

REVIEW ARTICLE

Leveraging Artificial Intelligence for Enhanced Clinical Decision Support Systems (CDSS)

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Abstract

The integration of Artificial Intelligence (AI) into healthcare is driven by digitalization, aiming to enhance early disease diagnosis and treatment. Effective digital transformation in healthcare relies on assessing AI's potential and ensuring seamless collaboration between medical professionals and AI specialists. Clinical Decision Support Systems (CDSS) are crucial for assisting healthcare providers with decision-making. This review provides an overview of AI's role in healthcare, focusing on CDSS, and addresses epistemic concerns in their development. It highlights the need for alignment between technology and practitioners, emphasizing collaboration and cognitive responsibilities in patient profiling. A comprehensive search in PubMed, Scopus, and Google Scholar using keywords like AI, CDSS, and Machine Learning consolidates insights on evaluating AI-enabled CDSS across design, development, selection, implementation, and monitoring stages. The review also discusses practical evaluation approaches, AI performance indicators, and the importance of explainable CDSS for fostering direct patient connections.

Keywords: Artificial Intelligence (AI), Clinical Decision Support Systems (CDSS), Digitalization in Healthcare, Medical Diagnostics Epistemic Challenges, Machine Learning Algorithms.

INTRODUCTION

Artificial intelligence (AI) significantly improves healthcare by easing the workload on healthcare providers, enhancing decision-making accuracy, and boosting overall service efficiency [1]. It is often seen as a solution to the challenges facing the medical

sector in the near future. The integration of AI technologies into healthcare is driven by the increasing digitalization of society. To ensure the successful digitalization of both society and the clinical sector, it is essential to thoroughly evaluate the potential impacts on specific practices and individuals early in

the development process [2]. Protecting core societal values such as fairness, privacy, autonomy, and human dignity is crucial. It is also vital to equip individuals and professionals with the skills needed to manage the new responsibilities and tasks that come with digital technologies. Our review focuses on the epistemological challenges that arise from the development and use of AI technologies, particularly clinical decision support systems (CDSS), in medical screening practices [3]. We explore CDSS in the knowledge-related roles and responsibilities of healthcare professionals. Despite the rapid advancements in CDSS research, the integration of these technologies into medical practice is progressing at a slower pace. Kelly et al. highlighted that the limited suitability of randomized controlled trials for clinical assessment contributes to this phenomenon [4]. The criteria used in machine learning research to evaluate technological accuracy often do not align with the metrics used in comprehensive medical assessments, such as the quality of care provided and patient outcomes. Greenes et al. provides an in-depth

analysis of the key factors that must be considered to address the challenges associated with the adoption of CDSS [5]. These factors include integrating frameworks into clinical workflows, presenting and using CDSS outputs for cognitive support, implementing legal and organizational systems, evaluating technical quality and efficiency, and providing cognitive advancements for healthcare professionals. Our inquiry delves into the specific impact of CDSS on the epistemic activities of healthcare specialists. These professionals work collaboratively to diagnose patients and develop treatment plans based on diverse data from various sources. We outline the cognitive responsibilities, that medical practitioners undertake in their clinical duties and how computer-based systems can facilitate epistemic tasks while also highlighting activities that remain within the human domain [6]. This comprehensive examination aims to clarify the interplay between AI technologies and the cognitive roles of healthcare providers, ultimately enhancing their ability to deliver effective patient care was also reviewed fig 1 and 2.

