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AI-Enabled Clinical Decision Support for Standardized Nurse-Led Emergency Care Pathways: A Multisite Mixed-Methods Implementation Study

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Abstract

Emergency departments face persistent challenges in triage consistency, delayed clinical decisions, fragmented workflows, and uneven adoption of artificial intelligence (AI) decision support, creating uncertainty about benefits for nurse-led care. This study examines how AI-enabled clinical decision support relates to standardized emergency nursing pathways and which organizational conditions influence implementation. Guided by the Consolidated Framework for Implementation Research, it uses a qualitative-led, cross-sectional documentary multiple-case synthesis of published quantitative, qualitative, and mixed-methods investigations, rather than an original quantitative hospital survey. The intended sample comprises 97 peer-reviewed publications, with documented emergency department and hospital cases as embedded comparisons; complete screening and extraction remain unverified. Key variables include predictive discrimination, triage agreement, care timeliness, protocol adherence, nursing acceptance, workflow compatibility, explainability, governance, and institutional readiness. Analysis employs structured evidence extraction, CFIR-guided thematic coding, descriptive comparison of reported metrics, cross-site appraisal, and provisional five-point ratings for seven hypotheses without pooled inference. In a source study of 135,470 emergency visits, machine learning achieved critical-care AUC 0.86 versus 0.74 for conventional triage, and hospitalization AUC 0.82 versus 0.69. A separate study of 1,491 assessments across seven departments found electronic triage agreement increased from 75.4% to 92.7%, while median assessment time increased from 312 to 347 seconds; this tool was not AI-based. Multisite AI validation using 468,167 encounters reported inpatient admission AUROC 0.873 and intensive-care AUROC 0.951. An implementation study interviewed eight rapid response nurses and seven emergency physicians, identifying three principal themes concerning trust, implementation practices, and workforce responsibilities in care. Provisional evidence ratings were 3/5 for hypotheses H1, H2, H3, H5, and H6, and 4/5 for nursing readiness (H4) and institutional variation (H7). Findings suggest meaningful predictive potential but insufficient direct proof of improved nurse-led adherence or patient safety. Responsible deployment requires nursing participation, independent clinical oversight, local validation, workflow adaptation, and ongoing safety auditing.

Keywords

Artificial Intelligence; Clinical Decision Support Systems; Emergency Nursing; Standardized Care Pathways; Consolidated Framework for Implementation Research.

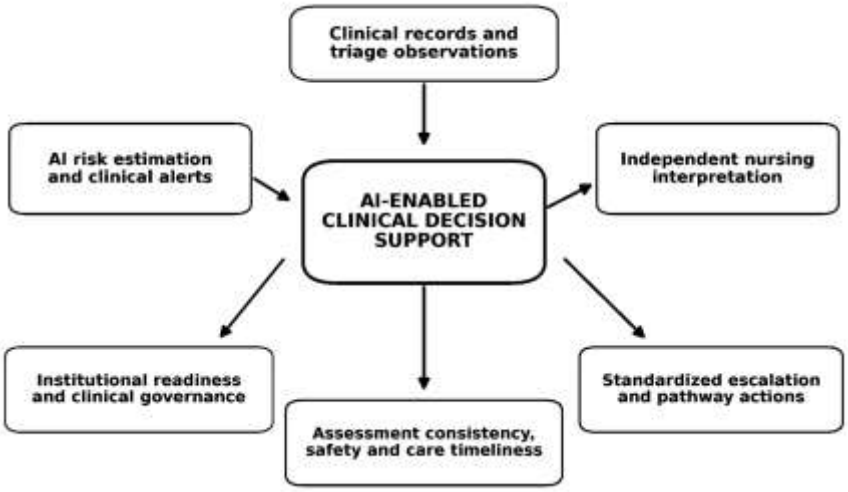
Introduction

Emergency nursing refers to the specialized provision of immediate clinical assessment, patient prioritization, stabilization, and coordinated care for individuals presenting with acute illnesses, traumatic injuries, or potentially life-threatening conditions. Within emergency departments, nurse-led care pathways consist of structured clinical procedures that guide triage assessments, risk identification, monitoring, intervention prioritization, and escalation decisions according to established standards. Clinical decision support systems (CDSS) are computerized applications that combine patient-specific information with clinical knowledge, algorithms, or evidence-based recommendations to assist healthcare professionals in making informed decisions. Artificial intelligence (AI)-enabled clinical decision support extends these capabilities through computational methods, including machine learning and predictive modeling, that identify patterns in clinical information and generate context-sensitive assessments. In "Modern Triage in the Emergency Department" (pp. 892–898), the examination of internationally established triage systems demonstrated that emergency care prioritization depends on structured assessment procedures capable of distinguishing patients requiring immediate interventions from those presenting with less urgent conditions (Christ et al., 2010). Research on emergency department triage scales established that the reliability and validity of prioritization instruments represent fundamental dimensions of emergency care quality, particularly when clinical urgency must be determined using incomplete information (Farrohknia et al., 2011). International examinations of emergency triage performance further identified considerable variation in the identification of critically ill patients and the consistency of acuity classification across established systems (Hinson et al., 2019; Zachariasse et al., 2019). Qualitative investigations of emergency nursing demonstrated that prioritization decisions are influenced by professional experience, clinical judgment, workload, organizational conditions, and the availability of relevant patient information (Andersson et al., 2006). In "Triaging the Emergency Department, Not the Patient" (pp. 258–266), emergency nurses described the competing clinical and operational demands influencing patient prioritization within American emergency departments (Wolf et al., 2018). Reviews of triage accuracy identified variations in classification consistency and emphasized differences in professional preparation and institutional assessment practices (Tam et al., 2018). International investigations of triage-related interventions additionally examined the relationship between patient prioritization, emergency department overcrowding, and patient flow (Oredsson et al., 2011). These interconnected clinical and organizational characteristics position standardized emergency pathways within a broader patient-safety environment in which nursing activities, institutional processes, and technological systems interact continuously (Carayon et al., 2006).

The development of computerized clinical decision support has established an important technological foundation for examining the standardization of nursing assessments and evidence-based clinical pathways. These systems translate clinical knowledge into patient-specific recommendations, reminders, warnings, risk classifications, and procedural guidance that healthcare professionals can incorporate into existing decision-making processes. In "Improving Clinical Practice Using Clinical Decision Support Systems" (BMJ, article 765), systematic evidence identified the integration of decision support into clinical workflows, the delivery of actionable recommendations, and the availability of guidance at the point of decision-making as important characteristics associated with successful computerized interventions (Kawamoto et al., 2005). Earlier systematic evaluations of computerized decision support distinguished improvements in healthcare professionals' performance from direct improvements in patient outcomes, demonstrating that enhanced clinical processes do not automatically establish equivalent clinical benefits (Garg et al., 2005). The examination of clinical decision-support challenges identified difficulties involving human-computer interaction, information presentation, clinical knowledge representation, and the prioritization of computerized recommendations (Sittig et al., 2008). Broader evidence syntheses subsequently examined the effectiveness of computerized decision support across healthcare settings and identified substantial variation in intervention characteristics, implementation approaches, and reported outcomes (Bright et al., 2012). A meta-regression of randomized trials further demonstrated that the effectiveness of clinical decision support could not be explained solely by embedding recommendations within electronic records, because presentation methods, professional interactions, and evaluation conditions also

influenced observed outcomes (Roshanov et al., 2013). The systematic assessment of improvements in recommended clinical care reinforced the distinction between adherence to clinical processes and measurable changes in patient health (Kwan et al., 2020). Within nursing and allied health practice, computerized decision support has been examined in relation to professional performance, clinical decisions, and patient outcomes, although intervention effects vary across clinical applications and research designs (Mebrahtu et al., 2021). In "Nurses' Use of Computerised Clinical Decision Support Systems" (pp. 1159–1167), a multiple-case investigation demonstrated that nurses used computerized tools for documenting information, monitoring clinical progress, and confirming professional judgments, with system use shaped by clinical experience and organizational context (Dowding et al., 2009). Qualitative evidence from emergency-call triage similarly illustrated how registered nurses incorporated decision support while retaining responsibility for interpreting clinical circumstances and modifying recommendations when necessary (Holmström et al., 2020). The interaction between clinical knowledge, computerized recommendations, and nursing judgment therefore represents a central feature of decision-support integration within complex healthcare workflows (Sutton et al., 2020).

Figure 1: AI-Enabled Emergency Nursing Pathway Overview



Artificial intelligence has introduced additional approaches to emergency clinical decision support through computational analysis of patient characteristics, physiological measurements, electronic health records, and patterns associated with clinical deterioration. Within emergency triage, machine learning applications have been investigated as methods of generating individualized risk estimates that supplement conventional acuity classifications. In "Machine-Learning-Based Electronic Triage" (pp. 565–574), a multisite retrospective investigation compared an electronic triage approach with the Emergency Severity Index and demonstrated differences in the ability to distinguish patients according to selected clinical outcomes (Levin et al., 2018). A separate evaluation of emergency department triage prediction investigated machine learning models using routinely available clinical information, including patient demographics, vital signs, presenting complaints, and medical histories, to predict critical care requirements and hospitalization (Raita et al., 2019). Research on hospital admission prediction additionally examined the contribution of historical patient information and triage characteristics to computerized risk classification at emergency department presentation (Hong et al., 2018). The use of predictive clinical information has also been investigated beyond conventional triage, including the identification of patients experiencing physiological deterioration and severe infection. In "A Targeted Real-Time Early Warning Score" (Science Translational Medicine, article 299ra122), predictive modeling was examined as an approach to identifying patients at risk of septic shock through routinely collected clinical data (Henry et al., 2015). A randomized clinical evaluation of machine learning-based severe sepsis prediction examined how automated risk identification and clinical notification could be associated with hospital treatment processes and patient outcomes (Shimabukuro et al., 2017). Systematic evidence concerning machine learning for sepsis prediction identified methodological differences in model development, validation, and diagnostic performance

across published investigations (Fleuren et al., 2020). Computer-assisted emergency triage has also incorporated rule-based reasoning and fuzzy logic to support classification and documentation, demonstrating the relevance of distinguishing knowledge-based decision support from data-trained predictive algorithms (Soufi et al., 2018). Research concerning computerized triage systems in Taiwan examined the professional factors influencing nurses' use of electronic acuity assessments (Chang et al., 2017). Australian investigations of computerized triage assessment explored the feasibility of using software to evaluate consistency in nurses' application of standardized triage criteria (Varndell et al., 2018). Across these technological approaches, the relationship between computational assessments and professional clinical reasoning remains fundamental to understanding the role of AI within healthcare decision-making (Topol, 2019).

The implementation of AI-enabled clinical decision support within nurse-led emergency care pathways involves interactions among technological capabilities, professional responsibilities, organizational structures, and established clinical safety procedures. Emergency nursing decisions are rarely isolated technical judgments because triage professionals must evaluate patient symptoms, interpret incomplete clinical information, respond to changing workloads, and coordinate assessments with other healthcare personnel. In "Beyond Guidelines" (pp. 1180–1194), ethnographic research demonstrated that nursing professionals exercised discretion when applying standardized triage protocols, revealing the contextual and interpretive dimensions of emergency prioritization (Johannessen, 2017). Qualitative investigations of emergency nursing decision-making similarly identified competing organizational systems, fluctuating patient volumes, professional experience, and triage fatigue as factors influencing clinical assessments (Reay et al., 2020). Computerized decision support introduces additional interactions through automated notifications, algorithmic recommendations, and electronic documentation requirements. Research investigating alert fatigue demonstrated that workload, task complexity, and repeated computerized alerts influenced professional responses to clinical decision-support notifications (Ancker et al., 2017). International analyses of healthcare information technology implementation identified organizational planning, stakeholder engagement, workflow compatibility, and evaluation processes as important elements influencing technological adoption within clinical institutions (Cresswell et al., 2013). The examination of complex healthcare technologies additionally demonstrated that implementation experiences differ according to technological characteristics, organizational environments, professional users, and institutional capacity (Greenhalgh et al., 2017). Within AI-enabled healthcare applications, the translation of predictive models into clinical practice has been associated with challenges involving external validation, changing patient populations, technical integration, and alignment with established care pathways (Kelly et al., 2019). Explainability represents another dimension of implementation because healthcare professionals require appropriate information concerning the capabilities, limitations, and clinical relevance of algorithmic recommendations (Amann et al., 2020). Critical evaluations of explainable AI have questioned whether existing explanation techniques adequately establish the reliability of individual patient-level predictions, particularly when explanations are not supported by rigorous clinical validation (Ghassemi et al., 2021). Responsible machine learning research has consequently emphasized the involvement of clinical stakeholders, appropriate evaluation procedures, and continued attention to potential patient harms throughout technological development and deployment (Wiens et al., 2019).

