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Additional material is published online only. To view, please visit the journal online

Cite this as: Limiri DM. AI-Assisted Clinical Decision Support in Nursing: A Narrative Review of Implementation Outcomes and Frontline Adoption Barriers. Premier Journal of Science 2026;24:100280

DOI: <https://doi.org/10.70389/PJS.100280>

Peer Review:

Received: 01 July 2026

Last revised: 14 August 2026

Accepted: 21 September 2026

Version accepted: 4

Published: 28 September 2026

Ethical approval: N/a

Consent: N/a

Funding: N/a

Conflicts of interest: N/a

Author contribution: Dinah Mwendwa Limiri: Writing – original draft

Guarantor: Dinah Mwendwa Limiri

Provenance and peer-review: Unsolicited and externally peer-reviewed

AI-Assisted Clinical Decision Support in Nursing: A Narrative Review of Implementation Outcomes and Frontline Adoption Barriers

Dinah Mwendwa Limiri

ABSTRACT

Clinical practice has transformed due to a surge in the development of artificial intelligence tools to support decision-making. AI-Assisted Clinical Decision Support (AI-CDS) is one of the most promising technological tools in improving care outcomes. AI-CDS tools are digital systems relying on artificial intelligence (AI) to assist healthcare professionals in making clinical decisions. There exists a research gap in two aspects of the phenomenon: AI-CDS implementation outcomes and frontline adoption barriers. This narrative review assessed and synthesized evidence on the implementation outcomes reported for AI-CDS tools used by nurses as the primary clinical users and identified the main barriers to frontline adoption of AI-CDS from the perspective of nurses. The review found that AI-CDS tools can boost nurse confidence and improve workflow efficiency, patient safety, and care outcomes, but some barriers undermine their potential. The barriers include workflow integration and cognitive burden, trust issues, organizational support and training, technical capacity, and data management. These barriers are associated with ongoing frontline personnel resistance or with circumvention of tool adoption, with poorly characterized outcomes. They also affect the healthcare system and health outcomes. However, there are intervention strategies and recommended guidelines that can improve adoption and implementation rates. The review highlights that AI-CDS should be nurse-centered, supported by a robust governance framework, and locally validated to help institutions realize the full benefits of these tools while ensuring patient safety. The review prioritizes the input of frontline personnel, policymakers, and researchers in improving the benefits of AI-CDS tools.

Keywords: Adoption barriers, Artificial intelligence (AI), Clinical Decision Support, Implementation outcomes, Nursing.

Abbreviations

Abbreviation	Full Term
AI	Artificial Intelligence
AI-CDS	Artificial Intelligence-Assisted Clinical Decision Support
CASP	Critical Appraisal Skills Program
CDS	Clinical Decision Support
EHR	Electronic Health Record
JB	Joanna Briggs Institute
LMIC	Low- and Middle-Income Countries
MMAT	Mixed-Methods Appraisal Tool
NHS	National Health Service

SEIPS

Systems Engineering Initiative for Patient Safety

UTAUT

Unified Theory of Acceptance and Use of Technology

Introduction

One of the major advancements in healthcare in recent years is the integration of Artificial Intelligence (AI) into nursing practice. It offers promising improvements in patient care management, clinical decision-making, and workflow efficiency. The implementation of AI-assisted clinical decision support (AI-CDS) is one of the most promising uses of AI in healthcare, considering that it helps clinicians obtain real-time, evidence-based recommendations that are informed by the most recent evidence base. With these tools, there is a promise for reduced cognitive load, enhanced patient safety, and improved clinical outcomes, and this is evidenced by early warning systems for sepsis, medication safety alerts, deterioration indices, and fall risk prediction.^{1,2} Today, most major healthcare systems around the world, including US hospital networks and UK's National Health Service (NHS), have already deployed Artificial Intelligence-Assisted Clinical Decision Support (AI-CDS) tools into their healthcare settings.^{3,4} Despite the acceleration in the deployment of AI-CDS, a critical problem remains: there is high resistance to or circumvention of these tools by frontline nurses, and their implementation outcomes are poorly characterized.

As per past research, the success of clinical decision support is highly tied to its integration into clinical workflows, alignment with cognitive processes, and the trust that end users have in it and not just algorithmic accuracy only.^{5,6} There has been documentation on AI-CDS adoption barriers for physicians, with some of the issues documented being liability concerns, explainability deficits, and alert fatigue.^{7,8} Nursing decision-making is different, considering that it encompasses coordination across multiple care transitions, frequent task interruption, and continuous, holistic, and context-sensitive assessment.⁹ Reliance on AI-CDS tools that have been designed to help physicians is usually met with failures, considering that nursing environments are characterized by the unfolding of urgent decisions that require a critical examination of clinical, environmental, and behavioral factors.¹⁰

A substantial evidence gap exists, considering that to date, there is no comprehensive review that has a specific focus on the synthesis of two interconnected domains for AI-CDS in nursing: implementation outcomes and frontline adoption barriers. Most

Data availability statement:

N/a

Acknowledgements statement:

N/a

Assistance with the study: N/a

Presentation: N/a

past studies focus on physician-facing systems, which means that nurse-led implementation evidence often remains theoretically underdeveloped and fragmented. The current review has two main aims. First, it aims to systematically identify and synthesize empirical evidence on the implementation outcomes of AI-CDS tools utilized by frontline nurses in clinical settings. Second, the review aims to thematically map the key barriers to the adoption of AI-CDS tools as reported by the nurses themselves. These research questions are addressed by the narrative review:

- i. What implementation outcomes have been reported for AI-CDS tools where nurses are the primary clinical users?
- ii. What are the main barriers to frontline adoption of AI-CDS from the perspective of nurses?

Peer-reviewed empirical studies that have been published between January 2016 and June 2026 have been included, as there is substantive AI-CDS deployment in nursing during this period. Included studies that have met the eligibility criteria must focus on an AI-driven CDS tool, have nurses as the direct users, and report either at least one adoption-related barrier or implementation outcome. Through the delineation of the state of implementation of AI-CDS in nursing, this narrative review can be considered a foundation for the development of better tools and policy aimed at ensuring that nursing benefits more from the AI revolution.

Methods

Search Strategy

The narrative review was conducted in line with the existing guidelines for narrative synthesis and reporting recommendations. The review began with a systematic search of literature across various electronic databases, such as CINAHL (Cumulative Index to Nursing and Applied Health Literature), PubMed, Web of Science, and Scopus. The search targeted studies between January 2016 and June 2026, which significantly coincides with the period of deployment of AI-CDS tools in nursing practice. The final search was conducted on June 15, 2026, and after that, no other search was conducted.

For the search strategy, the researcher combined three concept groups using Boolean operators, and they included the following:

- i. Artificial Intelligence Terms: (“artificial intelligence” OR “AI” OR “machine learning” OR “deep learning” OR “predictive analytics”).
- ii. Clinical Decision Support Terms: (“clinical decision support” OR “CDS” OR “decision support system” OR “CDSS” OR “clinical decision support tool”).
- iii. Nursing and Implementation Terms: (“nursing” OR “nurse” OR “frontline” OR “clinical staff” OR “implementation” OR “adoption” OR “barriers” OR “facilitators” OR “outcomes”).