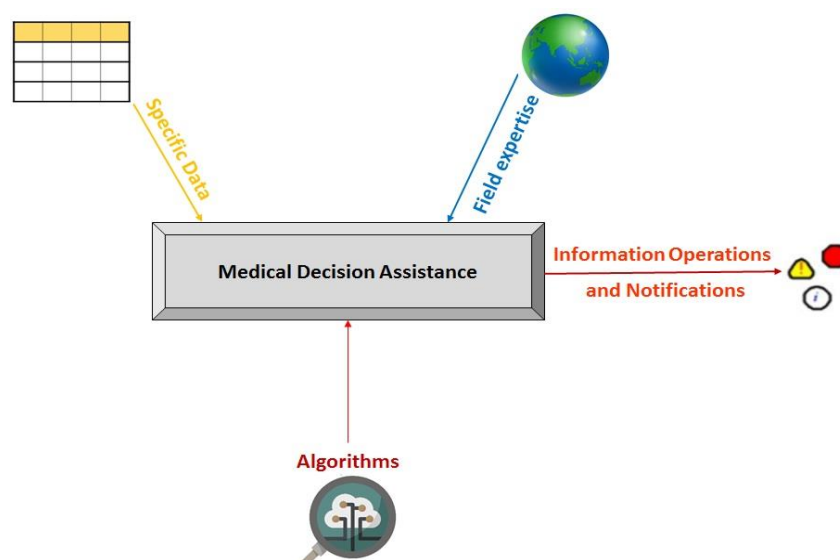


Figure 1: Principles of CDSS

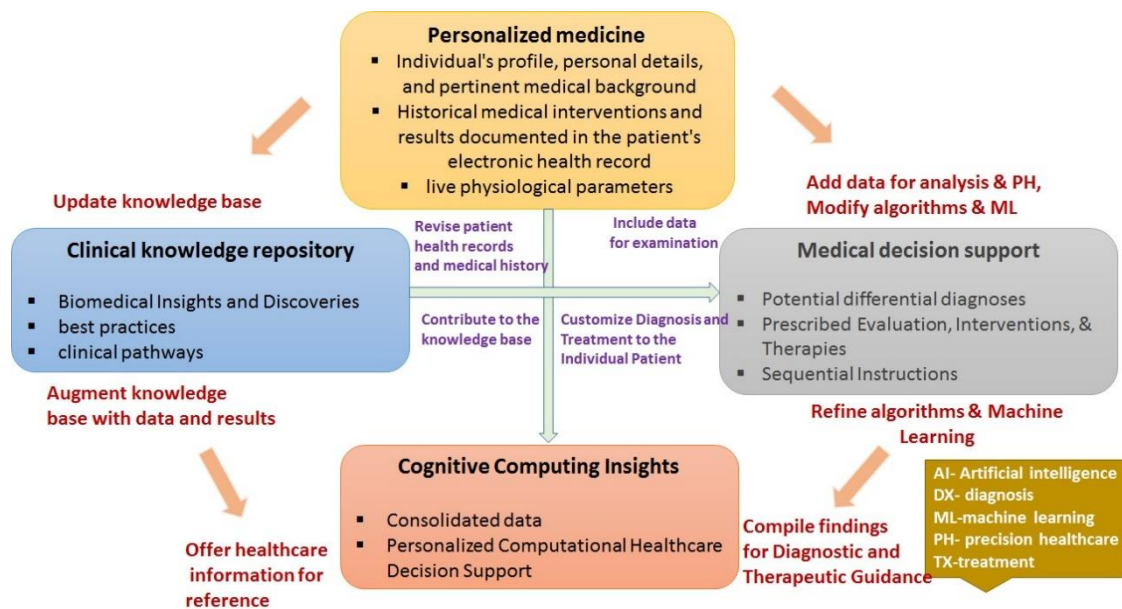


Figure 2: CDSS and AI in Effective Diagnosis

Search strategy

We conducted a search on PubMed/MEDLINE for publications published in English up to March 2024. We considered all articles using completely automated methodologies as well as those utilizing conventional or empirical knowledge modeling techniques, such as manually produced scores and decision trees. Our search journals included biology, healthcare, bioinformatics, and several AI journals indexed in MEDLINE, including Artificial Intelligence in Medicine. The search was then enhanced by examining the Web of Science (WoS) to locate scientific research and reviews not listed in MEDLINE, including the Journal of Artificial Intelligence Research (JAIR) and the Artificial Intelligence Journal (AIJ). We also analyzed citations obtained from Ovid's Evidence-Based Medicine Reviews and Inspec bibliographic databases up to January 2024, and conducted a manual search of the reference lists of included papers and pertinent reviews. Additional search engines

(Institute of Medicine, RAND Health, Agency for Health Care Research and Quality, Food and Drug Administration) were also used to extract studies and reviews about CDSS and its AI effect, chosen based on both temporal and thematic significance. The key words for the search have to be sufficiently wide to capture the greatest number of relevant articles while yet being precise enough to minimize false positives. Appropriate search key words were selected to include the three elements of interest: decision support systems, diagnostics, AI in CDSS, Machine learning in CDSS, and "challenges in Clinical diagnosis ". In the PubMed query, Medical Subject Headings (MeSH) phrases were included with keywords from titles and abstracts. We concluded our search by examining the bibliographies of relevant studies and identifying "similar articles" recommended by PubMed. The inquiry further used the MeSH phrases, "Decision Support Systems, Clinical" [MeSH] and "Primary Health Care" [MeSH].

Leveraging CDSS

CDSS are AI-driven solutions designed to aid medical professionals and patients in making effective clinical decisions [7]. These advanced knowledge systems utilize patient data to provide personalized guidance for individual cases. CDSS offers various forms of assistance, including alerts during patient monitoring, highlighting clinical guidelines during treatment, detecting drug-drug interactions, and suggesting potential diagnoses or treatment plans. CDSS can perform numerous tasks in diagnosis and therapy, such as forecasting therapy outcomes, interpreting medical images (e.g., contouring, segmentation, pathology identification), recommending drug dosages, and conducting screenings and preventative measures. AI is used in CDSS to analyze and evaluate patient information, comparing it with data stored in the system to make informed decisions. CDSS are designed to mimic the reasoning processes of medical experts, but with increased speed, reduced susceptibility to human error, and lower costs. These systems follow standards for analyzing patient data, configured either by programmers in rule-based expert systems or derived from extensive patient data using statistical AI methods like machine learning or deep learning algorithms (data-driven systems) [8]. While CDSS significantly enhance clinical decision-making, they also present certain risks. These include challenges in translating medical knowledge into data, shifting decision-making authority from humans to machines, lack of personalization, and changes in workload distribution. These risks imply the importance of understanding CDSS impacts the cognitive processes involved in diagnosing and treating patients. Effective CDSS implementation requires a blend of

human and AI, leveraging the system's ability to identify data patterns and trends that may elude human observations. Medical professionals must integrate CDSS outputs into their clinical reasoning, considering the patient's diagnosis, individual circumstances, and hospital conditions. Although CDSS can provide therapy recommendations based on evaluations, clinicians must gather, contextualize, and incorporate various clinical data and patient information, similar to evidence-based medicine practices. Physicians remain ultimately responsible for clinical decisions, a complex and nuanced intellectual task. Several recommendations for doctor-CDSS collaboration include: (a) CDSS should be based on well-processed, relevant information requiring expert preparation, (b) clinicians should be able to interact with CDSS, asking questions and understanding the generated responses, and (c) there should be a clear empirical relationship between CDSS data and patient knowledge. Clinicians must maintain the intellectual capacity to perform tasks that CDSS cannot, such as gathering and contextualizing patient information. The effective use of CDSS results in hybrid knowledge, combining cognitive abilities of both systems. This collaboration, with clear delineation of roles and responsibilities, enhances the performance of CDSS in supporting clinical decisions.

AI-Powered CDSS

There are generally two primary types of AI applications in CDSS: 'knowledge-based' AI, which is typically rule-based and relies on expert frameworks, and 'data-driven' AI. Since the late 1970s, knowledge-based AI systems have been employed to mimic human decision-making, aiming to encode expert principles and judgment processes into computer-readable terms. These systems

essentially act as repositories of 'best-practice' guidelines, helping to determine the most appropriate course of action (e.g., examination or therapy) for specific patients. On the other hand, data-driven AI has seen significant advancements in the last decade, using statistical machine-learning algorithms to extract trends from extensive datasets [9]. In supervised ML, CDSS is developed by providing the system with substantial information, including patient data tagged with clinical diagnoses, known as the 'training dataset.' The system learns to identify patterns within this dataset to predict outcomes for new cases. Unlike knowledge-based CDSS, which relies on predefined rules, data-driven CDSS utilizes case analogies to make decisions, comparing outcomes of similar instances. While data-driven CDSSs can uncover intricate correlations within vast datasets, the decisions they make are not easily justifiable or explained, raising concerns about their robustness, comprehensibility, reliability, and accountability.

Analytical Logic and Pattern Detection in CDSS Cognitive Functions

Knowledge-based systems can be seen as repositories of optimal procedures based on evidence, resembling rules. Automation can use a patient's key attributes to determine appropriate rules. Data-driven systems lack strict rule adherence but have automated learning. Epistemic activities can be classified using algorithmic learning, analyzing input data for patterns and comparisons [10]. Information is categorized by human-defined criteria, deducing additional characteristics. AI excels in complex computations and simulations, surpassing human deductive and inductive reasoning. AI is proficient in pattern recognition, particularly in medical imaging,

efficiently identifying diseases. CDSS utilizing ML algorithms are transforming clinical decision-making, integrating patient data for personalized treatment plans. ML enhances diagnostic accuracy by identifying subtle patterns in vast datasets, as seen in breast cancer diagnosis. CDSS can aid therapeutic decision-making by contrasting professionals' knowledge with database insights. Epistemic activities aim to acquire knowledge for effective management or engagement with specific phenomena in professional domains, such as medicine. In medicine, epistemic activities aim to create treatments for accurate diagnosis or interventions for patient health [11]. This requires cognitive input into CDSS, evaluating information and assessing results.

