Trust in AI-Based Clinical Decision Support Systems Among Healthcare Workers: A Systematic Review

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Abstract

Background: Artificial intelligence-based Clinical Decision Support Systems (AI-CDSS) have offered personalized medicine and improved healthcare efficiency to healthcare workers. Despite opportunities, trust in these tools remains a critical factor for their successful integration. Existing research lacks synthesized insights and actionable recommendations for providing healthcare workers' trust in AI-CDSS.

Objective: The study aims to identify and synthesize factors for guiding in designing systems that foster healthcare worker trust in AI-CDSS.

Methods: We performed a systematic review of published studies from January 2020 to November 2024 that were retrieved from PubMed, Scopus, and Google Scholar, focusing on healthcare workers' perceptions, experiences, and trust in AI-CDSS. Two independent reviewers utilized the Cochrane Collaboration Handbook and PRISMA 2020 guidelines to develop a data charter and synthesize the study data. The CASP tool was applied to assess the quality of the studies included and evaluate the risk of bias, ensuring a rigorous and systematic review process.

Results: The review included 27 studies that met the inclusion criteria, across diverse healthcare workers predominantly in hospitalized settings. Qualitative methods dominated (n=16,59%), with sample sizes ranging from small focus groups to over 1,000 participants. Seven key themes were identified: System Transparency, Training and Familiarity, System Usability, Clinical Reliability, Credibility and Validation, Ethical Considerations, and Customization and Control through enablers and barriers that impact healthcare workers' trust in AI-based CDSS.

Conclusions: From seven thematic areas, enablers such as transparency, training, usability, and clinical reliability, while barriers include algorithmic opacity and ethical concerns. Recommendations emphasize the explainability of AI models, comprehensive training, stakeholder involvement, and human-centered design for healthcare worker trust in AI-CDSS.

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Original Manuscript

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Registration and protocol: The review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 checklist for systemic review, no registration was applied for systemic review.

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Glossary of Terms:

AI : Artificial intelligence
APA. : AI-enabled Prescription Advisory
BUC. : Blood Utilization Calculator
CASP. : Critical Appraisal Skills Programme
CDSS. : Clinical Decision Support Systems
DR. : Diabetic Retinopathy
EHR. : Electronic Healthcare Records
OCT. : Optical Coherence Tomography
TAP. : Think Aloud Protocol (TAP)
SDM. : Shared Decision Making
RL. : Reinforcement learning
XAI : Explainable AI

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***Keywords**: Artificial Intelligence, Decision Support Systems, Healthcare Workers, Trust, Systematic Review, Meta-Analysis, Clinical Decision-Making*

Background

The adoption of Artificial intelligence (AI) in healthcare has a potentially transformative impact on healthcare workers by enabling advancements in diagnostics, treatment planning, and patient management, which lead to improving the healthcare system. With the increasing availability of digitalized healthcare data and technological advancements in machine learning and deep learning algorithm have enhanced the potential of AI-based Clinical Decision Support Systems (CDSS). These systems can assist can healthcare workers by predicting patient outcomes and recommending optimal interventions, contributing to personalized medicine and improved healthcare efficiency. [1,2] Despite these advancements, healthcare professionals' trust in AI-based Clinical Decision Support Systems (CDSS) remains a critical factor for their successful integration and effective use in clinical practice. Furthermore, hesitation persists regarding AI's ability to provide substantial clinical value, particularly among highly skilled professionals. [2,3,4]

Trust is a complex construct that affects how healthcare workers interact with AI-driven systems which developed through complex and opaque mathematical mechanisms of ML models. [2] Trust holds value only when directed toward agents or systems that are genuinely reliable, as placing trust in untrustworthy sources can result in severe, even life-threatening, outcomes. Trust can be understood through three interconnected elements: belief in the truthfulness of claims (such as trusting the accuracy of advice), confidence in commitments (like relying on a bank to send monthly statements), and faith in competence (for example, trusting a dentist to carry out a procedure properly).[5]. Without adequate trust, healthcare workers may disregard AI recommendations, undermining the potential benefits of AI for enhancing patient care and optimizing clinical workflow.

Clinicians' concerns about the opacity of AI decision-making processes, the potential for algorithmic bias, and the fear of technology replacing human judgment can undermine trust in these systems. [6,7,8,9] Furthermore, trust in AI-based systems is not a static concept; it evolves as healthcare workers interact with the technology and gain experience with its functionality and outcomes. Vereschak et al. mention the importance of integrating theoretical elements of trust, such as vulnerability, positive expectations, and attitude, into the understanding of human-AI trust. Trust can also be supplemented by other behavioural dimensions that include decision time, reliance or accepting recommendations and compliance dimensions or requesting recommendations. These recommendations have been designed to reflect passive behaviours towards trust such as immediate agreement, disagreement or mild agreement with the recommendations, and can certainly offer additional insights through trust, particularly the level of trust and how it informs decision-making. [10,11]

A growing body of research has explored trust in AI-based Clinical Decision Support Systems (AI-CDSS) from various perspectives, including those of clinicians, nurses, and pharmacists. These studies have examined trust through different lenses, such as algorithmic development and mathematical considerations, the use of devil's advocate approaches of large language models such as ChatGPT, qualitative explorations of healthcare workers' perspectives through a sociotechnical lens, AI confidence levels, and the impact of technology-induced dehumanization in healthcare. Trust has also been studied in the context of upstream relationships among different stakeholders. [4,8,9,10,12] Several factors influencing trust have been identified, including transparency, explainability, interpretability, privacy, ethical concerns, and the actionability or contestability required by decision-makers. The attitudes, perceptions, and individual experiences of healthcare workers have also been recognized as critical elements shaping trust. [10,11,12,13]

Despite these findings, there does not seem to be any synthesized insights and recommendations as regards the factors that touch on the healthcare workers' trust in AI-CDSS. Our study aims to fill this gap by systematically reviewing and qualitatively meta-analyzing the literature to identify the constraints and facilitators of trust in AI-CDSS. Guided by the existing literature, we plan to formulate practical recommendations for the design and implementation of AI systems that would be trusted and accepted by healthcare practitioners. This research will contribute to developing strategies that will promote the use of AI-CDSS in healthcare in a manner that these technologies will complement clinical decision-making rather than disrupt it.

2. Methods

Our systematic review follows the Cochrane Collaboration Handbook and reported the findings following Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 checklist to consolidate findings on healthcare workers' trust in artificial intelligence-based decision support systems in the last five years from January 2020 to November 2024.[14,15,16] The Critical Appraisal Skills Programme (CASP) tool was used to assess the quality and risk of bias.[17]

2.1 Literature search Strategies

We reviewed published articles systematically between 1st January 2020 and 30th November 2024 following the PRISMA guideline with PICO (population, intervention, comparison and outcome) framework. [14,15] Our study source included PubMed, Scopus, and Google Scholar. The search strategy employed a combination of English keywords, including: "trust" or "acceptance" or "perception" and "artificial intelligence" or "AI" and "decision support systems" or "clinical decision support" or "AI-based decision support" and "healthcare workers" or "clinicians" or "nurses" or "medical professionals" or "healthcare providers". Publication date filters were applied to include only studies within the specified timeframe. Additionally, we employed the snowball strategy to identify further sources from the references of relevant full texts. Medical Subject Headings (MeSH) and free-text terms were used to maximize search sensitivity and ensure comprehensive coverage of relevant literature.

2.2 Eligibility Criteria

We included research articles explicitly describing the use of healthcare professionals' trust, acceptance, or reliance on AI-driven DSS, specifically in clinical and primary care settings. Both qualitative, quantitative studies and mixed method studies were included, provided they explored aspects of trust or acceptance among healthcare workers. We excluded papers that are unrelated to the relation between trust in healthcare providers and AI-based decision support systems. Non-peer-reviewed articles, editorials, opinion pieces, and other non-research literature were also excluded to maintain the scientific credibility of our review.

2.3 Data Extraction

Two researchers initially screened titles and abstracts to determine if they met the inclusion. After removing duplicates, full texts were reviewed to identify potential exclusion criteria. Any disagreements regarding eligibility criteria were resolved through discussion with another team member. The Mixed Methods Appraisal Tool (MMAT) was used to assess studies, allowing for the evaluation of studies with diverse methodologies. [18] We extracted data on key study details, including the author, country of data origin, study design, and the type of AI method utilized. Additional information was systematically extracted for each study, emphasizing the type of AI application, the role of healthcare workers, the study setting and location, the specific department or focus area, and the type of AI-based decision support system. We also captured details on trust measurement tools, qualitative questions related to trust, assessed trust factors, outcomes related to trust, trust level findings, influencing factors, study limitations, conclusions or recommendations, and funding sources. Additionally, qualitative information such as quotes, themes, or findings from interviews, focus groups, and open-ended survey responses was extracted. The quality of the available studies was assessed by the match between the study objective and results.

2.4 Data Synthesis and Analysis

Data synthesis and analysis were conducted to integrate and interpret the findings systematically. Relevant data were organized into an evidence matrix using a standardized template in Google Sheets. Advanced tools for systematic review and data extraction, including Zotero 6, Elicit, and Rayyan, were employed to screen and analyze abstracts from 30 studies that met the inclusion and exclusion criteria. A comprehensive data charter was developed to summarize study characteristics, the year the study was published, the geography of the study, studies, settings of clinical decision support systems (CDSS), method of evaluating trust, description of AI-based CDSS, and evaluation of trust factor for AI-CDSS. For qualitative data analysis, a data charter was developed for outcomes of the included studies along with the quotes and quantitative results related to trust in AI-based CDSS to explore recommendations from included studies. The data charter also incorporated evaluation matrices, providing a structured summary of trust-related findings into a thematic summary of trust factors in AI-Based CDSS: enablers, barriers, and recommendations. Thematic synthesis was conducted to identify how these themes interrelated and contributed to a broader understanding of trust. Further analysis was performed to provide enablers, barriers and recommendations for actionable implementation to grain trust for AI-based CDSS for practice, policy, and future research.

2.5 Quality and Risk of Bias Assessment

The quality of qualitative studies and the qualitative components of mixed-methods studies were assessed using the Critical Appraisal Skills Programme (CASP) tool. Each question within the tool was evaluated with responses of ‘yes,’ ‘no,’ or ‘cannot determine.’ Instead of producing a summative score, the CASP tool provides an overall assessment, categorizing studies as ‘not valuable,’ ‘semi-valuable,’ ‘valuable,’ or ‘very valuable,’ as documented in previous literature. These assessments were based on a judgmental approach, where reviewers determined the relevance and contribution of each study to understanding interaction traits within the AI–clinician quality of interaction construct.[17] Quality assessments were conducted independently by two reviewers, and any disagreements were resolved by consensus. This process ensured a rigorous and transparent evaluation of study quality.

3.Results

3.1 Study Selection

The article selection process consisted of two phases: (1) a review of titles and abstracts and (2) a full-text review. Figure 1 illustrates the study selection process. Initially, 333 records were identified from three databases: PubMed (69 records), Scopus (142 records), and Google Scholar (122 records). An independent reviewer screened these records to remove duplicates and articles deemed irrelevant based on their titles and abstracts, resulting in 60 records advancing to the next stage. Further screening excluded 20 articles due to unsuitable study designs, leaving 40 for eligibility assessment. Following an in-depth full-text analysis and final discussions among reviewers, 13 articles were excluded for lacking a focus on trust in AI-Based Decision Support Systems among healthcare workers. Ultimately, 27 studies were included in the final analysis.