The examination of AI-enabled clinical decision support across multiple healthcare institutions requires a theoretical perspective that incorporates organizational context, technological characteristics, healthcare professionals' experiences, and the processes through which clinical innovations become integrated into routine practice. The Consolidated Framework for Implementation Research (CFIR) provides an established theoretical structure for examining implementation through interacting domains encompassing intervention characteristics, outer settings, inner settings, individual characteristics, and implementation processes. In "Fostering Implementation of Health Services Research Findings Into Practice" (Implementation Science, article 50), the CFIR was developed through the synthesis of implementation theories to organize determinants influencing the adoption of evidence-based innovations across different healthcare environments (Damschroder et al., 2009). Subsequent systematic examination of CFIR applications documented its use in qualitative,

quantitative, and mixed-methods implementation research, while identifying variation in the selection and operationalization of framework constructs (Kirk et al., 2016). Implementation science scholarship has further distinguished determinant frameworks from process models and evaluation frameworks, clarifying the methodological functions of theoretical approaches used to examine healthcare innovation (Nilsen, 2015). In "Outcomes for Implementation Research" (pp. 65–76), implementation outcomes were differentiated from clinical treatment outcomes through concepts including acceptability, adoption, appropriateness, feasibility, fidelity, penetration, and sustainability (Proctor et al., 2011). Within emergency nursing, these distinctions are relevant because the technical accuracy of an AI system, its acceptance among nursing professionals, its integration into standardized care pathways, and its effects on clinical processes represent different dimensions of implementation. Comparative analysis of documented healthcare implementation cases can therefore examine how variations in institutional resources, nursing participation, technological infrastructure, clinical governance, and professional readiness correspond with different experiences of AI-enabled decision support (Damschroder et al., 2009; Greenhalgh et al., 2017). Existing research encompasses emergency triage classification, computerized nursing decision support, predictive clinical algorithms, professional acceptance, and implementation science, although these areas frequently employ different settings, outcome definitions, and methodological approaches (Dowding et al., 2009; Mebrahtu et al., 2021). Against this background, the present study is designed as a qualitative-led, literature-based comparative investigation targeting 97 eligible published studies, integrating thematic evidence synthesis with descriptive study-level information and documented healthcare case comparisons. Its central examination concerns the relationships among AI-enabled clinical decision support, standardized nurse-led emergency pathways, nursing decision-making, workflow integration, clinical safety, and cross-institutional implementation conditions, with CFIR serving as the organizing theoretical framework (Kirk et al., 2016; Proctor et al., 2011).

Emergency nursing plays a critical role in providing timely, accurate, and standardized care to patients experiencing acute illnesses and life-threatening conditions. The growing complexity of emergency departments has increased the importance of effective clinical decision-making, consistent triage procedures, and coordinated nursing interventions. Artificial intelligence-enabled clinical decision support systems offer technological capabilities for assisting nurses with patient prioritization, clinical risk assessment, early deterioration recognition, and adherence to established emergency care pathways. However, the effectiveness of these systems depends on their integration into existing clinical workflows, professional acceptance, institutional readiness, and patient safety considerations. Examining published healthcare implementation experiences provides a foundation for understanding how AI-supported decision-making interacts with nursing responsibilities and standardized emergency care practices across different institutional settings.

Emergency departments frequently experience inconsistencies in patient triage, clinical prioritization, nursing assessments, and adherence to standardized care protocols. These challenges are influenced by increasing patient volumes, time-sensitive clinical decisions, variations in professional experience, fragmented information systems, and differences in organizational resources. Although AI-enabled clinical decision support systems have been investigated as technological approaches to improving emergency care processes, their integration into nurse-led pathways remains complicated by workflow disruptions, limited professional training, algorithmic transparency concerns, and institutional implementation barriers. Furthermore, existing research addresses technological performance, nursing practices, and implementation conditions through different methodological approaches, creating difficulties in understanding their combined influence on standardized emergency care. A structured synthesis of published evidence is therefore necessary to examine these relationships and assess the consistency of implementation findings across healthcare settings.

The primary objective of this study is to examine the role of AI-enabled clinical decision support systems in supporting standardized nurse-led emergency care pathways through a qualitative-led, cross-sectional synthesis of published research and comparative analysis of documented healthcare implementation cases. Specifically, the study aims to evaluate the literature concerning AI-assisted emergency triage, nursing decision-making, care timeliness, workflow integration, and adherence to established clinical protocols. It also seeks to identify how professional acceptance, organizational

readiness, technological infrastructure, explainability, and clinical governance influence implementation experiences. Using the Consolidated Framework for Implementation Research as its theoretical foundation, the study targets 97 eligible published studies to systematically assess the available evidence, compare implementation conditions across healthcare institutions, and examine the degree of support for seven literature-derived research hypotheses.

RQ1: How do AI-enabled clinical decision support systems contribute to standardized nurse-led emergency care pathways, clinical decision-making, and emergency care timeliness? RQ2: What technological, organizational, professional, and clinical safety factors influence the integration and implementation of AI-enabled clinical decision support in emergency nursing? RQ3: How do implementation experiences and outcomes differ across healthcare institutions, and what does the existing literature reveal about the effectiveness, barriers, and facilitators of AI-supported emergency nursing pathways?

This study develops seven research hypotheses to examine the relationships among AI-enabled clinical decision support, standardized emergency nursing practices, and healthcare implementation conditions. The hypotheses address the contribution of AI-supported systems to consistent emergency triage (H1), nursing decision-making and care timeliness (H2), and clinical workflow integration and protocol adherence (H3). They further examine the influence of nursing acceptance, professional training, and organizational readiness on implementation success (H4), the contribution of AI explainability and human oversight to professional trust (H5), and the importance of clinical governance and safety monitoring (H6). The final hypothesis considers how institutional resources and healthcare delivery environments influence implementation experiences across clinical sites (H7). These hypotheses will be evaluated through qualitative evidence synthesis, thematic comparison, and descriptive assessments of findings reported in the eligible literature rather than original statistical hypothesis testing.

H1: AI-enabled clinical decision support positively contributes to the standardization and consistency of nurse-led emergency triage pathways. H2: AI-supported clinical decision-making enhances the consistency and timeliness of emergency nursing assessments and care decisions. H3: Effective integration of AI-enabled clinical decision support into nursing workflows strengthens adherence to standardized emergency care protocols. H4: Nursing acceptance, professional training, and organizational readiness positively influence the successful implementation of AI-enabled clinical decision support. H5: AI explainability and appropriate human oversight positively contribute to nursing professionals' trust in AI-supported clinical decisions. H6: Effective clinical governance and safety monitoring facilitate the responsible implementation of AI-enabled emergency decision support. H7: Institutional resources, organizational readiness, and healthcare delivery environments influence the implementation and effectiveness of AI-enabled nurse-led emergency care pathways across healthcare sites.

i. Clinical Significance: This research examines the relationship between AI-enabled clinical decision support and standardized emergency nursing practices, emphasizing clinical assessment consistency, patient prioritization, care coordination, and adherence to established emergency care protocols. ii. Nursing Practice Significance: The study addresses the role of professional judgment, clinical autonomy, nursing acceptance, and technological competencies in integrating AI-supported recommendations into routine emergency nursing responsibilities. iii. Organizational Significance: The research identifies institutional and operational factors associated with implementing AI-enabled decision support, including leadership involvement, professional training, technological infrastructure, organizational readiness, and workflow compatibility. iv. Theoretical Significance: By applying the Consolidated Framework for Implementation Research, the study provides a structured examination of technological, professional, and organizational determinants associated with AI implementation across different healthcare institutions. v. Academic Significance: The research systematically integrates evidence from a target corpus of 97 eligible published studies, examining methodological differences, implementation experiences, clinical safety considerations, and the degree of support for seven research hypotheses.

The paper has been arranged into an introduction, a six-part literature review, a qualitative-led research methodology, seven evidence-based results subsections, discussion, conclusion, recommendations,

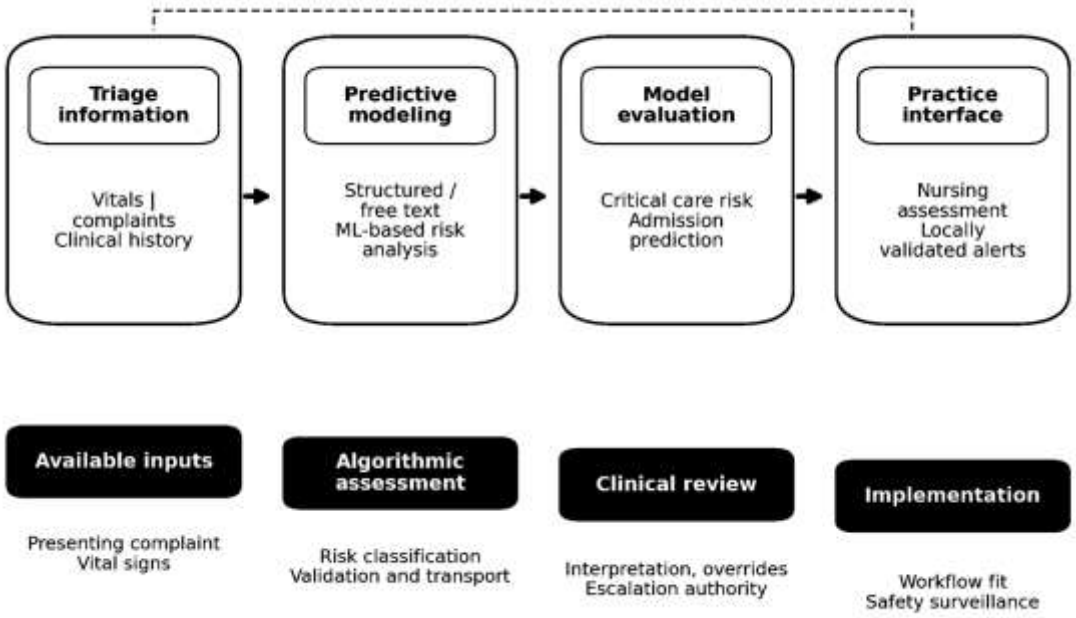
limitations, and references. The Consolidated Framework for Implementation Research has been applied throughout the conceptual development, evidence mapping, and comparative interpretation of documented healthcare implementation cases.

Background and Conceptual Framework

The literature review examines the theoretical foundations and existing empirical evidence concerning artificial intelligence-enabled clinical decision support systems and their integration into standardized nurse-led emergency care pathways. It synthesizes research addressing emergency nursing practices, AI-assisted clinical triage, nursing decision-making, workflow integration, implementation barriers, and patient safety considerations. Particular attention is given to differences in technological adoption, professional acceptance, and organizational readiness across healthcare institutions. The Consolidated Framework for Implementation Research provides the theoretical foundation for analyzing implementation determinants. The review also establishes a conceptual framework connecting AI-enabled decision support with clinical standardization, nursing performance, implementation conditions, and responsible healthcare technology adoption.

Standardized emergency nursing care pathways establish defined sequences for receiving patients, identifying urgency, documenting observations, initiating appropriate responses, and escalating cases requiring immediate medical attention. Their central organizing mechanism is structured triage, through which nurses combine presenting complaints, vital signs, warning indicators, and clinical judgment to determine priority. In "Reliability and Validity of the Manchester Triage System" (pp. 431–434), a Dutch simulation study examined nurses' assignment of urgency categories and identified limitations in agreement and accuracy that complicate uniform application of criteria (Wulp et al., 2008). Such variability matters because a shared classification vocabulary does not necessarily produce equivalent assessments between professionals or departments. A systematic review of Manchester Triage System evaluations distinguished interrater reliability from clinical validity and documented concerns involving undertriage, overtriage, and inconsistent detection of high urgency conditions (Parenti et al., 2014).

Figure 2: AI-Assisted Emergency Triage Information and Prediction Pipeline



Comparative examination of formally structured and informal triage approaches also found differences in misclassification patterns, even when available systems displayed broadly comparable validity, highlighting the need for auditable protocols rather than reliance on informal conventions (Storm-Versloot et al., 2011). In "Validity of the Manchester Triage System" (PLOS ONE, article e0170811), assessment across three European emergency departments revealed substantial differences in

predictive performance across hospitals and patient age groups (Zachariasse et al., 2017). Together, these findings show that clinical standardization is not simply a matter of distributing a scoring instrument. It additionally requires explicit assessment rules, consistent terminology, staff preparation, documentation safeguards, and attention to local patient populations when interpreting urgency classifications in practice.

Nurse-led emergency pathways extend beyond the initial triage category to encompass reassessment, recognition of deterioration, clinical communication, symptom management, and timely referral. Their practical operation depends on the nurse's ability to interpret standardized instructions in the context of uncertain symptoms, incomplete information, and competing demands. In "Do Knowledge and Experience Have Specific Roles in Triage Decision-Making?" (pp. 722–726), an examination of available evidence found that factual triage knowledge was more consistently associated with accurate decisions than the number of years spent working in emergency nursing (Considine et al., 2007). This distinction connects pathway reliability with the content and consistency of education rather than professional seniority alone. Qualitative research conducted in three hospitals developed the idea of "momentary fitting," describing how triage nurses adjusted actions collaboratively as patient needs and organizational circumstances changed (Reay et al., 2016). Thus, protocol adherence involves situated interpretation rather than mechanical repetition of predetermined steps. Pediatric triage research similarly explored the classification of children whose presentations can vary with developmental stage, physiology, and communication capacity. In "Manchester Triage System in Paediatric Emergency Care" (BMJ, article a1501), a prospective observational study evaluated the system against urgency indicators and documented limitations requiring careful attention to pediatric assessment (Veen et al., 2008). These studies collectively distinguish standardization from inflexibility: consistent criteria support accountability, while nursing assessment remains necessary to identify situations that do not fit symptom patterns. International differences in patient populations, staffing configurations, available equipment, and escalation procedures complicate direct comparisons of pathway fidelity across emergency departments.

