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RESEARCH ARTICLE

A Systematic Review of AI-based Clinical Decision Support Systems: From Development and Implementation to Applications

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ABSTRACT

AI-CDSS can be integrated into healthcare to improve the quality of care for patients, reduce differences in treatment, and maximize the usage of resources. For instance, such systems can offer meaningful insights into actionable evidence through the help of advanced data analytics and machine learning. All this, however, brings a plethora of challenges when trying to integrate AI into a clinical environment, such as ethical concerns about algorithmic bias, strong regulatory frameworks, and changes in workflow. Published sources were used between 2014 and 2024 in PubMed, Scopus, and Google Scholar databases. The review encompasses randomized controlled trials, observational studies, and meta-analyses but excludes non-clinical encounters, conference proceedings, and editorials. The five main themes of AI and clinical decision-making hinge on the need for XAI to be transparent and the role that multidisciplinary specialties contribute. The findings presented here speak to the high promise that AI-CDSS offers in various health-related areas but point out the need for regulatory measures, ethical issues, and user interfaces for effective utilization in clinical practice.

I. INTRODUCTION

The rapid emergence of artificial intelligence (AI) and machine learning (ML) has transformed several industries, but most importantly, healthcare, which increasingly applies these technologies to clinical decision-making [1]. Clinical Decision Support Systems (CDSS) use patient data and clinical knowledge to support healthcare professionals in making decisions about the care of patients [2]. Integrating AI with CDSS not only enhances the accuracy of diagnosis but also increases efficiency and effectiveness in the delivery of healthcare [3]. CDSS has existed for decades and has evolved from simple rule-based systems to more sophisticated, data-driven approaches [4].

Early CDSSs were mainly based on expert systems, which relied on predefined rules to guide clinical decisions [5]. However, such systems could not adapt to new information or the complexities of real-life clinical scenarios [4], [5]. The revolution in AI, especially the ML algorithms, has redefined CDSS since such systems can learn from vast amounts of existing data, recognize patterns, and make predictions based on real-time patient information [3]. Given the exponential growth in health data because of EHRs and other monitoring technologies, AI would form the future for betterment in CDSS [6].

In integration with NLP, deep learning, and predictive analytics [7], AI techniques enable CDSS to make much more personalized and context-sensitive recommendations to fit the exact requirements of the patient [6]. Traditional diagnosis and treatment planning takes time and makes room for human error [8]. CDSS based on AI provides the solution, synthesizing vast clinical data, including patient history, diagnostic imaging, lab results, and treatment guidelines, to create evidence-based recommendations [9]. AI-based CDSS promotes standardization to reduce variability in healthcare delivery, clinical activities, and compliance by healthcare providers with recent evidence-based guidelines [7].

Despite the promise of AI-based CDSS, several obstacles must be overcome to integrate it adequately into clinical practice. There is perhaps significant concern about ethics in the use of AI in healthcare; data privacy, algorithmic bias, and potential overreliance on technology raise questions about the responsible use of AI in patient care [10]. In addition, adopting an AI-based CDSS must involve a cultural transformation among healthcare organizations [11]. Clinicians need to adopt workflows regarding new technologies and the acceptance of AI-driven recommendations [12]. Proper training and education regarding healthcare professionals' interpretation and utilization skills generated through AI systems must be provided.

This systematic review aims to analyze the development and applications of AI-based CDSS and the potential benefits and challenges facing the realities of their clinical application. Through the synthesis of the literature, this review aims to lead to a further understanding of the role that AI plays in healthcare development. Advanced data analytics and machine learning can help improve patient outcomes, reduce variability in care, and optimize healthcare resources, among other benefits. However, successful integration of AI into clinical practice would require considerations of ethical implications, adaptations of workflow, and frameworks for regulation.

