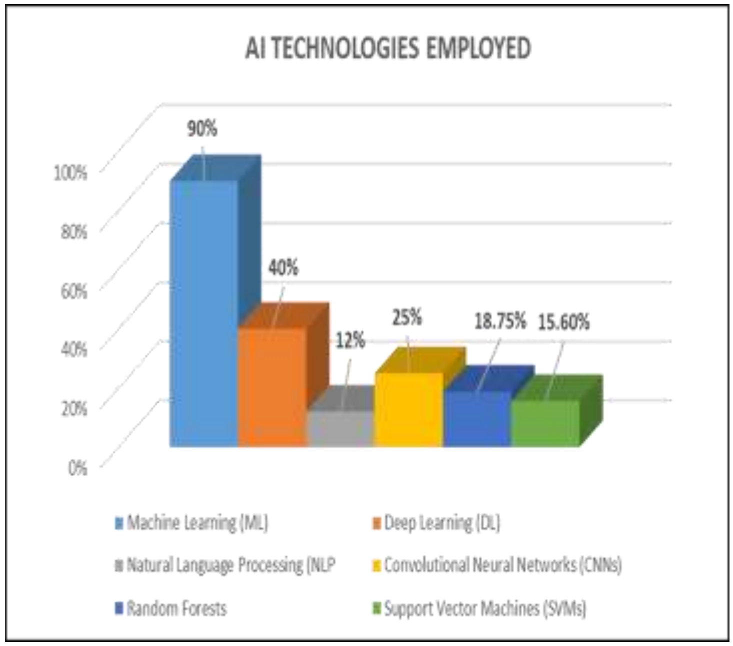

Figure 2: AI Technologies Employed

The review identified several significant positive impacts of AI-powered CDSS on clinical practice:

Impact on Clinical Decision-Making and Treatment Quality	
Enhanced Diagnostic Accuracy	Eighteen studies reported significant improvements in diagnostic accuracy. For instance, AI algorithms achieved high accuracy in diagnosing infections (N. Peiffer et al., 2020) and detecting cutaneous melanoma with 90% sensitivity (Jonatan Helenason et al., 2024). AI-powered CDSS also aided in the early diagnosis and detection of dementia, reducing clinician subjectivity (Amirhossein Eslami Andargoli et al., 2024).
Timely Medical Interventions	Twelve studies highlighted that AI-CDSS facilitated more

	timely medical interventions. This included improved responses to sepsis prediction, earlier intervention for carbapenem and colistin resistance (Ming-Jr Jian et al., 2024), and prompt management of patient care based on real-time insights (Omar Ali et al., 2023).
Personalized Treatment Recommendations and Protocol Optimization	Ten studies reported that AI-CDSS provided personalized treatment recommendations, with eight further demonstrating optimization of treatment protocols. AI tools assisted in optimizing discharge after major surgery (Davy van de Sande et al., 2022), providing personalized treatment plans for cancer patients (Robert Oehring et al., 2023), and enhancing embryo selection in assisted reproductive technology (Carlo Bulletti et al., 2024).
Improved Practitioner Performance and Patient Outcomes	CDSS often led to improved clinician adherence to clinical guidelines, enhancing patient care coordination (Cesar A. Gomez-Cabello et al., 2024). While fewer than 25% of studies measured statistically significant improvements in patient outcomes, some showed positive impacts on chronic condition control and reduced hospital lengths of stay (Amit X Garg et al., 2005). AI-driven insights also supported prognostic predictions for ICU patients, mortality, and ventilator weaning (Sobhan Moazemi et al., 2023).

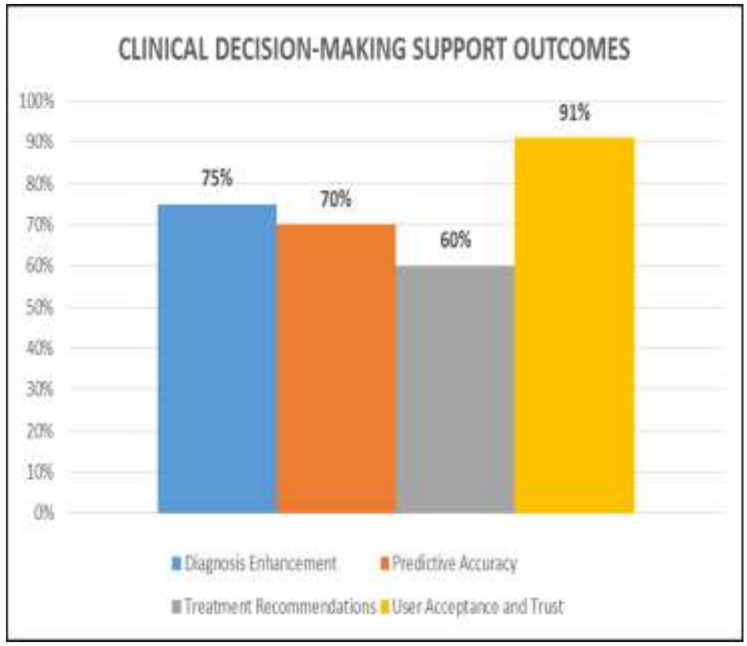

Figure 3. Clinical decision-making support outcomes

Despite the promising benefits, the review identified several persistent challenges in the successful

Challenges in Implementation	
Data Privacy and Management	Ten studies underscored critical concerns regarding data privacy and the ethical management of vast health datasets (Amirhossein Eslami Andargoli et al., 2024; Soliman.S.M. Aljarboa et al., 2024).
Clinician Training and Acceptance	The need for comprehensive training for clinicians in using AI tools and addressing resistance to adoption was highlighted in ten studies. Clinicians expressed interest in understanding contributing features and uncertainty in AI models (Oskar Wysockia et al., 2023) and required trust in AI systems for effective decision-making (Jessica M Schwartz et al., 2022; Susanne Gaube et al., 2021).

Ethical Considerations	Five studies specifically addressed ethical considerations, emphasizing the importance of human empathy and clinical judgment to complement AI recommendations (Soliman.S.M. Aljarboa et al., 2024).
Technical Limitations and Generalizability	Concerns about model overfitting, lack of real-world generalizability, and the need for robust validation were raised (Ela Marie Z. Akay et al., 2023). The interpretability and explainability of AI models are crucial for clinician trust and effective clinical integration (Anna Markella Antoniadi et al., 2024).

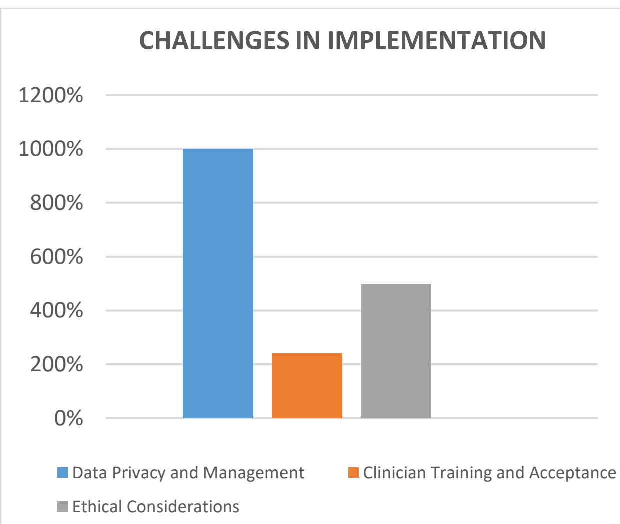

Figure 4. Graphical summary of the methodological quality (risk of bias) assessment across the included studies

The comprehensive risk of bias assessment, detailed in Figure 2, revealed a varied methodological quality among the included studies.