The following search strategy was applied to each database:

PubMed

(“artificial intelligence” [Mesh] OR “artificial intelligence” [tiab] OR “AI” [tiab] OR “machine learning” [tiab] OR “deep learning” [tiab] OR “predictive analytics” [tiab])

AND

(“decision support systems, clinical” [Mesh] OR “clinical decision support” [tiab] OR “CDS” [tiab] OR “decision support system” [tiab] OR “CDSS” [tiab] OR “clinical decision support tool” [tiab])

AND

(“nursing” [Mesh] OR “nurse” [tiab] OR “frontline” [tiab] OR “clinical staff” [tiab] OR “implementation” [tiab] OR “adoption” [tiab] OR “barriers” [tiab] OR “facilitators” [tiab] OR “outcomes” [tiab])

CINAHL

(MH “Artificial Intelligence”) OR TI “artificial intelligence” OR AB “artificial intelligence” OR TI AI OR AB AI OR TI “machine learning” OR AB “machine learning” OR TI “deep learning” OR AB “deep learning” OR TI “predictive analytics” OR AB “predictive analytics”

AND

(MH “Decision Support Systems”) OR TI “clinical decision support” OR AB “clinical decision support” OR TI CDS OR AB CDS OR TI “decision support system” OR AB “decision support system” OR TI CDSS OR AB CDSS OR TI “clinical decision support tool” OR AB “clinical decision support tool”

AND

(MH “Nursing”) OR TI nurse OR AB nurse OR TI frontline OR AB frontline OR TI “clinical staff” OR AB “clinical staff” OR TI implementation OR AB implementation OR TI adoption OR AB adoption OR TI barriers OR AB barriers OR TI facilitators OR AB facilitators OR TI outcomes OR AB outcomes

Web of Science

TS = (“artificial intelligence” OR AI OR “machine learning” OR “deep learning” OR “predictive analytics”)

AND TS = (“clinical decision support” OR CDS OR “decision support system” OR CDSS OR “clinical decision support tool”)

AND TS = (nurse OR frontline OR “clinical staff” OR implementation OR adoption OR barriers OR facilitators OR outcomes)

Scopus

TITLE-ABS-KEY (“artificial intelligence” OR AI OR “machine learning” OR “deep learning” OR “predictive analytics”)

AND TITLE-ABS-KEY (“clinical decision support” OR CDS OR “decision support system” OR CDSS OR “clinical decision support tool”)

AND TITLE-ABS-KEY (nurse OR frontline OR “clinical staff” OR implementation OR adoption OR barriers OR facilitators OR outcomes)

Table 1 | Inclusion and exclusion criteria

Criterion	Inclusion	Exclusion
Publication type	Tier 1: Peer-reviewed primary empirical studies. Tier 2: Systematic reviews, conceptual papers.	Conference abstracts, editorials, and opinion pieces
Publication date	January 2016–June 2026	Studies published before January 2016
Language	English	Other languages
Study design	All study designs accepted	Studies that do not report empirical data
AI-CDS focus	Studies focusing on AI-CDS tools	Studies that focus on other AI tools that do not focus on clinical decision support.
Target users	Tier 1: Nurses as the primary users of the AI-CDS tools. Tier 2: Nurses are included but not the exclusive focus, or where nursing perspectives are captured.	Studies with physicians or other clinicians as the primary users of the AI-CDS tools; no nursing involvement.
Reported outcomes	Studies that report at least an implementation-related outcome or adoption-related barrier from the perspective of a nurse.	Studies that do not report implementation outcomes or adoption barriers.
Clinical setting	Any clinical setting	Non-clinical settings
Duplicate publications	Only the most recent or comprehensive publication is included.	Duplicate publications from the same study.

Inclusion and Exclusion Criteria

Table 1 presents a detailed summary of the inclusion and exclusion criteria and following these, 17 studies were included in the narrative review. The researcher adopted a tiered evidence approach to reflect the nature of the included studies. For instance, Tier 1 comprised primary empirical studies where the primary users of AI-CDS tools were nurses ($n = 6$), with these studies forming the core evidence base for the synthesis. Tier 2 ($n = 11$) consisted of systematic reviews and conceptual papers that played a crucial role in providing contextual and theoretical support but did not form part of the primary evidence synthesis. The researcher applied this distinction consistently throughout the study.

Screening and Selection Process

A two-stage approach was followed during the screening process, and it included (1) title and abstract screening and (2) full-text review. In the first stage, the researcher contacted two independent reviewers, who helped with screening the titles and abstracts against the inclusion criteria, with a third reviewer contacted only when there was a disagreement, which was ultimately resolved through discussion. The second stage encompassed conducting a full-text review, with the two reviewers assessing the studies against the inclusion criteria. The process of screening is presented below in a PRISMA-style flow diagram (Figure 1). The diagram shows the identification, screening, eligibility, and inclusion process for studies published between January 2016 and June 2026. Notably, the two reviewers independently screened a random sample of 10% ($n = 36$) before formal screening, and this was done to calibrate the screening process. The calculation of inter-rater agreement was carried out using Cohen's kappa coefficient ($\kappa = 0.85$, 95% CI: 0.780.92), an indication of strong agreement, with disagreements being resolved through discussion and the involvement of a third reviewer in circumstances where no decision could be reached.

Study Characteristics

As per the PRISMA flow diagram, a total of 17 studies met the inclusion criteria and were included in this narrative review. Six of the 17 studies were classified as Tier 1 and the remaining 11 studies were classified as Tier 2. Tier 1 studies included Benfatah et al. (2025),¹¹ Álvarez (2025),¹² Ramadan et al. (2024),¹³ Finkelstein et al. (2024),¹⁴ Zackoff et al. (2025),¹⁵ and Alruwaili et al. (2024),¹⁶ all of which formed the core evidence base for the synthesis, with the rest providing contextual and theoretical support. See Table B1 in Appendix B for a detailed breakdown.

Data Extraction

The researcher developed a standardized data extraction form, with piloting of five studies being conducted before its full implementation. The researcher's focus was on the extraction of data such as bibliographic information, study characteristics, AI-CDS tool description, implementation outcomes, adoption barriers, and key findings. Two reviewers (Author A and Author B) independently reviewed the extracted data. A third reviewer (Author C) cross-checked a random sample of 20% of the extracted data for accuracy and completeness.

Quality Appraisal

The researcher relied on various appropriate appraisal tools to assess the included studies' methodological quality, and the choice of the selected tool was based on the study design. For instance, for mixed-methods studies, the researcher relied on the Mixed Methods Appraisal Tool (MMAT) version 2018. For quantitative studies, the researcher relied on the Joanna Briggs Institute (JBI) Critical Appraisal Checklists that were in line with a particular study design. For qualitative studies, the Critical Appraisal Skills Programme (CASP) Qualitative Checklist was used. The two independent reviewers (Author A and Author B) independently rated each study as high quality, moderate quality, or low quality, with meeting the criteria being the main scoring point.