II. METHODOLOGY

The methodology for conducting this review included search strategy, defining inclusion and exclusion criteria and filtering of articles according to PRISMA guidelines [13], [14], [109], [110]. Artificial Intelligence or AI, Clinical Decision support systems or CDSS, Explainable AI (XAI), multidisciplinary clinical decision, were among the keywords we used in our extensive literature search across the databases PubMed, Scopus, and Google Scholar [111], [112]. Articles published between 2014 and 2024 were considered in the literature search. Randomized controlled trials, observational studies, meta-analyses, and papers focusing on the use of AI in clinical decisions were among the requirements for inclusion. Editorials, letters to the editor, commentaries, books and book chapters, conference proceedings, and non-clinical encounters were all excluded from consideration [113]. The role of Artificial Intelligence in the development of Clinical Decision Support Systems is the focus of this study.

Fig. 1 provides a summary of the study's methodology and findings. 285 of the 672 abstracts found in the literature search were duplicates. After screening 387 abstracts, the authors eliminated 189 of them using the exclusion criteria. 198 complete papers were evaluated by the authors for eligibility, and 86 of them were disqualified for failing to satisfy the requirements for inclusion. 112 complete papers were the subject of this literature review. Five major themes pertaining to the function of clinical decision-making, artificial intelligence, and machine learning emerged from the literature review. Nearly every facet of the healthcare decision-making process might benefit from the ever-growing use of AI techniques and tools.

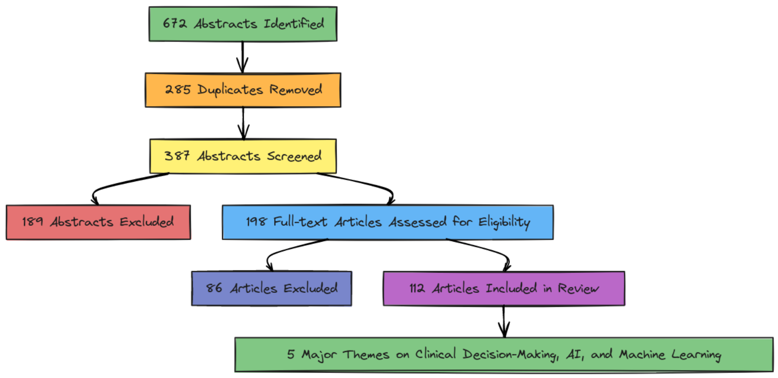

Fig. 1. The PRISMA diagram for the systematic review

III. RESEARCH FINDINGS

i. Design and Development of AI-CDSS

As an emerging area of healthcare technology, the design, development, and implementation of AI in the clinical decision support system underlines how it can improve the accuracy of diagnosis and forecast patient outcomes for better-informed clinician decisions. This review covers the steps of AI design, development, and evaluation. In this context, a particular focus has been placed on the role of XAI in clinical decision-making and how diverse multidisciplinary specialties, such as radiology and pathology, are being brought together to work to advance these systems.

a. Design and Development of AI-Based Clinical Decision Support Systems

The two initial phases of AI-CDSS development include the design of algorithms and their assessment within controlled settings [17]. Historically, the evaluation process has centered on these early stages because AI was not widely applied in everyday clinical practice. Discrimination, accuracy, and precision performance metrics top the list of what such evaluation criteria typically consider, and the priority may vary with the intended use case [18]. For example, an algorithm for triage prioritization discrimination should have high discrimination to ensure proper categorization of cases. In contrast, an algorithm predicting patient mortality risks requires a trade-off between accuracy and precision across heterogeneously distributed patient populations. The first challenge is to ensure that AI models generalize well beyond the training data [19]. After all, the algorithm tends to fail to interpret cases outside those datasets, thus leading to errors in diagnosis and treatment recommendation. This problem is enhanced particularly in the tasks dealing with image interpretation, where differences in data-capture technology or patient demographics affect the algorithm's performance [20].