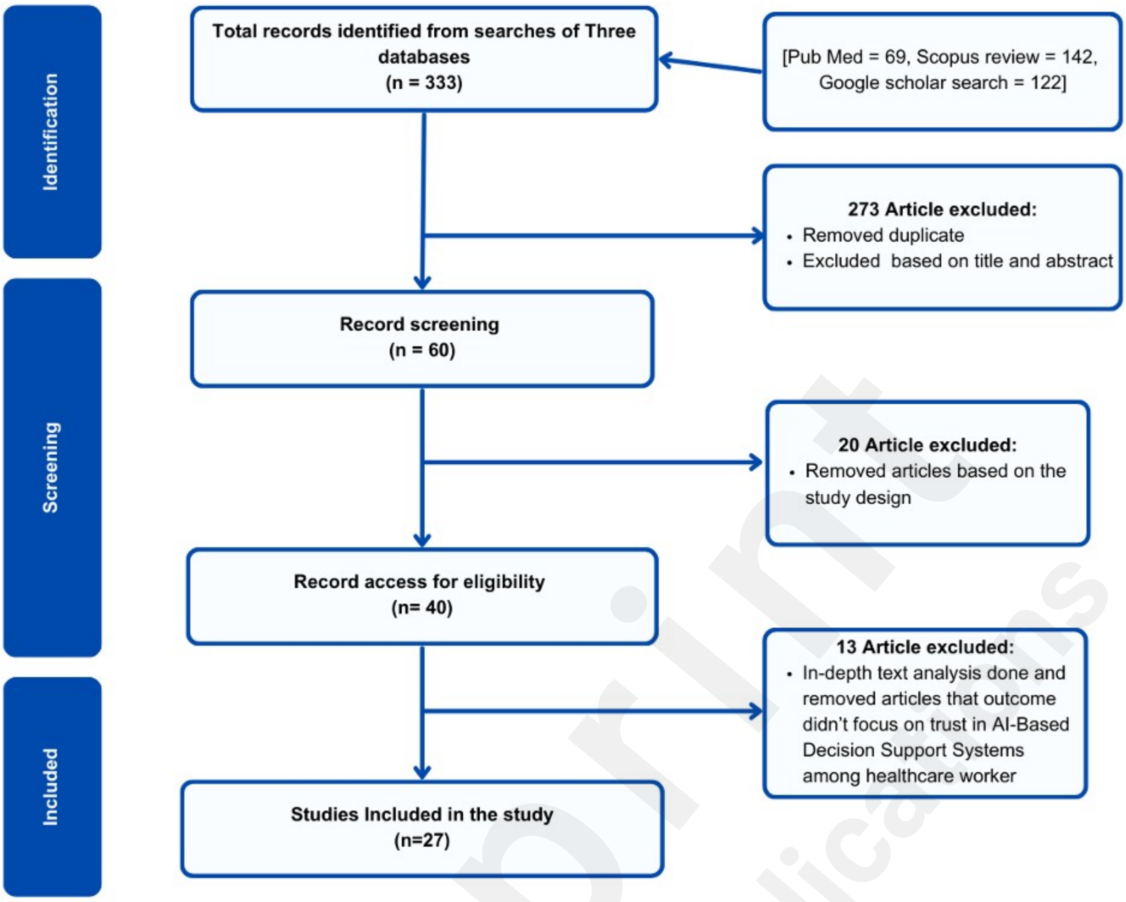

Figure 1: Flow Chart for Study Selection Process

3.2 Quality Assessment of Included Studies

A total of 23 studies were assessed using the CASP checklist for qualitative analysis (Table 1), while 4 studies employed other methodologies. Among the 23 studies, the majority (n=19,83%) received an overall rating of “valuable” or “very valuable” in the quality assessment. Studies (n=4,17%) rated as “semi-valuable” were flagged for issues such as inappropriate use of qualitative methods to measure non-subjective outcomes, suboptimal sample recruitment strategies, or insufficient consideration of bias. Although quality assessment was not a criterion for inclusion in the systematic review, it was conducted to provide an overview of the quality of the eligible literature. Consequently, studies rated as “semi-valuable” were still included in the data analysis. While these studies were limited in their methodological rigor for offering meaningful insights into the tool being evaluated, they contributed unique perspectives on the healthcare worker trust on AI based clinical support decision system tools that were absent from other included studies. The included studies discuss limitations related to small sample size and biases such as potential selection bias, cognitive biases like anchoring bias and interviewer bias associated with qualitative studies, self-reported data inaccuracies, regional differences in AI exposure, participants' familiarity with the study context, and a focus on specific AI solutions or decision domains, which may hinder generalizability.

3.3 Characteristics of Included Studies

Of the 27 included articles, summarized in Table 2 and Supplementary Figure S1, most were published recently, with 2023(n=12,44%), followed by 2022(n=8,30%), 2024(n=4,15%) and 2021(n=3,11%). Geographically, most studies were conducted in the United States (n=12,44%), followed by Europe (n=7,26%), multinational (n=3,11%), the United Kingdom (n=2,7%) and China, Singapore, and Egypt (n=1,4% each). Most studies are conducted in hospital settings (n=17,63%) across departments such as emergency care, radiology, and oncology, while 5 studies (19%) were conducted in primary care and 5 studies (19%) spanned both settings. Study designs included qualitative research (n=16,59%), mixed-methods studies (n=6,22%), quantitative cross-sectional surveys (n=4,15%), and comparative evaluation studies(n=1,4%) of AI-generated versus human-generated suggestions for clinical decision support. The study population include a wide range of healthcare including physicians, nurses, nurse practitioners, general practitioners, ICU clinicians, pharmacists, ophthalmologists, oncologists, interdisciplinary teams, behavioural health specialists, and AI practitioners, with sample sizes ranging from small focus groups to cohorts exceeding 1,000 individuals.

Table 1: Critical Appraisal Skills Programme (CASP) Responses for each qualitative study included in the analysis (n = 23)

Study ID (Year)	1. Was there a clear statement of the aims of the research?	2. Is a qualitative methodology appropriate?	3. Was the research design appropriate to address the aims of the research?	4. Was the recruitment strategy appropriate to the aims of the research?	5. Was the data collected in a way that addressed the research issue?	6. Has the relationship between researcher and participants been adequately considered?	7. Have ethical issues been taken into consideration?	8. Was the data analysis sufficiently rigorous?	9. Is there a clear statement of findings?	10. How valuable is the research?
Jacobs et al.2021[20]	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes	Yes	Can't Tell	Semi-valuable
Wang et al.2021[21]	Yes	Yes	No	Yes	Yes	Can't Tell	Yes	Can't Tell	Yes	Valuable
Micocci et al.2021[22]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Henry et al.2022[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Choudhury et al.2022[23]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Gunasekeran et al.2022[25]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes	Semi-valuable
Choudhury et al.2022[26]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Ankolekar et al.2022[27]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Van Biesen et al.2022[28]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Sivaraman et al.2023[29]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes	Semi-valuable
Amann et al.2023[13]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes	Valuable
Bach et al.2023[30]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes	Valuable
Burgess et al.2023[31]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Liu et al.2023[32]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Anjara et al.2023[33]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Jones et al.2023[5]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Very valuable
Liu et al.2023[34]	Yes	Yes	Can't Tell	Yes	Yes	Yes	Yes	Yes	Yes	Semi-valuable
Chiang et al.2023[12]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Liaw et al.2023[36]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Nair et al.2023[37]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Yoon et al.2024[7]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Zheng et al.2024[4]	Yes	Yes	Yes	Can't Tell	Yes	Yes	Yes	Can't Tell	Yes	Semi-valuable
Vereschak et al.2024[11]	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes	Can't Tell	Yes	Valuable

*Choudhury et al.2022[25],Stacy et al.2022[2],York et al.2023[35],Elareed et al.2024[38] are cross sectional quantiative study are not included in the CSAP analysis.

The included studies featured a wide range of AI-based Clinical Decision Support Systems (CDSS) showcasing their application across various clinical functions and specialties. (Table 2). These systems utilize advanced technologies such as machine learning (ML), deep learning, reinforcement learning, and explainable AI (XAI) to enhance diagnostics, treatment planning, and decision-making. Examples include the AI-based Blood Utilization Calculator (BUC) for improving transfusion procedures, the "Brilliant Doctor" system for dermatological diagnosis, machine learning models, and reinforcement learning to provide sepsis treatment recommendations in ICU setting, QRhythm to identify optimal rhythm management strategies for atrial fibrillation. Additional innovations include AI-based CDSS for detecting and managing diabetic retinopathy, glaucoma, and cataracts, ChatGPT-enhanced EHR alerts, for medication optimization in diabetes, lung cancer relapse prediction, vancomycin dosing, cardiovascular risk prediction, trauma radiography, and asthma management.

Table 2: Study characteristics and evaluation of healthcare worker trust factor for AI-CDSS(n=27)

Study ID (Year)	Geography	Setting	Study Design	Study Population (n of participant)	Method of evaluating trust	Description of AI Based CDSS	Evaluation of healthcare worker trust factor for AI-CDSS
Jacobs et al.(2021) [20]	Multinational United Arab Emirates, Singapore, and Hong Kong.	Hospital	Qualitative Study	Physicians(n=9),nurse practitioners (n=1) who are Primary care providers (PCPs)	Semi-structure qualitative interview	Machine learning (ML) models to provide prognostic predictions and treatment selection support for major depressive disorder (MDD).	▪ Previous system utilization, including its use by other clinicians and validation through randomized controlled trials. ▪ Level of training received
Wang et al. (2021) [21]	China	Primary Care	Qualitative Study	Clinicians with experties in both western and Traditional Chinese medicine (n=22)	Semi-structure qualitative interview	Deep learning and knowledge graph based AI-CDSS system ("Brilliant Doctor")	▪ The "black box" nature of the AI algorithm, lacking transparency in its recommendations. ▪ Perceived threat to professional autonomy and decision-making, with the "Click-Through" approach disrupting workflows. ▪ Insufficient training on system features and functionality, reducing clinicians' understanding and
Micocci et al.(2021) [22]	United Kingdom	Primary care	Mixed Method Study	General practitioners (n=50)	Semi-structure qualitative interview	AI system designed to support the diagnosis of dermatological conditions.	▪ Accuracy of the AI system, ▪ GPs' familiarity with AI, ▪ Previous experiences with similar technologies.
Henry et al. (2022) [3]	United States	Hospital	Qualitative Study	Physicians (n=13) and Nurse (n=7) worked at emergency department, critical care, and general ward	Semi-structure qualitative interview	Machine learning-based system called Targeted Real-time Early Warning System(TREWS) for to alert sepsis detection,evaluate patients, and manage treatment.	▪ Direct experience with the system and observing its behavior over time ▪ Endorsement and recommendations from colleagues and experts ▪ Understanding the system's development and validation process ▪ Ability to customize the system and ask questions about its design
Choudhury et al.(2022) [23]	United States	Hospital	Qualitative Study	Clinicians involved in decision-making for blood transfusions (n=10)	Semi-structure qualitative interview	AI-based Blood Utilization Calculator (BUC) designed to optimize blood transfusion practices	▪ Workload, ▪ Usability, ▪ Impact on decision-making, and ▪ Alignment with clinical judgment
Gunasekeran et al. (2022) [24]	Multinational more than 70 countries	Primary Care and Hospital	Mixed Method Study	Ophthalmologists (n=1,176)	Likert scales and dichotomous questions	Various AI based assistive tools, clinical decision support applications relevant to ophthalmology for detection and management of eye diseases such as diabetic retinopathy, glaucoma, age-related macular degeneration (AMD), and cataract	▪ Usability, ▪ Acceptable error levels and concerns over medical liability ▪ Professional acceptance, ▪ Organizational support
Choudhury et al.(2022) [25]	United States	Hospital	Mixed Method Study	Clinicians who utilized Blood Utilization Calculator (BUC) (n= 119)	Semi-structure qualitative interview	AI-based Blood Utilization Calculator (BUC)	▪ Perception of AI, ▪ Expectancy(effort and performance expectancy), ▪ Perceived risk.
Ankolekar et al.(2022) [26]	The Netherlands	Hospital	Mixed Method Study	Non-small cell lung cancer (NSCLC) patients (n=257) treated at Single radiotherapy clinic and Lung cancer specialists (n=9)	Semi-structure qualitative interview	Clinical Decision Support Systems (CDSSs) that support shared decision-making (SDM) for prognosis of lung cancer	▪ Lack of external validation, ▪ Clinician experience, ▪ Perceived usefulness of CDSSs.
Stacy et al. (2022) [2]	United States	Hospital	Quantative Study	The healthcare workers involved include clinicians who manage patients with atrial fibrillation (n= 33)	Likert scale (0-5)	2-stage machine learning (ML) model-based tool QRhythm model that identify the optimal rhythm management strategy	▪ Accuracy of the AI recommendations, ▪ Transparency of the AI processes, ▪ Clinicians' previous experiences with AI.
Choudhury et al.(2022) [27]	United States	Hospital	Quantative Study	Physicians resident and fellow (n=111) and nurses(n=8)	Semi-structure qualitative interview	AI-based decision support system known as the Blood Utilization Calculator (BUC).	▪ Perceived risk, ▪ Expectancy, ▪ Acceptance of AI system
Van Biesen et al.(2022) [28]	Belgium.	Hospital	Qualitative Study	Physician(n=30)	Semi-structure qualitative interview	AI based Clinical Decision Support Systems (CDSS) integration into into electronic healthcare records (EHR).	▪ Transparency, ▪ Reliability, ▪ Perceived accuracy of the CDSS.
Sivaraman et al.(2023) [29]	United States	Hospital	Mixed Method Study	ICU clinicians(n=24)	Likert scale (0-10)	Reinforcement learning (RL) model based tool called the "AI Clinician" to provide interpretable treatment recommendations for sepsis patients in the ICU.	▪ The credibility of the developers who created the AI. ▪ The perceived soundness of the methodology used to develop the AI.
Amann et al.(2023) [13]	Germany and Switzerland	Primary Care	Qualitative Study	Healthcare professional including Physician (n=7), Occupational therapist (n=1),Physiotherapist (n=4),Neuropsychologist (n=2) and Stroke survivor (n = 14), Family members (n = 6)	Semi-structure qualitative interview	AI based clinical decision support systems (CDSS) to act asadministrative assistants for routine tasks, aid in diagnosis and teatment of complex cases of stroke	▪ Concerns about AI causing dehumanization in healthcare and eroding patient-clinician trust.
Bach et al. (2023) [30]	Denmark	Hospital	Qualitative Study	Ophthalmologists (n=7)	Semi-structure qualitative interview	AI system for detecting diabetic retinopathy (DR) by analyzing colour-coded assessment of fundus images and optical coherence tomography (OCT) scans to indicate the presence and severity of lesions.	▪ Accuracy and reliability of AI assessments, including its ability to minimize false positives/negatives. ▪ Failure of the AI system to detect severe abnormalities beyond its intended scope. ▪ Limitations in the AI system's performance due to factors like image quality.