Developing Patient Profiles: Epistemic Tasks for Clinicians

Sophisticated clinical decision-making is a multifaceted process that demands a high level of cognitive engagement and adaptability from healthcare professionals [12]. It involves the intricate interplay of various forms of reasoning, including deductive, inductive, and abductive reasoning. These reasoning processes are essential for physicians to navigate the complex web of information and uncertainties inherent in clinical practice. Physicians must constantly infer and confirm their choices based on the information available to them. They must consider not only the presented facts, but also the context in which those facts exist. This context includes the patient's medical history, lifestyle factors, and socio-economic background, among others [13]. Each piece of information contributes to the formulation of a comprehensive understanding of the patient's condition and informs the decision-making process. Creative thinking is another

critical component of sound clinical decision-making. Physicians often encounter cases that do not fit into the established diagnostic categories. In such situations, they must think creatively to consider alternative explanations and treatment approaches. This creative thinking is essential for solving complex diagnostic puzzles and providing personalized care to patients [14]. Narrative techniques are commonly used in clinical practice to integrate all available data into a coherent and meaningful story. By constructing a narration, physicians can organize information in a way that highlights relevant details and relationships. This narrative approach helps physicians make sense of complex clinical scenarios and communicate their findings effectively to other healthcare professionals and patients. Moreover, clinical decision-making often involves a process of hypothesis generation and testing [15]. Physicians formulate hypotheses based on their initial assessment of the patient's condition and then gather additional information to confirm or refute these hypotheses. This iterative process requires physicians to remain open-minded and flexible in their thinking, as new information may necessitate a reassessment of their initial hypotheses. Collaboration among healthcare professionals is also crucial for effective clinical decision-making. In complex cases, multiple specialists may need to work together to develop a comprehensive treatment plan. This collaborative approach allows for the integration of diverse perspectives and expertise, leading to more informed and effective decision-making. By leveraging these abilities, healthcare professionals can provide the best possible care for their patients and navigate the complexities of modern healthcare delivery.

Accountability in Acquiring Knowledge

High-quality decision-making in the medical field necessitates a sophisticated and intricate form of clinical reasoning. This is essential because physicians are constantly faced with complex situations where they must make informed decisions based on the available information. Various instances of clinical reasoning can be observed in medical practice, highlighting the diverse ways in which physicians analyze and solve problems [16]. One critical aspect of clinical reasoning is the ability to infer and confirm choices while considering the facts. Physicians must be able to weigh the different pieces of evidence before them and make decisions that are in the best interest of their patients. This process is crucial because a single consequence may have multiple causes, and it is up to the physician to determine the most likely cause based on the available information. Creative understanding and sophisticated thinking approaches are also essential components of sound clinical decision-making. In addition to algorithmic, deductive, and rule-based reasoning, physicians must be able to think outside the box and consider alternative explanations for a patient's symptoms. This ability to think creatively can lead to more accurate diagnoses and more effective treatment plans. For example, when trying to arrive at a potential diagnosis, physicians often rely on case reports. These reports provide detailed accounts of individuals or small groups of patients who exhibit "unexpected" or "complicated" symptoms. By studying these cases, physicians can gain insights into rare or unusual conditions and apply this knowledge to their own patients. Physicians also use narrative techniques to help them make sense of the data they collect. By organizing the information into a coherent

narrative, physicians can better understand the underlying causes of a patient's symptoms and make more informed decisions about their care. It is important to note that clinical decision-making is not just about analyzing data and making a diagnosis. It also involves understanding the mechanics behind a disease and considering the broader context in which the patient is living. This holistic approach to decision-making ensures patients receive the most appropriate care for their individual needs. Furthermore, clinical decisions frequently require collaboration among medical professionals with various specialties. This interdisciplinary approach allows for a more comprehensive understanding of a patient's condition and ensures that all aspects of their care are taken into account. Effective collaboration among specialists requires not only expertise in their respective fields, but also the ability to communicate effectively with one another. This involves being receptive to the opinions and contemplation of others while also being able to clearly articulate how they arrived at their particular interpretation of the data.

Utilizing CDSS to Enhance Clinical Thought Processes

Developing a diagnosis and treatment plan is a multifaceted process that requires a comprehensive investigation overseen by medical specialists. This procedure involves a series of steps, starting with gathering information about the patient's medical history, conducting a physical examination, and performing relevant tests and screenings [17]. Medical experts employ deductive reasoning during the identification process, which includes asking pertinent questions about the patient's symptoms, determining

which parameters (such as medical data and other factors) are relevant to the case, and formulating potential explanations for the observed symptoms Fig 3. These systems can provide valuable data about the patient's medical records, as well as statistical information regarding illnesses and therapies used in similar cases. By leveraging this information, medical professionals can make more informed decisions about diagnosis and treatment options. When using a CDSS, the system generates recommendations based on the patient's data input. However, the ultimate responsibility for decision-making lies with the clinical expert, who must formulate relevant queries and evaluate the responses. The standards used by a CDSS to evaluate responses may differ from those used by medical professionals. CDSS typically employ epistemological standards such as statistics and technological precision, whereas physicians must consider a broader range of epistemic standards, including sufficiency, credibility, coherency, and comprehensibility, as well as practical standards to assess the significance and applicability of the information in the given clinical context. Physicians are not only responsible for making accurate diagnoses and choosing appropriate treatment options, but also for ensuring that their decisions are ethically sound and in the best interest of their patients. This process involves weighing the available evidence, considering the patient's preferences and values, and being aware of potential biases that may influence decision-making. Physicians must also remain up-to-date with the latest medical research and guidelines to provide the best possible care for their patients.