Another area of development is that AI algorithms represent the current state of medical knowledge, which is always changing [21], [22]. Designers need to answer questions about how an algorithm gets its knowledge, how it has been substantially supported by evidence, and how often it will need to be updated to be of any relevance clinically [23], [24]. There is also the issue of ethical concerns regarding the potential biases that may arise [25]. For instance, predictive algorithms developed to give outputs of organ transplants may inadvertently make decisions due to socio-demographic factors by applying predictors that are correlated with the social determinants of health and might thus lead to biased treatment recommendations [26].

b. Explaining Explainable AI in Clinical Decision Support Systems (XAI)

Explainable AI is increasingly recognized as critical in clinical environments where clinicians must understand and trust the decisions of AI [27]. Users will be able to see the rationale for any recommendation delivered by AI and improve decisional confidence and trust in the system [28]. This ability to provide explanations well as local explanations specific to individual predictions demonstrated recently to improve clinician acceptance of AI recommendations and will be necessary for the widespread integration of AI into clinical workflows [29].

Although promising, XAI has yet to be leveraged well in clinical decision support systems, particularly when processing text-based and tabular data [30]. Most implementations of XAI focus on local explanations and achieving a balance between model-specific and model-agnostic approaches. Local explanations are more important in terms of individual predictions rather than the logic of the overall model; this is a critical requirement for healthcare settings, where each case may demand a unique pathway for deciding. Besides, post-hoc explanations provide interpretability (as shown in Fig. 2) after the model has made its predictions, and ante-hoc methods build interpretability into the model from the start [32].

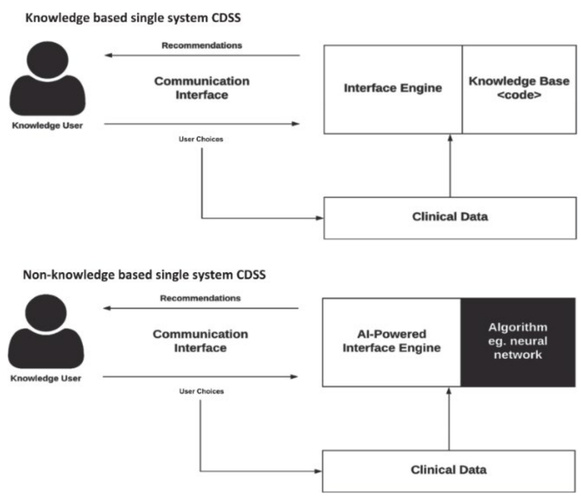

Fig. 2. The comparison of Knowledge based, and non-knowledge based CDSS

XAI holds out the promise to address the concerns of clinicians and build trustworthiness in AI-CDSS [33]. However, to date, a marked lack of user studies focusing on clinician-specific needs is evident. Unless clinician feedback is incorporated into the design of XAI systems, they risk being judged by real-world expectations [33]. Effective XAI for CDSS should allow context-specific explanations tailored to the complex workflows of clinical environments. The guidelines for developing the implementation of XAI should be expanded, in the first place, by evaluating the types of explanations most useful for clinicians and the degree of interpretability that must be ensured as it provides "responsible and safe use of AI in clinical practice" [29].

Table II. Studies using XAI module in clinical decision support systems

Ref	Preprocessing	Input	Disease	Methodology
85	Data cleansing, transformation, feature extraction	Patient demographics, audiology data, TRT visit details	Tinnitus, hyperacusis	Three-tier explainable AI CDS, with rule-based

				knowledge representation
86	Histogram matching, rib shadow suppression, lung region segmentation using PIXGAN, CLAHE for contrast enhancement, data augmentation	X-ray images, patient demographics, radiologist reports	COVID-19	XAI multimodal clinical decision support system
87	Harmonization according to the Common clinic Index for Chronic Diseases (CLINIC) common data model	EMR data, clinical visit records, patient demographics	CKD	Use of DEPOT graph XAI model for trajectory learning
88	Questionnaire data encoded into numerical values; normalization (0-1) for age and time-related variables; standardization for training, validation, and testing datasets	30-32 input variables including age, gender, patient history, symptoms, and physical examination	Renal failure	Two XAI Models
89	One-hot encoding of features, correlation matrix for redundancy, removed redundant variables	age, sex, chest pain type, blood pressure, cholesterol, fasting blood sugar, max heart rate, exercise-induced angina, ST segment depression, slope of ST segment, number of major vessels, thalassemia	Heart disease	explainable AI CDS

c. Multidisciplinary Expertise for Developing AI-CDSS

AI is expected to help enhance clinical decision support by involving multidisciplinary specialties, particularly domains such as radiology and pathology [34]. Radiology and pathology are fields where there is a large amount of complex data in the form of medical images or biopsies that AI can analyze for decision-making support [35], [36]. For example, radiology itself is better if AI algorithms are prepared with thousands of pictures of different scans [37]. These can help in the early detection of cancers as it may find abnormalities that go unnoticed by the naked eye-the conditions that can now be detected faster because of early interventions they allow [38].