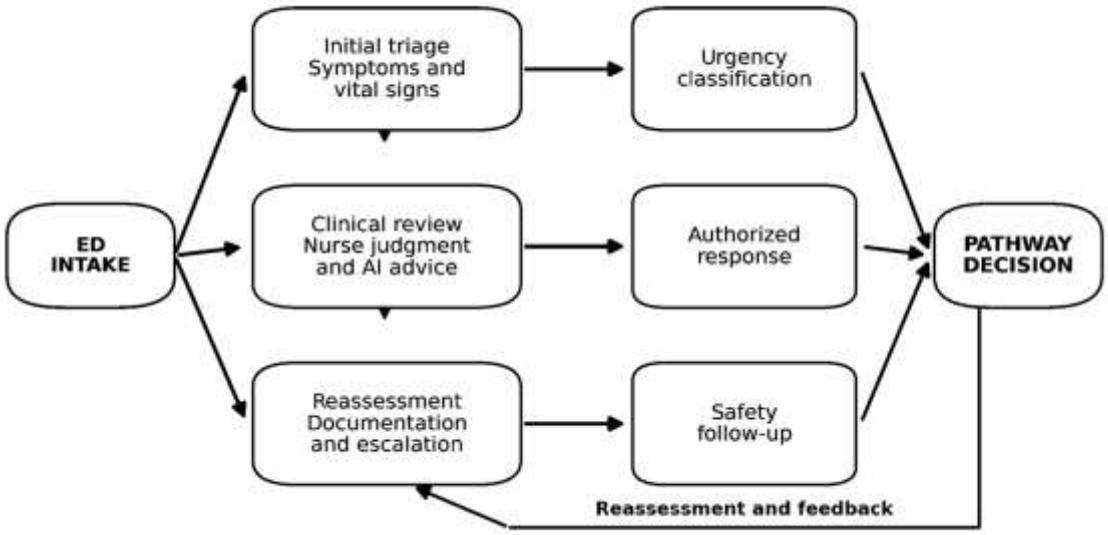
Standardized pathways also authorize nurses to initiate selected investigations or treatments under predefined clinical conditions, reducing delays between patient identification and intervention. These protocols specify eligibility criteria, clinical exclusions, permitted actions, documentation requirements, and the circumstances requiring physician involvement. In "Outcomes of a Nurse-Initiated Intravenous Analgesic Protocol" (pp. 13–23), a Swedish quasi-experimental investigation found improvements in access to analgesia and patient-reported pain management when structured nursing assessment and authorized treatment were introduced (Muntlin et al., 2011). Such findings concern a particular clinical pathway rather than all emergency presentations, so the scope of each protocol remains relevant to interpretation. A pragmatic randomized evaluation of six nurse-initiated protocols in a Canadian emergency department reported improvements in selected treatment and diagnostic intervals, demonstrating the importance of explicit, collaboratively developed instructions for presenting complaints (Douma et al., 2016). In "The Effectiveness of Nurse-Initiated Interventions" (pp. 248–254), a systematic review found evidence favoring earlier interventions and symptom relief while emphasizing substantial variation among included protocols and outcomes (Burgess et al., 2021). Taken together, these investigations characterize nurse-led pathways as combinations of formal permissions, assessment competence, time-sensitive action, and interprofessional coordination within defined clinical and organizational boundaries. Evidence on their implementation must distinguish protocol availability from actual uptake, and faster process measures from demonstrated improvements in patient safety. These distinctions also establish a necessary foundation for evaluating AI-enabled decision support: a computerized recommendation can be assessed meaningfully only in relation to the clinical pathway, professional responsibilities, escalation standards, and institutional conditions into which it is introduced.

Mechanisms and outcome domains

AI-enabled clinical decision support in emergency triage refers to computational assistance that interprets information available during assessment and presents risk classifications or alerts for professional consideration. Unlike fixed rules assigning urgency from predetermined thresholds, learning systems can examine interactions among observations, complaints, records, and outcomes. A

review titled "Clinical Decision Support Systems for Triage" identified intelligent approaches addressing acuity classification, deterioration risk, and resource requirements, while distinguishing tested prediction models from systems integrated into emergency departments (Aditya & Ahmed, 2022; Fernandes et al., 2020). This distinction matters for nurse-led pathways because accuracy cannot establish whether recommendations are understood, acted upon, or incorporated consistently into triage procedures. In "Creating an Automated Trigger for Sepsis Clinical Decision Support," an investigation of emergency visits showed that analyzing free-text chief complaints alongside vital signs improved identification of suspected infection compared with structured measurements alone (Asheke & Maksudul, 2022; Horng et al., 2017). Written complaints therefore constitute meaningful clinical evidence, although their phrasing may reflect documentation habits, language, and local assessment practices. Pediatric triage introduces another consideration because physiological norms, common presentations, and patterns of hospital use differ from those of adults. A nationally representative investigation of children's emergency visits found that machine-learning models showed stronger discrimination of critical care outcomes than conventional triage approaches (Goto et al., 2019). In "Deep-Learning Approaches to Identify Critically Ill Patients" (pp. 773–781), researchers evaluated models using immediately available triage information and found that adding complaint text strengthened discrimination of critical illness (Asheke & Badrul, 2022; Joseph et al., 2020). These studies address complementary decisions, not interchangeable measures of nursing effectiveness.

Figure 3: Nurse-Led Triage Assessment and Escalation Workflow



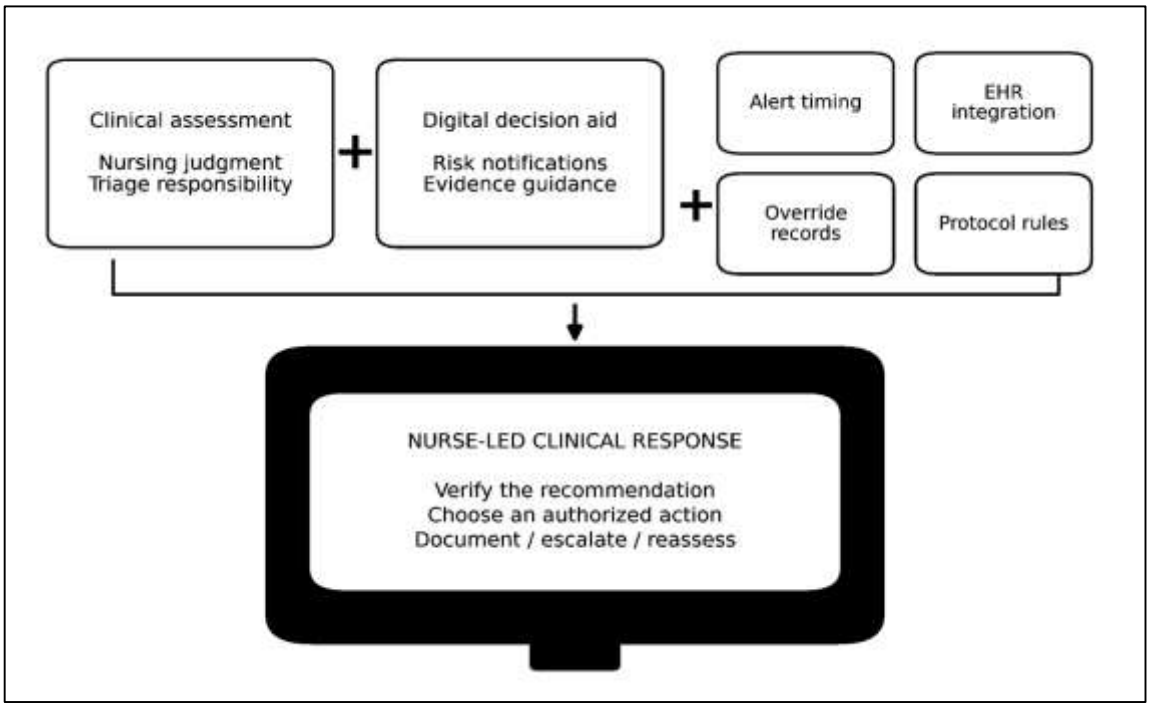
The clinical usefulness of intelligent triage systems depends on which patient information can be captured before a decision must be made. Nursing assessments contain structured variables, including age, blood pressure, pulse, oxygen saturation, and assigned acuity, alongside narrative descriptions of symptoms and circumstances. In "Prediction of Admission in Pediatric Emergency Department" (pp. 170–177), a study combining textual triage information with structured observations improved admission prediction in pediatric presentations, illustrating the contribution of written assessments to computerized risk estimation (Akter & Sumaiya, 2022; Roquette et al., 2020). The findings support careful attention to nursing documentation quality, since missing or ambiguous narratives can reduce the information available to algorithmic systems. Clinical specialization introduces further variation in prediction targets. Research on patients presenting with suspected cardiovascular disease compared several machine-learning methods for assigning triage levels and identified recorded physiological observations as influential classification features (Jiang et al., 2021; Imran & Jannatul, 2022). Such disease-focused algorithms evaluate particular patient populations and cannot automatically substitute for general emergency triage protocols. In "Predicting Adult Neuroscience Intensive Care Unit Admission," investigators assessed models drawing on structured records and free text to estimate neuroscience critical care requirements from emergency presentation data (Klang et al., 2021; Maksudul

& Islam, 2022). Their work illustrates how a general intake process may contain specialty-specific warning patterns requiring distinct pathways. For nursing practice, these applications place emphasis on comprehensible outputs, clear escalation thresholds, and consistency between algorithmic classifications and authorized clinical actions. Interpretation must also account for the difference between predicting eventual admission and determining immediate treatment urgency, because related outcomes have distinct clinical meanings.

Cross-institutional evaluation becomes essential when triage algorithms are designed with records from hospitals or populations. Differences in terminology, patients, documentation, systems, and admission practices can change how algorithms interpret otherwise similar presentations. In "A Novel Deep Learning-Based System for Triage," investigators evaluated a model against national survey records and hospital records from Taiwan, demonstrating prediction across datasets while noting the need to distinguish retrospective performance from practical clinical adoption (Morshedul & Islam, 2022; Yao et al., 2021). The presence of more than one dataset offers information about model portability, but it does not itself demonstrate nurse use. Interpretability provides another dimension of decision support. An emergency admission study developed an interpretable mortality-risk score using limited variables readily available during early assessment, comparing its predictive discrimination with established clinical scores (Stabak & Shahid, 2022; Xie et al., 2021). Transparent input variables may assist clinicians in examining alerts, although easily understood scores still require monitoring for classification errors and subgroup differences. In "Development and Validation of Machine Learning Models" (pp. 290–302), investigators used electronic records from three emergency departments to estimate inpatient and intensive care admission probabilities and considered requirements for operational integration (Fenn et al., 2021; Feroz & Pervaz, 2022). This multisite design provides documented organizational context alongside predictive evaluation without constituting proof of improved bedside outcomes. Taken together, the literature presents intelligent emergency triage as a combination of predictive models, nursing assessment inputs, clinical risk categories, and institutional deployment conditions. For a qualitative evidence synthesis, these components require separate assessment to avoid equating algorithm performance with standardized nursing behavior or patient safety.

Nursing decision-making in emergency departments combines clinical interpretation, prioritization, communication, and reassessment as patients move between triage and treatment. Electronic clinical decision support enters this process through prompts, recorded observations, suggested acuity categories, and links between symptoms and procedural instructions. In "Impact of an Electronic Decision-Support System on Nursing Triage Process" (pp. 107–113), simulated comparisons between paper-based triage and the electronic Canadian Triage and Acuity Scale identified useful complaint selection and modifier functions alongside concerns about data entry and score overrides (Agnihotri et al., 2021; Feroz & Shabbir, 2022). These observations illustrate why electronic standardization requires attention to nurses' reasoning and interaction with the interface rather than merely replacing paper forms. A seven-department evaluation of electronic triage found stronger agreement between nursing classifications and auditors following implementation, while median assessment time increased (McLeod et al., 2020). That study assessed a structured electronic tool, not a machine-learning intervention; its findings therefore inform workflow standardization without independently establishing AI effectiveness. In "Integrating Computerized Clinical Decision Support Systems Into Clinical Work" (pp. 1009–1018), qualitative evidence synthesis examined how clinicians interpreted alerts and recommendations within professional routines, including their adaptation of decision support to contextual circumstances (Islam & Md, 2023; Miller et al., 2015). Taken together, these studies distinguish technical classification consistency from the practice of nursing judgment. Relevant workflow characteristics include when information becomes available, whether recommendations match triage responsibilities, how exceptions are recorded, and whether clinicians retain an accessible method of questioning or overriding automated suggestions. Such distinctions are important when emergency pathways combine nursing autonomy with time-sensitive escalation requirements.