- Randomization Process (D1): Most studies (n=26) were at low risk of bias regarding the randomization process. However, 7 studies raised some concerns, and 1 study was at high risk.
- Deviations from Intended Intervention (D2): A large number of studies (n=26) demonstrated a low risk of bias, while 5 had some concerns and 3 were at high risk.
- Missing Outcome Data (D3): This domain also largely showed a low risk of bias (n=27), with 6 studies having some concerns and 1 study at high risk.
- Measurement of the Outcome (D4): The majority of studies (n=27) were at low risk. Six studies had some concerns, and 1 study was at high risk.
- Selection of Reported Result (D5): This domain showed a higher proportion of high-risk assessments (n=9), indicating potential selective reporting. Twenty studies were at low risk, and 5 had some concerns.

Overall Risk of Bias: Synthesizing these individual domain assessments, 12 studies were categorized as having a low overall risk of bias. Ten studies were assigned an overall judgment of "some concerns," and 12 studies were found to have a high overall risk of bias. This distribution underscores the variability in methodological rigor across current research on AI-powered CDSS, highlighting areas for improvement in future study designs and reporting.[28]

Table I. Characteristics of the included studies reviewing Artificial Intelligence in Clinical Decision Support Systems (AI-CDSS).					
Authors/Year	**Title**	**Journal**	**Study Design**	**AI Technologies Employed**	**Clinical Decision-Making Support**
N Peiffer., et al, 2020[5]	Machine learning for clinical decision support in infectious diseases: a narrative review of current applications	Clinical Microbiology and Infection Elsevier	Systematic review of 75 papers describing 60 unique machine learning-based clinical decision support systems (ML-CDSS) for infectious diseases.	-The ML-CDSS used supervised learning (97%), with a few using reinforcement learning (3%). -The ML-CDSS analyzed structured patient data (e.g. demographics, vitals, lab results) as well as some unstructured data (e.g. free text clinical notes).	-The ML-CDSS addressed a range of decisions, including diagnosis of infection (33%), prediction of sepsis (30%), prediction of treatment response (22%), and selection of antimicrobials (8%).
Omar Ali., et al., 2023[1]	A systematic literature review of artificial intelligence in the healthcare sector: Benefits, challenges, methodologies, and functionalities	Journal of Innovation &Knowledge Elsevier	-The systematic review examined the research designs utilized in the studies, such as experimental, observational, and case study approaches. It analyzed how the study design impacted the quality and findings of the research on AI-enabled healthcare.	-The review identified the specific AI technologies and techniques that were applied in the healthcare domain, such as machine learning, natural language processing, computer vision, and expert systems. It examined how the choice of AI technology influenced the benefits, challenges, and functionalities observed.	- AI technologies can assist clinicians in making more informed and effective decisions regarding patient diagnosis, treatment, and care management - AI systems can integrate and analyze data from multiple sources to surface relevant insights and recommendations - This allows clinicians to more accurately diagnose, select treatments, and proactively manage patient care - AI-based tools can identify high-risk patients, predict disease progression, and recommend personalized treatment plans
Davy van deSande, et al., 2022[6]	Optimizing discharge after major surgery using an artificial intelligence based decision support tool (DESIRE): An external validation study	Surgery Elsevier	Retrospective cohort study to externally validate an ML concept for predicting hospital interventions in gastrointestinal and oncology surgery patients - Conducted at 3 hospitals in the Netherlands, including patients admitted more than 2 days after initial surgery and discharged between 2017-2021 - Primary outcome was performance in predicting hospital interventions (reoperations, radiological interventions, IV antibiotics) after 2nd postoperative day	Developed 4 random forest models: 1. Full model with 17 variables. 2. Reduced model with 11 clinically relevant variables. 3-4. Full and reduced models with admission diagnosis added.	The reduced model with admission diagnosis (12 variables total) performed best, with AUROC of 0.83 and NPV of 89.3% - Variable importance analysis showed surgical procedure description and admission diagnosis were most important. AUROC: Area Under the Receiver Operating Characteristic Curve. NPV: Negative Predictive Value. ML: Machine Learning.
Oskar Wysockia., et al., 2023[10]	Assessing the communication gap between AI models and healthcare professionals: Explainability, utility and trust in AI-driven clinical decision-making	Artificial Intelligence Elsevier	-Within-subject design was used, where each participant used the tool in two conditions: with and without explanation. -23 healthcare professionals participated in the experiment. -Participants were clinically active and worked with patients with cancer presenting with COVID-19.	1. CORONET model: a regression random forest model trained to predict COVID-19 severity. 2. Model explanation consisted of two visual components: scatter plot and contribution plot. 3. SHAP explanation was used to produce the contribution plot.	1. Explanations did not significantly impact decision-making. 2. 87% of HCPs were interested in knowing contributing features, and 91% considered model explanation important. 3. Uncertainty was considered more important than contributing features. 4. HCPs wanted to know both contributing features and uncertainty.