Study ID (Year)	Geography	Setting of the study	Study Design	Study Population (n of participant)	Method of evaluating Trust	Description of AI Based CDSS	Evaluation on Trust factor for AI-CDSS
Burgess et al. (2023) [31]	United States	Primary Care and Hospital	Qualitative Study	Primary Care Provider (MD/DO)(n=14), Nurse Practitioner (NP) /Physician Assistant(PA) (n=18),Endocrinologist (MD/DO) (n= 5), Pharmacist(n=2),Internal Medicine (MD/DO)(n=2)	Semi-structure qualitative interview	Machine learning model trained on a large dataset of 141,625 patients with Type 2 diabetes mellitus to optimize medication selection and predict the relative efficacy of different drug regimens for reducing hemoglobin A1c levels.	▪ Comparison of AI-based CDS systems to the "gold standard" of randomized controlled trials in generating insights. ▪ Clinicians' understanding of how insights are calculated and what outcomes the system optimizes for. ▪ Clinicians' trust in the data, such as claims data, used to train the AI model.
Liu et al. (2023) [32]	United States	Hospital	Comparative Evaluation	Clinicans(n=5)	Likert scale (0-5)	ChatGPT (a large language model by OpenAI)to improve CDSS alerts in electronic health records	▪ Understanding, ▪ Relevance and clarity of AI suggestions ▪ Usefulness, ▪ Acceptance, ▪ Workflow impact, ▪ Redundancy, ▪ Potential for bias
Anjara et al.(2023) [33]	Spain	Hospital	Qualitative Study	Oncologists with specialize training in treating lung cancer (n=10)	Think Aloud Protocol (TAP)	Explainable AI (XAI) system using a graph representation learning model for lung cancer relapse prediction	▪ Perception of clarity,credibility and utility, ▪ Information overload and the presence of example-based explanations ▪ System's alignment with clinical decision-making needs
Jones et al. (2023) [5]	Multinational Belgium, the UK, Italy, and China	Primary Care and Hospital	Qualitative Study	Physician(n=24)	Semi-structure qualitative interview	Artificial Intelligence (AI)-powered CDSS in the context of ophthalmology (i.e., clinical care specialising in eye and vision care)	▪ Perception on clinicians' control over decision-making, ▪ Medical errors, and legal responsibility/liability
Liu et al. (2023) [34]	United States	Hospital	Qualitative Study	Critical Care Pharmacists (n=13)	Semi-structure qualitative interview	AI-based clinical decision support system (CDSS) to facilitate vancomycin dosing for hospitalized patients.	▪ Accuracy of recommendations, ▪ Rationale behind dosing, and ▪ Transparency of the AI model. ▪ Black-box nature of AI recommendations, complexity of algorithms
York et al. (2023) [35]	United Kingdom	Hospital	Quantative Study	Clinician with different level of training including FY1 (n=108), FY2 (n=28) ,ST/CT 1–2 (n=35),ST3/SpR or Above (n=49) and Medical Student (n=77)	Semi-structure qualitative interview	AI based CDSS applied in development skeletal radiography for trauma.	▪ Knowledge of AI, ▪ Confidence in interpreting radiographs ▪ Level of training and experience of clinican,
Chiang et al.(2023) [12]	United States	Primary Care	Qualitative Study	Ophthalmologists and optometrists from University of California San Diego (n=10)	Semi-structure qualitative interview	AI-based decision support system (DSS) for predicting the risk of cardiovascular disease.	▪ Accuracy, ▪ Reliability, ▪ Usefulness.
Liaw et al. (2023) [36]	United States	Primary Care and Hospital	Mixed Method Study	Physician(n=24)	Semi-structure qualitative interview	Diabetes Artificial Intelligence Prediction Tool to predict the risk of poor diabetes control	▪ Accuracy of the tool, ▪ Transparency of the AI processes, ▪ The clinicians' familiarity with AI.
Nair et al. (2023) [37]	Sweden	Primary Care and Hospital	Qualitative Study	Physician (n=14), Nurse practitioner/Nurse/Physici an assistant (n=3), Behavioural specialist (n=1),Social worker(n=1),Other staff including front desk, administrative, or medical assistant (n=3)	Semi-structure qualitative interview	Artificial Intelligence-Based Decision Support Tool to Reduce the Risk of Readmission of Patients With Heart Failure	▪ Stakeholder engagement, ▪ Perceived benefits, ▪ Transparency
Yoon et al. (2024) [7]	Singapore	Hospital	Qualitative Study	Clinicans(n=13) in 4 focusing group	Focus group discussion	AI-enabled Prescription Advisory (APA) tool.	▪ Interpretability of AI-generated recommendations, ▪ Transparency of the system, ▪ Clinicians' previous experiences with AI.
Zheng et al. (2024) [4]	United States	Hospital	Qualitative Study	Clinicans(n=14) who encountered pediatric asthma patients at 2 outpatient facilities	How-Might-We (HMW) questions	Machine learning-based clinical decision support system (CDSS) as Asthma Guidance and Prediction System (A-GPS) for asthma management.	▪ Accuracy, ▪ Reliability, ▪ Explainability of the AI tool.
Elareed et al.(2024) [38]	Egypt	Hospital	Quantative Study	Physician(n=249)	Likert scale (0-5)	General AI applications in healthcare, including potential applications in disease management and treatment	▪ Job replacement by AI, ▪ Perceived usefulness, ▪ Reduction in workload, ▪ Impact on physician-patient relationship ▪ AI to handle patient data responsibly
Vereschak et al.(2024) [11]	France and Germany	Primary Care	Qualitative Study	AI practitioners which include Bio. Eng. & Research (n=1),other(n=6) and AI decision subjects which include medical student(n=1),other (n=6)	Semi-structure qualitative interview	AI-assisted decision-making systems, particularly those using machine learning techniques.	▪ AI transparency, ▪ AI literacy, ▪ interpersonal relationships between stakeholders (developer and user), the complexity of tasks.

3.4 Factors Influencing Healthcare Workers' Trust in AI-Based CDSS

To analyze healthcare workers' trust in AI-based Clinical Decision Support Systems (CDSS), we identified methods used across 27 studies to assess trust-related elements. The majority, 70% (n=19), employed semi-structured qualitative interviews(n=19,70%), followed by Likert scales (n=4,15%), focus group discussions(n=1,4%), How-Might-We (HMW) questions (n=1,4%), Likert scales combined with dichotomous questions (n=1,4%), and the Think Aloud Protocol (TAP) (n=1,4%) (Table 2). The assessment of trust in AI-based Clinical Decision Support Systems (CDSS) revealed various factors that need to be addressed (Table 2). Factors described in the study include experience with the AI system, colleagues' recommendations, or results of a randomized controlled trial, and clinicians' direct experience with the system over time. Transparency, accuracy, and reliability of AI recommendations were critical, with concerns about the "black box" nature of algorithms and insufficient clarity on how insights are calculated. Additional factors described as affecting trust include perceived or actual risks, ease of use, organisational fit, and congruence with clinical judgment are also mentioned. Healthcare workers emphasized the importance of adequate training, customizable features, and developer credibility, while factors such as workload impact, acceptable error rates, and medical liability concerns further shaped trust perceptions. Involvement and engagement of the stakeholders and understanding of AI increased comfort described as favour trust in AI-based CDSS systems. However, concerns about job replacement and dehumanization of care highlighted potential described as challenges to trust for AI-based CDSS.

Theme	Enablers	Barriers	Recommendations
System Transparency	• Prior system utilization and validation through randomized controlled trials.	• Lack of transparency in AI algorithms ("black box" nature) and unclear recommendations.	• Enhance transparency by using interpretable algorithms and providing clear, actionable recommendations.
Training and Familiarity	• Training and experience with the AI system, improving confidence and familiarity.	• Insufficient training on system functionality, reducing understanding.	• Provide comprehensive training programs to build user familiarity and confidence in the AI system.
System Usability	• Direct observation of system behavior and colleague endorsements.	• Perceived threat to professional autonomy and workflow disruption ("Click-Through" approach).	• Conduct hands-on training and peer-led workshops to improve understanding and system usability.
Clinical Reliability	• System usability, alignment with clinical judgment, and reduced workload.	• Concerns about the accuracy and reliability of AI recommendations.	• Validate AI systems through randomized trials and real-world applications to ensure reliability.
Credibility and Validation	• Perceived soundness of AI development methodology.	• Limited external validation and generalizability to diverse clinical settings.	• Include external validation and diverse settings to enhance trust and generalizability.
Ethical Considerations	• Credibility of developers and stakeholder engagement .	• Medical liability concerns and fear of errors in clinical decision-making.	• Address liability concerns by clarifying roles and responsibilities and ensuring robust validation of AI tools
Human-Centric Design	• Explainability and interpretability of AI-generated recommendations.	• Concerns about dehumanization of care and its impact on the patient-clinician relationship.	• Design AI as a supportive tool to complement human judgment and maintain humanistic care.
Customization and Control	• Clinicians' ability to customize the system and ask questions.	• Perceived risks, including biases, potential job replacement, and ethical concerns.	• Foster stakeholder collaboration in system design to address biases and ethical considerations effectively

Figure 3: Thematic summary of trust factors in AI-Based CDSS: enablers, barriers, and recommendations(n=27).

3.5 Insights into Healthcare Workers' Trust in AI

The synthesis of the study findings on trust for AI-based CDSS brings seven key thematic insights. (Figure 3). These include 1) System Transparency, which emphasizes the need for clear and interpretable AI-making processes, and 2) Training and Familiarity, which defines the importance of the knowledge sharing of these tools to healthcare workers. 3) System Usability focuses on effective integration into clinical workflow and 4) Clinical Reliability addresses the importance of consistency and accuracy of the system performance. 5) Credibility and Validation describe how the system is meant to be performed in diverse contexts, while 6) Ethical Consideration examines medicolegal liability, fairness and adherence to ethical standard. Finally, 7) Customization and Control reflects the role of the tools to specific clinical needs and ensure healthcare providers maintain decision-making autonomy.

These themes were explored through the enablers and barriers that impact healthcare workers' trust in AI-based CDSS. Under the enablers, healthcare workers cited prior system utilization and validation through randomized controlled trials as a confidence booster in trusting AI systems. Familiarity and training with AI tools further enhanced clinicians' confidence, enabling them to make informed decisions. Observing the system's performance over time, as well as endorsements from colleagues and experts, also contributed to building trust. Additionally, the usability of the system, its alignment with clinical judgment, and its ability to reduce workloads stood out as factors positively influencing trust. Transparency in the AI development process and the perceived credibility of developers played a critical role in fostering confidence. Finally, the explainability and interpretability of AI recommendations, along with the ability to customize the system and seek clarity, provided clinicians with greater control, further enhancing trust.

However, the study revealed several barriers that erode trust in AI-based CDSS. One major issue with AI algorithms is their "black box" nature, which makes recommendations opaque. Clinicians expressed worry about inadequate training, which diminishes their comprehension and self-assurance in efficiently utilizing these systems. Workflow disruptions, perceived threats to professional autonomy, and doubts over the precision and dependability of AI recommendations were also emphasized. Ethical considerations such as the fear of dehumanization in patient care and perceived risks of job replacement added further complexity. Furthermore, there were concerns regarding the efficacy of AI systems due to their inadequate external validation and generalizability to other clinical situations. Lastly, trust was further undermined by unanswered concerns about medical liability, possible biases, and ethical risk

Discussion

The systematic review included 27 studies analyzing healthcare workers' trust in AI-based Clinical Decision Support Systems (CDSS). The article selection process identified 333 records, narrowed to 27 after rigorous screening through inclusion criteria. Most studies were recent (n=12, 44% from 2023) and conducted in hospitalized settings across diverse healthcare workers. Qualitative methods dominated (n=16,59%), with sample sizes ranging from small focus groups to over 1,000 participants. The synthesis of findings highlights seven thematic areas influencing healthcare workers' trust in AI-based CDSS, encompassing both enablers and barriers. The key enablers include prior system validation, transparency, training, usability, and alignment with clinical judgment, while barriers such as algorithmic opacity, inadequate training, workflow disruptions, and ethical concerns undermine trust. Our finding of synthesis of results provides seven thematic areas that facilitate trust in AI-CDSS for healthcare workers. Based on this theme, we provide recommendations for the design and implementation of AI systems that would be trusted and accepted by healthcare practitioners. (Figure 3).