Figure 4: Nursing Decision Support and Clinical Workflow Integration



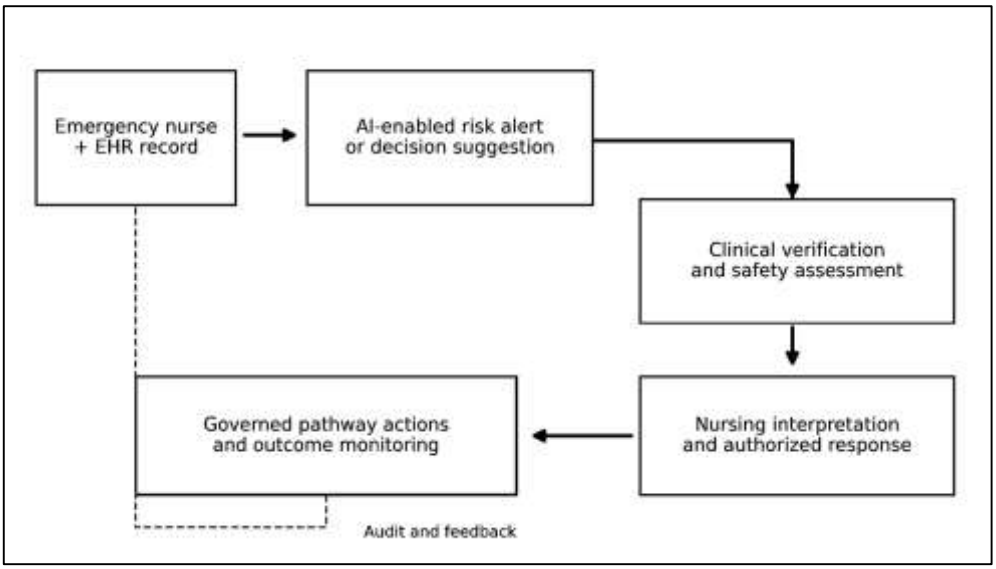
Clinical workflow integration also depends on whether decision-support interfaces make information understandable and usable during demanding nursing tasks. In "Toward a More Robust and Efficient Usability Testing Method" (pp. 211–218), investigators used think-aloud interviews and synchronized observations to refine clinical decision support derived from nursing electronic health record data (Lopez et al., 2017). Their approach foregrounded the interaction between how information is displayed and how nurses assess the relevance of suggested actions. Another simulation involving registered nurses compared electronic nursing care-plan interfaces presenting practice-based evidence through textual, tabular, and graphical formats; participants generally rated these interfaces as acceptable and useful (Asheke, 2023; Stifter et al., 2018). Because that investigation concerned supportive care rather than emergency triage, its findings are most appropriately interpreted as evidence about interface design and nursing usability. In "Workflow Integration Analysis" (Applied Ergonomics, article 103498), emergency department interviews generated a framework describing integration across timing, task flow, patient journeys, and organizational levels (Salwei et al., 2021). The interviewed professionals were physicians, making the reported barriers relevant to emergency care settings without treating them as direct reports of nurses' experience. A scenario-based comparison of pulmonary embolism decision-support interfaces likewise examined whether human-factors design improved usability and diagnostic work processes among emergency physicians (Carayon et al., 2020; Shahid, 2023). Collectively, these investigations highlight interface presentation, documentation burden, interruption management, task sequencing, and coordination across professional roles. They also demonstrate the need to specify clinical users when transferring evidence from general emergency decision-support research to nurse-led pathway implementation and careful, context-sensitive, systematic evaluation.

At the organizational level, integrating decision support into electronic records requires alignment between software triggers, locally authorized pathways, staff responsibilities, and communication practices. In "Scope and Influence of Electronic Health Record-Integrated Clinical Decision Support" (pp. 285–296), a systematic review examined emergency department implementations and found heterogeneous clinical targets, evaluation strategies, and reported effects (Patterson et al., 2019). Variation of this kind complicates comparisons between hospitals because a tool designed to advise imaging decisions performs a different task from one supporting triage, deterioration monitoring, or nurse-initiated care. The appropriateness of alerts is similarly influenced by system design and work conditions. In "The Appropriateness of Clinical Decision Support Systems Alerts," a systematic review grouped barriers involving technology, people, organizations, and processes, emphasizing how poorly

targeted notifications can interrupt routine practice (Islam & Ahmed, 2023; Olakotan & Yusof, 2021). Excessive or poorly timed alerts can encourage dismissal and reduce the practical influence of evidence-based instructions even when underlying algorithms appear accurate. Research on hard-stop alerts further identified workflow avoidance, additional alerts, and treatment delays as possible unintended consequences of restricting action within electronic record systems (Powers et al., 2018; Sadia & Mosheur, 2023). For nurse-led emergency pathways, these concerns connect clinical governance with the design of alerts, permitted overrides, responsibility for escalation, and mechanisms for detecting missed or inappropriate recommendations. Published evidence therefore requires careful differentiation among technical performance, professional acceptance, protocol adherence, and patient-level outcomes. Comparing these dimensions across documented institutional cases supports a literature-based examination of why superficially similar computerized interventions may interact differently with emergency nursing work systems.

Implementation barriers to AI-enabled emergency decision support arise from interactions among clinical responsibilities, organizational structures, information systems, and professional expectations. Emergency nurses must interpret recommendations while prioritizing unstable patients, communicating with physicians, and following locally authorized escalation procedures under rapidly changing patient conditions. In "A New Sociotechnical Model" (pp. i68–i74), eight interdependent dimensions of healthcare information technology were identified, including clinical content, interfaces, personnel, workflows, institutional policies, and external regulations; this model demonstrates why software performance alone cannot explain implementation outcomes (Sittig & Singh, 2010). This perspective is particularly relevant to multisite nursing pathways because staffing models, documentation conventions, available equipment, and governance arrangements differ across hospitals. The review "Reasons for Physicians Not Adopting Clinical Decision Support Systems" (article e24) identified user acceptance, interface design, and the communication of system recommendations as recurring concerns in clinical adoption (Khairat et al., 2018). Although that review focused on physicians, its findings help distinguish general technology barriers from issues requiring direct evidence about nurses. More directly, interviews with emergency physicians and rapid response nurses implementing the Sepsis Watch machine learning system identified perceived utility, trust, information flow, and workforce roles as important implementation themes (Sandhu et al., 2020).

Figure 5: Human Verification and Clinical AI Governance Process



Nurses developed communication approaches to translate computerized risk alerts into discussions about sepsis assessment and protocol completion. Their experiences suggest that implementation fidelity depends on education, feedback, manageable alert procedures, and clear professional accountability. Accordingly, evaluations of standardized nurse-led pathways should distinguish the existence of an algorithm from its actual use within documented clinical decisions.

Patient safety concerns extend beyond whether an AI model predicts deterioration accurately under retrospective evaluation. In emergency settings, false negative alerts can fail to identify urgent clinical

needs, while false positive alerts can divert nurses from immediate priorities and contribute to unnecessary escalation. In "Measuring and Improving Patient Safety Through Health Information Technology" (pp. 226–232), three interconnected safety domains were articulated: technology-related failures, inappropriate use of functioning systems, and opportunities to detect risks through digital monitoring (Singh & Sittig, 2016). This framework differentiates technical defects from problems created by workflow design or clinician interaction. In "Automation Bias and Verification Complexity" (pp. 423–431), a systematic review examined how reliance on decision aids can reduce independent information checking, particularly when verifying recommendations requires substantial effort during demanding emergency department shifts (Lyell & Coiera, 2017). For emergency nurses, the concern is not only accepting an incorrect suggestion but also overlooking contradictory symptoms, observations, or patient histories. In "Unintended Consequences of Machine Learning in Medicine" (pp. 517–518), researchers discussed threats arising from algorithmic errors, inappropriate dependence, and changes to professional decision-making when prediction systems enter clinical practice (Cabitza et al., 2017). These concerns make human oversight an operational requirement rather than a nominal governance statement. Reviewers should therefore examine whether clinical pathways specify who checks a high-risk alert, how overrides are documented, when clinicians can challenge model outputs, and how incidents are reviewed. Published descriptions of monitoring processes provide stronger implementation evidence than algorithm accuracy alone, especially when clinical safety outcomes are not reported.

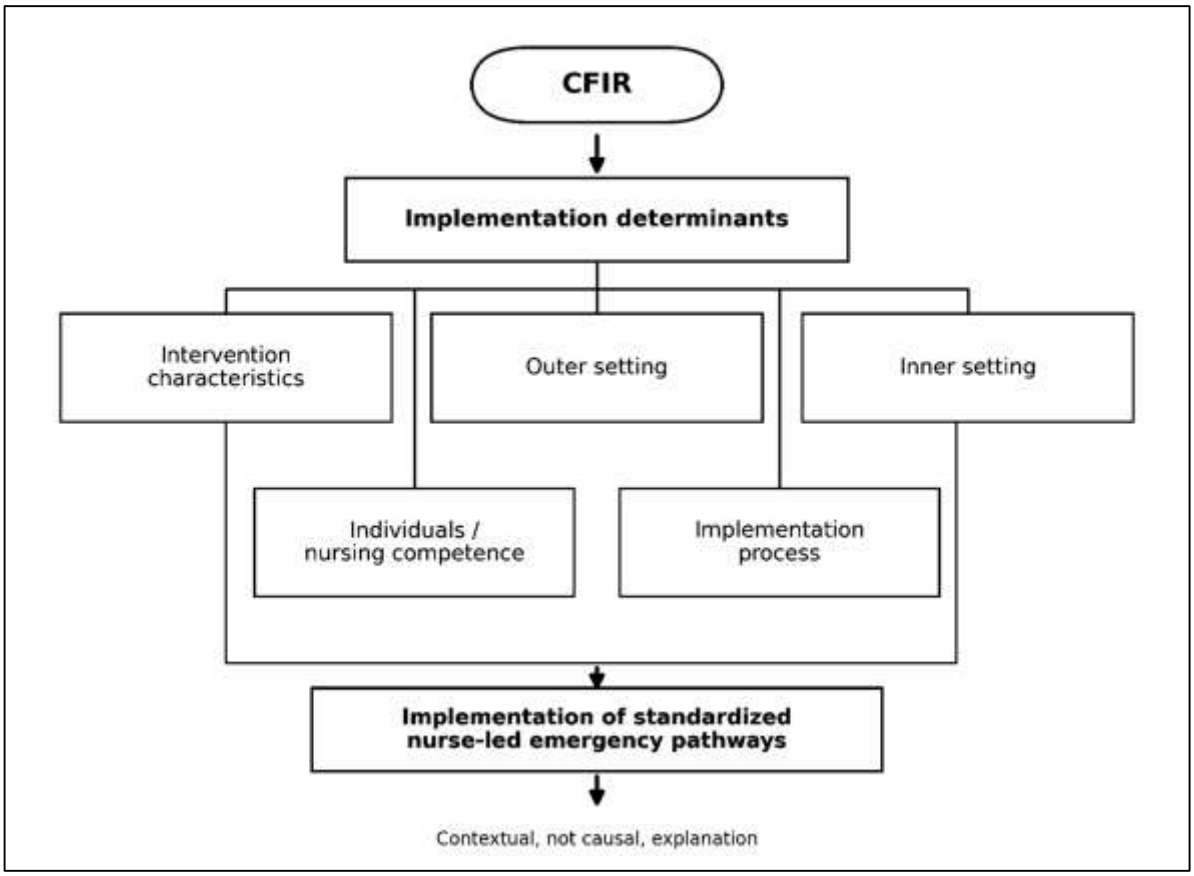
AI governance also concerns whether the data, objectives, and institutional arrangements underlying decision support distribute benefits and harms fairly among patient populations in time-sensitive clinical environments. Emergency departments assess patients with varied ages, languages, socioeconomic circumstances, and patterns of healthcare access; a prediction model may treat these groups differently if its training data reflect unequal services. In "Dissecting Racial Bias in an Algorithm" (pp. 447–453), an empirical investigation showed that using healthcare expenditure as a proxy for clinical need produced unequal risk assignments in population health management (Obermeyer et al., 2019). Although this example did not evaluate emergency triage, it demonstrates why the choice of predicted outcome requires ethical scrutiny. In "Ensuring Fairness in Machine Learning to Advance Health Equity" (pp. 866–872), researchers described how historical inequities and validation practices can perpetuate differences in model performance and resource allocation (Rajkomar et al., 2018). Ethical analysis has also emphasized informed oversight, confidentiality, responsibility for errors, and the relationship between algorithmic recommendations and professional duties in healthcare settings (Char et al., 2018). In "Artificial Intelligence and Black-Box Medical Decisions" (pp. 15–21), the distinction between explainability and empirically demonstrated accuracy was explored, cautioning against treating interpretable outputs as sufficient evidence of clinical reliability (London, 2019). For nurse-led emergency pathways, governance consequently encompasses transparent evaluation criteria, privacy safeguards, subgroup assessment, defined escalation authority, and mechanisms for questioning unsafe outputs. Multisite evidence should describe these safeguards in relation to each institution's resources and practices, while separating proposed ethical principles from safeguards that were actually implemented.