AI-CDSS can improve efficiency and accuracy in the diagnosis of conditions by reading histopathological images in pathology [39]. These systems will help pathologists identify regions of interest in tissue sections, predict types of diseases, and even suggest treatment plans based on information gathered from similar past cases [40]. Other areas, including oncology, cardiology, and emergency medicine, are also contemplating adopting AI-based CDSS applications, especially predictive analytics, which may pre-sort complications and enhance patient monitoring [41].

These specialties enhance the ingenuity of AI-CDSS by providing the complex datasets needed to train robust models and test them in specific clinical contexts [42]. Their engagement ensures that AI solutions are domain-specific, addressing the types of diagnostic and workflow needs each domain presents. This makes AI-CDSS more reliable and practical for a variety of applications in healthcare as shown in Fig. 3 [43].

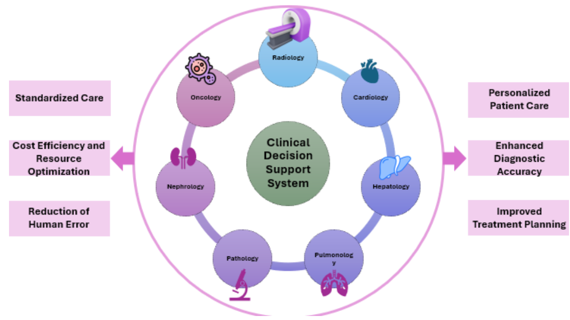

Fig. 3. Introduction of Multi disciplinarity in Clinical Decision Support Systems

d. Future Directions and Human-Computer Interaction

The development in human-computer interaction and scalable, explainable frameworks will provide a lot of potential for the future of AI in CDSS [44]. As the systems grow to increase in complexity, making them user-friendly is of the essence to clinicians [45]. For an effective CDSS, it must ensure that besides predicting events correctly, a plausible explanation is provided for such recommendations [46]. Scalable solutions like three-tier implementations can easily fit into large healthcare systems, and the greatest advantage of rule-based knowledge representation is its flexibility when changing clinical guidelines is needed [47]. This requires continuous research and development to improve not only the technological but also the human aspects of AI-CDSS, with transparent algorithms, clinician-driven design, and ethical considerations in developing an AI that could help in clinical decision-making and patient outcomes [48].

ii. Comparison of AI-CDSS and CDSS

In fact, clinical decision support systems, depending on AI or traditional techniques in their core logic, fundamentally differ in the approach taken towards data processing and adaptability of decisions [49]. These AI-based systems implement machine learning, deep learning, and other highly complex algorithms that process vast amounts of rich data, from tens to thousands of images or raw scans at a time and complex, unstructured clinical notes [50]. Such capability to learn from data enables AI-CDSS to identify patterns, make probabilistic inferences, and independently assist with complex clinical decisions, such as diagnostics or the planning of personal treatment courses [51]. AI-based CDSS, however, requires enormous amounts of initial data to be learned from and continuous retraining as and when clinical knowledge and patient data are updated [52]. Even though AI systems can be very accurate, especially when the tasks are complicated, this depends upon the quality and diversity of the training data [53]. Furthermore, AI-CDSS is difficult for clinicians to understand, especially when using complex models such as deep learning, often called "black boxes." To establish trust, explainable AI methods are increasingly being included in AI-CDSS so that the rationale behind the recommendations is understandable [54], [55].