System Transparency

Fostering trust in AI-based CDSS for healthcare workers involves enhancing the transparency of AI algorithms and offering clear practical actionable recommendations for healthcare decision making. According to Nasarian et al., the challenges of using Black-Box models in CDSS are difficult to interpret compared to simpler White-Box models, which offer transparent results without the need for additional parameters. Black-Box models deliver high accuracy, but they lack transparency leading to confusion about their decision-making processes in some instances it might risk to risk of over-trusting these tools, particularly among less experienced clinicians who may lack the expertise to interpret AI outputs effectively.[22] Grey-box models, positioned between these two extremes, provide a balance between complexity and interpretability, assuming they are designed effectively.[39] Interpretability should be incorporated throughout the entire process of the development process, from data pre-processing and model selection to the post-modelling phases. while most existing AI-based CDSS tools concentrate on post-modelling explainability. From data pre-processing and model selection to the post-modeling phases, interpretability should be incorporated into every step of the process. [39] Developers should ensure clarity in the rationale behind recommendations to lessen scepticism about the "black box" aspect of AI systems.

Training and Familiarity

To improve trust in AI-based CDSS, comprehensive training programs on AI tools for healthcare workers play a vital role. This will not only build familiarity with the system but also improve confidence in the AI system. Dlugatch et al., discuss the role of AI impact on healthcare workers. As AI technology surpasses human capabilities, the epistemic authority of medical practitioner's risks being undermined, challenged, or even supplanted. This results in healthcare professionals viewing the AI-based CDSS tools as replacements rather than an assistant. [6] To address these challenges, training programs should educate healthcare workers on how AI systems are developed, including their capabilities, limitations, and potential pitfalls.

System Usability

To improve system usability and alignment with clinical judgment, hands-on training and peer-led workshops should be conducted. This can improve not only the understanding of AI systems but also the usability of these systems. According to the Task Technology-Fit (TTF) theory, users adopt a technology only if it meets their needs and enhances their performance. However, external influences and uncertainty surrounding AI can create biases that either promote or discourage clinicians from using such technologies in the future. [25] This highlights the need for peer-to-peer sharing of experience on AI-based CDSS system.

Clinical Reliability

To ensure clinical reliability, AI systems validate accuracy and reliability through real-world testing, and randomized controlled trials. Micocci et al. discuss that AI systems, like human clinicians, are inherently imperfect, and their role should complement, not replace, the clinician's holistic understanding of each clinical scenario. While AI can provide valuable decision support, the responsibility for diagnostic resilience ultimately lies with the clinician, who can choose to accept or reject AI recommendations. [22]

Credibility and Validation

Trust in AI-based CDSS can be further fostered by external validation of the system on utilisation in diverse settings which might enable us to show the soundness of the AI methodology utilized for the development of this system. Nair et al. mentioned that clinicians are concerned fatigue about from the incorporation of AI-based tools with workflows, particularly when organizations are reluctant to abandon ineffective technologies. It further suggests the crucial role of tool developers to manage thoughtfully and thoroughly validate through diverse settings to avoid risks further burdening healthcare workers. [37]

Human-Centric Design

The importance of human-centric design cannot be overstated in fostering trust in AI-based CDSS. According to Amann et al. raised concern over technology-induced dehumanization in patient care and the impact of AI on the patient-clinician relationship.[13] Sivaraman et al. and Jacobs et al., discuss on important role of the sociotechnical lens in designing AI-based CDSS to ensure the environmental and social factors are integrated in the development of the system.[5,29] Furthermore, Alruwailiili et al., discuss that healthcare profession such as nurses have varying concern about its impact on the human aspect of care and others recognizing its potential benefits. [8] In addition, It highlight that it is important to humanistic elements in designing AI based CDSS as supportive tools that enhance.

Ethical Considerations

Clear guidelines on roles and responsibilities and ensuring robust validation of AI tools will address liability related to ethical concerns which will help alleviate concerns and build trust. Gunasekeran et al. and Jones et al. raised that healthcare workers fear the medicolegal impact of AI-based CDSS systems. [5,25] Providing explicit guidance on the capabilities of AI-based CDSS and delineating the engagement and responsibilities of healthcare workers can further mitigate concerns related to medical errors and liability.

Customization and Control

Trust in AI-based CDSS can be fostered by collaboration, coordination, and meaningful stakeholder engagement in designing the system to eliminate barriers of ethical concern and fear of job replacement among healthcare workers. Chiang et al mentioned the importance of securing support from a variety of stakeholders such as organizational leadership and end-users early in the development process to improve trust in AI-based tools.[12] Ball et al. emphasis a similar point on the role of collaboration and continuous communication through a “human-in-the-loop” approach to incorporate human expertise and address the limitations of AI algorithms.[41] This system allows direct end users such as healthcare workers in the development phase to enable them and understand the assistant role of AI-based CDSS rather than feel like a threat of job replacement. Furthermore, the involvement of different stakeholders will reduce ethical concerns by raising the issue of possible harm to the patient which in-term allow developer to modified and improve trust in the system implementation of the AI-based CDSS.[11] There are certain limitations to this systematic review. Firstly, it exclusively included studies published in English and did not account for AI system studies from non-indexed journals, which would limit the findings' relevance to populations that do not speak English or to unpublished research. Secondly, the quality assessment relied on the CASP checklist and only assessed the qualitative elements of the research included, independent of their design. This could have limited the generalizability of the results from non-qualitative studies. Thirdly, the review was unable to conduct sub-analyses or meta-analyses due to a lack of detailed demographic data, such as the gender or background of each healthcare worker's specific roles. Lastly, the study was formative, with categories and components generated through a subjective process, which may introduce interpretive biases. Despite these limitations, the synthesis and recommendations from the study bridge existing gaps and provide specific themes to explore in future research or integration of AI-based CDSS in the health sector.

Conclusion

Our systemic review of 27 studies reveals seven key themes of healthcare workers’ trust in AI-based Clinical Decision Support Systems (CDSS). We identified the important facilitators like transparency, training, usability, clinical reliability, and alignment with the medical judgment system, as well as constraints such as algorithmic obscurity, insufficient training, and ethical concerns. From these enablers and barriers, we were able to recommend the importance of having clear AI models, thorough training initiatives, practical workshops, and real-life testing of AI systems to boost trust. Furthermore, integrating human-centered design and addressing ethical aspects are crucial for ensuring that AI tools enhance rather than hinder the patient-healthcare worker relationship. Despite some limitations, such as the exclusion of non-English studies and the focus on qualitative aspects, the synthesis offers valuable recommendations for the design and implementation of AI-based CDSS that can foster trust and acceptance among healthcare workers. The identified thematic areas establish a foundation for forthcoming research and development of AI-based tools to ensure that AI-based CDSS are both efficient, reliable and trustworthy for healthcare workers.

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Supplementary materials

Figure S1: The characteristic of included studies (n=27)

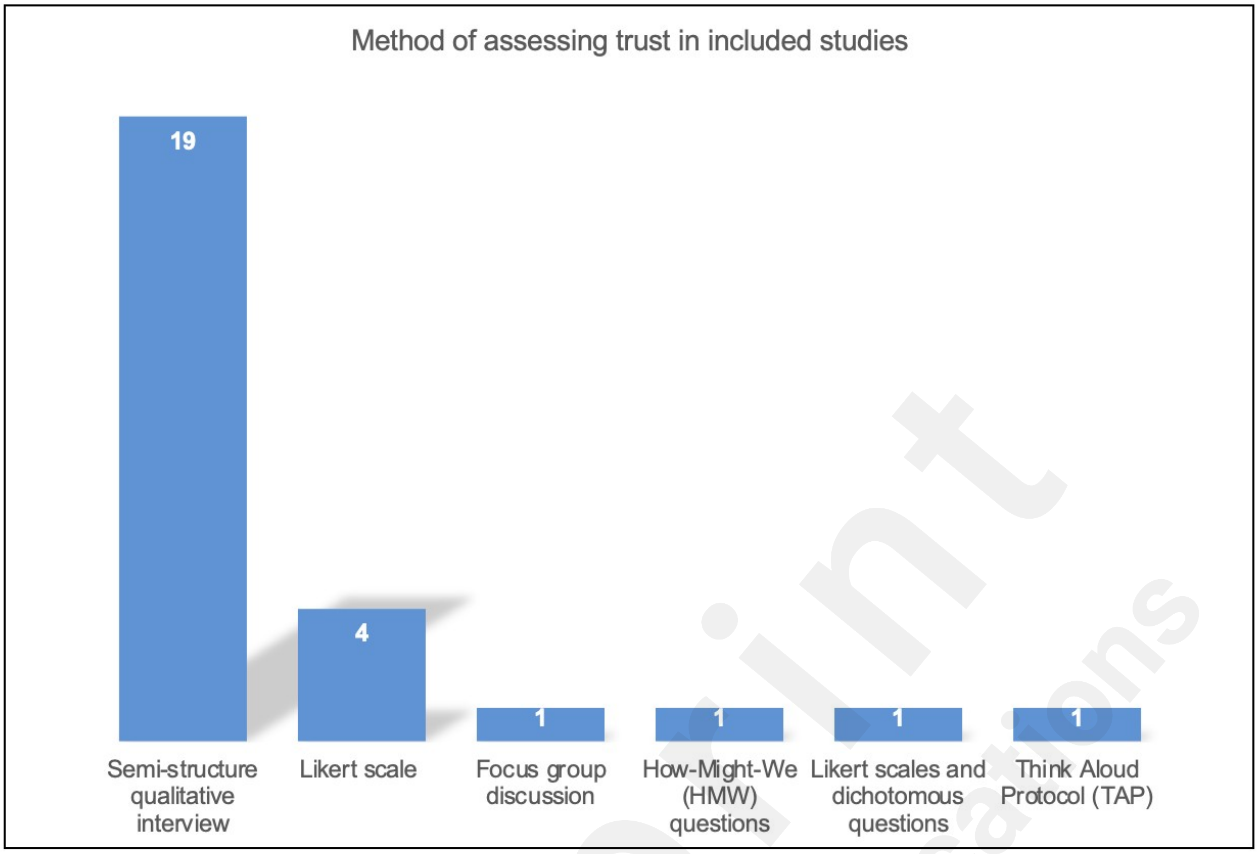

Figure S2: Method for evaluating Trust in the included study (n=27)

Table S1: PRISMA 2020 Checklist for systemic review for this study

Section and Topic	Item #	Checklist item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	1
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	2
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	3-4
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	4
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	5
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	5
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	5
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	5
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	5-6
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	5-6
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	5-6
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	6-7
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	6
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	6
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	6
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	6
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	N/A

	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	N/A
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	N/A
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	6
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	6
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	7-8
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	7-8
Study characteristics	17	Cite each included study and present its characteristics.	9-12
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	8-9
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	10-12
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	8-12
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	N/A
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	N/A
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	N/A
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	9
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	13
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	14-15
	23b	Discuss any limitations of the evidence included in the review.	15
	23c	Discuss any limitations of the review processes used.	15
	23d	Discuss implications of the results for practice, policy, and future research.	15
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	1
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	1
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	1
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	1
Competing interests	26	Declare any competing interests of review authors.	1

Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	1

Table S2: Mixed Methods Appraisal Tool (MMAT) of included studies (n=27)

	SCREENING QUESTIONS		3. NON-RANDOMIZED STUDIES				
Study ID	S1. Are there clear research questions?	S2. Do the collected data allow to address the research questions?	3.1. Are the participants representative of the target population?	3.2. Are measurements appropriate regarding both the outcome and intervention (or exposure)?	3.3. Are there complete outcome data?	3.4. Are the confounders accounted for in the design and analysis?	3.5. During the study period, is the intervention administered (or exposure occurred) as intended?
Jacobs et al.2021[20]	Yes	Yes	Yes	Yes	Yes	Yes	Can't Tell
Wang et al.2021[21]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Micocci et al.2021[22]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Henry et al.2022[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Choudhury et al.2022[23]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gunasekeran et al.2022[24]	Yes	Yes	Yes	Can't Tell	Yes	Yes	Can't Tell
Choudhury et al.2022[25]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ankolekar et al.2022[26]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stacy et al. 2022 [2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Choudhury et al.2022[27]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Van Biesen et al.2022[28]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sivaraman et al.2023[29]	Yes	Yes	Yes	Yes	Yes	Yes	Can't Tell
Amann et al.2023[13]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bach et al.2023[30]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Burgess et al.2023[31]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Liu et al.2023[32]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Anjara et al.2023[33]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jones et al.2023[5]	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes
Liu et al.2023[34]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
York et al.2023[35]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chiang et al.2023[12]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Liaw et al.2023[36]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nair et al.2023[37]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yoon et al.2024[7]	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes
Zheng et al.2024[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Elareed et al.2024[38]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vereschak et al.2024[11]	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table and figure