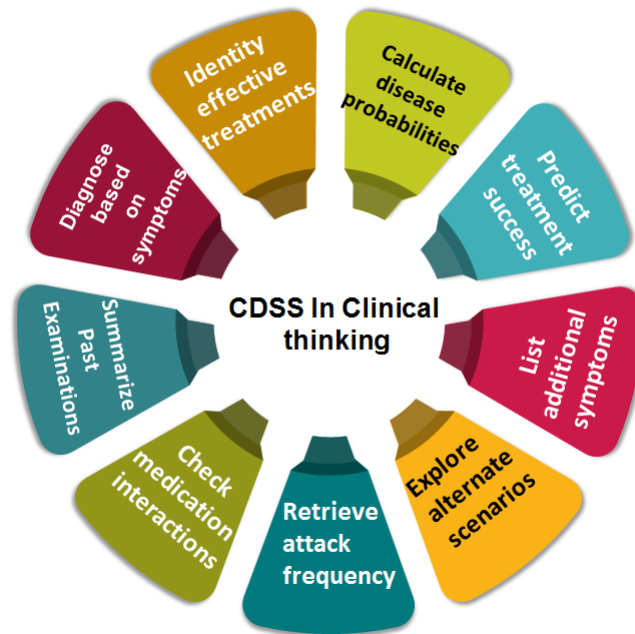


Figure 3: CDSS in clinical thinking

Expert Involvement in Developing CDSS

Clinical Decision Support Systems (CDSS) are invaluable tools, but the expertise of physicians in diagnosing and treating patients remains paramount. Collaboration between clinical and AI specialists is crucial in developing effective CDSS. The process involves three critical stages: input, processing, and output, with human intellect playing a vital role in each phase. In the input stage, the CDSS relies on current medical knowledge and available data. Clinical specialists' input is crucial for determining the relevance and accuracy of information. For data-driven CDSS, reliable labeled data are needed for training, while relevant, reliable, and unlabeled data help identify patterns and correlations. Machine learning (ML) is integral to CDSS development, with supervised learning ensuring statistical accuracy and unsupervised learning identifying significant relationships in data [18]. Clinical specialists' expertise is

essential in selecting relevant data sets and determining appropriate labeling and classifications. Collaboration between AI and clinical specialists is essential throughout the development process. While AI specialists are responsible for planning, creating, and applying the AI procedures, clinical specialists provide the necessary expertise in clinical data and ensure the final model's relevance and reliability [19]. The output of the development process is a CDSS model, which must be validated by human specialists before implementation. Accurate models are crucial for establishing connections in labeled data and identifying relationships in unlabeled data. Medical professionals, working alongside AI specialists, must assess the final model's relevance and dependability to ensure its effectiveness in clinical practice.

Enhancing Clinician Interaction with Transparent Clinical Decision Support Systems

CDSS plays a critical role in modern healthcare by assisting clinicians in making

informed decisions about patient care [20]. These systems must be designed to allow doctors to assess the responses for correctness and applicability to individual patients. However, one of the most significant criticisms of AI in therapeutic settings is its lack of transparency, particularly in its algorithms. The "black-box" nature of AI, where it determines results from provided data without clear explanation, makes it challenging for physicians to assess the correctness and significance of the results. This opacity of CDSS contradicts therapists' ethical and epistemological duties to their patients, as it hinders their ability to fully understand and validate the decisions made by these systems [21]. In Europe, the "Declaration of Barcelona for the Appropriate Development of AI" highlights concern about the use of AI in healthcare. It emphasizes that judgments made by AI through algorithmic learning are often incorrect due to the opaque nature of the algorithms, leading to potential biases and prejudices. Therefore, there is a growing call for AI systems to provide justifications for their decisions in a language that is understandable to everyone, allowing for informed challenges to be made against these decisions. Explainable AI (XAI) is a concept that advocates for AI systems to be designed in a way that their decision-making process can be explained to humans. This approach aims to make the reasoning behind AI decisions more transparent and understandable, especially in critical domains such as healthcare. However, implementing XAI in CDSS may come with challenges, as it could limit the complexity of the algorithms and potentially negate the advantages of using AI in healthcare settings. Despite these challenges, understanding key aspects of AI algorithms is crucial for

clinicians to make informed decisions. They need to understand which features the algorithm considers essential and the relative importance of each aspect. This knowledge enables clinicians to determine if the characteristics identified by the CDSS, such as artifacts in medical images or faulty measurements, are meaningful and relevant to the patient's care. In an ideal scenario, clinicians should be able to provide feedback to the system based on their experience and expertise, allowing the algorithm to learn and improve its predictions over time. This iterative process of feedback and learning can enhance the accuracy and reliability of CDSS, ultimately improving patient outcomes. Moreover, employing an understandable AI algorithm can also help clinicians clarify their thought processes. By understanding the criteria used by the algorithm, clinicians can articulate and defend their decisions more effectively. This not only improves the quality of care, but also enhances the patient-physician dialogue, as patients are empowered to participate in the decision-making process about their healthcare. While the implementation of Explainable AI in CDSS may present challenges, it has the potential to significantly improve the transparency, accuracy, and effectiveness of AI in healthcare. By making AI algorithms more understandable and transparent, clinicians can make more informed decisions, leading to better patient outcomes and a more collaborative approach to healthcare decision-making.

Tailoring CDSS to Individual Patient Characteristics

The effectiveness of machine learning (ML) techniques in enhancing understanding is occasionally hindered by their complexity or opacity [22]. Algorithms should aid users (e.g., scientists, medical professionals) in

grasping relevant conditions, aligning algorithmic components with actual phenomena to reduce uncertainty. For instance, an ML algorithm categorizing cutaneous melanoma instances can assist medical professionals in understanding treatment relevance by linking lesion appearance to potential treatments [23]. This connection bridges AI-predicted treatments with skin lesion characteristics, aiding physicians in answering treatment-related questions. Transparency in algorithms is crucial; understanding their assessment processes enhances comprehension. Employing complex yet transparent algorithms is feasible, provided there is clarity in discovering data patterns. To ensure an algorithm detects illnesses accurately, it is vital to verify that it identifies actual distinction makers and not substitutes, requiring an understanding of particular datasets. In CDSS, AI revolutionizes rare cancer diagnosis and treatment by uncovering imperceptible patterns in vast datasets, empowering oncologists with comprehensive insights for accurate diagnosis and tailored treatment plans. CDSS amalgamates patient data, medical literature, and case studies, offering personalized care pathways, especially beneficial for rare cancers with unique characteristics and limited treatment data, significantly improving patient outcomes.

However, the application of ML and AI in healthcare raises ethical and practical concerns. One major issue is the potential for algorithmic bias, where the algorithms may reflect or reinforce existing biases in the data used to train them. This can lead to unfair treatment of certain groups or individuals, particularly in sensitive areas such as healthcare. To address this, it is essential to carefully consider the data used to train AI

systems and to regularly audit them for bias.

Moreover, there are concerns about the impact of AI on the role of healthcare professionals. While AI can enhance decision-making and improve efficiency, there are fears that it could lead to job displacement or de-skilling of healthcare workers. To mitigate these risks, it is important to involve healthcare professionals in the development and implementation of AI systems, ensuring that they are seen as tools to augment rather than replace human expertise. Another challenge is the need for AI systems to be transparent and interpretable. In healthcare, it is critical for clinicians to understand how AI systems arrive at their recommendations or decisions, especially when they have a direct impact on patient care [24]. This requires AI systems to be designed in a way that is understandable to humans, with clear explanations provided for their outputs. Despite these challenges, the potential benefits of AI in healthcare are substantial [25]. By harnessing the power of AI, we can improve diagnostic accuracy, personalize treatment plans, and ultimately improve patient outcomes. However, to realize these benefits, we must address the ethical, practical, and technical challenges associated with the use of AI in healthcare.