In contrast, traditional CDSS are often rule-based systems operating based on a pre-specified logic system, that is often "if-then" rules or clinical guidelines [56]. While they are easier to maintain and update, such systems cannot learn or adapt autonomously as shown in Fig. 4. Such systems fit in well-defined clinical scenarios such as medication dosing, where these rules can be applied to structured data within EHRs or lab results [57]. Since the conventional CDSS functions are based on a set of rules, it is transparent and interpretative, hence a more trusting recommendation for clinicians in simple and predictable cases [58]. The limitation, however, is applicability to complex and evolving clinical cases whereby they require manual updates to adapt new medical knowledge [59]. Although they may look simple, traditional CDSSs are reliable for a host of clinical applications. But they can never be compared to AI-driven systems in their agility, adaptability, or predictive capabilities [60].

Table II. The comparison of AI-CDSS with traditional CDSS

Feature	**AI-Based CDSS**	**Traditional CDSS**
Data Processing	Analyzes complex and unstructured data	Processes predefined, structured data
Decision-Making	Predicts outcomes with probabilistic models	Follows set "if-then" rules
Adaptability	Learns and improves with new data	Static, requires manual updates
Explainability	Complex; requires XAI for interpretability	Highly transparent and easy to understand
Application Scope	Broad; supports complex tasks like diagnostics	Limited; suited to specific, simple tasks
Training and Maintenance	Needs extensive data and ongoing retraining	Minimal maintenance and simple updates
Accuracy	High accuracy for complex cases, data-dependent	Consistent for simple, well-defined cases
User Trust	Gaining trust with XAI	High trust due to transparency

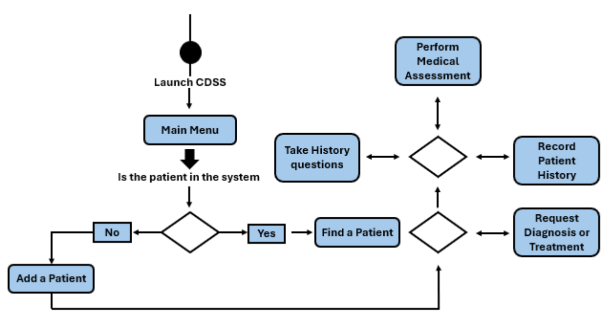

Fig. 4. A Rule-based Clinical Decision Support System

iii. Implementation of an AI-CDSS

The deployment of an AI-based Clinical Decision Support System takes systematic stages, which are equally important to ensure that the AI solution reflects the clinical workflow, is safe, and meets the expectations of the users involved. A structured approach below, based on each key deployment phase, follows:

a. *Selection*

The selection of the appropriate AI-based CDSS from the growing range of commercial options is crucial in the first instance [61]. This evaluation will consider the alignment of the CDSS with the clinical case it is designed for, how it fits into existing work activities, and all performance measures [61]. AI-based CDSSs should be judged according to the "five rights" principle by releasing the correct information to the proper people at the correct time, in the appropriate form, and through the appropriate channels [62]. This process should be led by a multidisciplinary committee of clinicians, patient representatives, IT specialists, and administrators for the CDSS to be clinically relevant and cost-effective without being cumbersome in its integration with systems such as the EHR [61]. The demands of AI systems, and specifically machine learning algorithms, are high-quality input data to ensure that the results drawn out from them are accurate; therefore, it's worthwhile scrutinizing the quality of data and the risk of bias [63].

b. *Acceptance Testing*

Acceptance testing views an AI-based CDSS as a medical device; thus, the system would need to meet defined standards regarding safety, privacy, and usability [64]. It should include, among other things, tests on the operation of APIs, navigation for the user interface, security protocol compliance, and testing for system installation [65]. Edge cases, or rare clinical scenarios or unexpected data inputs, are also key in testing how well the system will behave under extreme conditions [66]. Statistical validation of the output accuracy of the CDSS can be made possible through the Mann–Whitney U test, where the results from the pilot test are compared with the accuracy claimed by the AI vendor [67]. Testing for a representation sample of local users ensures the feasibility of the clinical expectations and clinical needs of the end user [66].