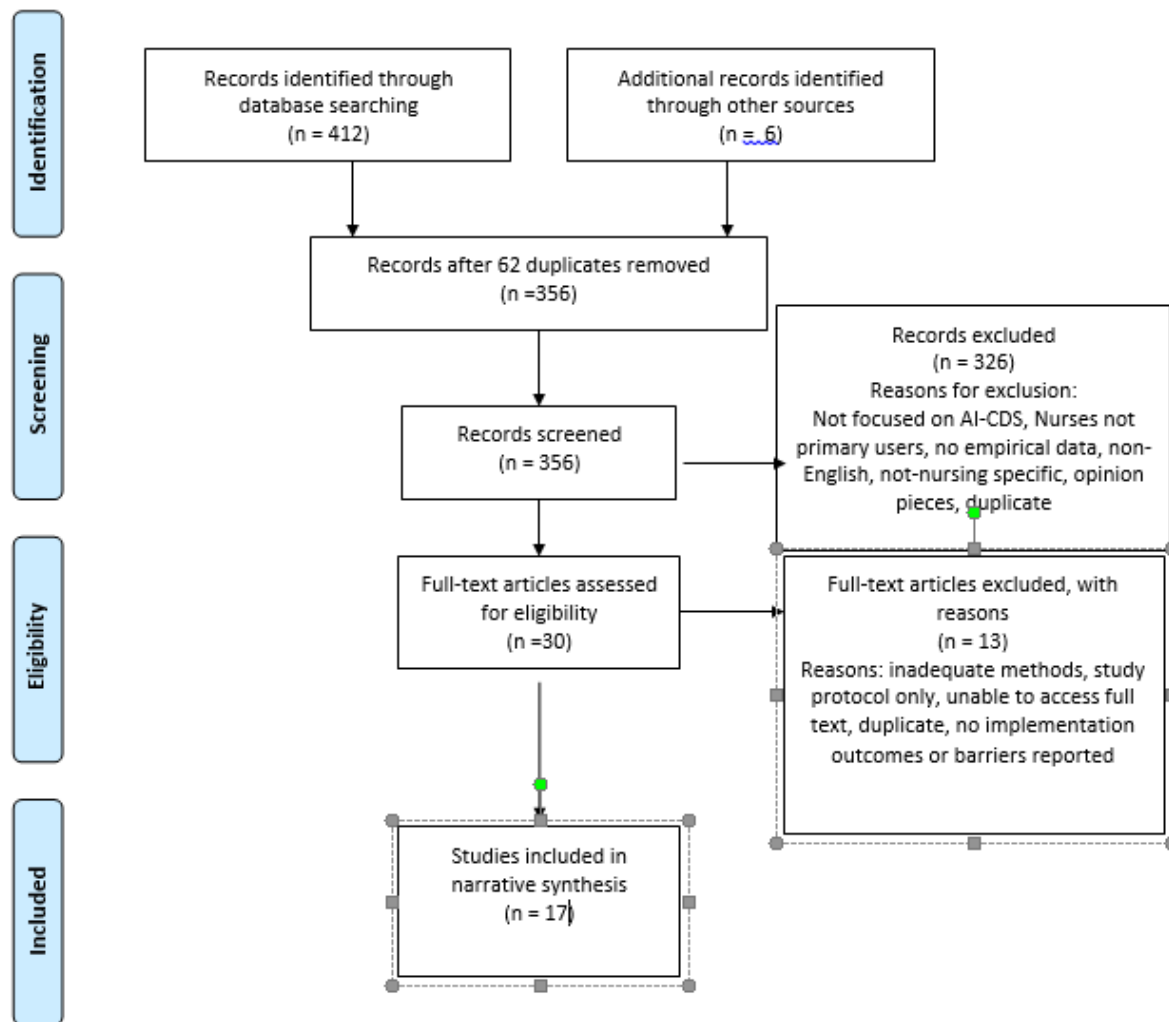


Fig 1 | PRISMA flow diagram of study selection for the narrative review of AI-assisted clinical decision support (AI-CDS) in nursing

It is important to understand that the researcher relied on the quality ratings of the included studies to inform the strength of the conclusions, with studies rated as low quality being given less weight in the synthesis of the findings. The calculation of inter-rater agreements was carried out using Cohen's kappa coefficient ($\kappa = 0.82$, 95% CI: 0.74–0.90), an indication of strong agreement, with disagreements being resolved through discussion and the involvement of a third reviewer in circumstances where no decision could be reached. Table A1 in Appendix A summarizes the quality ratings of the included studies. The full evidence summary table (Table C1 in Appendix C) provides detailed characteristics of all 17 included studies, including author, year, country, study design, AI-CDS tool description, clinical setting, sample characteristics, quality rating, implementation outcomes, and adoption barriers identified.

Framework Alignment

The researcher ensured that the review's findings were mapped to established implementation science and socio-technical frameworks in a bid to enhance its analytical rigor.

Implementation Outcomes Framework

The study's implementation outcomes were mapped to Proctor's taxonomy of implementation outcomes,¹⁷ which provides a comprehensive framework to help with the evaluation of implementation success:

- Acceptability: Nurses' perception that AI-CDS tools are agreeable, palatable, or satisfactory.
- Adoption: Nurses' intention, initial decision, or action to try and use AI-CDS tools.
- Appropriateness: AI-CDS tools' perceived fit, relevance, or compatibility for nursing practice.
- Feasibility: The level or extent to which AI-CDS tools can be successfully used within nursing settings.
- Fidelity: The degree to which AI-CDS tools were implemented as intended and expected by their designers.
- Implementation Cost: AI-CDS tools' cost impact.
- Penetration: AI-CDS tools' integration within nursing practice and service delivery.
- Sustainability: AI-CDS tools' maintenance and institutionalization over time.

Socio-Technical Barriers Framework

The SEIPS (Systems Engineering Initiative for Patient Safety) model was relied upon,¹⁸ with adoption barriers being mapped to it. The model's concept is that healthcare work is a socio-technical system that encompasses five interrelated components: person dimension, technology/tools dimension, organization dimension, physical environment dimension, and tasks dimension.¹⁸

Besides these two frameworks, elements from the Unified Theory of Acceptance and Use of Technology (UTAUT) were incorporated to help in enhancing the understanding of technology adoption dynamics, and these include performance expectancy, effort expectancy, social influence, and facilitating conditions.¹⁹ Through reliance on a dual-framework approach, the researcher managed to achieve a better analysis of both implementation outcomes and barriers, thereby allowing for the identification of intervention targets.

Implementation Outcomes of AICDS in Nursing

The growing body of evidence on AI-CDS in nursing reveals a complex picture characterized by various implementation challenges, despite the glimpse of promise that is clearly evident. In recent years, systematic reviews have attempted to synthesize the studies to help understand the impact of these tools in practice. According to Benfatah et al., AI-CDS in nursing is associated with improved nurses' clinical competencies and confidence, which ultimately translates to improved operational efficiency and enhanced patient safety.¹¹ According to their quasi-experimental mixed-methods study, nurses showed a significant increase in confidence (from 35.9% to 81.3%) regarding the use of AI after training. Additionally, there was a

significant reduction (8.4 s) in clinical response time. As shown in Figure 2, structured AI training was associated with significant improvements in both nurse confidence and clinical response time.