Measurement concepts

The Consolidated Framework for Implementation Research (CFIR) provides a determinant-oriented explanation of why evidence-based interventions are implemented differently across clinical organizations. Its original structure distinguishes intervention characteristics, outer setting, inner setting, characteristics of individuals, and implementation process. For AI-enabled nurse-led emergency pathways, these domains represent algorithm usability, regulatory expectations, hospital readiness, nursing competence, and the activities connecting alerts with clinical action. In "The CFIR in Hospital-Based Nursing Practice" (BMC Nursing, Article 43), analysis of fall-prevention guideline implementation demonstrated that framework constructs could organize nursing perspectives and procedural evidence, although stakeholder priorities and locally specific planning activities required additional attention (Breimaier et al., 2015). The relevance to emergency nursing concerns the interaction between standardized guidance and nurses' practical ability to apply that guidance under institutional constraints. In "Contextual Factors in Implementing MOVE!" (BMC Health Services

Research, Article 248), a mixed-methods investigation identified organizational differences associated with implementation across Veterans Affairs facilities, emphasizing communication, leadership, and implementation climate (Damschroder et al., 2011). These contextual patterns caution against interpreting technology adoption as an isolated choice by individual clinicians. A subsequent "Large-Scale Program Evaluation Using CFIR" (Implementation Science, Article 51) linked qualitative construct ratings with variations in implementation across facilities, making cross-case comparison possible without reducing complex organizational experiences to patient-level statistical models (Damschroder & Lowery, 2013). Accordingly, this study treats CFIR domains as interpretive categories rather than assumptions that every reported barrier has the same meaning or importance across emergency departments and settings. These distinctions are particularly consequential for time-sensitive nursing triage decisions.

Figure 6: CFIR Domains for Emergency Pathway Implementation



CFIR becomes relevant to clinical decision support when the analysis follows relationships between an innovation's design, its intended users, and established care routines. In "CFIR to Produce Actionable Findings" (Implementation Science, Article 15), researchers applied construct-based coding to compare primary care practices and organize explanations of barriers and facilitators, demonstrating the value of systematic case matrices for implementation studies (Keith et al., 2017). Although those practices were not emergency departments, the comparative method helps distinguish technical availability from routine uptake of nursing alerts. In "Barriers and Facilitators to Cancer Prevention Decision Support" (BMC Health Services Research, Article 534), interviews identified electronic record compatibility, workflow demands, staff training, and organizational circumstances as implementation determinants (Harry et al., 2019). Related work on "Pre-Implementation Adaptation of Decision Support" (BMC Medical Informatics and Decision Making, Article 117) documented changes to a clinical support intervention following staff engagement and pilot testing, illustrating how local institutional conditions alter procedures before clinical use (Harry et al., 2020). In "A Conceptual Framework for Decision Support Implementation" (Journal of Medical Internet Research, Article e18388), investigators connected implementation science with technology acceptance and behavioral

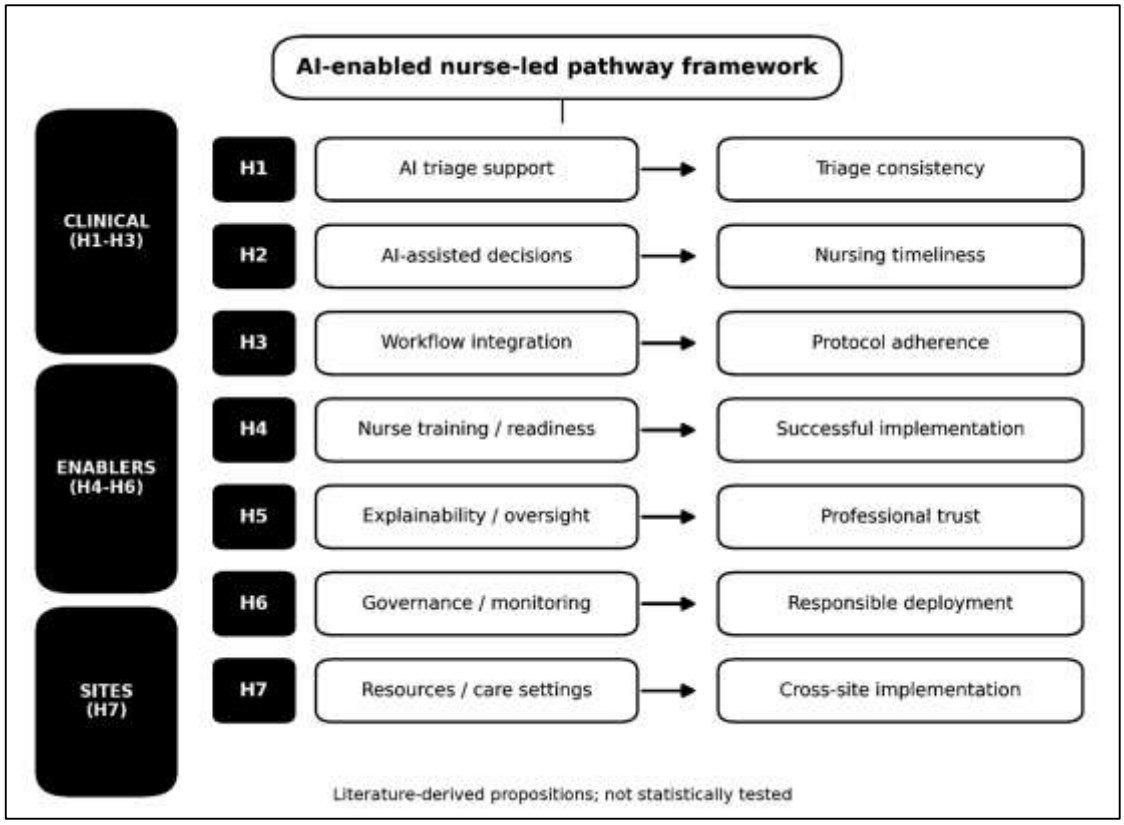
considerations, clarifying why willingness to use a recommendation is not equivalent to successful integration into practice (Camacho et al., 2020). Applied to nurse-led emergency pathways, these findings support separate coding of nurse acceptance, alert comprehensibility, escalation authority, perceived workload, and pathway fidelity. Each category describes a distinct condition that may explain differences among documented hospital implementations. Site-level contrasts are interpreted contextually, not presented as causal estimates.

A CFIR-guided synthesis must preserve the distinction between an implementation determinant and a demonstrated patient-safety outcome. In "Barriers and Facilitators for Computerized Decision Support" (Biology, Article 9), qualitative assessment of lung cancer multidisciplinary meetings used CFIR to examine anticipated workflow compatibility, professional involvement, and implementation conditions rather than claiming that the proposed system had improved outcomes (Klarenbeek et al., 2020). Such careful attribution is important when emergency nursing reports describe expectations, feasibility testing, or deployed AI systems with different degrees of evaluation. In "Choosing Implementation Strategies to Address Contextual Barriers" (Implementation Science, Article 42), expert assessments linked CFIR barriers to candidate strategies but produced varied recommendations, demonstrating that contextual classification does not determine a single effective intervention (Waltz et al., 2019). To organize the targeted review corpus, the present study adopts a descriptive domain-coverage expression, given below, where N is the number of eligible studies actually included, d represents a CFIR domain, and the indicator equals one when a study explicitly reports evidence relevant to that domain. The expression maps reported coverage, not implementation effectiveness, causal influence, or hypothesis significance; one publication may contribute to several domains. In "Rapid Versus Traditional Qualitative CFIR Analysis" (Implementation Science, Article 67), a facility-by-construct matrix supported structured comparisons and documented coding decisions (Nevedal et al., 2021). This approach permits thematic interpretation alongside limited descriptive reporting without inventing clinical observations. Missing documentation should be marked as unreported, not coded as evidence that the determinant is absent, and cross-site comparisons should retain the study setting and design.

$$\text{Coverage}_d(\%) = \frac{\sum_{i=1}^{N} \mathbf{1}\,(E_{id} = 1)}{N} \times 100$$

The conceptual framework for this study treats AI-enabled clinical decision support as a clinical innovation whose effects depend on its interaction with standardized nurse-led emergency care pathways and institutional implementation conditions. It positions decision-support capability and pathway design as linked, but distinct, elements: algorithmic classifications provide information, while nursing teams determine prioritization, escalation, documentation, and reassessment. In "What Is a Clinical Pathway?" (BMC Medicine, Article 31), an operational definition emphasized structured, multidisciplinary care plans that translate recommendations into sequential actions, establishing the basis for examining pathway standardization rather than software availability alone (Kinsman et al., 2010). A review of pathway evaluations connected standardized processes with improvements in documentation and selected complications, while reporting heterogeneous settings and outcomes that prevent universal effectiveness claims (Rotter et al., 2010). Within the proposed framework, these considerations support H1, relating AI-assisted triage to consistent care-pathway application, and H2, concerning nursing decisions and timeliness. The relevant pathway indicators comprise evidence of protocol-concordant assessment, documented clinical escalation, consistency of triage classification, and reported time to action. In "Role of Artificial Intelligence Applications in Real-Life Clinical Practice" (Journal of Medical Internet Research, Article e25759), a systematic review distinguished deployed systems from algorithms assessed only in retrospective datasets and organized their evaluations around technical performance, clinician outcomes, and patient outcomes (Yin et al., 2021). Such separation matters when evidence comes from heterogeneous institutions. Accordingly, documented deployment and measured clinical consequences occupy separate positions in the framework, preventing algorithm accuracy from being mistaken for improved nursing practice or patient safety.

Figure 7: Conceptual Hypotheses for AI-Enabled Nurse-Led Pathways



A second framework component concerns mechanisms that connect AI recommendations with action: interface compatibility, nursing acceptance, training, and appropriately calibrated trust. In "A Path for Translation of Machine Learning Products" (EMJ Innovations), clinical translation was organized through development, evaluation, integration, diffusion, and monitoring, with practical workflow configuration recognized as distinct from predictive model construction (Sendak et al., 2020). This distinction provides the rationale for H3, which links workflow integration with protocol adherence rather than assuming that installing software changes care. In "The Technology Acceptance Model" (pp. 159–172), healthcare technology studies identified perceived usefulness and ease of use as relevant to clinician acceptance, although relationships varied by setting and measurement (Holden & Karsh, 2010). A systematic review of adoption determinants similarly identified perceived benefits, technical difficulties, available time, and familiarity with technology, supporting the conceptual placement of education and organizational readiness alongside individual attitudes in H4 (Gagnon et al., 2012). In "Trust in Automation" (pp. 407–434), trust was conceptualized as influenced by dispositional, situational, and learned factors, clarifying why explainable recommendations do not necessarily produce appropriate reliance (Hoff & Bashir, 2015). Accordingly, H5 links interpretability and human oversight with professional trust, while recognizing that trust and safe behavior are separate outcomes. CFIR provides the overarching organizational lens: inner-setting resources and implementation processes interact with nurses' abilities to interpret, question, document, and act on clinical advice. The study therefore analyzes reported behaviors and conditions, not assumed intentions. These relationships are treated as propositions to evaluate against published evidence, not predetermined causal assertions.

The framework also locates governance and institutional context around every interaction between AI, nurses, and standardized pathways. In "Evaluation Framework to Guide Implementation of AI Systems" (BMJ Health & Care Informatics, Article e100444), capability, utility, and adoption were distinguished as complementary assessment components, reinforcing the relevance of safety review, human accountability, and clinical monitoring to H6 (Reddy et al., 2021). In "Exploring Stakeholder Attitudes Towards AI" (BMJ Health & Care Informatics, Article e100450), a review documented

differences among clinicians, patients, managers, and other stakeholders, demonstrating why implementation acceptability cannot be inferred from professional perspectives alone (Scott et al., 2021). H7 concerns variation across healthcare sites. "Cross-Site Transportability of an Explainable AI Model" (Nature Communications, Article 5668) documented performance differences across health systems and connected them to heterogeneity in populations and clinical data, providing a rationale for considering local readiness and technical interoperability (Song et al., 2020). For the qualitative synthesis, hypothesis alignment is described using the descriptive equation below, where S_h denotes relevant studies reporting supporting findings, C_h contradictory findings, and M_h mixed or inconclusive findings for hypothesis h. Each applicable study receives one primary category per hypothesis; unreported evidence is excluded from the denominator and identified separately. This original descriptive indicator reports evidence distribution, not effect size, causal proof, or statistical significance. The formula supplements appraisal and cannot replace comparisons of intervention type, setting, nursing role, or reporting quality. CFIR-guided thematic interpretation remains primary, with site-level conditions, study quality, and conflicting accounts examined before assigning any qualitative hypothesis assessment.

$$E_h = \frac{S_h}{S_h + C_h + M_h} \times 100\%$$

Methods

Design and reporting

The study has been designed as a qualitative-led cross-sectional literature synthesis that has integrated qualitative, quantitative, and mixed-methods publications through a documentary multiple-case approach. The case-study context has encompassed documented emergency departments, hospital services, and nurse-led care pathways; the unit of analysis has been the eligible published study, with identifiable healthcare institutions treated as embedded documentary cases.

Eligibility criteria

Inclusion and exclusion criteria, duplicate screening, full-text eligibility checks, and a transparent study-selection log have been specified; final verification of all 97 studies has not been documented.