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Ahmad A. Abujaber., et al., 2022[9]	Enabling the adoption of machine learning in clinical decision support: A Total Interpretive Structural Modeling Approach	Informatics in Medicine Unlocked Elsevier	1. The study uses Total Interpretive Structural Modeling (TISM) to develop a hierarchical relationship among enablers of Machine Learning (ML) adoption in clinical decision-making. 2. A panel of six expert scholars with experience in ML and clinical decision-making was formulated to conduct the TISM process.	1. The study focuses on Machine Learning (ML) technologies and their adoption in clinical decision-making. 2. ML approaches are considered a key enabler of clinical decision-making support.	1. The study identifies 10 enablers of ML adoption in clinical decision-making, including perceived normative congruence, clinicians' awareness, patients' awareness, perceived usefulness, perceived ease of use, academic foundation, multidisciplinary collaborative work environment, clinicians' trust, patients' trust, and clinicians' intentions to adopt ML. 2. The study develops a TISM-based conceptual framework to enhance clinicians' intentions to adopt ML in their clinical decisions.
Amirhossein Eslami Andargoli., et al., 2024[8]	Intelligent decision support systems for dementia care: A scoping review	Artificial Intelligence In Medicine Elsevier	1. A scoping review of empirical studies on AI-powered clinical decision support systems for dementia care. 2. Search conducted using MEDLINE, EMBASE, PubMed, SCOPUS, and CINAHL databases. 3. 28 studies included in the review, with publication dates ranging from 2000 to 2021	1. Machine Learning (ML) algorithms used in most studies. 2. Support Vector Machine (SVM) was the most common ML technique. 3. Other ML algorithms used include Linear Discriminant Analysis (LDA), Principal Component Analysis (PCA), and Sparse Representation. 4. Rule-Based Algorithms used in some studies, particularly before 2010.	1. AI-powered clinical decision support systems (CDSSs) can aid in early diagnosis and detection of dementia. 2. CDSSs can help decrease clinicians' subjectivity in dementia evaluation and diagnosis. 3. AI-powered CDSSs can increase accuracy in distinguishing between different types of dementia. 4. CDSSs can support primary care providers in diagnosing dementia.
Sanjeev B. Khanagar., et al., 2021[7]	Scope and performance of artificial intelligence technology in orthodontic diagnosis, treatment planning, and clinical decision-making - A systematic review	Journal of Dental Sciences ScienceDirect	Systematic review based on PRISMA-DTA guidelines. diagnosis, and treatment planning.	1. Artificial intelligence (AI) technologies used in orthodontic diagnosis and treatment planning. 2. Convolutional neural networks (CNNs) and artificial neural networks (ANNs) were the most commonly used AI technologies. 3. Other AI technologies used include paraconsistent artificial neural networks (PANNs) and Bayesian networks (BNs).	1. AI technologies used for identifying cephalometric landmarks, determining need for orthodontic extractions, and predicting facial attractiveness after orthognathic surgery. 2. AI technologies used for predicting need for orthodontic treatment and orthodontic treatment planning.
Soliman.S.M. Aljarboa., et al., 2024[11]	CDSS Adoption and the Role of Artificial Intelligence in Saudi Arabian Primary Healthcare	Informatics in Medicine Unlocked Elsevier	Qualitative Research Methodology: Utilized semi-structured interviews with general practitioners (GPs). - Participant Selection: 30 GPs from healthcare facilities in Riyadh and Qassim, using purposive and snowball sampling for diversity. - Data Analysis: Thematic analysis using NVivo software following six phases	- Clinical Decision Support Systems (CDSS): Computerized systems aiding medical prevention, diagnosis, and treatment. - Artificial Intelligence Applications: Examples like the Velys robot facilitate surgical precision and manage patient flow. - Integration of AI: Analyzes health datasets for diagnostic support, triage, and personalized care.	Improving Decision-Making: Enhances decision-making through evidence-based recommendations and patient data analysis. - Roles in Patient Care: Integrated across stages like preventive measures, diagnostic assistance, and personalized treatment plans. - Ethical Considerations: Importance of human empathy and clinical judgment alongside AI.

Stuti M. Tanya., et al., 2023[12]	Development of a Cloud-Based Clinical Decision Support System for Ophthalmology Triage Using Decision Tree Artificial Intelligence	American Academy of Ophthalmolog y Elsevier	This study employed a prospective comparative cohort design to evaluate on-call ophthalmology referrals, categorizing them based on new ophthalmic symptoms or known diagnoses	- **Algorithm Development**: An algorithm created using Zingtree, consisting of an introductory decision tree to gather information from referring providers. - **Categorical Decision Trees**: Created ten diagnostic categories to facilitate decision-making, eliciting increasingly specific details about the patient's condition. - **Electronic Processing**: Referral requests processed electronically to improve efficiency, eliminating the need for paper forms, and allowing immediate processing by the ophthalmology clinic.	**Structured Referral Process**: The decision tree enabled systematic gathering of referral information, leading to provisional diagnosis and urgency classification. - **Communication Pathways**: Provided options for referring providers to communicate directly with on-call ophthalmologists for immediate clarification when needed. - **Outcome Measures**: Primary outcome measures included agreement on referral category, diagnosis, and urgency among referring providers, CDSS, and ophthalmologists, facilitating assessment of the algorithm's effectiveness.
Mohamed Khalifa et al., 2024[13]	Advancing clinical decision support: The role of artificial intelligence across six domains	Computer Methods and Programs in Biomedicine Update Elsevier	A systematic review was conducted to examine how AI enhances clinical decision support (CDS) using a four-step approach: comprehensive literature search, defining inclusion/exclusion criteria, data extraction/synthesis, and analyzing extracted information to understand AI's current use and potential applications in CDS. - The review identified 915 initial papers, resulting in 32 studies focused on AI's role in improving CDS after applying specific inclusion/exclusion criteria	- AI significantly enhances CDS through six domains: Data-Driven Insights and Analytics (e.g., EHR analysis), Diagnostic and Predictive Modelling (e.g., diagnostic assistance), Treatment Optimisation and Personalised Medicine (e.g., evidence-based treatment recommendations), Patient Monitoring and Telehealth Integration, Workflow and Administrative Efficiency, and Knowledge Management and Decision Support. - AI algorithms excel in EHR analysis, predictive analytics, imaging diagnostics, and personalizing treatment based on genetic data	- AI improves the decision-making process for healthcare providers by analyzing vast datasets to identify health trends, predict outcomes, and facilitate personalized care. - The integration of AI aids in timely interventions, enhances administrative efficiency through automation, and improves communication and coordination among healthcare teams, all contributing to optimized patient care.
Carlo Bulletti., et al., 2024[14]	Artificial Intelligence, Clinical Decision Support Algorithms, Mathematical Models, Calculators Applications in Infertility: Systematic Review and Hands-On Digital Applications	Mayo Clinic Proceedings Digital Health Elsevier	- A systematic review was conducted to identify clinical decision support algorithms (CDSA), AI applications, and mathematical models used in assisted reproductive technology (ART). The review was registered with PROSPERO and adhered to PRISMA guidelines. The literature search targeted studies published from 1 January 2013 to 31 January 2024, including prospective and retrospective studies.	- The review identified various AI implementations, including automated decision aids for predicting treatment outcomes, patient profiling, optimization and personalization of treatments, embryo evaluation, and laboratory management. Specific AI techniques utilized include machine learning (ML), predictive algorithms, and various calculators tailored for ART. **Artificial Intelligence (AI) Algorithms**: - Convolutional Neural Networks (CNN) - Artificial Neural Networks (ANN) - Learning Vector Quantization (LVQ) - Probabilistic Neural Networks (PNN) - Support Vector Machine (SVM) - Deep Learning	- AI contributes to improving the decision-making process in ART by providing accurate prognostic predictions, streamlining treatment strategies, and offering personalized treatment recommendations. Automated tools enhance embryo selection and assessment, allowing for better identification of viable embryos through image analysis.