Figure 2 illustrates single-study findings from Benfatah et al. (2025)¹¹ regarding training effects on nurse confidence and clinical response time. While the findings seem highly promising, they require replication before firm conclusions can be drawn.

In her study, Alvarez found that AI-CDS is linked to improved triage accuracy as well as a reduced median time for critical interventions,¹² which corroborates the findings of the study carried out by Benfatah et al. According to Alvarez, the study found an increase in triage accuracy from 72.0% to 88.3% and a reduction in the median time for critical intervention from 27 min to 18 min. These significant changes translated to enhanced workflow efficiency and increased nurse confidence.¹² While AI-CDS has played an important role in revolutionizing nursing through the optimization of nursing workflows, the integration of AI is characterized by various challenges that are linked to ethical considerations, data privacy, and appropriate training.¹² The findings from the most recent studies that examined the application of AI-CDS in nursing revealed a substantial increase in efficiency regarding nursing workflows, specifically in clinical contexts characterized by time sensitivity. While AI-CDS has revolutionized nursing, specifically when it comes to patient outcomes, there is a need to focus on AI literacy training for nursing staff and continued infrastructure development, as these aspects are crucial for future use.¹² The implementation of AI-CDS in nursing is associated with various benefits, including enhanced workflow efficiency, increased nurse confidence, and

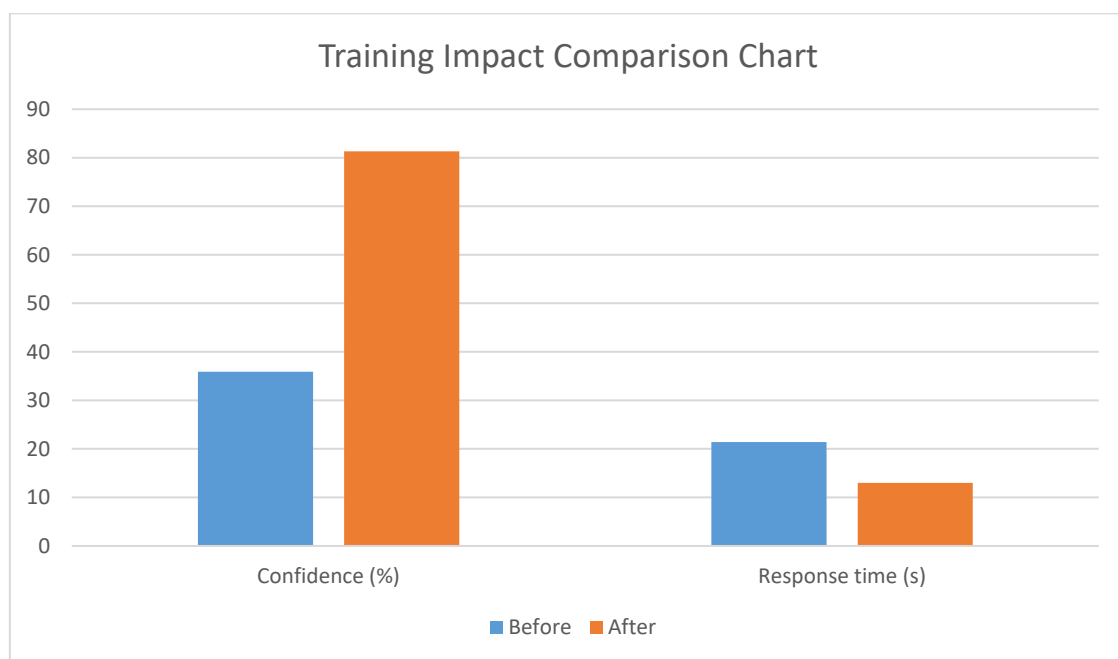


Fig 2 | Impact of AI training on nurse confidence and clinical response time (based on Benfatah et al., 2025¹¹)



Fig 3 | Reported implementation outcomes of AI-CDS in nursing (based on Benfatah et al., 2025¹¹ and Alvarez, 2025¹²)

reductions in clinical response times; however, evidence on implementation outcomes also reveals the importance of focusing on training nursing staff to ensure that these tools are used effectively, considering that nurses play an important role in the provision of care. Specifically, nurses need to assume a central role in the implementation process, considering that AI-CDS, in this case, is focused on addressing the realities of nursing practice.²⁰ The reported implementation outcomes of AI-CDS in nursing are summarized in Figure 3.

A vote-counting summary of implementation outcomes as per the six Tier 1 studies revealed the following patterns: The most frequently reported positive outcome was acceptability (83% of the studies), adoption was the second most frequently reported positive outcome (67% of the studies), followed by appropriateness (50% of the studies) and feasibility (17% of the studies). The remaining outcomes, including fidelity, penetration, and sustainability, were not reported in any of the Tier 1 studies. As per this pattern, there is reasonable documentation of early-stage implementation outcomes, while longer-term outcomes remain critically understudied.

The researcher distinguished between findings supported by multiple Tier 1 studies and single studies throughout this synthesis. Multi-study findings (M) are findings that have been reported in at least two Tier 1 studies, while single-study findings (S) are those findings that have been reported only in one Tier 1 study and still need replication for firm conclusions to be drawn. An example of a multi-study finding is that trust is a consistent barrier to adoption, which is supported by Alruwaili et al., 2024,¹⁶ Zackoff et al., 2025,¹⁵ and Ramadan et al., 2024.¹³ Another example of a multi-study finding is that organizational support plays a crucial role in adoption, and this finding is supported by Ramadan et al., 2024,¹³ Alruwaili et al., 2024,¹⁶

Finkelstein et al., 2024,¹⁴ and Zackoff et al., 2025.¹⁵ An example of a single-study finding is that AI-CDS improved clinical response time, as reported by Benfatah et al., 2025.¹¹ Single-study findings need to be interpreted with caution until they have been replicated in additional settings.

A table is presented below that outlines the confidence assessments of the six Tier 1 studies (Table 2).

Frontline Adoption Barriers

Despite various studies reporting promising quantitative outcomes for the implementation of AI-CDS in nursing, translation of these tools into practice often faces formidable barriers that are largely socio-technical rather than purely technical. Various studies have been conducted recently on the barriers from the nursing perspective, and there are certain consistent themes across various clinical settings.