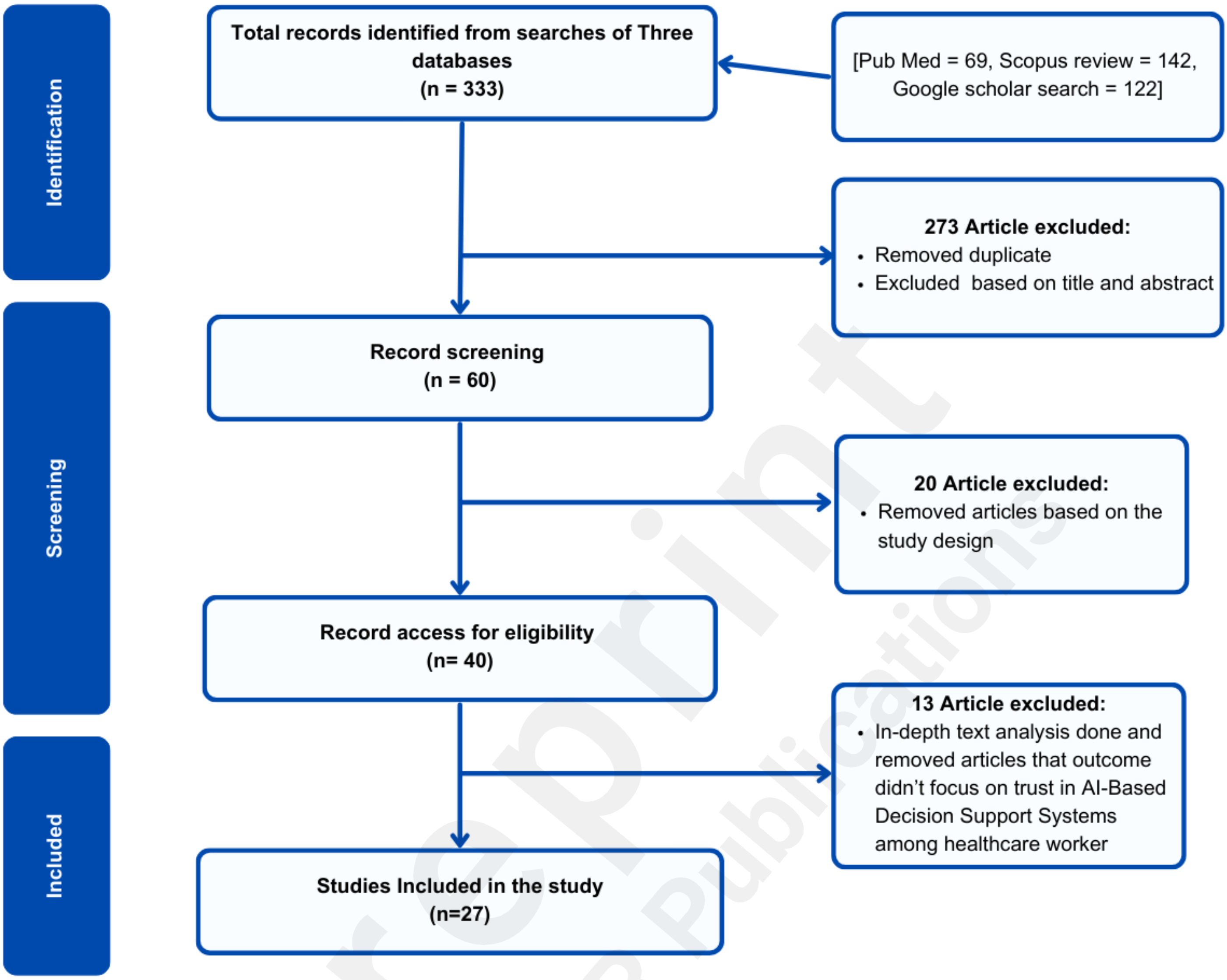

Figure 1: Flow Chart for Study Selection

Table 1: Critical Appraisal Skills Programme (CASP) Responses for Each Study Included in the Analysis (n = 23)

Study ID (Year)	1. Was there a clear statement of the aims of the research?	2. Is a qualitative methodology appropriate?	3. Was the research design appropriate to address the aims of the research?	4. Was the recruitment strategy appropriate to the aims of the research?	5. Was the data collected in a way that addressed the research issue?	6. Has the relationship between researcher and participants been adequately considered?	7. Have ethical issues been taken into consideration?	8. Was the data analysis sufficiently rigorous?	9. Is there a clear statement of findings?	10. How valuable is the research?
Jacobs et al.2021[20]	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes	Yes	Can't Tell	Semi-valuable
Wang et al.2021[21]	Yes	Yes	No	Yes	Yes	Can't Tell	Yes	Can't Tell	Yes	Valuable
Micocci et al.2021[22]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Henry et al.2022[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Choudhury et al.2022[23]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Gunasekeran et al.2022[25]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes	Semi-valuable
Choudhury et al.2022[26]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Ankolekar et al.2022[27]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Van Biesen et al.2022[28]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Sivaraman et al.2023[29]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes	Semi-valuable
Amann et al.2023[13]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes	Valuable
Bach et al.2023[30]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes	Valuable
Burgess et al.2023[31]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Liu et al.2023[32]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Anjara et al.2023[33]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Jones et al.2023[5]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Very valuable
Liu et al.2023[34]	Yes	Yes	Can't Tell	Yes	Yes	Yes	Yes	Yes	Yes	Semi-valuable
Chiang et al.2023[12]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Liaw et al.2023[36]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Nair et al.2023[37]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Yoon et al.2024[7]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Valuable
Zheng et al.2024[4]	Yes	Yes	Yes	Can't Tell	Yes	Yes	Yes	Can't Tell	Yes	Semi-valuable
Vereschak et al.2024[11]	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes	Can't Tell	Yes	Valuable

*Choudhury et al.2022[25],Stacy et al.2022[2],York et al.2023[35],Elareed et al.2024[38] are cross sectional quantiative study are not included in the CSAP analysis.

Study ID (Year)	Geography	Setting	Study Design	Study Population (n of participant)	Method of evaluating trust	Description of AI Based CDSS	Evaluation of healthcare worker trust factor for AI-CDSS
Jacobs et al.(2021) [20]	Multinational United Arab Emirates, Singapore, and Hong Kong.	Hospital	Qualitative Study	Physicians(n=9),nurse practitioners (n=1) who are Primary care providers (PCPs)	Semi-structure qualitative interview	Machine learning (ML) models to provide prognostic predictions and treatment selection support for major depressive disorder (MDD).	▪ Previous system utilization, including its use by other clinicians and validation through randomized controlled trials. ▪ Level of training received
Wang et al. (2021) [21]	China	Primary Care	Qualitative Study	Clinicians with experties in both western and Traditional Chinese medicine (n=22)	Semi-structure qualitative interview	Deep learning and knowledge graph based AI-CDSS system ("Brilliant Doctor")	▪ The "black box" nature of the AI algorithm, lacking transparency in its recommendations. ▪ Perceived threat to professional autonomy and decision-making, with the "Click-Through" approach disrupting workflows. ▪ Insufficient training on system features and functionality, reducing clinicians' understanding and
Micocci et al.(2021) [22]	United Kingdom	Primary care	Mixed Method Study	General practitioners (n=50)	Semi-structure qualitative interview	AI system designed to support the diagnosis of dermatological conditions.	▪ Accuracy of the AI system, ▪ GPs' familiarity with AI, ▪ Previous experiences with similar technologies.
Henry et al. (2022) [3]	United States	Hospital	Qualitative Study	Physicians (n=13) and Nurse (n=7) worked at emergency department, critical care, and general ward	Semi-structure qualitative interview	Machine learning-based system called Targeted Real-time Early Warning System(TREWS) for to alert sepsis detection,evaluate patients, and manage treatment.	▪ Direct experience with the system and observing its behavior over time ▪ Endorsement and recommendations from colleagues and experts ▪ Understanding the system's development and validation process ▪ Ability to customize the system and ask questions about its design
Choudhury et al. (2022) [23]	United States	Hospital	Qualitative Study	Clinicians involved in decision-making for blood transfusions (n=10)	Semi-structure qualitative interview	AI-based Blood Utilization Calculator (BUC) designed to optimize blood transfusion practices	▪ Workload, ▪ Usability, ▪ Impact on decision-making, and ▪ Alignment with clinical judgment
Gunasekeran et al. (2022) [24]	Multinational more than 70 countries	Primary Care and Hospital	Mixed Method Study	Ophthalmologists (n=1,176)	Likert scales and dichotomous questions	Various AI based assistive tools, clinical decision support applications relevant to ophthalmology for detection and management of eye diseases such as diabetic retinopathy, glaucoma, age-related macular degeneration (AMD), and cataract	▪ Usability, ▪ Acceptable error levels and concerns over medical liability ▪ Professional acceptance, ▪ Organizational support
Choudhury et al. (2022) [25]	United States	Hospital	Mixed Method Study	Clinicians who utilized Blood Utilization Calculator (BUC) (n= 119)	Semi-structure qualitative interview	AI-based Blood Utilization Calculator (BUC)	▪ Perception of AI, ▪ Expectancy(effort and performance expectancy), ▪ Perceived risk.

Study ID (Year)	Geography	Setting of the study	Study Design	Study Population (n of participant)	Method of evaluating Trust	Description of AI Based CDSS	Evaluation on Trust factor for AI-CDSS
Ankolekar et al. (2022) [26]	The Netherlands	Hospital	Mixed Method Study	Non-small cell lung cancer (NSCLC) patients (n=257) treated at Single radiotherapy clinic and Lung cancer specialists (n=9)	Semi-structure qualitative interview	Clinical Decision Support Systems (CDSSs) that support shared decision-making (SDM) for prognosis of lung cancer	▪ Lack of external validation, ▪ Clinician experience, ▪ Perceived usefulness of CDSSs.
Stacy et al. (2022) [2]	United States	Hospital	Quantative Study	The healthcare workers involved include clinicians who manage patients with atrial fibrillation (n= 33)	Likert scale (0-5)	2-stage machine learning (ML) model-based tool QRhythm model that identify the optimal rhythm management strategy	▪ Accuracy of the AI recommendations, ▪ Transparency of the AI processes, ▪ Clinicians' previous experiences with AI.
Choudhury et al. (2022) [27]	United States	Hospital	Quantative Study	Physicians resident and fellow (n=111) and nurses(n=8)	Semi-structure qualitative interview	AI-based decision support system known as the Blood Utilization Calculator (BUC).	▪ Perceived risk, ▪ Expectancy, ▪ Acceptance of AI system
Van Biesen et al.(2022) [28]	Belgium.	Hospital	Qualitative Study	Physician(n=30)	Semi-structure qualitative interview	AI based Clinical Decision Support Systems (CDSS) integration into into electronic healthcare records (EHR).	▪ Transparency, ▪ Reliability, ▪ Perceived accuracy of the CDSS.
Sivaraman et al. (2023) [29]	United States	Hospital	Mixed Method Study	ICU clinicians(n=24)	Likert scale (0-10)	Reinforcement learning (RL) model based tool called the "AI Clinician" to provide interpretable treatment recommendations for sepsis patients in the ICU.	▪ The credibility of the developers who created the AI. ▪ The perceived soundness of the methodology used to develop the AI.
Amann et al.(2023) [13]	Germany and Switzerland	Primary Care	Qualitative Study	Healthcare professional including Physician (n=7), Occupational therapist (n=1),Physiotherapist (n=4),Neuropsychologist (n=2) and Stroke survivor (n = 14), Family members (n = 6)	Semi-structure qualitative interview	AI based clinical decision support systems (CDSS) to act asadministrative assistants for routine tasks, aid in diagnisis and teatment of complex cases of stroke	▪ Concerns about AI causing dehumanization in healthcare and eroding patient-clinician trust.
Bach et al. (2023) [30]	Denmark	Hospital	Qualitative Study	Ophthalmologists (n=7)	Semi-structure qualitative interview	AI system for detecting diabetic retinopathy (DR) by analyzing colour-coded assessment of fundus images and optical coherence tomography (OCT) scans to indicate the presence and severity of lesions.	▪ Accuracy and reliability of AI assessments, including its ability to minimize false positives/ negatives. ▪ Failure of the AI system to detect severe abnormalities beyond its intended scope. ▪ Limitations in the AI system's performance due to factors like image quality.