Combining Clinical Expertise and CDSS: A Hybrid Intelligence Approach

Clinical decision-making is a multifaceted process that involves intricate cognitive mechanisms. CDSS have the potential to augment this process by providing assistance in reasoning, under the condition that the system is reliable, its outcomes are understandable and relevant, and it can establish evidence-based connections with the patient's condition [26]. A hybrid cognitive approach can be achieved by integrating human intelligence with the AI of

a CDSS, as long as specific criteria are met. For this to be effective, CDSS must be capable of performing highly standardized and trainable tasks. One of the key strengths of CDSS lies in its ability to identify similarities in data that are imperceptible to humans, allowing for accurate classification and analysis. CDSS can process vast amounts of data, enabling it to detect patterns and correlations among rare instances or patient subgroups. However, to harness the full potential of CDSS, clinicians must utilize the system's findings in their medical reasoning process. This involves formulating educated hypotheses about the underlying causes of a patient's symptoms and selecting appropriate tests to confirm or refute these hypotheses. Clinicians also play a crucial role in feeding relevant data into the CDSS and ensuring that the system's recommendations are applied in a clinically meaningful way [27]. They must be able to analyze, integrate, and contextualize the information provided by the CDSS, incorporating it into their decision-making process. Clinicians must collaborate closely with CDSS developers to ensure that the system is designed to address pertinent clinical questions and that the data used for training is appropriate for the patient population.

Furthermore, CDSS must be able to provide explanations for its recommendations, enabling clinicians to assess the credibility and relevance of the advice given [28]. This requires the system to not only provide the recommendation itself, but also to explain the rationale behind it, including the factors that influenced the recommendation. This transparency is essential for clinicians to trust and effectively use the CDSS in their decision-making process. Medical professionals must also acquire new skills to effectively utilize CDSS

in clinical practice. This includes the ability to create an empirical link between the CDSS model and the individual patient, as well as the skills needed to interpret and apply the CDSS's recommendations in a clinical setting. CDSS must be rigorously evaluated to ensure that their performance is on par with or superior to that of human clinicians, providing clinicians with the confidence to rely on the system's recommendations. CDSS has the potential to significantly enhance healthcare by improving the precision, consistency, and efficiency of clinical decision-making. However, for this potential to be realized, clinicians and developers must work together to integrate artificial and human intelligence effectively. This requires CDSS to be designed and trained in a way that supports medical reasoning and provides clinicians with the necessary tools and information to make informed decisions.

Autonomy of AI integration in CDSS

Autonomous AI in Clinical Decision Support Systems (CDSS) operates independently of direct human intervention to achieve goals or solve problems while maintaining the autonomy and expertise of clinicians. This capability involves anticipating potential outcomes, predicting possible issues, and setting actions that minimize risks and enhance factors like speed and reliability, all within defined constraints. The autonomy of AI integration in Clinical Decision Support Systems (CDSS) represents a significant shift in healthcare. Autonomous AI can independently analyze patient data, suggest diagnoses, and recommend treatments with minimal human intervention. This can streamline workflows and enhance decision-making efficiency.

However, ensuring AI autonomy requires careful calibration to align with clinical

guidelines and ethical standards. Challenges include maintaining accuracy, addressing potential biases, and ensuring the AI's decisions are transparent and understandable. Balancing autonomy with oversight is crucial to integrate AI effectively into CDSS, ensuring it supports healthcare professionals while safeguarding patient care and ethical standards. Autonomous AI in Clinical Decision Support Systems (CDSS) involves several key components maintaining the autonomy and expertise of clinicians and ensure effective integration and functionality. **Data collection** gathers comprehensive patient information from various sources such as electronic health records (EHRs), diagnostic imaging, and real-time monitoring systems. This data is then subjected to **data integration**, where diverse data types are combined into a unified and coherent model, addressing issues of data inconsistency and incompleteness. The **analysis** phase interprets this integrated data to identify relevant patterns and potential health issues. Subsequently, **decision support** uses these insights to generate actionable recommendations for diagnosis and treatment, incorporating additional context from clinical guidelines and patient history. Finally, action execution involves implementing the AI's recommendations within clinical workflows, ensuring practical and protocol-compliant outcomes [29, 30]. This process is dynamic, with continuous feedback loops that refine data integration, analysis, and decision-making, enhancing the overall effectiveness of the CDSS.

AI models for clinical decision-making in practice

ChatGPT, is a revolutionary tool for enhancing Clinical Decision Support Systems (CDSS). It has been recognized as highly effective in assisting with

comprehensive literature reviews and automating tasks like generating computer code, allowing clinicians and researchers to focus on more complex tasks such as experimental design. Wang et al. [31]. demonstrated ChatGPT's potential for generating precise queries in systematic reviews, though transparency and high-recall limitations remain. ChatGPT improves clarity in communicating research findings, streamlining the publication process, and making clinical insights available more quickly for decision support [32]. This AI plays a transformative role in Clinical Decision Support Systems (CDSS) by enhancing real-time decision-making [33], diagnosis, and treatment recommendations. AI can analyze vast amounts of patient data, medical records, and research literature to assist clinicians in identifying patterns, suggesting diagnoses, and proposing treatment options. ChatGPT can facilitate patient-clinician interactions, clarify complex medical information, and provide quick access to medical guidelines [34]. AI improves accuracy in diagnosis, reduces errors, and supports personalized medicine by integrating patient-specific data. Overall, AI and ChatGPT enable more informed, efficient, and precise healthcare delivery in clinical settings.

While ChatGPT offers many advantages for scientific research and academic writing, several limitations must be considered to maintain the quality of research. One key concern is the potential for generating superficial, inaccurate, or incorrect content, which can compromise the integrity of scientific work [35-37]. Ethical issues, including bias from training datasets and risks of plagiarism, are frequently highlighted, alongside the lack of transparency in content generation, leading to

ChatGPT being described as "black box" technology [38]. The concept of "ChatGPT hallucination," where plausible but incorrect content is produced, presents significant risks if not carefully reviewed by researchers and healthcare providers [39]. Citation inaccuracies, insufficient references, and even referencing non-existent sources have been documented in recent case studies, raising concerns about its use for generating scientifically accurate and current information. Researchers must meticulously supervise ChatGPT-generated content, especially when dealing with over-detailed or excessive information [40]. Proper prompt construction is essential to guide the model's output, as varied responses can result from subtle differences in input. Moreover, ChatGPT's knowledge is limited to data prior to 2021, making it unreliable for providing updated information [41]. Although it can assist in organizing literature, it must be supplemented with reliable and current sources. Legal issues, including copyright concerns, have also been raised, and current ICMJE and COPE guidelines do not support listing ChatGPT as an author, as it cannot meet the legal and ethical obligations associated with authorship.