Workflow Integration and Cognitive Burden

A qualitative study by Adler-Milstein et al. examined the barriers to clinical adoption of AI in medical diagnosis, and they organized their work into four main themes, including desire to use and reason to use.²¹ They argued that there was a need for clarity on why AI-CDS tools are useful in clinical practice as well as their outcomes. Most nurses have expressed the need for AI-CDS systems to incorporate their professional workflows, as most current systems fail to take into account the realities of nursing practice. The success of AI-CDS is dependent on nurses' desire to incorporate the tools into practice.²² It is in line with the findings of Adler-Milstein et al., who also add that the implementation of AI-CDS should take into account various psychological factors, including the role of the tools in the facilitation of professional fulfillment, so that nurses do not feel a cognitive burden that may sometimes lead to burnout.²¹

Table 2 | Confidence assessment for key findings

Finding	Supporting Tier 1 Studies	Quality of Evidence	Confidence Level
AI-CDS improves nurse confidence	- Benfatah et al. (2025)—High - Álvarez (2025)—Moderate	High	High
Organizational support is essential for adoption	- Ramadan et al. (2024)—Moderate - Alruwaili et al. (2024)—Moderate - Finkelstein et al. (2024)—Moderate - Zackoff et al. (2025)—High	Moderate	High
Trust is a consistent barrier to adoption	- Alruwaili et al. (2024)—Moderate - Zackoff et al. (2025)—High - Ramadan et al. (2024)—Moderate	Moderate	High
Workflow integration challenges are a barrier	- Álvarez (2025)—Moderate - Zackoff et al. (2025)—High - Ramadan et al. (2024)—Moderate	Moderate	High
Training improves adoption outcomes	- Benfatah et al. (2025)—High - Álvarez (2025)—Moderate - Alruwaili et al. (2024)—Moderate	Moderate	Moderate
Technology opaqueness is a barrier	- Finkelstein et al. (2024)—Moderate - Zackoff et al. (2025)—High	Moderate	Moderate
AI-CDS improves clinical response time	Benfatah et al. (2025)—High	High	Moderate*
AI-CDS improves triage accuracy	Álvarez (2025)—Moderate	Moderate	Low**

*Single-study finding; there is a need for replication.

**Single-study finding; moderate quality evidence; there is a need for replication.

High confidence = Supported by two or more high-quality or three or more moderate-quality studies with consistent findings; Moderate confidence = Supported by two or more moderate-quality studies or one high-quality study; Low confidence = Supported by a single moderate-quality study that requires replication.

The above findings are reinforced by Ramadan et al., who found that AI-CDS implementation in nursing is characterized by various primary barriers, including fears of job displacement, ethical concerns regarding patient privacy, and technical challenges.¹³ The study captured nurses' concerns regarding moral agency as well as role changes, with AI being considered both ideal and burdensome in nursing settings. The nurses described a perception that automating decision support through AI-CDS could lead to weakened professional judgment and limited opportunities for frontline workers to engage in clinical reasoning.¹³ Such concerns raise the possibility that some facilities implementing AI-CDS could outsource routine tasks to AI-CDS tool providers while retaining value-based decision-making. Ramadan et al.'s study also highlights nurses' perceptions of ethical concerns related to patient safety, including data security, exposure of sensitive details, and consent for secondary access to a patient's health information. Together, the barriers identified contribute toward an understanding that personnel in the healthcare setting consider AI-CDS integration as a tool intended for efficiency in care processes, but it is also limited by barriers such as workforce fears and patient trust.

Trust Issues

A quantitative study conducted by Dunker et al. investigated patients' and frontline personnel's trust, attitudes, expectations, and concerns regarding the use of the AI-CDS tool in the clinical neurophysiology setting.²³ The study established that trust is conditional when it comes to the adoption of tools in clinical care. Most patients are willing to share their health data to

aid the use of such tools in healthcare. Still, there is a need to build trust for AI-CDS to be successfully integrated into decision-making scenarios in commercial settings. Trust is a leading barrier to frontline adoption of AI-CDS, as clinicians must rely on tools that significantly influence patient care outcomes while being responsible for the ultimate outcomes.²³ When an AI model is used to produce medical recommendations that lack clear explanations, it subjects most of the frontline personnel to uncertainty, given the inability to ascertain whether to accept or question the outcome. Ratta et al. report that such instances of uncertainty are driven by concerns such as a higher risk of algorithmic bias and the fact that a significant percentage of the training data cannot accurately reflect the characteristics of local patients, thereby creating a vacuum for skewed suggestions. Trust is also highly associated with the demonstrated reliability of the AI-CDS, as recurrent errors and unexplained performance shifts affect the level of confidence in the tools.²³ Jones et al. add to the debate that social factors are also important in trust issues. Scenarios in which early adopters of the technology report negative experiences lead to sustained skepticism about AI-CDS use.²⁴ According to Dunker et al., trust has to be restored to ensure smooth adoption of AI-CDS, and this necessitates transparency in model behavior, an accountability framework to help define clinicians' responsibilities, structured documentation of the tool's limitations, and local case studies to demonstrate the tool's performance within the limits of a facility's caseload. The lack of such elements in the adoption process pushes frontline personnel to treat the AI-CDS as an untrusted tool, thereby limiting its potential impact in the clinical setting.¹⁶

Organizational Support and Training

Organizational support and personnel training are critical to determining whether the frontline team can safely and effectively implement the AI-CDS tools. According to Cangelosi et al., the probability of inconsistent or failed adoption of AI-CDS is higher when healthcare facilities deploy technological tools without first ensuring the presence of structured organizational support, such as technical assistance and personnel training to support hands-on practice.²⁵ Clinicians should undergo extensive training that includes practical, scenario-based simulations, a review of local case studies, and opportunities to practice overrides; such efforts ensure that personnel have the procedural fluency to adopt and use the tools effectively. Leadership and team structure clarity are also important, as frontline personnel should be aware of when to comply with or override an AI-CDS recommendation and how to facilitate liability management.²⁶ According to Li et al., failure to ensure practical organizational support and proper personnel training increases the risk of friction and discourages sustained use of AI-CDS tools. Without proper investment in support and learning, AI-CDS adoption ends up as a mandate that encourages the misuse of technological tools, creates a workload risk factor, and is definitely ignored by frontline teams.

Technical Capacity

According to Finkelstein et al., failure to carefully factor in technical issues associated with the adoption and maintenance of AI-CDS tools increases the risk of unanticipated effects, low acceptance, and missed opportunities across different healthcare settings.¹⁴ The problem is widely associated with the technicalities of AI models' operations as black boxes capable of producing outputs and recommendations without proper interpretable reasoning.¹⁴ The frontline personnel trained to produce and justify clinical decisions to their colleagues and patients experience challenges in reconciling opaque clinical outputs with professional standards. The opaqueness of the AI models also increases the complexity of error analysis, as most of the adverse outcome scenarios involve clinicians facing limitations in tracing whether the input and architecture of the tool are the source of the problem.¹⁴ Such limited traceability impedes sustainable remediation of the tool's risks and continuous technical improvement. Therefore, the technical capacity barrier is only avoidable with the input of clinicians in co-designing AI-CDS tools to ensure that output can align with clinical guidelines and improve adoption compliance by frontline personnel.

Data Management

Maddela established that AI tools have transformed clinical data management, with effects evident in data collection, cleaning, validation, analysis, and interpretation processes, as clinicians now experience more accurate decision-making.²⁷ AI tools, including AI-CDS, have automated most processes on the frontline,

as the performance of models in clinical decision-making is driven by the accuracy, completeness, consistency, validity, and timeliness of the input data. Incidents of poor data labeling or outdated datasets increase the risk that AI-CDS will produce unreliable outputs, thereby contributing to increased health disparities and limiting the tool's adoption.²⁷ Maddela also reported that gaps in data management, such as unclear policy guidelines for consent and secondary access, increase the risk of legal and ethical problems in the adoption of AI-CDS.²⁷ This implies that implementation of AI-CDS tools without clear data governance guidelines for tracking, quality checks, and model update mechanisms by frontline personnel can result in patient privacy breaches and data misuse. Therefore, the lack of strong data management exposes institutions to the risk of experiencing failures in AI-CDS adoption and implementation in real-world healthcare settings.