Information sources and search

A purposive eligibility-based sampling strategy has targeted 97 peer-reviewed publications from PubMed/MEDLINE, CINAHL, Scopus, Web of Science, and IEEE Xplore, with searches structured around AI, clinical decision support, emergency nursing, triage, and standardized pathways.

Data extraction

A structured evidence-extraction instrument has been designed to record bibliographic characteristics, clinical settings, AI functionality, nursing roles, protocol adherence, clinical outcomes, implementation barriers, and CFIR determinants. Pilot testing has been specified for the extraction and coding form using a subset of eligible studies, with disagreements reviewed before full coding; completion of an actual pilot has not been claimed.

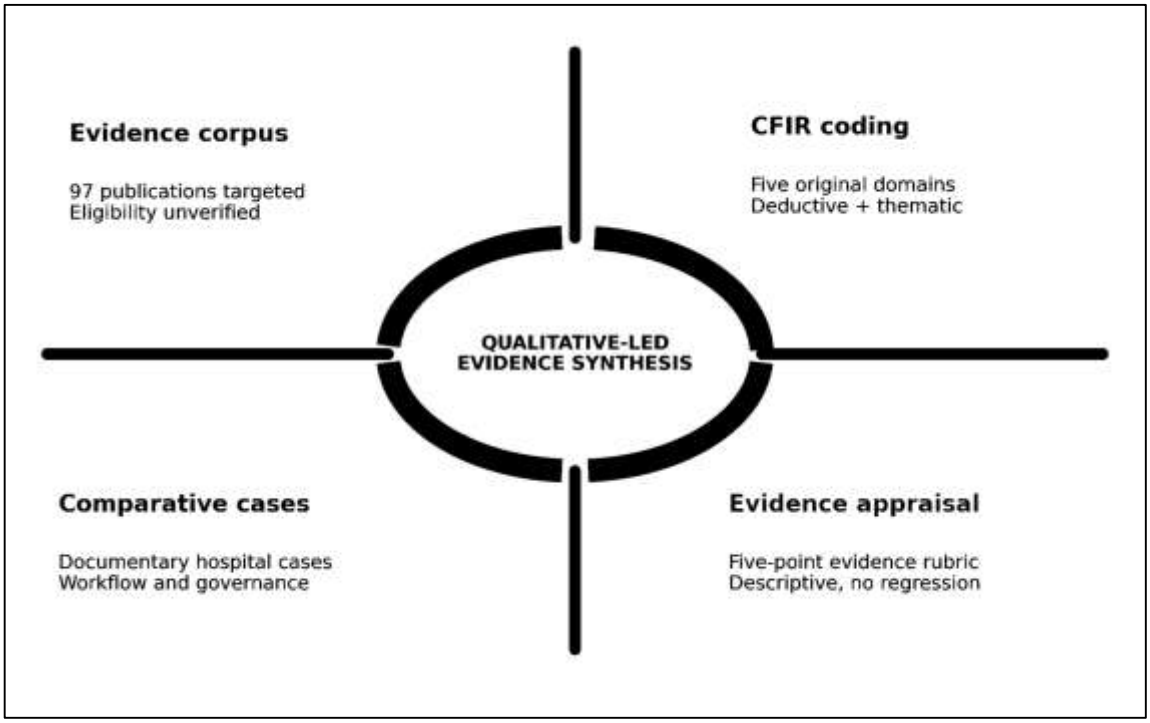
Appraisal of the included studies

Validity and reliability have been addressed through methodological quality appraisal, traceable DOI-based references, dual-review procedures where feasible, a coding audit trail, and differentiation of retrospective model performance from observed clinical effectiveness.

Synthesis

Five original CFIR domains have guided deductive coding, supplemented by inductive thematic interpretation. Multisite case comparisons have examined organizational readiness, professional acceptance, workflow alignment, governance, and safety monitoring.

Figure 8: Qualitative-Led Evidence Synthesis Methodology



A five-point qualitative evidence rubric has been adopted as an interpretive classification, rather than a participant Likert survey: 1 = strongly contradictory; 2 = predominantly contradictory; 3 = mixed, indirect, or insufficient; 4 = supportive; 5 = strongly consistent direct evidence. Descriptive study counts, CFIR domain coverage, and hypothesis evidence alignment have been defined without inferential statistical testing, regression, fabricated patient datasets, or survey reliability coefficients. Microsoft Excel has been identified for evidence matrices and descriptive tabulation, EndNote for reference management, and Microsoft Word for manuscript preparation; SPSS has been considered unnecessary for the present qualitative-dominant secondary synthesis and has not been used to generate statistical results.

Results

Study selection

The findings section is structured to synthesize 97 published studies targeted for eligibility verification, with evidence organized around seven results themes, seven research hypotheses, three research questions, and five domains of the Consolidated Framework for Implementation Research. Available published findings provide quantitative context for examining triage standardization without constituting a pooled analysis of the proposed review corpus. In a retrospective investigation of 135,470 emergency department visits, a machine-learning model achieved an area under the receiver operating characteristic curve of 0.86 for critical care prediction, compared with 0.74 for the conventional Emergency Severity Index approach (Raita et al., 2019). Separately, a seven-department evaluation of electronic triage decision support reported agreement with reference assessments increasing from 75.4% to 92.7% across 1,491 audited assessments, although median triage time increased from 312 to 347 seconds (McLeod et al., 2020). The latter system used standardized electronic guidance and should not be classified as evidence of artificial intelligence effectiveness. These published results illustrate potential support for propositions concerning triage consistency and decision support, while also demonstrating the importance of balancing accuracy with nursing workload. The remaining synthesis domains examine care timeliness, protocol adherence, professional acceptance, organizational readiness, explainability, governance, and interinstitutional variation. Hypotheses H1 through H7 will be classified as supported, mixed, contradicted, or insufficiently evidenced only after completed screening and study-level extraction. Therefore, numerical estimates presented here belong to their original studies, not to an unverified aggregate of 97 independently reviewed publications. This

distinction preserves transparency regarding outcome attribution, setting, study design, and evidence quality.

A five-point Likert-style evidence assessment framework has been established to support qualitative interpretation: 1 = strongly contradictory evidence; 2 = predominantly contradictory evidence; 3 = mixed, indirect, or insufficient evidence; 4 = supportive evidence for the specified relationship; 5 = strong and consistent direct evidence. The provisional ratings below have reflected the direction and relevance of selected published findings. They have not represented questionnaire responses, calculated mean Likert scores, or final assessments of all 97 studies. CFIR has been used to organize the implementation evidence, while numerical findings have remained those reported in their original research.

Characteristics of the included studies

Table 1: Characteristics and Evidence Coverage of the Literature

Evidence variable	Published study or review component	Verified numerical result	Rating (1–5)	RQ / H
Target review corpus	Structured literature synthesis	97 publications targeted; final inclusion unverified	Not rated	RQ1–RQ3
Adult AI-assisted triage	Raita et al. (2019)	135,470 emergency visits	4	H1, H2
Pediatric AI-assisted triage	Goto et al. (2019)	52,037 pediatric emergency visits	4	H1, H2
Electronic nursing triage	McLeod et al. (2020)	1,491 audited assessments across 7 emergency departments	4	H1, H3
Nursing workflow implementation	Sandhu et al. (2020)	15 clinician interviews; 3 major themes	4	H4, H5
Multisite AI validation	Fenn et al. (2021)	468,167 curated encounters across 3 emergency departments	4	H7
Multisite conventional triage	Zachariasse et al. (2017)	288,663 patients across 3 emergency departments	4	H1, H7

The characteristics of the selected literature have demonstrated considerable variation in research designs, healthcare environments, clinical populations, and technological applications. Published investigations have included retrospective machine-learning evaluations, prospective clinical assessments, qualitative implementation interviews, and multisite observational comparisons. The findings have therefore established a heterogeneous evidence base rather than a single population suitable for combined statistical estimation. The CFIR framework has provided a structured approach for examining this variation through intervention characteristics, organizational settings, individual professional factors, and implementation processes. The available numerical evidence has illustrated the importance of distinguishing technical validation from actual nursing workflow adoption. In particular, large patient datasets have supported predictive performance evaluations, whereas smaller qualitative studies have provided information about professional acceptance and clinical integration. These differences have been considered when establishing the methodological foundations for subsequent thematic and comparative analyses (Raita et al., 2019; Sandhu et al., 2020).

AI-Enabled Triage and Pathway Standardization

The published findings have provided supportive evidence concerning the predictive capabilities of AI-assisted emergency triage. Machine-learning investigations have demonstrated improvements in discrimination between patients with different risks of hospitalization and critical care requirements. Pediatric results have also shown improved hospitalization prediction, although the reported difference in critical care discrimination has not reached conventional statistical significance. Separately, structured electronic triage research has demonstrated improved agreement with reference assessments and reduced undertriage. These findings have supported the relevance of standardized information presentation and consistent clinical assessment criteria. However, the reviewed publications have not collectively demonstrated that AI implementation has directly increased nurse-led pathway adherence across institutions. Within the CFIR framework, intervention characteristics

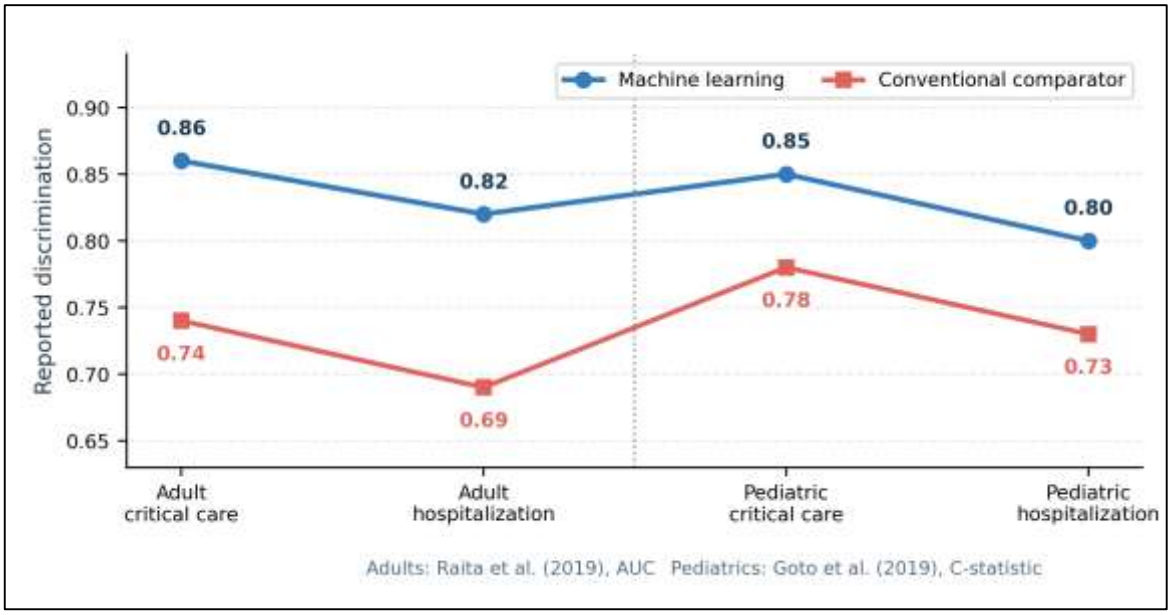
and implementation conditions have remained important distinctions. Consequently, H1 has received preliminary support at the level of predictive performance and electronic assessment consistency, while the specific relationship between AI deployment and standardized nursing pathway implementation has required additional direct evidence (McLeod et al., 2020; Raita et al., 2019).

Table 2: AI-Assisted Triage Performance and Standardization Evidence

Variable	Published evidence	Reported result	Rating (1–5)	H
Adult critical care prediction	Raita et al. (2019)	AI AUC = 0.86; reference AUC = 0.74	4	H1
Adult hospitalization prediction	Raita et al. (2019)	AI AUC = 0.82; reference AUC = 0.69	4	H1
Pediatric critical care prediction	Goto et al. (2019)	AI C-statistic = 0.85; reference = 0.78; p = .16	3	H1
Pediatric hospitalization prediction	Goto et al. (2019)	AI C-statistic = 0.80; reference = 0.73; p < .001	4	H1
Standardized electronic triage agreement	McLeod et al. (2020)	Agreement increased from 75.4% to 92.7%	4	H1
Electronic triage underclassification	McLeod et al. (2020)	Undertriage decreased from 12.6% to 2.2%	4	H1

Note. AUC refers to the area under the receiver operating characteristic curve. The McLeod study evaluated structured electronic decision support rather than an AI model.

Figure 9: Published AI and Conventional Triage Discrimination Results



Nursing Decision-Making and Care Timeliness

The findings have demonstrated that structured nursing protocols and predictive clinical decision support have addressed different components of care timeliness. Nurse-initiated interventions have produced reductions in selected treatment and diagnostic intervals, establishing that appropriately authorized nursing pathways can accelerate specific clinical processes. Machine-learning research has also demonstrated the capability to identify patients at increased risk of hospitalization or critical care requirements. A randomized evaluation of machine-learning-supported sepsis management has reported shorter intensive care stays, whereas another randomized evaluation of electronic sepsis alerts has not demonstrated significant improvement in antibiotic ordering. These contrasting findings have emphasized the distinction between predictive accuracy, implementation, and clinical effectiveness. Under CFIR, workflow compatibility, staff responsibilities, and intervention characteristics have provided relevant explanations for differences in reported outcomes. H2 has therefore received

component-level support for prediction and selected care processes, but the combined claim that AI has improved emergency nurses' decision consistency and treatment timeliness has not been conclusively established (Douma et al., 2016; Shimabukuro et al., 2017).