Bias in AI – CDSS

Bias in AI-driven Clinical Decision Support Systems (CDSS) occurs when algorithms reflect or amplify existing inequities in healthcare data. For instance, if training data lacks diversity or is skewed towards certain demographics, the AI may provide less accurate or equitable recommendations for underrepresented groups. Bias can result from historical healthcare disparities or imbalanced data, leading to unequal treatment outcomes. Additionally, the opaque nature of some AI models complicates the identification and

correction of biases. To address these issues, it is essential to use diverse data, implement fairness-aware algorithms, and regularly audit and test AI systems for equitable performance across different patient groups. The challenge of defining fairness in AI is highlighted by a consumer study showing that only 11% of image search results for "CEO" were female, despite women comprising 20% of CEOs in the U.S [42,43]. This discrepancy raises questions about whether the algorithms are biased or merely reflecting existing data inequalities. Systematic inequities embedded in societies and health systems complicate the creation of a universal fairness standard. AI algorithms are trained on data reflecting the current world, necessitating careful stewardship, yet there is no widely accepted quantitative metric for fairness, making evaluations largely qualitative and subject to evaluators' biases. Health systems differ significantly in design, objectives, and demographics, and AI models often lack data reflecting this diversity, leading to underrepresentation and imprecise predictions for some groups. Finally, deep learning's "black-box" nature, where complex data transformations and multiple layers of processing obscure how outcomes are derived, creates challenges in understanding and trusting algorithmic decisions, despite their powerful results.

Strategies to prevent bias in AI – CDSS

To prevent bias in AI-driven Clinical Decision Support Systems (CDSS), it is crucial to adopt a multifaceted approach. This includes ensuring diverse data collection to represent various demographic groups, utilizing fairness-aware algorithms that detect and mitigate biases, and maintaining transparency in the AI model's decision-making processes. Regular audits and performance testing across different

populations are essential to identify and address disparities. Additionally, involving multidisciplinary teams, including ethicists and healthcare experts, in the design and oversight of AI systems helps to spot and rectify potential biases, ensuring that the CDSS delivers equitable and effective healthcare solutions.

Explainable artificial intelligence (XAI) in clinical settings and its challenges

Explainable Artificial Intelligence (XAI) has been implemented in clinical settings to enhance the transparency and interpretability of AI-driven decisions, making it easier for healthcare professionals to understand and trust AI recommendations. XAI aims to demystify complex models, improving patient safety and adherence to medical guidelines. However, challenges remain in ensuring transparency, such as balancing the trade-off between model accuracy and explain ability, dealing with the "black box" nature of certain algorithms, and maintaining patient data privacy. Additionally, integrating XAI into clinical workflows requires training healthcare professionals to interpret and act on AI insights effectively. In recent years, Explainable AI (XAI) has gained significant attention for improving how predictive modeling results are presented and fostering better communication between humans and AI systems. AI systems must include explanation models to convey their internal decisions, behaviors, and actions to users [44]. Effective explanations involve both cognitive and social processes. Healthcare professionals need to understand how AI algorithms reach decisions in different scenarios, facilitated by question-answering, case analysis, examples, and data visualization. Liao et al. developed an XAI question bank by interviewing UX and design practitioners working on AI systems

[45]. This bank includes 10 key types of questions: input/data, output, performance, how, why, why not, what if, how to be that, how to still be this, and others. The first four types of questions address the AI system's initial stage, including the dataset, sample size, variables, and predictions. The remaining six questions focus on understanding AI behavior in specific scenarios. "Why" questions explore the rationale behind a prediction, while "why not" questions address why certain predictions were not made. "What if" questions help users understand how predictions might change if input conditions were altered. Without transparency, gaining the trust of healthcare professionals and integrating predictive models into daily operations is challenging. XAI is crucial for answering information-based questions about input, output, performance, and processes, as well as instance-based clarification through "why" and "what if" scenarios [46]. Allowing users to create instances and explore AI decisions enhances transparency, enabling healthcare institutions to confidently adopt predictive models in their operations.

Over-reliance on AI

Over-reliance on AI in Clinical Decision Support Systems (CDSS) poses significant risks, including reduced clinical judgment, errors from incorrect AI recommendations, and potential biases in algorithms. Clinicians may become overly dependent on AI outputs, leading to diminished critical thinking and a failure to question automated decisions. Furthermore, AI systems trained on incomplete or biased datasets can perpetuate disparities in healthcare, impacting diagnosis and treatment accuracy. In cases where AI lacks transparency, it becomes difficult to identify errors or limitations, potentially

compromising patient outcomes. Therefore, careful oversight and human intervention are essential to mitigate these risks in CDSS. The black-box nature of certain AI algorithms, learning processes, and natural language processing systems significantly contributes to automation bias and over reliance. Physicians or users of AI-driven Clinical Decision Support Systems (CDSS) may struggle to validate outputs due to a lack of understanding of the underlying mechanisms. The increasing complexity of interpreting these algorithms, including their learning processes and the validity of their outputs, poses considerable challenges. AI developers recognize that the intricate nature of these systems often reduces transparency and understanding, leading to over trust in their performance. Despite the high accuracy and efficiency of AI-based CDSSs, issues arise when algorithms are trained on flawed or incomplete data, affecting their reliability. For instance, research by Larrazabal et al. highlighted that a machine learning model for image diagnosis performed poorly on underrepresented genders due to insufficient data [47]. Similarly, Obermeyer et al. found that an algorithm predicting healthcare needs underestimated the requirements of black patients compared to white patients with similar risk scores, leading to a significant disparity in care [48]. Excessive reliance on AI can limit physicians' exposure to diverse cases, reducing their practical experience and potentially eroding their clinical skills over time [49]. As physicians depend more on automated systems, their proficiency with complex, nuanced cases may decline, impacting overall healthcare competence. In CDSS applications, machine learning (ML) and deep learning (DL) models require extensive datasets for training and rely on human input for ongoing refinement.

Automation bias, driven by increasing dependence on AI outputs, may lead to a decrease in the amount of data reviewed by physicians, which is crucial for model improvement. This reliance on AI systems may create a cycle where clinicians engage less in hands-on training, potentially compromising the quality and effectiveness of AI algorithms over time. over-reliance on AI in CDSS can undermine clinical skills, reduce data validation, and perpetuate inaccuracies due to flawed training data. Ensuring transparency, maintaining human oversight, and balancing AI use with direct clinical experience are essential to mitigate these risks and enhance overall healthcare effectiveness.