c. Commissioning

Commissioning prepares the AI-CDSS for the real world, tailoring the system to the clinical environment [67]. It may require some minor adjustments in configuration settings so that it will fit well with the site's local EHR system or adjust the thresholds of alerts and decision logic as needed in that clinical environment [68]. This customization helps reduce "alert fatigue" since it eliminates the need for extra messages, and alert messages become more relevant. CDSS would also ensure that it becomes part of the clinical workflow [69]. During the test of commissioning, it evaluates the real-world performance with retrospective case analyses and pilot programs in which the CDSS runs parallel to the traditional systems so that they can catch and deal with potential problems before full implementation [70].

d. Implementation

An AI-based CDSS is a change in workflow, which requires well-planned training and infrastructure support for its implementation [67]. Training sessions should focus on educating clinicians as to how and when to use the AI-CDSS, how to interpret its outputs, and whether to accept its recommendations or override them [71]. Such a communication stage is crucial to influencing users' expectations so that they appreciate the benefits of the system but also its limitations [67]. A gradual roll-out in selected units or departments helps identify potential problems and makes the transition easier. Hands-on training, followed by continuous vendor support, boosts the confidence level of the clinicians and assures that they will eventually use the system effectively [72].

e. *Quality Assurance*

Quality assurance (QA) aims to ensure that the deployed AI-CDSS remains dependable, accurate, and clinically relevant [67]. An ideal QA plan involves time-to-time monitoring of the performance of the system based on some predefined efficacy and efficiency criteria like sensitivity, specificity, and clinical impact on outcomes, specifically patient safety [73]. Regular feedback mechanisms allow users to report any problems, and performance monitoring tools track trends such as the frequency of alerts or recommendation overrides, which can be used to detect any drift in the accuracy of the AI model over time [74]. Internal (model) drift and external (context) drift are also closely monitored because they may result in discrepancies between recommendations of the CDSS and evolving clinical guidelines [74]. Routine re-validation, whereby the recommendations of the system are constantly evaluated against updated clinical data, would be required to ensure that the AI remains effective and relevant to the medical standards prevailing at the time [75].

iv. Application in diagnostics, Prognostics, and Treatment Planning:

AI-integrated CDSS is beneficial in health systems to offer more patient-centered care at high-quality levels [76]. AI-based CDSS has vast applications in diverse healthcare areas as shown in Fig. 5, including diagnostics, treatment planning, risk assessment, and patient monitoring [77]. In diagnostics, algorithms from AI can help clinicians better understand imaging studies such as X-rays, CT scans, and MRIs by establishing the presence of abnormalities to a high degree of accuracy [78]. For example, deep learning algorithms have been shown to be superior to human radiologists in specific conditions like pneumonia and breast cancer [79], [80]. Moreover, AI-based CDSS facilitates risk assessment activities, which help clinicians identify patients at a higher risk for adverse outcomes, such as hospital readmission or complications [81]. Predictive models could analyze historical data to discern patterns and risk factors so that interventions could be carried out before adverse outcomes become inevitable, thereby improving the patient's outcomes and reducing healthcare costs [82].

In treatment planning, AI-based CDSS can search patient information to prescribe and recommend personalized therapy options tailored to unique characteristics and needs [83]. Such a use case applies strongly in the field of oncology: treatment typically depends on specific molecular characteristics, and using genomic information within clinical will help guide AI systems assisting oncologists in selecting the appropriate therapies [84].