Study ID (Year)	Geography	Setting of the study	Study Design	Study Population (n of participant)	Method of evaluating Trust	Description of AI Based CDSS	Evaluation on Trust factor for AI-CDSS
Burgess et al. (2023) [31]	United States	Primary Care and Hospital	Qualitative Study	Primary Care Provider (MD/DO)(n=14), Nurse Practitioner (NP) /Physician Assistant(PA) (n=18),Endocrinologist (MD/DO) (n= 5), Pharmacist(n=2),Internal Medicine (MD/DO)(n=2)	Semi-structure qualitative interview	Machine learning model trained on a large dataset of 141,625 patients with Type 2 diabetes mellitus to optimize medication selection and predict the relative efficacy of different drug regimens for reducing hemoglobin A1c levels.	▪ Comparison of AI-based CDS systems to the "gold standard" of randomized controlled trials in generating insights. ▪ Clinicians' understanding of how insights are calculated and what outcomes the system optimizes for. ▪ Clinicians' trust in the data, such as claims data, used to train the AI model.
Liu et al. (2023) [32]	United States	Hospital	Comparative Evaluation	Clinicans(n=5)	Likert scale (0-5)	ChatGPT (a large language model by OpenAI)to improve CDSS alerts in electronic health records	▪ Understanding, ▪ Relevance and clarity of AI suggestions ▪ Usefulness, ▪ Acceptance, ▪ Workflow impact, ▪ Redundancy, ▪ Potential for bias
Anjara et al.(2023) [33]	Spain	Hospital	Qualitative Study	Oncologists with specialize training in treating lung cancer (n=10)	Think Aloud Protocol (TAP)	Explainable AI (XAI) system using a graph representation learning model for lung cancer relapse prediction	▪ Perception of clarity,credibility and utility, ▪ Information overload and the presence of example-based explanations ▪ System's alignment with clinical decision-making needs
Jones et al. (2023) [5]	Multinational Belgium, the UK, Italy, and China	Primary Care and Hospital	Qualitative Study	Physician(n=24)	Semi-structure qualitative interview	Artificial Intelligence (AI)-powered CDSS in the context of ophthalmology (i.e., clinical care specialising in eye and vision care)	▪ Perception on clinicians' control over decision-making, ▪ Medical errors, and legal responsibility/liability
Liu et al. (2023) [34]	United States	Hospital	Qualitative Study	Critical Care Pharmacists (n=13)	Semi-structure qualitative interview	AI-based clinical decision support system (CDSS) to facilitate vancomycin dosing for hospitalized patients.	▪ Accuracy of recommendations, ▪ Rationale behind dosing, and ▪ Transparency of the AI model. ▪ Black-box nature of AI recommendations, complexity of algorithms
York et al. (2023) [35]	United Kingdom	Hospital	Quantative Study	Clinician with different level of training including FY1 (n=108), FY2 (n=28) ,ST/CT 1–2 (n=35),ST3/SpR or Above (n=49) and Medical Student (n=77)	Semi-structure qualitative interview	AI based CDSS applied in development skeletal radiography for trauma.	▪ Knowledge of AI, ▪ Confidence in interpreting radiographs ▪ Level of training and experience of clinican,
Chiang et al.(2023) [12]	United States	Primary Care	Qualitative Study	Ophthalmologists and optometrists from University of California San Diego (n=10)	Semi-structure qualitative interview	AI-based decision support system (DSS) for predicting the risk of cardiovascular disease.	▪ Accuracy, ▪ Reliability, ▪ Usefulness.

Study ID (Year)	Geography	Setting of the study	Study Design	Study Population (n of participant)	Method of evaluating Trust	Description of AI Based CDSS	Evaluation on Trust factor for AI-CDSS
Liaw et al. (2023) [36]	United States	Primary Care and Hospital	Mixed Method Study	Physician(n=24)	Semi-structure qualitative interview	Diabetes Artificial Intelligence Prediction Tool to predict the risk of poor diabetes control	▪ Accuracy of the tool, ▪ Transparency of the AI processes, ▪ The clinicians' familiarity with AI.
Nair et al. (2023) [37]	Sweden	Primary Care and Hospital	Qualitative Study	Physician (n=14), Nurse practitioner/Nurse/Physician assistant (n=3), Behavioural specialist (n=1),Social worker(n=1),Other staff including front desk, administrative, or medical assistant (n=3)	Semi-structure qualitative interview	Artificial Intelligence-Based Decision Support Tool to Reduce the Risk of Readmission of Patients With Heart Failure	▪ Stakeholder engagement, ▪ Perceived benefits, ▪ Transparency
Yoon et al. (2024) [7]	Singapore	Hospital	Qualitative Study	Clinicans(n=13) in 4 focusing group	Focus group discussion	AI-enabled Prescription Advisory (APA) tool.	▪ Interpretability of AI-generated recommendations, ▪ Transparency of the system, ▪ Clinicians' previous experiences with AI.
Zheng et al. (2024) [4]	United States	Hospital	Qualitative Study	Clinicans(n=14) who encountered pediatric asthma patients at 2 outpatient facilities	How-Might-We (HMW) questions	Machine learning-based clinical decision support system (CDSS) as Asthma Guidance and Prediction System (A-GPS) for asthma management.	▪ Accuracy, ▪ Reliability, ▪ Explainability of the AI tool.
Elareed et al.(2024) [38]	Egypt	Hospital	Quantative Study	Physician(n=249)	Likert scale (0-5)	General AI applications in healthcare, including potential applications in disease management and treatment	▪ Job replacement by AI, ▪ Perceived usefulness, ▪ Reduction in workload, ▪ Impact on physician-patient relationship ▪ AI to handle patient data responsibly
Vereschak et al. (2024) [11]	France and Germany	Primary Care	Qualitative Study	AI practitioners which include Bio. Eng. & Research (n=1),other(n=6) and AI decision subjects which include medical student(n=1),other (n=6)	Semi-structure qualitative interview	AI-assisted decision-making systems, particularly those using machine learning techniques.	▪ AI transparency, ▪ AI literacy, ▪ interpersonal relationships between stakeholders (developer and user), the complexity of tasks.

Table 2: Study characteristics and evaluation of healthcare worker trust factor for AI-CDSS(n=27)

Theme	Enablers	Barriers	Recommendations
System Transparency	• Prior system utilization and validation through randomized controlled trials.	• Lack of transparency in AI algorithms ("black box" nature) and unclear recommendations.	• Enhance transparency by using interpretable algorithms and providing clear, actionable recommendations.
Training and Familiarity	• Training and experience with the AI system, improving confidence and familiarity.	• Insufficient training on system functionality, reducing understanding.	• Provide comprehensive training programs to build user familiarity and confidence in the AI system.
System Usability	• Direct observation of system behavior and colleague endorsements.	• Perceived threat to professional autonomy and workflow disruption ("Click-Through" approach).	• Conduct hands-on training and peer-led workshops to improve understanding and system usability.
Clinical Reliability	• System usability, alignment with clinical judgment, and reduced workload.	• Concerns about the accuracy and reliability of AI recommendations.	• Validate AI systems through randomized trials and real-world applications to ensure reliability.
Credibility and Validation	• Perceived soundness of AI development methodology.	• Limited external validation and generalizability to diverse clinical settings.	• Include external validation and diverse settings to enhance trust and generalizability.
Ethical Considerations	• Credibility of developers and stakeholder engagement .	• Medical liability concerns and fear of errors in clinical decision-making.	• Address liability concerns by clarifying roles and responsibilities and ensuring robust validation of AI tools
Human-Centric Design	• Explainability and interpretability of AI-generated recommendations.	• Concerns about dehumanization of care and its impact on the patient-clinician relationship.	• Design AI as a supportive tool to complement human judgment and maintain humanistic care.
Customization and Control	• Clinicians' ability to customize the system and ask questions.	• Perceived risks, including biases, potential job replacement, and ethical concerns.	• Foster stakeholder collaboration in system design to address biases and ethical considerations effectively

Figure 3: Thematic summary of trust factors in AI-Based CDSS: enablers, barriers, and recommendations(n=27).

Supplementary materials

Figure S1: The characteristic of included studies (n=27)

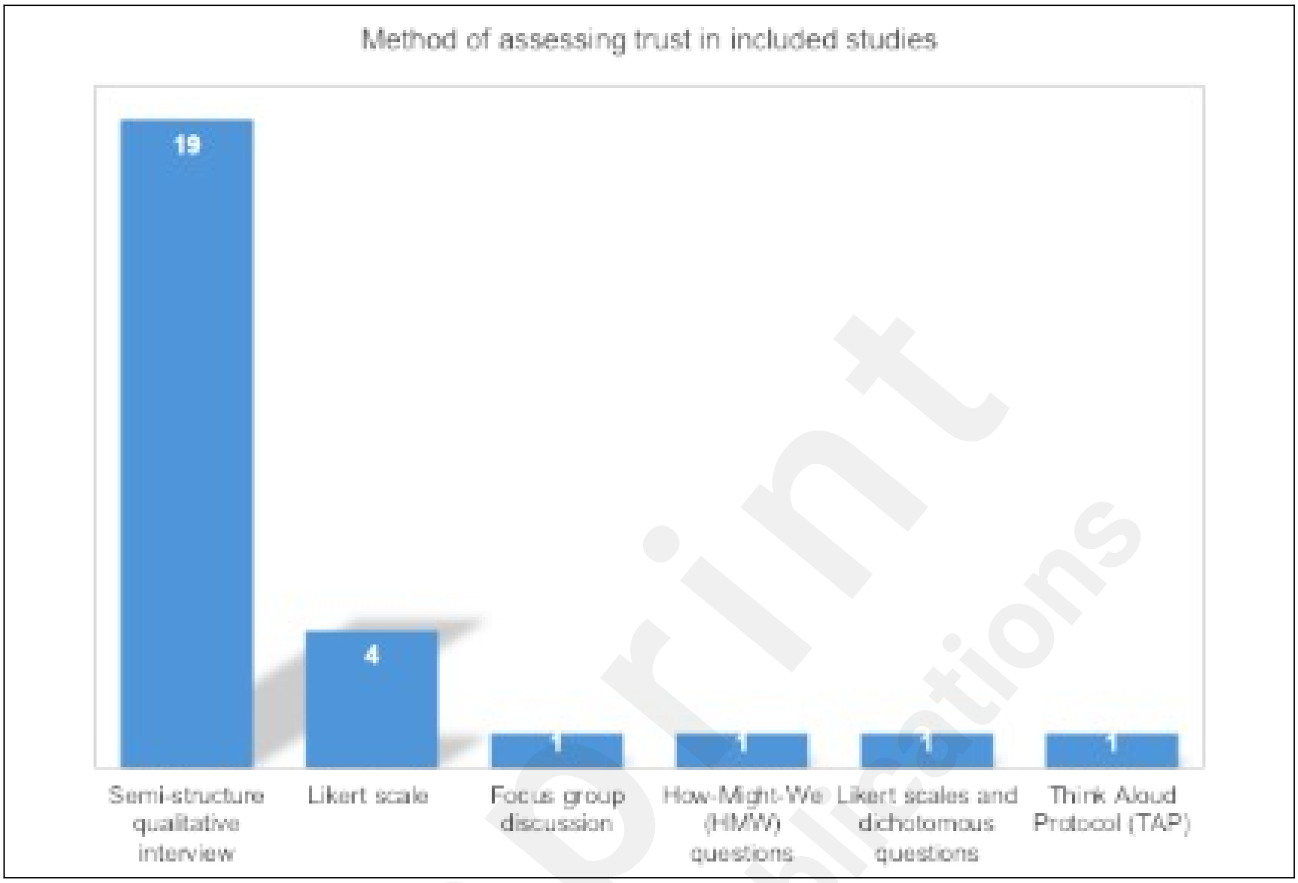

Figure S2: Method for evaluating Trust in the included study (n=27)

Section and Topic	Item #	Checklist item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	1
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	2
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	3-4
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	4
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	5
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	5
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	5
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	5
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	5-6
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	5-6
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	5-6
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	6-7
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	6
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	6
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	6
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	6
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	N/A
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	N/A
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	N/A
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	6
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	6

Section and Topic	Item #	Checklist item	Location where item is reported
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	7-8
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	7-8
Study characteristics	17	Cite each included study and present its characteristics.	9-12
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	8-9
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	10-12
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	8-12
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	N/A
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	N/A
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	N/A
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	9
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	13
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	14-15
	23b	Discuss any limitations of the evidence included in the review.	15
	23c	Discuss any limitations of the review processes used.	15
	23d	Discuss implications of the results for practice, policy, and future research.	15
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	1
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	1
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	1
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	1
Competing interests	26	Declare any competing interests of review authors.	1
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	1

From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71. This work is licensed under CC BY 4.0. To view a copy of this license, visit https://creativecommons.org/licenses/by/4.0/

Table S1: PRISMA 2020 Checklist for systemic review for this study

Table S2: Mixed Methods Appraisal Tool (MMAT) of included studies (n=27)