CONCLUSION

The integration of AI and CDSS into healthcare has the potential to revolutionize clinical practice by enhancing decision-making processes, improving efficiency, and ultimately improving patient outcomes. However, several challenges need to be addressed to maximize the benefits of AI in healthcare. These include ensuring the transparency and interpretability of AI algorithms, mitigating the risk of algorithmic bias, and effectively integrating AI into clinical workflows. To achieve these goals, it is essential to foster collaboration between AI specialists and healthcare professionals, ensuring that AI systems are developed and implemented in a way that complements and enhances human expertise. Ongoing research and evaluation are needed to assess the impact of AI on clinical practice and patient care continually. By leveraging the strengths of AI and human intelligence in a collaborative and transparent manner, we can harness the full potential of AI in healthcare and improve the quality and efficiency of patient care.

ETHICS STATEMENT

This narrative review does not require approval from institutional human research review committees or animal welfare

committees, nor is it necessary to follow ethical guidelines for writing this article.

COMPETING INTEREST

The authors declare no competing interest

REFERENCES

1. Lee D, Yoon SN. Application of artificial intelligence-based technologies in the healthcare industry: Opportunities and challenges. *International journal of environmental research and public health*. 2021 Jan; 18(1): 271.
2. Marchetti E, Petersen CK. Digitalization of Healthcare Practice. *Conjunctions. Transdisciplinary Journal of Cultural Participation*. 2021 Jan 7; 8(1).
3. Boer JY. *Intelligent clinical decision support and current medical practice An Exploration of Compatibility and Epistemological Issues* (Master's thesis, University of Twente).
4. Kelly M, Morgan A, Ellis S, Younger T, Huntley J, Swann C. Evidence based public health: A review of the experience of the National Institute of Health and Clinical Excellence (NICE) of developing public health guidance in England. *Social science & medicine*. 2010 Sep 1; 71(6): 1056-62.
5. Musen MA, Middleton B, Greenes RA. Clinical decision-support systems. In *Biomedical informatics: computer applications in health care and biomedicine* 2021 Jun 1 (pp. 795-840). Cham: Springer International Publishing.
6. Patel VL, Yoskowitz NA, Arocha JF, Shortliffe EH. Cognitive and learning sciences in biomedical and health instructional design: A review with lessons for biomedical informatics education. *Journal of biomedical informatics*. 2009 Feb 1; 42(1): 176-97.
7. Elhaddad M, Hamam S. AI-Driven Clinical Decision Support Systems: An Ongoing Pursuit of Potential. *Cureus*. 2024 Apr 6; 16(4).
8. Sahu M, Gupta R, Ambasta RK, Kumar P. Artificial intelligence and machine learning in precision medicine: A paradigm shift in big data analysis. *Progress in molecular biology and translational science*. 2022 Jan 1; 190(1): 57-100.
9. Raschka S, Patterson J, Nolet C. Machine learning in python: Main developments and technology trends in data science, machine learning, and artificial intelligence. *Information*. 2020 Apr 4; 11(4): 193.
10. Lowrie I. Algorithmic rationality: Epistemology and efficiency in the data sciences. *Big Data & Society*. 2017 Mar; 4(1): 2053951717700925.
11. Loughlin M, Bluhm R, Fuller J, Buetow S, Borgerson K, Lewis BR, Kiouss BM. Diseases, patients and the epistemology of practice: mapping the borders of health, medicine and care. *Journal of Evaluation in Clinical Practice*. 2015 Jun; 21(3): 357-64.
12. Higgs J, Jones MA. Clinical decision making and multiple problem spaces. *Clinical reasoning in the health professions*. 2008 Feb 14; 3: 3-17.
13. Van Ryn M, Burke J. The effect of patient race and socio-economic status on physicians' perceptions of patients. *Social science & medicine*. 2000 Mar 1; 50(6): 813-28.
14. Taimoor N, Rehman S. Reliable and resilient AI and IoT-based personalised healthcare services: A survey. *IEEE Access*. 2021 Dec 22; 10: 535-63.
15. Banning M. A review of clinical decision making: models and current research. *Journal of clinical nursing*. 2008 Jan; 17(2): 187-95.
16. Elstein AS, Shulman LS, Sprafka SA. *Medical problem solving: An analysis of clinical reasoning*. Harvard University Press; 1978 Dec 31.
17. Bickley L, Szilagyi PG. *Bates' guide to physical examination and history-taking*. Lippincott Williams & Wilkins; 2012 Nov 1.

18. 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 May 1; 26(5): 584-95.
19. Magrabi F, Ammenwerth E, McNair JB, De Keizer NF, Hyppönen H, Nykänen P, Rigby M, Scott PJ, Vehko T, Wong ZS, Georgiou A. Artificial intelligence in clinical decision support: challenges for evaluating AI and practical implications. *Yearbook of medical informatics*. 2019 Aug; 28(01): 128-34.
20. Belard A, Buchman T, Forsberg J, Potter BK, Dente CJ, Kirk A, Elster E. Precision diagnosis: a view of the clinical decision support systems (CDSS) landscape through the lens of critical care. *Journal of clinical monitoring and computing*. 2017 Apr; 31: 261-71.
21. Bleher H, Braun M. Diffused responsibility: attributions of responsibility in the use of AI-driven clinical decision support systems. *AI and Ethics*. 2022 Nov; 2(4): 747-61.
22. Sullivan E. Understanding from machine learning models. *The British Journal for the Philosophy of Science*. 2022 Mar 1.
23. Bhatt H, Shah V, Shah K, Shah R, Shah M. State-of-the-art machine learning techniques for melanoma skin cancer detection and classification: A comprehensive review. *Intelligent Medicine*. 2023 Aug 28; 3(03): 180-90.
24. Braun M, Hummel P, Beck S, Dabrock P. Primer on an ethics of AI-based decision support systems in the clinic. *Journal of medical ethics*. 2021 Dec 1; 47(12): e3-.
25. Moulaei K, Yadegari A, Baharestani M, Farzanbakhsh S, Sabet B, Afrash MR. Generative artificial intelligence in healthcare: A scoping review on benefits, challenges and applications. *International Journal of Medical Informatics*. 2024 May 8: 105474.
26. Gholamzadeh M, Abtahi H, Safdari R. The application of knowledge-based clinical decision support systems to enhance adherence to evidence-based medicine in chronic disease. *Journal of Healthcare Engineering*. 2023 May 29; 2023.
27. Wasylewicz AT, Scheepers-Hoeks AM. Clinical decision support systems. *Fundamentals of clinical data science*. 2019: 153-69.
28. Bussone A, Stumpf S, O'Sullivan D. The role of explanations on trust and reliance in clinical decision support systems. In *2015 international conference on healthcare informatics* 2015 Oct 21 (pp. 160-169). IEEE.
29. Gershov S, Raz A, Karpas E, Laufer S. Towards an autonomous clinical decision support system. *Engineering Applications of Artificial Intelligence*. 2024 Jan 1; 127: 107215.
30. Ferber D, El Nahhas OS, Wölflein G, Wiest IC, Clusmann J, Leßman ME, Foersch S, Lammert J, Tschochohei M, Jäger D, Salto-Tellez M. Autonomous artificial intelligence agents for clinical decision making in oncology. *arXiv preprint arXiv: 2404.04667*. 2024 Apr 6.
31. Liu M, Liu R, Wang H, Buntine W. A Survey on the Real Power of ChatGPT. *arXiv preprint arXiv: 2405.00704*. 2024 Apr 22.
32. Zohery M. ChatGPT in academic writing and publishing: A comprehensive guide. *Artificial intelligence in academia, research and science: ChatGPT as a case study*. 2023 Apr 5: 10-61.
33. Ostropolets A, Zhang L, Hripcsak G. A scoping review of clinical decision support tools that generate new knowledge to support decision making in real time. *Journal of the American Medical Informatics Association*. 2020 Dec; 27(12): 1968-76.
34. Walker HL, Ghani S, Kuemmerli C, Nebiker CA, Müller BP, Raptis DA, Staubli SM. Reliability of medical information provided by ChatGPT: assessment against clinical guidelines and patient information quality instrument. *Journal of Medical Internet Research*. 2023 Jun 30; 25: e47479.
35. Wang KD, Burkholder E, Wieman C, Salehi S, Haber N. Examining the potential and pitfalls of ChatGPT in science and engineering problem-