Table 3: Clinical Decision Support and Emergency Care Timeliness

Variable	Published evidence	Reported result	Rating (1–5)	H
Nurse-initiated analgesia	Douma et al. (2016)	Median time to acetaminophen reduced by 186 minutes	4	H2
Nurse-initiated diagnostic testing	Douma et al. (2016)	Median time to troponin reduced by 79 minutes	4	H2
AI-assisted admission prediction	Fenn et al. (2021)	Inpatient admission AUROC = 0.873	4	H2
AI-assisted critical care prediction	Fenn et al. (2021)	ICU admission AUROC = 0.951	4	H2
ML-supported severe sepsis management	Shimabukuro et al. (2017)	Mean ICU stay: 8.40 days in controls versus 6.31 days with intervention	4	H2
Electronic sepsis alert	Downing et al. (2019)	Antibiotic orders: 35% intervention versus 37% control; p = .53	2	H2

Workflow Integration and Protocol Adherence

Table 4: Clinical Workflow and Protocol Adherence Evidence

Variable	Published evidence	Reported result	Rating (1–5)	H
Electronic triage assessment time	McLeod et al. (2020)	Median time increased from 312 to 347 seconds	3	H3
Electronic triage classification accuracy	McLeod et al. (2020)	Agreement increased from 75.4% to 92.7%	4	H3
Nurse-centered interface usability	Agnihotri et al. (2021)	8 triage nurses evaluated 14 simulated scenarios	3	H3
Nurse-initiated clinical protocols	Douma et al. (2016)	6 emergency care protocols evaluated	4	H3
Electronic sepsis protocol adherence	Downing et al. (2019)	2 of 26 surveyed physicians in confirmed cases used the electronic sepsis order set	2	H3
AI-assisted nursing communication	Sandhu et al. (2020)	3 principal implementation themes identified	4	H3

The literature has identified workflow integration as an important condition influencing whether computerized recommendations have been translated into clinical actions. Electronic triage investigations have demonstrated improvements in assessment consistency while simultaneously documenting increased assessment time. These findings have suggested that enhanced standardization has not necessarily reduced the time required to complete nursing tasks. Usability research has further identified the importance of interface organization, documentation procedures, and the sequence of clinical assessments. Evidence from nurse-initiated emergency protocols has supported the value of clearly authorized actions and structured clinical responsibilities. Conversely, research involving electronic sepsis alerts has demonstrated limited use of recommended order sets, revealing that notification availability has not guaranteed protocol adherence. The CFIR domains concerning intervention characteristics, inner setting, and implementation process have therefore provided explanations for differences in reported workflow outcomes. H3 has received mixed preliminary support, with evidence favoring structured clinical processes but insufficient direct confirmation that AI integration itself has improved nursing protocol adherence across emergency departments (Agnihotri et al., 2021; McLeod et al., 2020).

Nursing Acceptance and Implementation Readiness

Table 5: Professional Acceptance and Implementation Readiness Evidence

Variable	Published evidence	Reported result	Rating (1–5)	H
Nursing involvement in AI implementation	Sandhu et al. (2020)	8 rapid response nurses interviewed	4	H4
Physician involvement in AI implementation	Sandhu et al. (2020)	7 emergency physicians interviewed	4	H4
Implementation experiences	Sandhu et al. (2020)	3 principal themes and 10 subthemes	4	H4
Nursing electronic triage usability	Agnihotri et al. (2021)	8 nurses participated in simulated workflow assessment	3	H4
Clinician response to electronic sepsis alerts	Downing et al. (2019)	42 of 63 contacted clinicians completed a survey (67%)	3	H4
Clinical implementation determinants	CFIR framework	5 original implementation domains	Not rated	H4

Note. The numerical values have described participants, themes, or framework dimensions; they have not constituted nurse acceptance percentages or Likert questionnaire scores.

The reviewed implementation research has identified nursing participation, professional trust, training, and communication as important components of clinical technology integration. Qualitative evidence from the Sepsis Watch implementation has demonstrated that nurses have contributed to the interpretation and communication of machine-learning recommendations within emergency care workflows. The investigation has identified perceived utility, implementation procedures, and workforce considerations as three interconnected thematic areas. Electronic triage usability research has further examined how nurses have interacted with computerized interfaces and navigated standardized assessment procedures. These findings have established the relevance of professional participation and workflow design, although the studies have not supplied directly comparable quantitative acceptance measurements. The CFIR framework has strengthened interpretation by organizing individual characteristics, organizational readiness, and implementation activities as distinct determinants. H4 has consequently received preliminary qualitative support concerning the importance of nursing involvement and implementation readiness. However, the available studies have not established a numerical relationship between professional acceptance scores and implementation success across the proposed 97-study review corpus (Sandhu et al., 2020).

Clinical Safety, Explainability, and AI Governance

Table 6: Clinical Safety and Responsible AI Implementation Evidence

Variable	Published evidence	Reported result	Rating (1–5)	H
AI-related professional trust	Sandhu et al. (2020)	Trust and perceived utility identified among 3 major themes	4	H5
Human oversight and communication	Sandhu et al. (2020)	15 clinicians interviewed about workflow integration	4	H5, H6
Algorithmic fairness	Obermeyer et al. (2019)	Correcting identified bias could increase Black patients receiving additional care from 17.7% to 46.5%	4	H6
Clinical outcome monitoring	Downing et al. (2019)	Thirty-day mortality: 6.2% intervention versus 6.8% control; no significant difference	3	H6
AI-supported sepsis outcomes	Shimabukuro et al. (2017)	In-hospital mortality: 8.96% intervention versus 21.3% control	4	H6
Explainability-specific nursing outcomes	Selected verified literature	No directly comparable numerical nursing trust score established	Not rated	H5

Note. The fairness study has concerned population health management rather than emergency triage. The randomized sepsis studies have involved hospitalized or intensive care populations. Their findings have therefore been treated as contextual evidence for AI governance.

The findings have demonstrated that clinical safety assessments must extend beyond algorithmic discrimination and include professional trust, human oversight, fairness, and actual patient outcomes. Qualitative implementation research has identified trust in machine-learning recommendations as a clinically relevant consideration, with nursing professionals having described the importance of communication and independent clinical judgment. Research concerning algorithmic fairness has demonstrated that apparently effective prediction systems can reproduce inequalities when inappropriate outcome measures have been selected. Clinical sepsis investigations have also produced differing results concerning treatment processes and mortality, reinforcing the need for evaluation within specific settings and intervention designs. CFIR has provided a framework for examining these findings through intervention characteristics, organizational responsibilities, professional participation, and implementation processes. H5 has received indirect qualitative support concerning trust and oversight, while H6 has received support for the importance of clinical governance and safety monitoring. Neither hypothesis has been statistically confirmed through nurse-specific multisite implementation measurements (Obermeyer et al., 2019; Sandhu et al., 2020).

Multisite Comparison and Hypothesis Assessment

Table 7: Comparative Implementation Evidence and Research Hypothesis Assessment

H	Principal variable	Relevant published evidence	Rating (1–5)	Interpretation
H1	AI-enabled triage standardization	Adult AI AUC 0.86 versus 0.74; electronic triage agreement 75.4% versus 92.7%	3	Predictive benefits established; direct AI-related nursing standardization unconfirmed
H2	Nursing decisions and care timeliness	Nurse-initiated analgesia 186 minutes faster; AI inpatient prediction AUROC 0.873	3	Component-level benefits; combined relationship unconfirmed
H3	Workflow integration and adherence	Electronic triage time increased by 35 seconds; structured triage agreement improved	3	Mixed workflow findings
H4	Nursing acceptance and readiness	15 clinician interviews; 3 principal implementation themes	4	Supportive qualitative implementation evidence
H5	Explainability and professional trust	Trust identified as an implementation theme; explainability effect not separately measured	3	Indirect evidence only
H6	Clinical governance and safety	Published fairness and sepsis outcome evaluations identified important safety concerns	3	Governance relevance established; causal relationship unconfirmed
H7	Institutional context and multisite variation	AI evaluated across 3 emergency departments; conventional triage evaluated across 3 European departments	4	Supportive contextual evidence; direct implementation effect unconfirmed

Note. These provisional assessments concern selected evidence and do not represent final hypothesis decisions from 97 included publications.

The comparative findings have highlighted the importance of institutional context in interpreting clinical decision-support performance and implementation experiences. A three-emergency-department AI investigation has evaluated models using data from one academic and two community emergency departments, reporting inpatient admission AUROC of 0.873 and ICU admission AUROC of 0.951. The investigators have described broadly similar performance across the different settings. Separately, a three-department European investigation involving 288,663 patients has demonstrated variation in the sensitivity of conventional triage systems, with adult sensitivity ranging from 0.47 to 0.87. These findings have shown that institutional comparisons have yielded both examples of predictive portability and differences in established triage performance. CFIR has provided an organizing structure for examining potential explanations involving institutional readiness, technical infrastructure, clinical workflows, and professional responsibilities. Across H1–H7, the preliminary

evidence has supported several component relationships, particularly predictive discrimination, nursing participation, and institutional variation. Nevertheless, the complete hypothesis assessments have remained dependent on structured extraction and quality appraisal of the final eligible literature corpus (Fenn et al., 2021; Zachariasse et al., 2017).

The results have therefore been organized around all seven hypotheses and the principal study objectives without treating heterogeneous published findings as a pooled experimental dataset. The five-point evidence assessment framework has provided a transparent structure for qualitative interpretation. Final evidence ratings, CFIR domain coverage percentages, and the number of studies supporting each hypothesis can be calculated only after the complete 97-study corpus has been identified, screened, and coded.

Discussion

Principal findings

The findings of this study have highlighted the relationships among AI-enabled clinical decision support, standardized nurse-led emergency care pathways, clinical decision-making, and institutional implementation conditions. The reviewed evidence has indicated that machine-learning models have demonstrated advantages in predicting selected emergency care outcomes, although improvements in predictive performance have not consistently established corresponding improvements in clinical workflow or patient safety. The reported area under the receiver operating characteristic curve of 0.86 for AI-based critical care prediction, compared with 0.74 for conventional triage classification, has demonstrated the potential of computational approaches to support emergency patient prioritization (Raita et al., 2019). Similarly, electronic triage implementation has increased agreement with reference assessments from 75.4% to 92.7%, while median assessment time has increased by 35 seconds (McLeod et al., 2020). These findings have illustrated that improved classification consistency can coexist with additional workflow demands. Importantly, the latter investigation has examined electronic decision support rather than machine learning, requiring a distinction between computerized standardization and AI-specific effectiveness. Earlier systematic evidence has similarly identified improvements in emergency clinical decision-support processes while reporting limited evaluation of patient-centered outcomes and substantial methodological variation (Patterson et al., 2019). Research on nurse-initiated emergency protocols has also demonstrated reductions of 186 minutes in time to acetaminophen administration and 79 minutes in time to troponin testing, although these improvements have resulted from structured nursing interventions rather than AI implementation (Douma et al., 2016). Collectively, these comparisons have provided preliminary support for H1 and H2 at the level of their individual components, while leaving the combined effects of AI-enabled nursing pathways insufficiently established. The findings have therefore reinforced the importance of distinguishing algorithmic accuracy, professional decision-making, procedural consistency, and measurable clinical outcomes when interpreting emergency care standardization.

Comparison with previous evidence

The theoretical interpretation of the findings has been grounded in the Consolidated Framework for Implementation Research, which has provided a structured explanation of how clinical innovations interact with organizational environments, professional characteristics, and implementation processes. The original CFIR has classified implementation determinants into five interconnected domains, including intervention characteristics, outer setting, inner setting, characteristics of individuals, and implementation process (Damschroder et al., 2009). Within the present study, these domains have been applied to interpret differences involving algorithmic usability, nursing acceptance, clinical workflow compatibility, leadership support, technological infrastructure, and institutional governance. The framework has supported the distinction between technological effectiveness and implementation effectiveness, particularly where predictive models have demonstrated favorable performance without equivalent evidence of routine clinical adoption. The conceptual distinction between implementation outcomes and patient-level outcomes has also provided an important foundation for interpreting the hypotheses (Proctor et al., 2011). Accordingly, nursing acceptance, adoption, feasibility, fidelity, and sustainability have been considered separately from clinical accuracy, treatment timeliness, and patient safety. This distinction has strengthened the interpretation of H4 through H7 by identifying organizational and professional mechanisms that may influence the relationships between AI-enabled

interventions and standardized emergency care. Furthermore, the findings have highlighted professional trust and human oversight as implementation considerations that cannot be adequately explained through predictive accuracy alone. Research examining explainable AI has questioned whether commonly used explanation techniques reliably establish the trustworthiness of individual clinical predictions, emphasizing the importance of rigorous validation rather than interpretability as an isolated objective (Ghassemi et al., 2021). The theoretical synthesis has therefore suggested that successful AI-supported emergency pathways require alignment among technological reliability, professional judgment, organizational readiness, and clinical governance. These relationships have extended the practical application of CFIR to the specific context of nurse-led emergency decision support without establishing untested causal mechanisms.