By relying on the SEIPS framework to aid in the organization of barriers across Tier 1 studies, it was found that organizational barriers were the most frequently identified (83%), followed by person-related barriers (67%), task-related barriers (67%), technology-related barriers (50%), and environmental barriers (33%). As per this pattern, organizational and human factors are the most significant barriers to AI-CDS adoption in nursing. Evidently, physical environmental factors appear to be less influential as per current evidence.

Figure 4 presents the socio-technical barriers to frontline adoption of AI-CDS, synthesized from the reviewed studies.

Implications of Adoption Barriers on the Healthcare System and Health Outcomes

Barriers to frontline adoption of AI-CDS have implications that extend beyond individual personnel frustrations, as they affect the quality, cost, and safety of care. Scenarios in which personnel distrust the implementation of AI-CDS tools and there is limited organizational support increase the risk of uneven uptake. According to Finkelstein et al., the change drives some personnel to rely on AI-CDS recommendations or outputs, while others circumvent or disable the tools, thereby creating room for inconsistencies in healthcare decisions and undermining efforts to standardize care.¹⁴ Limited technical support subjects the healthcare system to the risk of unwarranted circumvention of AI-CDS outputs and inappropriate overreliance on the tool.¹⁴ Such problems affect health outcomes by causing diagnostic delays, the adoption of unnecessary procedures, and delayed intervention. The case of workflow misalignment and cognitive issues increases administrative burden for the health system.^{23,28} The health problems associated with these changes include clinician burnout and reduced time dedicated to direct patient care, leading to poor patient outcomes. Over time, the operational frictions that personnel and institutions implementing this tool experience significantly degrade output and increase avoidable costs.

Frontline personnel and health institutions experience the direct effects of data quality and data

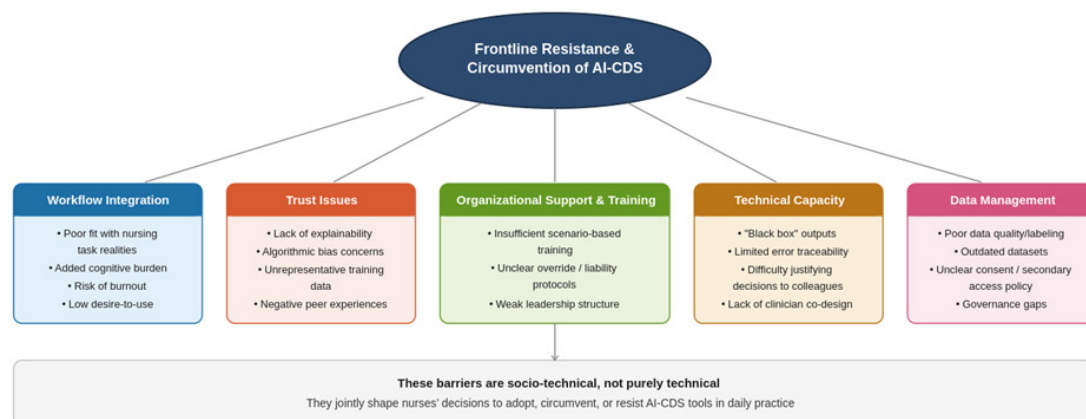


Fig 4 | Socio-technical barriers to frontline adoption of AI-CDS in nursing, synthesized from the studies reviewed (based on Benfatah et al. (2025),¹¹ Álvarez (2025),¹² Ramadan et al. (2024),¹³ Adler-Milstein et al. (2022),²¹ Finkelstein et al. (2024),¹⁴ Li et al. (2025),²⁶ Zackoff et al. (2025),¹⁵ Alruwaili et al. (2024),¹⁶ and Jones et al. (2023)²⁶)

management gaps.¹⁴ The problem directly affects patients' safety and health equity, as AI-CDS tools are sometimes trained on unrepresentative datasets, resulting in poorer outcomes for patient populations, particularly underrepresented groups. Such outcomes intensify health disparities in diagnosis, intervention, and outcomes.¹⁴ Inadequate data management also subjects the healthcare system to privacy risks, with the eventual erosion of patient trust in care associated with digital initiatives. The problem also directly affects patient engagement with institutions that implement AI-CDS tools. Besides, there are legal and ethical implications, as frontline personnel and institutions face liability uncertainty when accountability for AI-CDS-enabled outputs is unclear.¹⁴ The ripple effect of this problem on the healthcare system is the continued conservative use of AI-CDS tools.

High resistance or slow adoption of AI-CDS tools by frontline personnel undermines the projected broader positive gains of learning health systems. With minimal effort required to monitor, continuously update, and improve AI-CDS, the tools risk sustained stagnation, thereby limiting their intended functions of reducing errors in healthcare, personalizing care, and helping institutions scale best care practices. Ultimately, the barriers to frontline adoption of AI-CDS translate into slower tool implementation, widened health disparities, increased costs of care, compromised patient safety, and lost opportunities for institutions to achieve system-level efficiency.

Intervention Strategies

Addressing the slowed or high resistance problem driven by the adoption barriers is key to improving care. A structured intervention that combines organizational, technical, and management approaches is recommended to ensure effective, safe, and sustained adoption and implementation of AI-CDS tools. Research indicates that the proper implementation of these intervention strategies improves the adoption rates of AI-CDS tools when utilized appropriately. Peek et al. recommend exercising transparency to help build trust.²⁹

The strategy requires frontline personnel and institutions to document AI-CDS, rely on local case studies for validation, and ensure clinically standard explanations that map the tool's algorithmic recommendations to align with familiar clinical measures. The tool deployments should also align with prospective pilot study outcomes and monitoring conducted to establish changes in adoption rates, performance, and output.²⁹ Peek et al. added that investment in workforce preparedness through training is necessary. Institutions should adopt comprehensive personnel training approaches that emphasize simulations, case study reviews, and on-shift training.²⁷ Institutions should also ensure protection of learning time, integration of informatics contacts, and provision of help platforms to enable personnel to ask questions and report issues while adopting and implementing.

Adler-Milstein et al. also recommended prioritizing workflow integration.²¹ Institutions should adopt AI-CDS tools that align with existing systems, such as EHR workflows, to help minimize errors associated with extra clicks.²¹ Frontline personnel should also participate in designing the tools to ensure smooth adoption and actionable outputs. Maddela also recommends strengthening data management.²⁷ Institutions should prioritize data tracking, audits, and bias assessment, and ensure clear policies guiding consent and secondary access to improve accountability and transparency.²⁷ Lastly, frontline personnel and institutions should engage other stakeholders, including patients and the community, in the design and oversight of AI-CDS.³⁰ Brydges argues that this approach ensures that institutions can build public trust. Together, the intervention strategies are necessary in ensuring effective AI-CDS adoption and implementation to improve care outcomes.