- solving. In *Frontiers in Education* 2024 Jan 18 (Vol. 8, p. 1330486). Frontiers Media SA.
36. Sallam M, Al-Farajat A, Egger J. Envisioning the future of ChatGPT in Healthcare: insights and recommendations from a systematic identification of Influential Research and a call for Papers. *Jordan Medical Journal*. 2024 Feb 19; 58(2).
 37. Sallam M. ChatGPT utility in healthcare education, research, and practice: systematic review on the promising perspectives and valid concerns. In *Healthcare* 2023 Mar 19 (Vol. 11, No. 6, p. 887). MDPI.
 38. Chakraborty C, Bhattacharya M, Islam MA, Agoramoorthy G. ChatGPT indicates the path and initiates the research to open up the black box of artificial intelligence. *International Journal of Surgery*. 2023 Dec 1; 109(12): 4367-8.
 39. Li Z. The dark side of chatgpt: Legal and ethical challenges from stochastic parrots and hallucination. *arXiv preprint arXiv: 2304.14347*. 2023 Apr 21.
 40. Bhattacharjee A, Liu H. Fighting fire with fire: can ChatGPT detect AI-generated text? *ACM SIGKDD Explorations Newsletter*. 2024 Mar 28; 25(2): 14-21.
 41. Dadkhah M, Oermann MH, Hegedüs M, Raman R, Dávid LD. Diagnosis unreliability of ChatGPT for journal evaluation. *Advanced Pharmaceutical Bulletin*. 2024 Mar; 14(1): 1.
 42. Langston J. "Who's a CEO? Google image results can shift gender biases," *UW News*, April 2015
 43. Silberg J, Manyika J. Notes from the AI frontier: Tackling bias in AI (and in humans). *McKinsey Global Institute*. June 2019
 44. Jarrahi MH. Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business horizons*. 2018 Jul 1; 61(4): 577-86.
 45. Q. Vera Liao, Daniel Gruen, and Sarah Miller. 2020. Questioning the AI: informing design practices for explainable AI user experiences. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–15.
 46. Gong Y, Shang L, Wang D. Integrating Social Explanations into Explainable Artificial Intelligence (XAI) for Combating Misinformation: Vision and Challenges. *IEEE Transactions on Computational Social Systems*. 2024 Jun 19.
 47. Mullins, B.T., McGurk, R., McLeod, R.W., Lindsay, D., Amos, A., Gu, D., Chera, B.S., Marks, L., Das, S., Mazur, L., 2019. Human error bowtie analysis to enhance patient safety in radiation oncology. *Practical Radiation Oncology* 9, 465–478
 48. Murff, H.J., FitzHenry, F., Matheny, M.E., Gentry, N., Kotter, K.L., Crimin, K., Dittus, R.S., Rosen, A.K., Elkin, P.L., Brown, S.H., Speroff, T., 2011. Automated Identification of Postoperative Complications Within an Electronic Medical Record Using Natural Language Processing. *JAMA* 306, 848–855
 49. Knopp MI, Warm EJ, Weber D, Kelleher M, Kinneer B, Schumacher DJ, Santen SA, Mendonça E, Turner L. AI-enabled medical education: threads of change, promising futures, and risky realities across four potential future worlds. *JMIR Medical Education*. 2023 Dec 25; 9: e50373.

استخدام الذكاء الاصطناعي لتعزيز نظم دعم القرار السريري (CDSS)

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الملخص

الخلفية والاهداف: دمج الذكاء الاصطناعي (AI) في مجال الرعاية الصحية مدفوع بالرقمنة بهدف تعزيز تشخيص الأمراض المبكر وعلاجها. تعتمد التحول الرقمي الفعال في الرعاية الصحية على تقييم إمكانيات الذكاء الاصطناعي وضمان التعاون السلس بين المهنيين الطبيين وخبراء الذكاء الاصطناعي. تُعتبر أنظمة دعم القرار السريري (CDSS) أساسية لمساعدة مقدمي الرعاية الصحية في اتخاذ القرارات. يقدم هذا الاستعراض نظرة عامة على دور الذكاء الاصطناعي في الرعاية الصحية مع التركيز على أنظمة دعم القرار السريري، ويتناول القضايا المعرفية في تطويرها. يبرز أهمية التوافق بين التكنولوجيا والممارسين، مشددًا على التعاون والمسؤوليات المعرفية في تشكيل ملامح المريض.

منهجية الدراسة: تم إجراء بحث شامل في قواعد البيانات PubMed و Scopus و Google Scholar باستخدام كلمات مفتاحية مثل الذكاء الاصطناعي، أنظمة دعم القرار السريري، والتعلم الآلي لتجميع الرؤى حول تقييم أنظمة دعم القرار السريري المدعومة بالذكاء الاصطناعي عبر مراحل التصميم والتطوير والاختيار والتنفيذ والمراقبة.

الاستنتاج: يناقش الاستعراض أيضًا منهجيات التقييم العملية ومؤشرات أداء الذكاء الاصطناعي وأهمية أنظمة دعم القرار القابلة للتفسير لتعزيز التواصل المباشر مع المرضى

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