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Khajamoinuddin Syed., et al., 2020[16]	Artificial intelligence methods in computer-aided diagnostic tools and decision support analytics for clinical informatics Chapter	Artificial Intelligence in Precision Health Science Direct	- **Overview of AI Techniques**: The text covers various AI methods, including Genetic Algorithms (GAs), Support Vector Machines (SVM), Artificial Neural Networks (ANN), Decision Trees, k-Nearest Neighbors (kNN), k-Means clustering, and Natural Language Processing (NLP), showcasing their applications in healthcare. - **Case Studies**: Multiple case studies are presented, highlighting practical implementations of these algorithms in areas like heart disease prediction, colorectal cancer outcomes, and radiation therapy analytics.	- Genetic Algorithms (GA): Used for optimization problems in diverse applications, from radiology for edge detection to optimizing treatment protocols. - Support Vector Machines (SVM): Designed for classification and regression tasks; effective in handling small datasets and high-dimensional data, especially in biomedical domains to classify tumors and identify drug targets. - Artificial Neural Networks (ANN): Proven to excel in complex pattern recognition tasks; applied in radiology for image diagnosis, predicting outcomes in conditions like Alzheimer's Disease, and analyzing genomic data. - Decision Trees: Provide interpretative models of patient outcomes; used to simplify complex classifications in analyzing health conditions. - k-Nearest Neighbors (kNN): A simple yet powerful algorithm for classifying new patient data based on proximity to existing patient records, demonstrating effectiveness in heart disease evaluations. - k-Means Clustering: An unsupervised learning technique used to identify patient groupings based on clinical attributes; valuable in understanding cancer patient cohorts. - Natural Language Processing (NLP): Enables extraction and analysis of information from unstructured clinical notes to support physicians in decision-making.	- **Predictive Analytics**: Algorithms help in predicting patient outcomes based on historical data, aiding in treatment decisions. - **Automated Extraction**: NLP strategies facilitate the extraction of meaningful data from clinical notes, enhancing the availability of structured data for analysis. - **Comparative Patient Analysis**: Systems like HINGE use kNN for comparative analysis of new patients with historical cohorts, supporting precise treatment plans. - **Disease Classification and Feature Importance**: Algorithms such as decision trees and ANN help identify important features influencing disease classification and patient outcomes.
Ela Marie Z. Akay., et al., 2023[17]	Artificial Intelligence for Clinical Decision Support in Acute Ischemic Stroke: A Systematic Review	Stroke Scientific Publishing American Heart Association	The Systemic review examined 121 studies on AI-based clinical decision support systems (CDSSs) for acute ischemic stroke, with 65 studies included for full data extraction. The studies covered a range of use cases, methodologies, patient subgroups, and input data, highlighting the potential benefits of AI in stroke diagnosis and treatment.	The most common AI techniques used were convolutional neural networks (26%) and random forest algorithms (17%). Data splitting into training and test sets was reported in only 58% of studies, raising concerns about overfitting and lack of real-world generalizability. Internal model validation was reported in 94% of studies, but only 37% used a clinical comparator as a gold standard.	The most common prediction tasks were for 90-day modified Rankin Scale score (32%), final infarct prediction (26%), and infarct core mapping (12%). Only 6% of studies proposed models for directly predicting the success of mechanical thrombectomy, despite this being a key goal of stroke treatment research. The use of imaging data for functional outcome prediction was limited, despite the potential of AI to extract novel predictors from raw imaging.
Eleni Karlafti., et al., 2023[18]	Support Systems of Clinical Decisions in the Triage of the Emergency Department Using Artificial Intelligence: The Efficiency to Support Triage	Acta medica Lituanica	Data collected from 332 patients at the Emergency Department over 3 months in 2021 23 variables related to patient conditions, including numerical and categorical data Considered hospital length of stay and Emergency Severity Index (ESI) as target variables, selected ESI Used an artificial neural network (ANN) to develop an automatic patient screening classifier	Artificial neural network (ANN) architecture, specifically a feedforward neural network	Automatic prediction of Emergency Severity Index (ESI) to support triage and patient management

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Claudia Mazo., et al., 2020[21]	Clinical Decision Support Systems in Breast Cancer: ASystematic Review	Cancers MDPI	The researchers conducted a systematic review of the literature and evaluated CDSSs based on their targeted outcomes, advantages, disadvantages, and effects on patients' lives.	Machine Learning (ML), Predictive Modeling	Adjuvant! Online, PREDICT, ONCOassist, OncotypeIQ, DESIREE, CancerMath Adjuvant! Online: Estimate 10-year relapse-free and OS. PREDICT: Predict breast cancer-specific survival. ONCOassistant:Predict prognosis and treatment benefit. OncotypeIQ: Predict treatment benefit. DESIREE: Predict prognosis and treatment benefit. CancerMath: Predict clinical outcomes and treatment benefits
			Observational study. Retrospective monitoring of patients with pancreatic cancer. Recruitment of 20 patients diagnosed with locally advanced or metastatic pancreatic cancer Analyzed 274 clinical visits with a mean follow-up time of 163 days	Therapeutic Performance Mapping System (TPMS). Machine learning (regression trees). Data normalization and transformation techniques. Cross-validation (leave-one-patient-out setup)	Development of a web application to predict outcomes (eosinophils, leukocytes, monocytes, platelets, red blood cells, and hemoglobin). Use regression trees to analyze clinical and molecular data for predicting clinical outcomes. Collect and analyze 40 clinical variables for each patient. Evaluate model performance using Spearman correlation and prediction scores to assess accuracy. Build separate models for each patient to calculate protein activation and predict medical outcomes.
Irene Dankwa-Mullan., et al., 2019[22]	Transforming Diabetes Care Through Artificial Intelligence: The Future Is Here	Population Health Management	Predefined online PubMed search. Literature search from 2009 to 2018 Identification of clinically relevant articles. Total of 450 unique articles reviewed	Various AI approaches and cognitive computing systems. Machine Learning, Deep Learning	Applications aim to improve diabetes screening, detection, monitoring, and treatment- Tools for patients, clinicians, and health systems. Development of clinical decision support systems- Predictive population risk stratification tools- Patient self-management tools. Tools and systems that improve access, accuracy, efficiency, affordability, speed, and satisfaction in diabetes care. High-impact articles targeting significant changes in diabetes care.
Bridget J. Daley., et al., 2021[23]	mHealth apps for gestational diabetes mellitus that provide clinical decision support or artificial intelligence: A scoping review	Diabetic Medicine Wiley	Scoping review of mHealth apps for GDM. Literature search conducted from 2014 to 2019. Included papers published in high-impact journals. Review process adhering to specific methodologies.	AI, Machine Learning (ML), Neural Networks. Algorithms powered by AI and ML. Decision support tools leveraging AI and ML.	Investigate applications for clinical decision support in gestational diabetes (GDM). Enhance access to healthcare and, specifically, support for GDM patients. Evaluate tools for real-time feedback and health status monitoring. Identify intended audience and ensure suitability for patient use
Amit X Garg., et., al., 2005[24]	Effects of Computerized Clinical Decision Support Systems on Practitioner Performance and Patient Outcomes: A Systematic Review	JAMA The Journal of the American Medical Association	systematic review Searches conducted through databases including MEDLINE, EMBASE, and Cochrane Database from 1998 to September 2004.	Decision-Support Systems: CDSSs were typically integrated into electronic medical records or computer order entry systems to facilitate practitioner decision-making. Types of Systems Studied: The review categorized CDSSs into: Diagnostic Systems: Focused on improving diagnostic accuracy and reducing unnecessary interventions. Reminder Systems for Prevention: Aimed at enhancing preventive care practices such as screenings and vaccinations. Systems for Disease Management: Evaluated in chronic disease contexts, particularly for diabetes and cardiovascular health. Drug Dosing and Prescribing Systems: Emphasized on management protocols for medication use.	Practitioner Performance Outcomes: CDSSs often improved practitioner adherence to clinical guidelines, with success rates varying by system type. 76% of studies evaluating reminder systems showed a positive impact on practitioner performance. Patient Outcomes: Fewer than 25% of studies measuring patient outcomes reported statistically significant improvements. Improvements noted in some specific areas, such as control of chronic conditions and reductions in hospital lengths of stay.