As per a vote-counting summary of the implementation outcomes, the most frequently reported positive outcome was acceptability, followed by appropriateness (Table D1 in Appendix D). The least reported outcome was sustainability. In terms of barriers, the most reported were technology-related barriers, followed by

organizational barriers. The assessment of confidence in findings was based on study quality and consistency of evidence. Throughout the above synthesis, the researcher distinguished between findings supported by multiple studies versus those that are from single studies. For instance, the findings regarding the role of AI-CDS in improving triage accuracy (Alvarez, 2025)¹² represented a single-study finding that required further replication. On the other hand, the finding that trust is a consistent barrier to adoption is supported by multiple studies (Dunker et al., 2026²³; Ratta et al., 2025¹⁹; Jones et al., 2023²⁴).

Equity and LMIC Considerations

Evidently, most of the evidence on AI-CDS implementation comes from high-income countries (HICs), and it is important to consider the unique challenges and opportunities for AI-CDS adoption in low- and middle-income countries (LMICs). Infrastructure challenges are common in LMIC healthcare settings, and these usually affect AI-CDS implementation. Some of these include limited internet connectivity, unreliable electricity supply, and lack of hardware to support AI-CDS tools. Some other factors that pose significant barriers in LMIC settings include absence of interoperable health information systems and incomplete electronic health record implementation. In most LMIC settings, the nursing workforce struggle with higher nurse-to-patient ratios and this directly limits time available for training and AI-CDS use. Also, digital literacy varies considerably, and most AI-CDS interfaces are programmed in English language rather than local languages. It is necessary to adapt training programs to local contexts. It is also important to note that LMIC regulatory environments for AI in healthcare are usually less developed, with many LMICs lacking specific guidelines or laws for AI in healthcare. It is highly probable that AI-CDS tools trained predominantly on HIC patient populations may fail to perform optimally in LMIC settings due to healthcare system variations, data quality issues, and population differences. Therefore, it is important to ensure that AI-CDS tools are validated locally before deployment in LMIC settings. Despite the various challenges discussed, LMICs may offer unique opportunities for AI-CDS implementation.

Recommendations

Implementation of the recommended intervention strategies requires the involvement of frontline personnel in all areas of AI-CDS design, adoption, and implementation. Frontline personnel should be involved in co-designing the AI-CDS tools, engaged in scenario-based and ongoing training, documenting local real-world cases of failure modes, and be enabled to access reporting channels to share their reservations and safety concerns.^{15,31,32}

Also, all end users need to have structured and evidence-based training, considering that the data from the review reveal the existence of a stark difference between the performance of nurses and their confidence levels, specifically after receiving proper training (81.3% confidence level after training from 35.9%

and a clinical response time decrease of 8.4 s).¹² This demonstrates that adoption is more focused on competency development and not just tool availability. As per the Generative AI Nursing Competence (GANC) framework, there is a clear pathway for training nurses, and it contains specific domains, including clinical reasoning and evidence verification.³³

Also, clear governance and accountability frameworks need to be developed, considering that in recent years, there has been an increase in the recognition of the need for governance by most professional bodies. For instance, the updated documentation practice standard by the College of Nurses of Ontario reveals that AI should not substitute for nursing skill and knowledge; instead, it should be relied upon as a support tool. This means that nurses should be accountable for the use, review, and verification of AI-generated documentation, and such regulatory guidance needs to be adopted more widely. The SAFE CARE framework clearly outlines a practical method that can be relied upon for the operationalization of this accountability.³⁴ Other AI governance standards that healthcare institutions should adopt and adapt include WHO guidance on ethics and governance of AI for health (2024)³⁵ and ISO/IEC 23894:2023 guidance on AI risk management.³⁶ Institution-specific AI-CDS governance frameworks should focus on addressing patient consent and transparency, data privacy and security protocols, accountability and liability clarity, monitoring and reporting mechanisms, and clinical validation requirements before deployment. Overall, professional nursing organizations should focus on advocating for AI-CDS regulation that encompasses nursing-specific considerations in AI-CDS design and evaluation, equity-focused AI-CDS oversight, and mandatory nursing involvement in implementation decisions.

Limitations

Several limitations need to be considered when interpreting the findings of this narrative review. First, as per the inclusion and exclusion criteria, only English-language publications were included, and this means that there is a potential for the exclusion of relevant non-English sources. Second, there is a possibility of the presence of publication bias, as positive findings are more likely to be published compared to negative results. Third, it is evident that most of the studies were conducted in high-income countries, and this limits generalizability to low- and middle-income settings. Fourth, many studies included examined AI-CDS tools that were originally designed for physicians rather than nurses, which means that this potentially limits applicability to nursing-specific decision-making contexts. Next, it is important to acknowledge that considerable heterogeneity existed across studies in terms of AI-CDS tools, clinical settings, and outcome measures, and this limited direct comparability. Lastly, the quality of evidence had a significant influence on the strength of conclusions in the review; specifically, the researcher gave greater weight to high-quality

studies in the synthesis, with moderate-quality studies only providing supporting evidence. Despite the limitations, the review provides valuable insights into the current state of AI-CDS implementation in nursing.

Conclusion

Research continues to predominantly focus on the gradual inclusion and deployment of technologies such as AI-CDS in healthcare settings, rather than on the necessary changes to ensure successful adoption of such tools in nursing practice. In this review, by focusing on high resistance to or circumvention of AI-CDS tools by frontline nurses and the poor characterization of their implementation outcomes as a problem that remains, we have established that the adoption process faces socio-technical barriers, including workflow integration and cognitive burden, trust issues, organizational support and training, technical capacity, and data management. Using Proctor's implementation framework and the SEIPS socio-technical model,^{18,19} we have systematically mapped these barriers and outcomes to provide a structured understanding of implementation challenges. Such barriers prevent enabling of improved care with the tools, but can be addressed through a comprehensive approach that emphasizes co-designing the tools, personnel training, workflow integration, and data management. Institutions that can align validated AI-CDS with effective organizational and community support can ensure that the tool contributes to safe and efficient care. The review also recommends approaches to improve frontline adoption of AI-CDS. Without the proposed intervention strategies and recommended safeguards, institutions risk experiencing sustained AI-CDS frontline adoption inconsistencies and missed opportunities to improve care outcomes. However, AI-CDS has high potential in terms of enhancement of nursing practice and improving patient outcomes when implemented properly, which means that it must be equity-focused and nurse-centered.