Study ID	SCREENING QUESTIONS		3. NON-RANDOMIZED STUDIES				
	S1. Are there clear research questions?	S2. Do the collected data allow to address the research questions?	3.1. Are the participants representative of the target population?	3.2. Are measurements appropriate regarding both the outcome and intervention (or exposure)?	3.3. Are there complete outcome data?	3.4. Are the confounders accounted for in the design and analysis?	3.5. During the study period, is the intervention administered (or exposure occurred) as intended?
Jacobs et al.2021[20]	Yes	Yes	Yes	Yes	Yes	Yes	Can't Tell
Wang et al.2021[21]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Micocci et al.2021[22]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Henry et al.2022[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Choudhury et al.2022[23]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gunasekeran et al.2022[24]	Yes	Yes	Yes	Can't Tell	Yes	Yes	Can't Tell
Choudhury et al.2022[25]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ankolekar et al.2022[26]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stacy et al. 2022 [2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Choudhury et al.2022[27]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Van Biesen et al.2022[28]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sivaraman et al.2023[29]	Yes	Yes	Yes	Yes	Yes	Yes	Can't Tell
Amann et al.2023[13]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bach et al.2023[30]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Burgess et al.2023[31]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Liu et al.2023[32]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Anjara et al.2023[33]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jones et al.2023[5]	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes
Liu et al.2023[34]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
York et al.2023[35]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chiang et al.2023[12]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Liaw et al.2023[36]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nair et al.2023[37]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yoon et al.2024[7]	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes
Zheng et al.2024[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Elareed et al.2024[38]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vereschak et al.2024[11]	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Study ID	Outcome related to trust in AI based CDSS	Quotes / Quantitative result
Jacobs et al.2021[20]	• Decision support tools (DSTs) need to account for the broader healthcare sociotechnical system, including clinical processes, patient preferences, resource constraints, and existing domain knowledge. • Current trends in explainable AI may be inappropriate for clinical environments, and new approaches are needed to design DSTs for real-world medical systems.	• “I think the biggest thing is just getting behind how you validated your data, how you validated your model ...I don’t know if you necessarily need to get into super nitty-gritty details” - P6 • “If a major medical society is sort of putting this forth,my colleagues are using it, and I hear people saying that it’s that it works, then I am comfortable with it.” - P7 • “If you could show that patients have a better response to treatment by use of the algorithm, that would be amazing. If you can show that patients actually are more likely to adhere to treatment, that would be important as well, or that patients are less likely to develop adverse side effects that leads to stopping medications. It would be nice to do a trial with outcomes like that.” - P9
Wang et al.2021[21]	• The study found that the AI-CDSS system faced various challenges in being adopted by clinicians in the rural Chinese context, including misalignment with the local workflow and context, technical limitations and usability barriers, and issues related to transparency and trustworthiness of the AI system.	• “The medicine description provided by AI-CDSS, such as how much to take, is not always accurate. Take’tamsulosin’ as an example, it is used to treat prostate issues. AI-CDSS says take one pill per day so Ifollowed its guideline. But some older adults have very serious prostate problem, just taking one pill isnot effective. Some of them decided to take two pills per day without consulting us, but they said it workswell. Therefore, I went down to the pharmacy and checked the description of this medicine, and foundthat it says take one to two pills per day instead of strictly taking one.” • "Doctors and patients are friends, we usually have a good relationship. It is possible that the prescriptionwe gave to the patient is not working. I’ll just recommend them to go to higher-tier hospitals for furtherexamination. They understand us too, it is not like I intentionally gave you a wrong medicine or made youto be uncomfortable. [...] But if the AI system [directly] gives him a prescription that is not working, orunfortunately it causes some adverse events. The patient must complain about it. And more importantly,there is an accountability issue in there. Who is responsible for that?”"
Micocci et al.2021[22]	• AI has the potential to assist GPs, building trust through transparency and education is crucial for its successful integration.	• When the AI provided erroneous information, only 10% of the GPs were able to correctly disagree with the indication of the AI in terms of diagnosis (d-AIW M: 0.12, SD: 0.37), and only 14% of participants were able to correctly decide the management plan despite the AI insights (d-AIW M:0.12, SD: 0.32)
Henry et al.2022[3]	• Clinicians did not view the ML-based system as a replacement for their clinical judgment, but rather as a partner that augmented their diagnostic and treatment management processes. • Clinicians developed trust in the ML-based system through a variety of mechanisms, including direct	• “I think we try to get them in front of a provider a little bit quicker or get some of the stuff started out in triage.” • “For clinicians, I think just understanding [that] this is a machine learning tool and it does data mining, I think will be more than enough.” • “I’d want to understand the population it was derived from… and then I’d want to see the population that they validated it on afterwards…whether that group looks like the patients that I’m treating.” • “I need to understand the motivation behind that tool because when I apply that tool, I’m

	needs. • Some barriers to the use of ML in medicine remain, such as concerns about over-reliance on automated systems and the potential for standardization of care.	• "I think [that] there are a lot of people, frankly, that will quickly default to having a tool tell them what to do and stop assessing, and I hope that's not true, but I've seen it happen."
Choudhury et al.2022[23]	• BUC was beneficial for standard care patients but posed usability challenges in complex cases, highlighting the importance of a user-centered design	• "I think it's helpful because it explains like hemoglobin of several patients. If a patient has low platelets, you might have a higher hemoglobin goal. Um, so it's nice to have that spelled out for you, so you don't have to look it up elsewhere and then come back and make the decisions." • "I like having the guidelines built-in so that you know when you're doing something that is, um, the, that is the guideline or evidence based. And, you know, when you are deviating from that and therefore hopefully have a good reason for it and are at least cognizant of the fact that you're deviating." • "If BUC is telling me that I'm ordering too much blood, I go back, thinking, okay, does the patient need this much blood? So, it's more like I'm ensuring I follow the standard of care, except for those exceptional patient circumstances."
Gunasekeran et al.2022[24]	• AI has strong potential as an assistive tool in ophthalmology, but additional support for organizational adoption and training is recommended to address barriers. COVID-19 pandemic was found to catalyze interest in AI adoption due to reduced provider-patient contact and enhanced screening needs.	• Many participants indicated that they strongly agree or agree that clinical AI will facilitate improvements in accessibility (84.7%, n = 785/927), affordability (61.9%, n = 574/927), and quality (69.4%, n = 643/927) in eye care services
Choudhury et al.2022[25]	• Emphasized the benefits of AI technology and addressing risk perceptions can improve clinicians' intent to use AI-based systems.	• "the greatest challenge to AI in these healthcare domains is not whether the technologies will be capable enough to be useful, but rather ensuring their adoption in daily clinical practice"
Ankolekar et al.2022[26]	• CDSSs have the potential to support shared decision-making in lung cancer treatment, but require external validation and integration into clinical practice.	• '[Models] must naturally be validated on large groups, and clinical factors must be considered. And even then, there is still a large variation in a result of such a model. So yes, it still remains difficult'. (Clinician 8)
Stacy et al. 2022 [2]	• Enhancing transparency and providing education about AI systems can improve trust among healthcare professionals.	• Trust in the app similarly varied. To the prompt "I trust the recommendations provided by the QRhythm app," 1 provider (17%) somewhat disagreed, 2 (33%) were neutral, and 3 (50%) somewhat agreed
Choudhury et	• The mediating effect of trust (the direct negative association between 'risk	• Clinicians had moderately high 'trust' in BUC with a mean of 5.64. Clinicians also perceived the BUC as low risk, with a mean of 1.89 out of 5. Expectancy and intention to use BUC

	positive association between ‘trust’ and ‘intent to use’ BUC, and indirect negative association of ‘risk perception’ and ‘intent to use’ BUC) imply that increasing trust in BUC, in general, can result in low-risk perception and high willingness to use the system, both of which are potential precursors to ‘automation bias’.	trust the BUC." – (T1) [min 1-max 7,mean 5.66, Sd 0.92] “I trust the information I receive from the BUC.” – (T2) [min 1-max 7,mean 5.63, Sd 0.92]
Van Biesen et al.2022[28]	• The correctness of its advice absolute truth and certainty are rare in medical conditions. Therefore, it is essentialthat a CDSS can express this uncertainty in itsadvice. • CDSS can produce advice on request, but also in anunsolicited (automated) fashion while working with the system. This can interrupt the workflow, meaningthe user is distracted from her activity and needsto perform an unplanned action.	• “Not only the system, but also medicine [as a fieldof study] has to have a certain level of accuracy [inorder for these AI to function properly]. ” (R1) • “the quality and performance should be tested in arandomized trial” (R13) • “these (CDSS) should be peer reviewed, how elsewould I know their performance? ” (R12) • “if we start using them (CDSS), our confidence willgrow as we will better understand what triggers thesystem and what makes it go astray” (R3) • “In medicine it is always importantto doubt. … Our domain [medicine] is very hard toautomate, because it is difficult to reduce it to welldefinedpatterns. With us there are way too manydimensions to take into account.” (R23). • “[Unlike with medical decisions] I do trust the AI when it takes administrative decisions. Those do not look difficult to me. ” (R14). • “[Administrative tasks] are trivial. They are very easy and should, obviously, be integrated [in the system]. (R6)
Sivaraman et al.2023[29]	• Providing clinicians with explanations of AI recommendations increased their perceived usefulness of the AI and confidence in their own decisions. • Clinicians engaged in a nuanced process of selectively incorporating aspects of the AI's recommendations into their decision-making, rather than simply accepting or rejecting the recommendations. • AI systems could be designed to better support clinicians' negotiation of recommendations by highlighting the most important aspects rather than providing a single, rigid	• “I would not have guessed that the decision or the recommendation was being based on something like a BUN [blood urea nitrogen] change. I assumed it was based on the CVP [central venous pressure], and I don’t think that CVP was considered in [the Feature Explanation chart]. And so it kind of makes you try and guess where the recommendations are coming from, and you spend a little bit more mental energy thinking about that.” • AI usefulness - (F (2,69) = 4.251, p = 0.03), text only condition (delta =0.83 , 95% CI [0.24,1.43],p = 0.018), alteranative treatment(delta = 0.75,95%CI [-0.03,1.53],p=0.12)

al.2023[13]	potential roles for medical AI in stroke care, from administrative assistant to fully autonomous system • While participants were generally positive about the potential benefits of medical AI, they also cautioned against viewing it as a panacea that will solve all healthcare problems. • Participants emphasized the importance of relational aspects in healthcare and expressed concerns that medical AI could negatively impact the doctor-patient relationship.	future, which can make any programs more precise, which can set the focus more precisely for an evaluation and then a recommendation as to what is good for the individual in order to get well again [after suffering a stroke].” (Pat8) • "I just hope from something like that, so from computer programs or algorithms actually, that assumptions that we, I think, always make in everyday life as humans—because someone is old or somehow looks like that or is old on paper—will be less incorporated [in the decisionmaking process], so this subjectivity." (HCP13) • “I would rather assume that the problem is not that you have the wrong options [provided by the AI system], but rather that you generally lack the resources to properly implement the options that are available. So, for example, sufficient physiotherapy in the outpatient area or something like that. That a computer-aided decision or simulation of different options would not change anything about the problem that already exists. would not change the problem that already exists.” (HCP4) • “Well, one shouldn’t overestimate AI, I have a feeling. It’s not the solution.. [. . .] Nobody is thinking, should we really do this? Do we need to do that? And what are the long-term consequences? And that’s where I think we tend to go too far, especially in healthcare, and by [introducing] potential solutions or improvements often we create new problems, which you can’t really anticipate.” (HCP0) • “I can imagine that there is a danger that health professionals will rely more on artificial intelligence and perhaps fixate on it and pay less attention to the patients and their wishes.”(HCP8)
Bach et al.2023[30]	• Ophthalmologists were aware of cognitive biases like anchoring bias when using AI-powered decision support systems, but were concerned about the impact of bias mitigation strategies on workflow efficiency. • Ophthalmologists had mixed expectations about the potential benefits of bias mitigation strategies on diagnostic accuracy, with some believing their accuracy could not be further enhanced and others seeing potential benefits, especially for less experienced clinicians. • Ophthalmologists expressed a desire for more capable AI systems that could detect a wider range of abnormalities,	• “The AI system does not performwell enough for me to ignore the green images”. P1 (ophthalmologists) • there if all the images are green” (P5), and “I look through all of the images, and if it [the AI system] says they are all green, well then I go through the images slightly faster” (P5). Both P1 and P4 expressed a similar sentiment, with P4 specifically pointing to an increased sense of confidence when she agreed with the AI system: • “[the green labels] just give me a feeling of security” • “the colours do not matter, unless it’s all green, in which case I go through them quickly” • “If I have some that are yellow or red—and it really doesn’t matter whether they are one or the other—then I look at them very carefully”.

	open to bias mitigation techniques.	
Burgess et al.2023[31]	• The paper provides a set of 6 design principles for developing effective AI-supported CDS systems. 1. Account for what is possible and realistic for the patient and the clinical context. Algorithms that over-optimize disease outcome metrics can lead to unrealistic insights. 2. Give the clinician the ability to weigh patient-specific factors that cannot be easily inferred automatically; give the clinician agency/control over model output. 3. Do not introduce "research" tasks for clinicians into patient visit workflow. 4. The introduction of the AI tool is a core opportunity for trust building. 5. Create networked systems designed for collaborative use by patients and healthcare staff throughout the patient's care pathways. 6. Pinpoint where complex decisions need to take place in a clinical workflow versus tools that provide blanket data that physicians already know.	• "If you could show that patients have a better response to treatment by use of the algorithm, that would be amazing. If you can show that patients actually are more likely to adhere to treatment, that would be important as well, or that patients are less likely to develop adverse side effects that leads to stopping medications. It would be nice to do a trial with outcomes like that." - P9 • "So truthfully, I would take a step back because it's not that common that nortriptyline is a medication I think about as a first or even a second or third line agent, unless they have other conditions that I know [tricyclic antidepressants] can treat. So I would really take a step back and think about the patient's pain. Do they have really bad migraines, that I think will get significant benefit from the TCAs. It would definitely give me pause if that was the most favorable medication to come up as a suggestion on this." – P11
Liu et al.2023[32]	• AI-generated suggestions can complement human efforts in optimizing CDS but should be refined for greater acceptance and workflow integration	• AI generated suggestions received lower scores for usefulness (AI:2.761.4, human: 3.561.3, P<.001) and acceptance (AI: 1.861,human: 2.861.3, P<.001). The overall scores were human:3.660.6 and AI: 3.360.5 (P<.001).