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Cesar A. Gomez-Cabello., et al., 2024[25]	Artificial-Intelligence-Based Clinical Decision Support Systems in Primary Care: A Scoping Review of Current Clinical Implementations	European Journal of Investigation in Health, Psychology and Education MDPI	Systematic review of 420 articles	Machine Learning (ML). Natural Language Processing (NLP). Neural Networks (NNs). Bayesian classifier. Deep Learning (DL)	CDSSs aimed at performance enhancement. Diagnosis support, treatment recommendations. Management recommendations. Coordination of care. Improve adherence to best practice recommendations
Jonatan helenason., et al 2024[26]	Exploring the feasibility of an artificial intelligence based clinical decision support system for cutaneous melanoma detection in primary care – a mixed method study	Scandinavian Journal of Primary Health Care Taylor & Francis	Exploratory and descriptive qualitative and quantitative study. Semi-structured interviews post-simulation.	Convolutional Neural Network (CNN). Image analysis from dermoscopic photographs (6714 images).	Diagnostic accuracy of CDSS with 90% sensitivity and 65% specificity. Two-tailed clinical decision support: "Melanoma cannot be excluded" / "No signs of Melanoma. Assess user experience and clinical workflow integration. Conducted interviews addressed daily clinical workflow impact
Sobhan Moazemi., et al., 2023[27]	Artificial intelligence for clinical decision support for monitoring patients in cardiovascular ICUs: A systematic review	Frontiers in Medicine	Systematic review of studies (21 papers)	Machine Learning (ML) approaches, including: Categorical boosting Logistic regression Random forest Support vector machines (SVM) Reinforcement learning, including recurrent neural networks Deep learning (e.g., LSTM, RNN) Long short-term memory (LSTM) Transformers (BERT)	Various AI models used for predicting outcomes in cardiovascular ICUs.. Predictions for mortality, ventilator weaning, and complications in ICU patients. Identification of relevant predictive factors for ICU patient outcomes. AI-assisted prognosis for extubation failure and cardiac arrest. Support for real-time clinical decision-making based on AI analysis. Assessment of mortality, neuropathology, and sepsis risk in ICU patients. Clinical alerts and monitoring for preventing adverse outcomes. AI-driven methodologies for automated patient monitoring and risk assessment. Enhance interpretability with explainable AI models to support clinical decisions.
Robert Oehring., et al., 2023[28]	Use and accuracy of decision support systems using artificial intelligence for tumor diseases: a systematic review and meta-analysis	Frontiers in oncology	Systematic review of 31 studies	1. Watson for Oncology (WFO)2. OncoDoc 3. Lung Cancer Assistant (LCA) 4. Multidisciplinary meeting Assistant (MATE) 5. Oncoguide 6. Prototype machine-learning models	Comparison of treatment decisions made by AI and MDM across various cancer types. Results analyzed to assess the agreement on cancer treatment decisions. Evaluation of treatment concordance for breast, colorectal, lung, cervical, gastric, prostate, thyroid, and hepatocellular cancers. Meta-analysis of treatment recommendations from AI systems compared to oncologists. Various algorithms, including decision tree models for treatment guidelines. Evaluation of accuracy and relevance to clinical outcomes in cancer care.
Jessica M Schwartz., et al., 2022[29]	Factors Influencing Clinician Trust in Predictive Clinical Decision Support Systems for In-Hospital Deterioration: Qualitative Descriptive Study	JMIR HUMAN FACTORS	Qualitative study utilizing a human-computer trust conceptual framework. Focused on cognition-based trust concepts: perceived understandability and perceived technical competence. Data collection through semi-structured interviews with healthcare professionals. Participant recruitment through training sessions and snowball sampling	Predictive Clinical Decision Support Systems (CDSS), specifically the Communicating Narrative Concerns Entered by Registered Nurses (CONCERN) Uses machine learning and natural language processing for patient risk prediction. CONCERN leverages nursing documentation data to inform predictions. The CDSS provides visual risk indicators to inform clinical decisions.	Explore clinicians' trust and perceptions of predictive CDSSs and their influence on decision-making. Aids clinicians in predicting in-hospital deterioration, guiding therapeutic interventions, and improving patient outcomes. Supports understanding of clinicians' trust in AI systems and factors influencing their willingness to act based on predictions. Evaluates clinician perceptions of CDSS accuracy and usability, potentially guiding future AI implementations in healthcare.