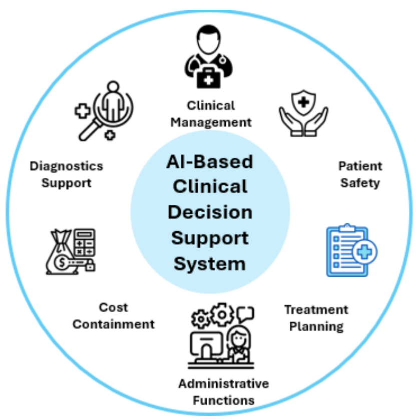

Fig. 5. The role of AI-Based Decision Support System in Clinical Workflow

IV. Limitations and Challenges

AI-based Clinical Decision Support Systems proved to be very promising regarding significant breakthroughs in health care, such as increased diagnostic accuracy, predictive analytics, and individualized recommendations for treatment. However, the integration of AI into clinical decision-making has its significant challenges and limitations. The development of AI-based CDSS involves several critical steps like data gathering, algorithm formulation, model training, and validation, each posing distinct obstacles.

i. Data Quality and Governance Challenges:

The quality and quantity of data that is collected during the development phase have been determined to affect the effectiveness of AI-based CDSS [90]. Sources include Electronic Health

Records, clinical trials, and patient registries, among others [91]. Because data governance applies toward management, cleaning, and standardization, poor-quality or unrepresentative data will not only jeopardize the model's performance and threaten accuracy in predictions but could also result from system data being dated and, thus, incomplete [92]. In addition, data from various sources of clinical input can vary in shape and content and, therefore, makes interoperability across systems challenging integration [93].

The other challenge is with the algorithm selection that serves to fulfill the clinical objectives of the CDSS. Several machine learning (ML) and deep learning algorithms require significant quality datasets to learn patterns and predict with precision [94]. However, these algorithms are quite prone to biases in data and generalizability when applied across different populations; further, AI-based CDSS face transportability when used in new clinical sites, as algorithms trained from specific patient demographics may not even perform well in other populations, thus emphasizing the need for continual validation and adjustment to retain effectiveness and relevance across clinically diverse environments [95].

ii. Ethical and Practical Challenges in AI Development of CDSSs:

The development of CDSSs via AI poses inherent ethical questions, particularly about potential biases that algorithms may introduce in the making of decisions [91], [96]. For example, when algorithms are trained using datasets that are believed to have reflected historical inequalities, the developed algorithm may treat some socio-economic groups unfairly [96]. Some situations that will be vulnerable if biased algorithms inadvertently cause a disparity in treatment for different groups or demographics include organ transplant eligibility or triage during emergency cases [91]. This concern, therefore, requires attention to ethical oversight and constant assessment for fairness in service delivery [97].

There are practical issues as well about taking AI-derived recommendations to the clinic. Algorithms trained mainly on correlations are going to come up with the least clinically relevant recommendations [98]. A great example of this is the frequently misused "weekend effect" whereby mortality is found to be higher when patients are admitted over weekends rather than weekdays, ignoring changes in case intensity or resource availability [99]. Recommendations based only on statistical patterns may lead to wrong clinical decisions if the AI needs to consider contextual inputs. For these reasons, both ethical and practical factors demand high validation of control over AI-CDSS to avoid clinically irrelevant yet statistically significant recommendations [100].

iii. Workflow Integration and Alert Fatigue:

The integration of AI-CDSS with clinical workflows also poses a challenge in that it must be directly integrated with EHR systems to avoid interference with routine practices [101]. The stand-alone or weakly integrated CDSS increases the clinicians' cognitive load, increases the time taken to complete tasks, and decreases the quality of interaction between clinicians and patients. Experienced practitioners can work around CDSS if the system is seen as intrusive or ineffective [102]. Such systems integrated well also lead to inefficiencies by taking the clinician's attention away from the patient and to the computer, away from the core clinician-patient relationship.

Alert fatigue is another significant limitation because AI-CDSS often produces a huge number of notifications which most are considered minor and not relevant [103]. It has been reported that clinicians ignore 95% of these alerts because common, low-priority alerts result in desensitization and loss of trust in the system. In fact, this phenomenon can cause important alerts to be missed by the physician when there are large numbers of unnecessary or low-priority messages [104]. Alert fatigue response should be approached by alert relevance improvement. Adaptive alerting mechanisms that rank in consideration of the context, urgency, and every clinician's historical alert response can enhance relevance [105].

iv. Skills, Training, Dependence on CDSS:

AI-CDSS adoption challenges retain clinician skills and technological skills. The likelihood of reduced independent verification skills becomes possible with AI-CDSS, like what happened with mental arithmetic when calculators first appeared [2]. Overdependence on CDSS could reduce clinicians' abilities to make autonomous decisions within non-AI settings. Although CDSS would expose clinicians to evidence-based recommendations, overdependence on automated systems compromises their ability to validate or challenge the system's recommendations [41].