Anjara et al.2023[33]	• The study recommends improving the explanation model and including context such as cohort size and accuracy metrics to build clinician trust	• ""I would like someone to explain it to me more. I know this is very difficult so I won't understand all the AI explanations. . .[but] I would want someone to explain the method more." • "Here everything is clearer, there's more data about the patients. It expresses pretty well the differences between them and what they have in common. It seems pretty clear, it's quite visual. It seems simple." • "This is more useful for research or for comparing patients but in our daily work it doesn't provide much information. It provides information to compare patients, it's more general,not for individual patients. To compare one, two or three patients it's not very relevant clinically speaking. The example is quite clear but it's not very relevant in our daily work, to tell you the truth.""
Jones et al.2023[5]	• Understanding the nuanced meanings of trust and trustworthiness is essential for advancing the debate on AI in healthcare	• [T]there cannot be two right answers to the question of how a patient should be diagnosed, as might be the case in a "negligent treatment" case. Rather the diagnosis is simply wrong, and an expert witness who claims that a pathologist would have acted competently by missing obvious signs of melanoma was not expressing a defensible opinion.
Liu et al.2023[34]	• To enhance compliance with AI recommendations, improve transparency and integration of AI into clinical workflows. • The study emphasizes the need for trust in AI tools to improve clinical decision-making and highlights the importance of understanding clinician perceptions for successful AI integration.	• "You know, if I was very different from the AI, I would double-check myself. I would take it out and takeit seriously, and maybe I missed something. So I think it would be beneficial even though I may notagree with its dose." • "I think if in this case, it's the AI suggested that there was a 70% probability that I was overdosing;otherwise, I won't change my dosage. In short, I don't fully trust it" • "I would change the dose because I was on the higher side and would want to minimize renal injury. It'sslightly lower than my dose. I prefer the AI's recommendation and would have chosen that" • "Oh, I think I would follow my dose. I don't think that trained model recommendation because I've given hisage and his body weight and is severity illness, I would want to be a little more aggressive." • So expected half-life for the patient, what the peak value would be, what the trough value would be, what area under the curve would be within AI's scheme compared to our scheme. And think that those would both be helpful tools as well to give us some sort of objective sense that my dosing really not appropriate here."
York et al.2023[35]	• There is clear support for the development of AI systems in healthcare, particularly in skeletal radiography, and efforts should be made to improve education on AI among clinicians.	• Participants indicated substantial favourability towards AI in healthcare (7.87) and in AI applied to skeletal radiography (7.75). There was a preference for a hypothetical system indicating positive findings rather than ruling as negative (7.26 vs 6.20).
Chiang et al.2023[12]	• The major conclusion of the study is that healthcare workers have varying levels of trust in AI-based DSSs, and that improving the transparency and	• There are two key findings in our study: 1) clinician perceptions were somewhat positive towards the trustworthiness and utility of AI-predicted VF metric, and 2) clinicians were less likely to use the AI output in their decision making as glaucoma severity increased. Overall, the mean Likert scale score for trustworthiness and utility of the predicted MD were 3.27 and

	help increase trust.	
Liaw et al.2023[36]	• Enhancing transparency and providing education about AI systems can improve trust among healthcare professionals.	• Would it make care worse? Yeah, potentially...So ifyou're prompted to prescribe medications...for peoplewho are not yet at a certain level of risk, the [benefitto harm] ratio becomes smaller. [Physician, academichealth center] • Racial bias is...something that's implicitly existent innormal data sets...this is something that justcompounds...It's like a small mistake that compoundsinto something bigger. [Physician, private solo orgroup practice] • If it's things that are [inaccurate and] manuallyentered into the EHR system that are driving this...,it certainly could create false alerts and waste timeor...miss people who actually are at riskbecause...things weren't...entered correctly, or leftblank. [Physician, private solo or group practice] • It's only useful if I trust the information. [Physician,academic health center] • ...you could apply the same sort of thing to preventivecare to any chronic disease to including depression,hypertension, coronary disease. [Physician, academichealth center]...how likely is this person going to follow through ontheir screenings, [like] getting their mammogram? [Physician, private solo or group practice]
Nair et al.2023[37]	• Fostering trust through transparency and stakeholder engagement is crucial for the successful implementation of AI in healthcare.	• We reduce enormous suffering. We make their qualityof life better at home, AND we can get an economiclift in our region. Every one of the days is expensive.If we see that it is a patient with high risk, we can prioritize a visit to the HF clinic instead of sending the remittance to primary care. That should also allow for a quicker management.
Yoon et al.2024[7]	• Enhancing transparency and understanding of AI tools is crucial for building trust among clinicians	• When it [APA] was launched, a lot of us were notvery sure how it was developed. I think part of thereason why we did not use it very much is alsobecause we are not so familiar with how this systemcame about, what kind of information was used, andwhere the information came from. Is it also possiblethat critical information was not captured in thesystem? I can't trust totally, and [I am] not confidentwith what I'm seeing at the moment. [FGD 3, seniorconsultant] • I would say that I'm as good or even better than thesystem. I don't feel the need to rely on it; I'll just dowhat I do. We are all trained endocrinologists, so wetrust our judgment because that has been our breadand butter for many years. At the end of the day, webear the responsibility for our patients, so you know,if the algorithm makes a sound decision, butsomething unfortunate ever happens to the patient,then it's still our own accountability on the line. [FGD1, consultant] • Some of the recommendations go against your clinical judgement. For example, I have two patients and theAI recommendation was to add a beta blocker tosomeone who doesn't have ischemic heart disease asa second line agent. That's just not something that we would normally do. So have to exercise caution too![FGD 1, consultant] • These recommendations would be more valuable in a primary healthcare setting, where doctors may not have extensive knowledge of clinical practices related to novel glucose-lowering medications and insulin titration, especially in complex cases. I think implementing the AP tool in such settings would greatly help doctors in improving patient engagement and

Zheng et al.2024[4]	• Improving the transparency and explainability of AI tools is essential for building trust among clinicians.	• Some patients probably have asthma that we don'tdetect, but that's where I think this tool would behelpful because maybe even though they don't havea diagnosis of asthma, they've had wheezing, or otherthings listed in their diagnosis and problem list. Thatwould be helpful to avoid missing those people. [P6] • Some kids had been given a bronchodilator becauseoften at 18 months, they present with like viralinduced wheezes, and we find it improves withalbuterol. So, we get a response to albuterol, and weknow that these kids are potentially likely to getasthma, but we typically don't make that diagnosisuntil after two. [P4] • If we are getting this risk score and especially if itwere telling them that this is somebody that is at highrisk of relapses and recurrences of episodes, then wecan make that effort to reach out to thoseindividuals. That should be flowing in my mind. Thatshould be going to our care teams. [P14] • I want to be able to see that risk score. When the patient is in front of me, I also want to be able to see a whole lot more information about thatpatient, preferably in an easy to find format that I don't have to go digging in Epic for it, like I currently do. [P14] • I would probably like something simpler, like not necessarily a percentage. And then I like, okay, it's red, which means they're at high risk. Inthe background, I could know what that means. And if you want more information, then you could click and find why it is high. [P13] • I think high, medium, low would, you know, would be sufficient. And if you would have something popping up or even color-coded too, like theyare low risk in green, medium in yellow. If they're high-risk and in red, that certainly will get your attention. I also want to know what is puttingthem at risk. Is it the severity of symptoms, their need for oral steroids, their hospitalization and ED visits? So that would certainly be helpful toknow exactly where their risk area is. [P9] • This prediction score is not meant to override. This is complimentary information for you. I know you do mental calculations, but this is adata-driven calculation that gives you other complementary information. If there's a discrepancy, is there anything you are thinking low inemotion, say “hi, just to think about it on this page.” So then, you know, you don't have to go to that page, just look through another page of thesectional summary. [P5] • Parents may worry about their child if the AI tool says, “high risk of AE” and subsequently change daily decisions, such as not sending their child to school or letting them play outside. [P7]

Elareed et al.2024[38]	• AI can support healthcare efficiency and workload reduction, but ethical and practical concerns need to be addressed for broader acceptance	• "Nearly 40% of participants disagreed that physicians will not fight for patient's life in case AI predicts low chance of survival for the patient. • Nearly 65% of participants agreed that AI will enhance patient care by making more data available for research and around 58% agreed with the opinion that AI-based decision support systems must be scientifically proven before using. • 44.2% of participants agreed that technical malfunction by AI is more serious than wrong decision by a physician. • More than half of participants agreed that AI will save time for physicians to deal more with patients. Around 40% of patients agreed that physicians should have the final control over diagnosis of patients and agreed that the use of AI impairs physician-patient relationship. • More than half of participants agreed that AI use will reduce the overload of physicians. "
Vereschak et al.2024[11]	• Understanding the perspectives of different stakeholders is essential for designing effective Human-AI interactions that foster trust.	• Positive expectations and perceived risk are prerequisites for the emergence of trust, but the nature of risk is debated “It is important that the owner [of an AI-embedded system] does not recommend something in the company’s interest” (P6). • Perceived risk associated with a decision as another prerequisite for the emergence of trust: “When my physical integrity or money is at risk, trust becomes a consideration, especially when something important is at stake for me” (P4).“... a foundation [for defining risk] would be the physical needs and individual and social integrity from the Maslow’s Hierarchy.” However, some, like P5 and P2, broaden the concept of risk to include “vulnerability” (P5) or “responsibility” (P2) • Task complexity as a new prerequisite for the emergence of Human-AI trust.“Sometimes you can’t evaluate everything, you sort of use that quick «I just trust you, I just trust you to do the right thing».” • Trust is differentiated from trust-related behaviors and trustworthiness.“can have a complex and elaborate way of thinking [about AI-embedded systems and recommendations]” (P4)“as long as there aren’t too many complaints, no negative comments, [...] and the user uses the solutions, we can consider that trust is not broken” (P2).“For me, it [trustworthiness] is not so much a question of AI, it’s more between the individual and the entity or the organization that makes the system.” • The team behind AI plays an important role in (Human-AI) trust."[...] is established before the system exists. [...] Trust is very strong in the co-design phase [between users and the AI team]” (P4).“We have 10,000 users, and 90% of them say «the feedback from the AI was very interesting», now [knowing this, current users] will tend to trust the AI” (P6). This trust in AI is further strengthened if “a domain expert confirms what the AI recommends” (P6). • “There is trust in the system and trust in those who use the system [...]. They [the users] should at least tell you they are using such a system [embedding AI] so you don’t lose your chance, just because you don’t know how it works [...]”.“I don’t trust mixing humans and machines. Either the decision should be entirely made by a machine or a human. If you have

	clear." • "[he] is building trust with people through his own presence in the media [...]. People trust him and love his personality, so they trust his product even if it does not benefit them in the end." • The effect of AI certification on Human-AI trust depends on who is behind it."AI certificates are very important [for Human-AI trust] if there are organizations [that issue them] that people can trust" (DS2)

Supplementary Files

CONSORT (or other) checklists

Figures, tables and checklist with supplementary materials.
URL: http://asset.jmir.pub/assets/d3612ca3a336d642c7ee0f2334895388.pdf