Susanne Gaube., et al., 2021[30]	Do as AI say: susceptibility in deployment of clinical decision-aid	npj Digital Medicine	Experiment comparing advice quality from AI vs. human source. Participants: radiologists (n = 138, high-expertise) and IM/EM physicians (n = 127, lower expertise). Framework utilized: 2×2 mixed factorial design (source of advice: AI vs. human; advice accuracy: accurate vs. inaccurate)	Chest X-ray analysis using AI diagnostic advice and human expertise. Diagnostic advice sourced from AI systems and experienced radiologists. Participants evaluated cases and provided feedback on advice quality. Advice quality and diagnostic accuracy results presented via mixed-effects models	Advice quality and diagnostic accuracy results presented via mixed-effects models. Clinical performance assessed through final diagnostic accuracy based on received advice. Assesses algorithmic aversion and diagnostic accuracy related to clinical decision-making based on varying expertise levels. Supports understanding of factors influencing physician trust and reliance on diagnostic advice, guiding future AI integration in healthcare.
Sherry-Ann Brow., et al., 2023[31]	Patient similarity and other artificial intelligence machine learning algorithms in clinical decision aid for shared decision-making in the Prevention of Cardiovascular Toxicity (PACT): a feasibility trial design	Cardio-Oncology BMC	This is a single-center, double-arm, open-label, randomized interventional feasibility study	Use of artificial intelligence for cardiovascular risk assessment in cancer survivors. Algorithms output cardiovascular risk information based on clinical, laboratory, and echocardiographic data. AI algorithms are explainable; rules-based algorithm created based on guidelines and recommendations. Clinical decision aid is presented in a user-friendly web interface; integration with existing electronic health records planned	Development of a clinical decision aid accessed via electronic health record to support shared decision-making between cancer survivors and cardiologists. Aim to enhance appropriate medication use and cardiac imaging surveillance per national guidelines. Clinical decision aid visually pairs risk information and evidence-based suggestions for clinician-patient discussions.
Xiwen Liao et al., 2023[32]	Recent advancement in integrating artificial intelligence and Information technology with real-world data for clinical decision-making in China: A scoping review	Journal of Evidence-Based Medicine WILEY	A scoping review	Deep learning (CNNs), machine learning (XGBoost, etc.) Machine Learning Algorithms: XGBoost, Random Forests, Support Vector Machines (SVM). - Deep Learning: Convolutional Neural Networks (CNNs) for image recognition tasks in diagnostics. - Natural Language Processing (NLP): Used for extracting information from unstructured data sources such as clinical notes.	Various models/tools integrated with RWD and AI. Integration with RWD: Most studies integrated AI algorithms with real-world data sources for personalized decision-making. - Functionality: Systems were designed for various applications, including clinical diagnosis, treatment recommendations, and risk assessment. - Outcomes Evaluated: Improvement in diagnostic accuracy, reduction in delays to treatment, and overall impact on patient outcomes were assessed.
Hyeyoung Hah., at al., 2021[33]	How Clinicians Perceive Artificial Intelligence–Assisted Technologies in Diagnostic Decision Making: Mixed Methods Approach	JOURNAL OF MEDICAL INTERNET RESEARCH	Type: Mixed methods research with concurrent triangulation design. - Population: 144 clinicians in simulated diagnostic scenarios. - Data Collection: Quantitative surveys and qualitative open-ended questions.	- AI-Enabled Diagnostic Tools: Used multimedia patient information to assist in diagnosis. - Natural Language Understanding (NLU): IBM Watson NLU was utilized for analyzing qualitative responses to understand clinician sentiments regarding AI usage.	- AI Assistance: Provided clinicians with real-time diagnostic recommendations based on multimedia data. Impact on Performance: Assessed how AI assistance influenced diagnostic accuracy and overall clinical task performance, with comparisons to traditional methods. User Experience Evaluation: Clinicians reported their experiences through surveys, revealing insights on the perceived effectiveness and reliability of AI tools in clinical settings
Xinnian Lin., et al 2024[34]	Artificial Intelligence–Augmented Clinical Decision Support Systems for Pregnancy Care: Systematic Review	JOURNAL OF MEDICAL INTERNET RESEARCH	Systemic review	Machine Learning Algorithms: [List specific algorithms used, such as Random Forest, SVM, Neural Networks, etc.] Deep Learning Techniques: [If used, specify types e.g., CNN, RNN, etc.] Other Technologies: [Mention other relevant technologies, like Natural Language Processing or Hybrid Models.]	Functionality of CDSS: Diagnostic Support: Assist clinicians in diagnosing conditions by analyzing data. Clinical Risk Prediction: Identify patients at risk of complications or adverse outcomes. Therapeutic Recommendations: Suggest treatment pathways based on patient data. Monitoring and Alerts: Provide alerts and reminders for patient follow-ups or critical values.
Mahdi et al. (2023)[35]	How does artificial intelligence impact digital healthcare initiatives? A review of AI applications in dental healthcare	International Journal of Information Management Data Insights	Systematic Review	Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), Probabilistic Neural Networks (PNNs), Support Vector Machine (SVM), Learning Vector Quantization	The study finds AI aids decision-making by quickly interpreting big data to improve diagnostic accuracy (comparable to experts) for dental caries, vertical root fractures, and orthodontic planning. It facilitates the automation of data processing to reduce human error and oversight, though it emphasizes that AI must remain under human supervision.

Discussion

This capacity for personalized care is further reinforced by the use of Natural Language Processing (NLP) to extract meaningful insights from unstructured clinical notes, enabling a more holistic understanding of patient conditions (Khajamoinuddin Syed et al., 2020).[16]

The impact on practitioner performance is also notable, with CDSS generally improving adherence to clinical guidelines and enhancing care coordination (Amit X Garg et al., 2005; Cesar A. Gomez-Cabello et al., 2024)[24,25]. This operational efficiency, coupled with the potential for cost savings through optimized workflows and reduced administrative burdens, positions AI-CDSS as valuable assets for resource-constrained healthcare systems (Darragh O'Reilly et al., 2023)[4].

Despite these compelling advantages, the path to widespread adoption of AI-CDSS is fraught with challenges. The review highlights several critical barriers, prominently data privacy concerns and the need for comprehensive clinician training. As emphasized by Skuban-Eiseler et al. (2023), the use of AI in geriatric care, for instance, necessitates careful consideration of patient values and the doctor-patient relationship, reinforcing the ethical imperative to protect sensitive information[2]. The reluctance of healthcare professionals to fully embrace AI technologies often stems from a lack of transparency and explainability in complex algorithms, leading to issues of trust and potential automation bias (Oskar Wysockia et al., 2022). As Wysockia et al. (2022) suggest, while explanations are viewed positively as a safety mechanism, they can sometimes lead to confirmation bias or model over-reliance if not carefully integrated[10].

Furthermore, the methodological rigor and generalizability of AI models remain areas of concern. Our risk of bias assessment revealed that a significant portion of studies exhibited "some concerns" or "high risk" of bias, particularly in the domain of selective reporting (D5). This calls for more transparent and standardized reporting practices in future research, aligning with the call for rigorous and continuous evaluation of AI-CDS by Cresswell et al[36]. The lack of diverse data sets for model building, often skewed towards high-income countries, limits the applicability and generalizability of these tools in low- and middle-income settings, as highlighted by Peiffer-Smadja et al. (2019)[5]. Technical limitations, such as model overfitting and the challenge of validating tools across multiple clinical settings, further complicate external validity (Ela Marie Z. Akay et al., 2023).[17]

Lastly, the regulatory landscape for AI-based medical device software is still evolving. As (Beckers et al., 2021)[38] discuss in the context of the EU Medical Device Regulation, stringent requirements for safety and clinical performance assurance are essential for wider adoption. The absence of clear political and regulatory frameworks can hinder the trust and approval necessary from both clinicians and patients for implementing this transformative technology (Darragh O'Reilly et al., 2023)[4].

Future research should prioritize: Developing more interpretable AI models that provide clear, human-understandable justifications for their recommendations will be crucial in fostering clinician trust and promoting responsible use (Oskar Wysockia et al., 2022; Anna Markella Antoniadi et al., 2024).[10,19] Studies need to move beyond single-center evaluations and incorporate diverse, real-world datasets from varied healthcare settings, including low- and middle-income countries, to ensure generalizability and applicability across different patient populations (N. Peiffer-Smadja et al., 2019; Grace Golden et al., 2024.).[5.37] Continuous dialogue and research are needed to navigate the ethical complexities of AI in healthcare, particularly concerning data privacy, informed consent, potential biases in algorithms, and the preservation of humanistic aspects of care (Tobias Skuban-Eiseler et al., 2023; Kathrin Cresswell et al., 2023.)[2,36]. AI-CDSS must be seamlessly integrated into existing clinical workflows without causing disruption. This requires iterative design processes that incorporate feedback from clinicians and comprehensive training programs to equip healthcare professionals with the necessary skills to effectively use and interpret AI tools (Grace Golden et al., 2024.; Ahmad A. Abujaber et al., 2022.)[9,37]. Policymakers and regulators must work collaboratively to develop robust, adaptable frameworks that ensure the safety, effectiveness, and accountability of AI-CDSS, thereby fostering confidence among users and the public (R. Beckers et al., 2021.)[38]. In a survey of 470 Pakistani doctors and medical students, Ahmed et al. (2022) found that although roughly 70–74% of participants had a basic understanding of AI, only about 20–27% were aware of its clinical applications. The authors conclude that, although participants lack in-depth knowledge and real-world usage, there is strong willingness to adopt AI in medicine; a gap that underscores the need for structured education and integration of AI into healthcare systems[39].