Also, AI-based CDSS is designed to be quite complex, demanding that a clinician have literacy skills in using the computer and the functions of the system itself [106]. The worst-case scenario in the application system design is when it does not closely align with clinical workflows; as a result, steep learning curves are experienced to avoid misinterpreting outputs from the CDSS [107]. Consequently, baseline user evaluation and training have become essential in this regard. Ideal system design should thus minimize additional technical skills needed, hence letting the clinicians focus solely on the patients rather than on the technology [105].

v. Maintenance and Interoperability Issues:

Such systems in AI-CDSS would, therefore, be kept up to date with the latest knowledge and standards in the medical field due to continuous maintenance [108]. Guidelines for medical conditions and treatment protocols are dynamic and change over time; the inability to update such changes in the CDSS might make their recommendations outdated. Standards such as ICD and SNOMED CT are necessary for maintaining the integrity of data; however, the need for constant updating of these standards would create another type of demand for maintenance [12]. In addition, the CDSS relies on high-quality, real-time data from external systems; hence, errors in data, either due to outdated records or system interoperability, might result in less efficient or wrong recommendations. The variability in the sources of data and complexities of programming is a significant challenge for interoperability among healthcare systems in CDSS. Efforts like HL7 and FHIR standardize, trying to bring ease with smooth data exchange; however, there is still complexity in integration with the many varied platforms. Cloud-based solutions promise to bypass some of these barriers, adhering strictly to data security and privacy regulations [76].

vi. Financial and Economic Barriers

The cost to implement and sustain AI-based CDSS is high, often leading to a significant financial burden to healthcare organizations. Some costs include the setup infrastructure and the expenses of updates, training, and follow-up support to the staff [73]. Calculating the cost-effectiveness of CDSS is very challenging because the metrics that assess financial impact are not standardized [65]. This will, therefore, make it difficult for the institutions to evaluate whether the expected benefits are worth the cost. It involves research into uniform cost-benefit analyses and metrics used in aiding an enterprise's decision related to AI-CDSS [108].

vii. Explaining AI (XAI) and the Future of AI-CDSS

Explainable AI is one of the most promising solutions proposed thus far too many of the issues AI-CDSS faces, especially concerning clinician trust and interpretability [29]. Clinicians in healthcare are less than thrilled to accept "black box" models where they cannot understand the rationale behind each recommendation [31]. The transparency and ability to understand XAI allow clinicians to "understand why" AI might predict something, hence making it easier for them to integrate AI insights into their reasoning and decision-making processes [32]. The XAI in CDSS might revolutionize health if the predictive models are more reliable and user-friendly. XAI-enabled CDSS can develop precise recommendations for individual patients by analyzing the relations between clinical variables, promoting precision medicine [33]. Eventually, improving XAI might ease clinicians' cognitive burden by providing them with transparent, evidence-based rationales for its outputs. Ultimately, XAI can create clinician trust in AI-CDSS and enhance care quality and patient outcomes through a smooth explanation of the machine's intelligence to human understanding [33].

V. CONCLUSION

AI-based CDSS can truly revolutionize healthcare and support diagnostics as well as treatment planning along with advanced predictive analytics capabilities. However, to avail these aspects for clinical practice, numerous critical challenges must be overcome. Explainable AI cannot be undervalued since it will set the grounds for gaining clinician trust by providing transparent insights into AI-based recommendations, making them more adoptable in decision-making processes. The future of AI-CDSS emphasizes standardized frameworks for regulations, advanced explanatory AI techniques for interpretability, and leadership in facilitating interdisciplinary collaboration and creating systems that are technically robust and clinically relevant. This will ensure that all AI-CDSS are placed on the right track toward realizing quality, efficiency, and outcomes in healthcare.

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