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Appendix A

Table A1 | Quality assessment of included studies

Author(s) & Year	Tier	Study Design	Appraisal Tool	Quality Rating
Benfatah et al. (2025)	1	Quasi-experimental mixed methods	MMAT	High
Álvarez (2025)	1	Quantitative	JBİ quasi-experimental	Moderate
Ramadan et al. (2024)	1	Qualitative	CASP qualitative	Moderate
Dunker et al. (2026)	2	Quantitative	JBİ cross-sectional	Moderate
Adler-Milstein et al. (2022)	2	Qualitative	CASP qualitative	High
Finkelstein et al. (2024)	1	Qualitative	CASP qualitative	Moderate
Li et al. (2025)	2	Quantitative	JBİ analytical cross-sectional	Moderate
Wei et al. (2025)	2	Systematic review	JBİ systematic review	High
O'Connor et al. (2023)	2	Systematic review	JBİ systematic review	High
Elhaddad & Hamam (2024)	2	Systematic review	JBİ systematic review	Moderate
Zackoff et al. (2025)	1	Qualitative	CASP qualitative	High
Alqaraleh et al. (2025)	2	Systematic review and a mixed-methods approach	JBİ systematic review and MMAT	Moderate
Thompson et al. (2024)	2	Systematic review	JBİ systematic review	High
Alruwaili et al. (2024)	1	Quantitative	JBİ cross-sectional	Moderate
Jones et al. (2023)	2	Qualitative	CASP qualitative	High
Ratta et al. (2025)	2	Quantitative	JBİ cross-sectional	Moderate
Peek et al. (2025)	2	Systematic review	JBİ systematic review	High

Appendix B

Table B1 | Tiered evidence classification

Tier	Description	Studies Included	Role in Synthesis
Tier 1	Primary empirical studies with nurses as primary users	Benfatah et al. (2025), Álvarez (2025), Ramadan et al. (2024), Finkelstein et al. (2024), Zackoff et al. (2025), Alruwaili et al. (2024)	Core evidence for implementation outcomes and barriers
Tier 2	Systematic reviews and contextual sources	Li et al. (2025), Adler-Milstein et al. (2022), Jones et al. (2023), Wei et al. (2025), O'Connor et al. (2023), Thompson et al. (2024), Peek et al. (2025), Elhaddad & Hamam (2024), Alqaraleh et al. (2025), Carayon et al. (2014), Dunker et al. (2026)	Contextualization and theoretical support

Appendix C

Table C1 Complete evidence summary								
Author(s) & Year	Country	Study Design	AI CDS Tool/Function	Clinical Setting	Sample Characteristics	Quality Rating	Key Implementation Outcomes	Key Adoption Barriers Identified
Benfatah et al. (2025)	Morocco	Quasi-experimental mixed methods	AI training program for nursing practice	Multiple clinical settings	Nurses	High	Confidence increased from 35.9% to 81.3%; Clinical response time reduced by 8.4 s	AI literacy gaps
Álvarez (2025)	Spain	Quantitative	AI-assisted triage decision support	Pediatric emergency department	Nurses	Moderate	Triage accuracy increased from 72.0% to 88.3%; Critical intervention time improved from 27 to 18 min	Training requirements
Ramadan et al. (2024)	Saudi Arabia	Qualitative	General AI adoption in nursing practice	Multiple hospital settings	Registered nurses	Moderate	Role perception changes	Technical challenges
Dunker et al. (2026)	Norway	Quantitative	AI-CDS in clinical neurophysiology	Clinical neurophysiology	Frontline personnel and patients	Moderate	Willingness to share data	Conditional trust
Adler-Milstein et al. (2022)	USA	Qualitative	AI in medical diagnosis	Various clinical settings	Clinicians and stakeholders	High	Professional fulfillment factors	Need for clarity on utility
Finkelstein et al. (2024)	USA	Qualitative	EHR-integrated AI-CDS	Healthcare system with EHR	Healthcare personnel (nurses included)	Moderate	Technical integration challenges	Limited traceability
Li et al. (2025)	Not specified	Quantitative integrative analysis	AI deployment in healthcare	Multiple healthcare settings	Leadership and clinical staff	Moderate	Leadership-dependent outcomes	Leadership clarity
Wei et al. (2025)	Not specified	Systematic review	AI integration in nursing	Multiple settings	Nursing staff	High	Improved patient outcomes	Training needs
O'Connor et al. (2023)	Not Specified	Systematic review	AI in nursing and midwifery	Various nurse settings	Nursing and midwifery professionals	High	Improved clinical outcomes	AI literacy gaps
Elhaddad & Hamam (2024)	Not specified	Systematic review	AI-driven CDSS	Healthcare settings	Healthcare professionals	Moderate	Potential for improved care	Integration barriers
Zackoff et al. (2025)	USA	Qualitative	Clinical decision support failures	Pediatric intensive care unit	PICU clinical staff	High	Safety improvement opportunities	Workflow disruption
Alqaraleh et al. (2025)	Not specified	Systematic review and a mixed-methods approach	AI integration for medication error reduction	Various nursing settings	Nurses	Moderate	CDSS reduced errors by up to 95%	Trust issues
Thompson et al. (2024)	Not specified	Systematic review	CDSS in nursing and allied health	Various healthcare settings	Nursing and allied health professionals	High	Mixed effects on performance	Implementation variability
Alruwaili et al. (2024)	Saudi Arabia	Quantitative cross-sectional	General AI awareness and attitudes	Nursing practice settings	Registered nurses	Moderate	Willingness pegged on support	Organizational support deficits
Jones et al. (2023)	UK	Qualitative	AI and clinical decision support	General clinical practice	Clinicians	High	Professional accountability	Trust issues
Ratta et al. (2025)	India	Quantitative cross-sectional	AI-driven CDSS	Healthcare settings	Healthcare professionals (Nurses included)	Moderate	Extended UTAUT explained adoption variance	Local patient representation concerns
Peek et al. (2025)	Not specified	Systematic review	AI-based CDSS	Various clinical settings	Implementation stakeholders	High	Implementation success dependent on bridging strategies	Implementation gaps

Appendix D

Table D1 | Proctor outcomes and SEIPS barriers mapping matrix

		Proctor Implementation Outcomes		SEIPS Barriers Dimensions									
Study	Quality	Acc	Ado	App	Fea	Fid	Pen	Sus	Per	Tec	Org	Env	Tas
TIER 1: Primary empirical studies													
Benfatah et al. (2025)	High	✓	✓	✓					✓		✓		
Álvarez (2025)	Moderate	✓	✓	✓	✓				✓	✓			✓
Ramadan et al. (2024)	Moderate			✓					✓	✓	✓		✓
Finkelstein et al. (2024)	Moderate									✓	✓		
Zackoff et al. (2025)	High									✓	✓	✓	✓
Alruwaili et al. (2024)	Moderate								✓		✓		
TIER 2: Supporting evidence													
Wei et al. (2025)	High	✓	✓	✓	✓				✓	✓	✓		✓
O'Connor et al. (2023)	High	✓	✓	✓	✓				✓	✓	✓		✓
Thompson et al. (2024)	High	✓		✓					✓	✓	✓		✓
Peek et al. (2025)	High	✓	✓	✓	✓			✓	✓	✓	✓		✓
Elhaddad & Hamam (2024)	Moderate	✓		✓	✓				✓	✓	✓		✓
Alqaraleh et al. (2025)	Moderate	✓	✓	✓	✓				✓	✓	✓		✓
Dunker et al. (2026)	Moderate								✓	✓			
Ratta et al. (2025)	Moderate		✓						✓	✓			
Jones et al. (2023)	High			✓					✓		✓		
Li et al. (2025)	Moderate		✓				✓		✓		✓		
Adler-Milstein et al. (2022)	High	✓	✓	✓					✓		✓	✓	✓