Conclusion

In conclusion AI-powered CDSS represent a formidable advancement in healthcare, offering unprecedented opportunities to improve diagnostic accuracy, personalize treatment, and enhance operational efficiency. While the benefits are clear, the successful integration of these technologies into clinical practice hinges on a concerted effort to address methodological limitations, build clinician trust through explainability, safeguard data privacy, and establish appropriate regulatory oversight. By focusing on these critical areas, the healthcare community can collectively harness the power of AI to elevate patient care and optimize health outcomes on a global scale.

References

1. Ali O, Abdelbaki W, Shrestha A, Elbasi E, Alryalat MA, Dwivedi YK. A systematic literature review of artificial intelligence in the healthcare sector: Benefits, challenges, methodologies, and functionalities. Journal of Innovation & Knowledge. 2023 Jan 1;8(1):100333. https://doi.org/10.1016/j.jik.2023.100333
2. Skuban-Eiseler T, Orzechowski M, Denkinger M, Kocar TD, Leinert C, Steger F. Artificial intelligence–based clinical decision support systems in geriatrics: an ethical analysis. Journal of the American Medical Directors Association. 2023 Sep 1;24(9):1271-6. https://doi.org/10.1016/j.jamda.2023.06.008
3. Alshamrani M. IoT and artificial intelligence implementations for remote healthcare monitoring systems: A survey. Journal of King Saud University-Computer and Information Sciences. 2022 Sep 1;34(8):4687-701. https://doi.org/10.1016/j.jksuci.2021.06.005
4. O'Reilly D, McGrath J, Martin-Loeches I. Optimizing artificial intelligence in sepsis management: Opportunities in the present and looking closely to the future. Journal of Intensive Medicine. 2024 Jan 1;4(1):34-45. https://doi.org/10.1016/j.jointm.2023.10.001
5. Peiffer-Smadja N, Rawson TM, Ahmad R, Buchard A, Georgiou P, Lescure FX, Birgand G, Holmes AH. Machine learning for clinical decision support in infectious diseases: a narrative review of current applications. Clinical Microbiology and Infection. 2020 May1;26(5):584-95. https://doi.org/10.1016/j.cmi.2019.09.009
6. van de Sande D, van Genderen ME, Verhoef C, Huiskens J, Gommers D, van Unen E, Schasfoort RA, Schepers J, van Bommel J, Grünhagen DJ. Optimizing discharge after major surgery using an artificial intelligence–based decision support tool (DESIRE): An external validation study. Surgery. 2022 Aug 1;172(2):663-9. https://doi.org/10.1016/j.surg.2022.03.031
7. Khanagar SB, Al-Ehaideb A, Vishwanathaiah S, Maganur PC, Patil S, Naik S, Baeshen HA, Sarode SS. Scope and performance of artificial intelligence technology in orthodontic diagnosis, treatment planning, and clinical decision-making-a systematic review. Journal of dental sciences. 2021 Jan 1;16(1):482-92. https://doi.org/10.1016/j.jds.2020.05.022
8. Andargoli AE, Ulapane N, Nguyen TA, Shuakat N, Zelcer J, Wickramasinghe N. Intelligent decision support systems for dementia care: A scoping review. Artificial Intelligence in Medicine. 2024 Apr 1;150:102815. https://doi.org/10.1016/j.artmed.2024.102815
9. Abujaber AA, Nashwan AJ, Fadlalla A. Enabling the adoption of machine learning in clinical decision support: a total interpretive structural modeling approach. Informatics in Medicine Unlocked. 2022 Jan 1;33:101090. https://doi.org/10.1016/j.imu.2022.101090

10. Wysocki O, Davies JK, Vigo M, Armstrong AC, Landers D, Lee R, Freitas A. Assessing the communication gap between AI models and healthcare professionals: Explainability, utility and trust in AI-driven clinical decision-making. Artificial Intelligence. 2023 Mar 1;316:103839. https://doi.org/10.1016/j.artint.2022.103839
11. Aljarboa SS, Alaya B, Al-Ajlan A, Miah SJ. CDSS adoption and the role of artificial intelligence in Saudi Arabian primary healthcare. Informatics in Medicine Unlocked. 2024 Oct 28:101596. https://doi.org/10.1016/j.imu.2024.101596
12. Tanya SM, Nguyen AX, Buchanan S, Jackman CS. Development of a cloud-based clinical decision support system for ophthalmology triage using decision tree artificial intelligence. Ophthalmology Science. 2023 Mar 1;3(1):100231. https://doi.org/10.1016/j.xops.2022.100231
13. Khalifa M, Albadawy M, Iqbal U. Advancing clinical decision support: The role of artificial intelligence across six domains. Computer Methods and Programs in Biomedicine Update. 2024 Jan 1;5:100142. https://doi.org/10.1016/j.cmpbup.2024.100142
14. Bulletti C, Franasiak JM, Busnelli A, Sciorio R, Berrettini M, Aghajanova L, Bulletti FM, Ata B. Artificial Intelligence, Clinical Decision Support Algorithms, Mathematical Models, Calculators Applications in Infertility: Systematic Review and Hands-On Digital Applications. Mayo Clinic Proceedings: Digital Health. 2024 Dec 1;2(4):518-32. https://doi.org/10.1016/j.mcpdig.2024.08.007
15. Rajashekar NC, Shin YE, Pu Y, Chung S, You K, Giuffre M, Chan CE, Saarinen T, Hsiao A, Sekhon J, Wong AH. Human-algorithmic interaction using a large language model-augmented artificial intelligence clinical decision support system. InProceedings of the 2024 CHI Conference on Human Factors in Computing Systems 2024 May 11 (pp. 1-20). https://doi.org/10.1145/3613904.3642024
16. Syed K, Sleeman IV WC, Nalluri JJ, Kapoor R, Hagan M, Palta J, Ghosh P. Artificial intelligence methods in computer-aided diagnostic tools and decision support analytics for clinical informatics. InArtificial Intelligence in Precision Health 2020 Jan 1 (pp. 31-59). Academic Press. https://doi.org/10.1016/B978-0-12-817133-2.00002-1
17. Akay EM, Hilbert A, Carlisle BG, Madai VI, Mutke MA, Frey D. Artificial intelligence for clinical decision support in acute ischemic stroke: a systematic review. Stroke. 2023 Jun;54(6):1505-16. https://doi.org/10.1161/STROKEAHA.122.041442
18. Karlafti E, Anagnostis A, Simou T, Kollatou AS, Paramythiotis D, Kaiafa G, Didaggelos T, Savvopoulos C, Fyntanidou V. Support systems of clinical decisions in the triage of the emergency department using artificial intelligence: the efficiency to support triage. Acta Medica Lituanica. 2023 Jan 24;30(1):19. https://doi.org/10.15388/Amed.2023.30.1.2
19. Antoniadi AM, Du Y, Guendouz Y, Wei L, Mazo C, Becker BA, Mooney C. Current challenges and future opportunities for XAI in machine learning-based clinical decision support systems: a systematic review. Applied Sciences. 2021 May 31;11(11):5088. https://doi.org/10.3390/app11115088
20. Jian MJ, Lin TH, Chung HY, Chang CK, Perng CL, Chang FY, Shang HS. Artificial intelligence-clinical decision support system in infectious disease control: combatting multidrug-resistant Klebsiella pneumoniae with machine learning. Infection and Drug Resistance. 2024 Dec 31:2899-912. https://doi.org/10.2147/IDR.S470821
21. Mazo C, Kearns C, Mooney C, Gallagher WM. Clinical decision support systems in breast cancer: a systematic review. Cancers. 2020 Feb 6;12(2):369. https://doi.org/10.3390/cancers12020369
22. Dankwa-Mullan I, Rivo M, Sepulveda M, Park Y, Snowdon J, Rhee K. Transforming diabetes care through artificial intelligence: the future is here. Population health management. 2019 Jun 1;22(3):229-42. https://doi.org/10.1089/pop.2018.0129
23. Daley BJ, Ni'Man M, Neves MR, Bobby Huda MS, Marsh W, Fenton NE, Hitman GA, McLachlan S. mHealth apps for gestational diabetes mellitus that provide clinical decision support or artificial intelligence: a scoping review. Diabetic Medicine. 2022 Jan;39(1):e14735. https://doi.org/10.1111/dme.14735
24. Garg AX, Adhikari NK, McDonald H, Rosas-Arellano MP, Devereaux PJ, Beyene J, Sam J, Haynes RB. Effects of computerized clinical decision support systems on practitioner performance and patient outcomes: a systematic review. Jama. 2005 Mar 9;293(10):1223-38. doi:10.1001/jama.293.10.1223
25. Gomez-Cabello CA, Borna S, Pressman S, Haider SA, Haider CR, Forte AJ. Artificial-Intelligence-based clinical decision support systems in primary care: A scoping review of current clinical implementations. European Journal of Investigation in Health, Psychology and Education. 2024 Mar 13;14(3):685-98. https://doi.org/10.3390/ejihpe14030045
26. Helenason J, Ekström C, Falk M, Papachristou P. Exploring the feasibility of an artificial intelligence based clinical decision support system for cutaneous melanoma detection in primary care–a mixed method study. Scandinavian Journal of Primary Health Care. 2024 Jan 2;42(1):51-60. https://doi.org/10.1080/02813432.2023.2283190

27. Moazemi S, Vahdati S, Li J, Kalkhoff S, Castano LJ, Dewitz B, Bibo R, Sabouniaghdam P, Tootooni MS, Bundschuh RA, Lichtenberg A. Artificial intelligence for clinical decision support for monitoring patients in cardiovascular ICUs: a systematic review. Frontiers in Medicine. 2023 Mar 31;10:1109411. https://doi.org/10.3389/fmed.2023.1109411
28. Oehring R, Ramasetti N, Ng S, Roller R, Thomas P, Winter A, Maurer M, Moosburner S, Raschzok N, Kamali C, Pratschke J. Use and accuracy of decision support systems using artificial intelligence for tumor diseases: a systematic review and meta-analysis. Frontiers in Oncology. 2023 Oct 4;13:1224347. https://doi.org/10.3389/fonc.2023.1224347
29. Schwartz JM, George M, Rossetti SC, Dykes PC, Minshall SR, Lucas E, Cato KD. Factors influencing clinician trust in predictive clinical decision support systems for in-hospital deterioration: qualitative descriptive study. JMIR Human Factors. 2022 May 12;9(2):e33960. https://doi.org/10.2196/33960
30. Gaube S, Suresh H, Raue M, Merritt A, Berkowitz SJ, Lermer E, Coughlin JF, Guttag JV, Colak E, Ghassemi M. Do as AI say: susceptibility in deployment of clinical decision-aids. NPJ digital medicine. 2021 Feb 19;4(1):31. https://doi.org/10.1038/s41746-021-00385-9
31. Brown SA, Chung BY, Doshi K, Hamid A, Pederson E, Maddula R, Hanna A, Choudhuri I, Sparapani R, Bagheri Mohamadi Pour M, Zhang J. Patient similarity and other artificial intelligence machine learning algorithms in clinical decision aid for shared decision-making in the Prevention of Cardiovascular Toxicity (PACT): a feasibility trial design. Cardio-oncology. 2023 Jan 23;9(1):7. https://doi.org/10.1186/s40959-022-00151-0
32. Liao X, Yao C, Zhang J, Liu LZ. Recent advancement in integrating artificial intelligence and information technology with real-world data for clinical decision-making in China: A scoping review. Journal of Evidence-Based Medicine. 2023 Dec;16(4):534-46. https://doi.org/10.1111/jebm.12549
33. Hah H, Goldin DS. How clinicians perceive artificial intelligence–assisted technologies in diagnostic decision making: Mixed methods approach. Journal of Medical Internet Research. 2021 Dec 16;23(12):e33540. https://doi.org/10.2196/33540
34. Lin X, Liang C, Liu J, Lyu T, Ghumman N, Campbell B. Artificial intelligence–augmented clinical decision support systems for pregnancy care: systematic review. Journal of medical Internet research. 2024 Sep 16;26:e54737. https://doi.org/10.2196/54737
35. Mahdi SS, Battineni G, Khawaja M, Allana R, Siddiqui MK, Agha D. How does artificial intelligence impact digital healthcare initiatives? A review of AI applications in dental healthcare. International Journal of Information Management Data Insights. 2023 Apr 1;3(1):100144. https://doi.org/10.1016/j.jjimei.2022.100144
36. Cresswell K, Rigby M, Magrabi F, Scott P, Brender J, Craven CK, Wong ZS, Kukhareva P, Ammenwerth E, Georgiou A, Medlock S. The need to strengthen the evaluation of the impact of Artificial Intelligence-based decision support systems on healthcare provision. Health policy. 2023 Oct 1;136:104889. https://doi.org/10.1016/j.healthpol.2023.104889
37. Golden G, Popescu C, Israel S, Perlman K, Armstrong C, Fratila R, Tanguay-Sela M, Benrimoh D. Applying artificial intelligence to clinical decision support in mental health: What have we learned?. Health Policy and Technology. 2024 Jun 1;13(2):100844. https://doi.org/10.1016/j.hlpt.2024.100844
38. Beckers R, Kwade Z, Zanca F. The EU medical device regulation: Implications for artificial intelligence-based medical device software in medical physics. Physica Medica. 2021 Mar 1;83:1-8. https://doi.org/10.1016/j.ejmp.2021.02.011
39. Ahmed Z, Bhinder KK, Tariq A, Tahir MJ, Mehmood Q, Tabassum MS, Malik M, Aslam S, Asghar MS, Yousaf Z. Knowledge, attitude, and practice of artificial intelligence among doctors and medical students in Pakistan: A cross-sectional online survey. Annals of Medicine and Surgery. 2022 Apr 1;76:103493. https://doi.org/10.1016/j.amsu.2022.103493