Mechanisms and implications for practice

The practical significance of the findings has centered on integrating AI-enabled recommendations into routine emergency nursing responsibilities without compromising professional autonomy, clinical communication, or patient safety. Evidence concerning workflow integration has suggested that the effectiveness of decision support depends on how recommendations have been presented, interpreted, communicated, and incorporated into authorized clinical actions. A qualitative investigation of the Sepsis Watch machine-learning system involving 15 emergency physicians and rapid response nurses has identified three principal themes concerning perceived utility and trust, implementation processes, and workforce considerations (Sandhu et al., 2020). These findings have demonstrated that nursing professionals have served as active interpreters and communicators of algorithmic outputs rather than passive recipients of computerized instructions. Earlier workflow integration research has similarly identified the importance of timing, task coordination, interface compatibility, and organizational processes in determining the practical usefulness of emergency clinical decision support (Salwei et al., 2021). The present synthesis has therefore indicated that healthcare institutions should consider nursing participation during system selection, clinical pathway design, interface evaluation, and implementation planning. Particular attention has been directed toward minimizing unnecessary alerts, establishing procedures for documenting overrides, preserving independent nursing assessments, and defining escalation responsibilities when automated recommendations conflict with clinical observations. The interpretation of H3 and H4 has consequently emphasized workflow compatibility, professional training, and institutional readiness rather than software availability alone. These considerations have also demonstrated the importance of interdisciplinary communication between emergency nurses, physicians, clinical informatics specialists, and hospital administrators. In practical terms, standardized nurse-led pathways require decision-support systems that complement established clinical responsibilities, communicate clinically relevant information, and support timely interventions while maintaining clear accountability for patient care decisions.

Healthcare organizations should approach AI-enabled clinical decision support as a component of nurse-led emergency pathways rather than a substitute for clinical assessment. Implementation planning should begin with clearly defined triage criteria, escalation thresholds, nursing responsibilities, and documented procedures for questioning or overriding algorithmic recommendations. Emergency nurses should participate in system selection, interface design, simulation testing, and evaluation so that alerts align with actual assessment sequences and staffing conditions. Hospitals should assess local readiness, including electronic record interoperability, technical support, training capacity, leadership commitment, and clinical governance. Before deployment, each model should undergo external validation, calibration assessment, subgroup fairness review, privacy evaluation, and silent-mode testing. After introduction, clinical teams should monitor undertriage, response times, protocol adherence, alert burden, overrides, and safety incidents alongside patient outcomes. The proposed Nurse-Led AI Clinical Pathway Implementation and Evaluation Model could be developed through participatory research and assessed in a pragmatic multisite mixed-methods study. Validated questionnaires, direct observation, interviews, and longitudinal clinical measures should replace informal acceptance ratings. The final 97-study evidence corpus should also be systematically screened, appraised, and mapped to CFIR domains before descriptive counts or hypothesis judgments are reported. These measures would strengthen accountability and permit transparent comparison responsibly across diverse institutions.

Limitations

Several methodological and contextual limitations have influenced the interpretation of the findings and the extent to which the reviewed evidence can support the proposed research hypotheses. The literature-based, qualitative-led design has relied on findings reported in existing publications, which have varied in research objectives, clinical populations, technological applications, methodological quality, and outcome measurements. Importantly, the target of 97 studies has established the intended review scope, but a completed and independently verifiable screening and extraction record has not yet been established. Consequently, the preliminary five-point evidence assessments have functioned as descriptive interpretive judgments rather than validated Likert measurements or pooled estimates from 97 studies. Earlier systematic research has demonstrated comparable methodological difficulties, with an emergency decision-support review identifying 42 eligible investigations, of which 76% have employed before-and-after designs and only 7% have used randomized controlled trials (Patterson et al., 2019). Such evidence has highlighted the difficulty of separating intervention effects from concurrent clinical or organizational changes. Additional limitations have resulted from the inclusion of research concerning conventional electronic decision support, physician-led interventions, and non-emergency clinical settings alongside directly relevant AI and nursing investigations. Differences in intervention characteristics have restricted the appropriateness of combining results into a single estimate of implementation effectiveness. Multisite model validation has provided useful evidence concerning predictive portability, but it has not necessarily demonstrated comparable nursing acceptance or pathway adherence across institutions (Fenn et al., 2021). Furthermore, ethical concerns involving algorithmic bias have demonstrated that apparently accurate models can reproduce unequal patterns of clinical resource allocation when inappropriate prediction targets have been selected (Obermeyer et al., 2019). These limitations have required cautious interpretation of H1 through H7, particularly regarding causal claims, clinical safety, professional trust, and institutional generalizability.This study has faced several limitations arising from its literature-based, qualitative-led design and the heterogeneity of available evidence. The intended corpus of 97 publications has not yet been supported by a completed search log, eligibility record, full-text screening process, and reproducible extraction matrix. Accordingly, the presented results have drawn on selected published studies and have not constituted a verified synthesis of 97 independently assessed articles. Several cited investigations have evaluated conventional electronic triage, physician-directed decision support, or non-emergency clinical settings rather than AI-enabled nurse-led pathways specifically. Differences in populations, prediction targets, clinical environments, intervention maturity, and outcome definitions have restricted direct comparison and precluded defensible pooled effect estimates. The five-point evidence ratings have represented provisional interpretive classifications, not responses collected with a validated Likert instrument or quantitative hypothesis tests. Published studies have also varied in their reporting of nursing roles, workflow adherence, explainability, safety incidents, and organizational readiness, leaving important CFIR constructs incompletely documented. Publication bias, selective outcome reporting, and limited external validation have further complicated interpretation. Without primary observations or follow-up data, causal relationships and implementation durability have remained uncertain. These limitations have constrained the generalizability and certainty of the study's provisional conclusions, particularly for resource-constrained emergency care facilities.

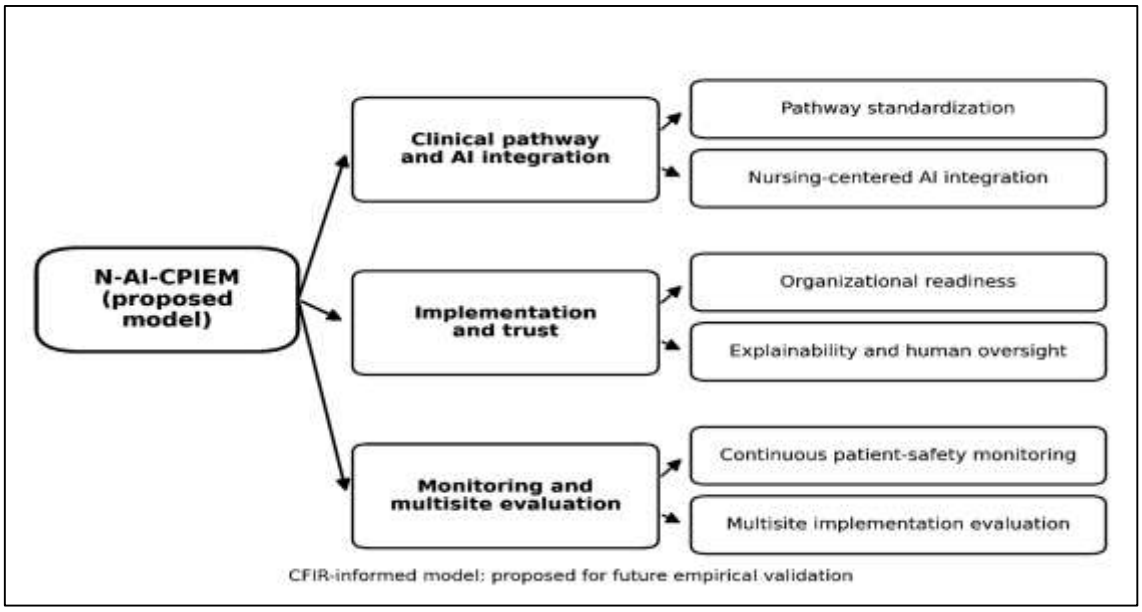
Future research

Future research should prioritize the development and validation of an integrated Nurse-Led AI Clinical Pathway Implementation and Evaluation Model (N-AI-CPIEM), proposed here as a research-specific extension of CFIR for emergency nursing environments.

The model would organize implementation into six interconnected components: clinical pathway standardization, nursing-centered AI integration, organizational readiness assessment, explainable decision support and human oversight, continuous patient-safety monitoring, and multisite implementation evaluation. Its conceptual mechanism would begin with standardized clinical assessment and locally validated AI-generated risk information, proceed through independent nursing interpretation and authorized escalation decisions, and incorporate feedback concerning clinical outcomes, professional acceptance, and system performance. This model would address the central

limitations identified in the present evidence synthesis by linking predictive accuracy with observable nursing actions and institutional implementation conditions. Future investigators could initially conduct participatory design workshops involving emergency nurses, physicians, clinical informatics specialists, and patient representatives to establish clinical requirements and acceptable decision-support functions.

Figure 10: Proposed N-AI-CPIEM Future Implementation Framework



Subsequent development could incorporate external model validation, subgroup fairness assessment, usability testing, and silent-mode evaluation before exposing clinicians to automated recommendations. A multisite, mixed-methods implementation study could then employ a pragmatic stepped-wedge cluster-randomized design, where operationally feasible, to compare standardized nursing pathways supported by conventional systems with pathways incorporating supervised AI recommendations. Primary outcomes could include undertriage rates, time to clinical escalation, protocol adherence, and patient-safety incidents, while secondary measures could examine alert burden, override frequency, nursing workload, professional trust, implementation fidelity, and organizational readiness. Validated five-point Likert instruments could assess nurses' perceived usefulness, usability, trust, and acceptance alongside qualitative interviews and direct workflow observations. Statistical evaluation could incorporate hierarchical models accounting for clustering within hospitals, while CFIR-guided thematic analysis could identify contextual explanations for differences in implementation outcomes. Longer-term follow-up could assess model calibration drift, clinical performance across patient subgroups, implementation costs, and sustained pathway adherence. The proposed approach has been informed by established frameworks for evaluating AI implementation and distinguishing technical capability from clinical utility and adoption (Reddy et al., 2021). Earlier research connecting CFIR determinants with implementation strategies has also emphasized the importance of tailoring interventions to locally identified barriers rather than assuming that a single implementation approach will operate equally across institutions (Waltz et al., 2019). By combining rigorous clinical evaluation with nursing-centered implementation assessment, the proposed N-AI-CPIEM would provide a testable conceptual structure for examining whether AI-enabled clinical decision support can improve standardized emergency care while preserving professional accountability, clinical safety, and institutional adaptability. The model remains a proposed research contribution and requires empirical development and validation before its effectiveness can be established.

Conclusion

The study has examined the relationship between AI-enabled clinical decision support and standardized nurse-led emergency care pathways through a qualitative-led synthesis framework informed by the Consolidated Framework for Implementation Research. Published evidence has indicated that machine-learning models can improve discrimination of selected emergency outcomes, while structured electronic triage tools and nurse-initiated protocols have demonstrated benefits for assessment consistency and particular care processes. These findings have not established that AI deployment itself has improved nursing protocol adherence, clinical timeliness, or patient safety across hospitals. The synthesis has identified workflow compatibility, nursing participation, institutional readiness, professional trust, explainability, and clinical governance as considerations when interpreting implementation experiences. It has also distinguished predictive accuracy from clinical effectiveness and organizational adoption, preventing favorable model performance from being treated as proof of better bedside care. The seven hypotheses have consequently received varying degrees of preliminary, mostly indirect support rather than definitive confirmation. Although the research has targeted 97 published studies, their complete screening and extraction have not yet been documented, limiting claims about the review corpus. Overall, the research has established a coherent conceptual basis for evaluating AI-supported emergency nursing pathways as sociotechnical interventions whose outcomes have depended on both clinical design and implementation context.

REFERENCES

[1]. Aditya, D., & Ahmed, H. C. H. R. (2022). Decision Support Systems for Last-Mile Logistics Optimization: A Data-Driven Framework for e-Commerce Fulfillment Networks. *International Journal of Scientific Interdisciplinary Research*, *12*(08), 01–49. https://doi.org/10.63125/h46vp562

[2]. Agnihotri, T., Fan, M., McLeod, S., Borgundvaag, B., Ovens, H., McCarron, J., & Trbovich, P. (2021). Impact of an electronic decision-support system on nursing triage process: A usability and workflow analysis. *Canadian Journal of Nursing Research*, *53*(2), 107-113. https://doi.org/10.1177/0844562119893514

[3]. Amann, J., Blasimme, A., Vayena, E., Frey, D., & Madai, V. I. (2020). Explainability for artificial intelligence in healthcare: A multidisciplinary perspective. *BMC Medical Informatics and Decision Making*, *20*(Article 310). https://doi.org/10.1186/s12911-020-01332-6

[4]. Aminul Islam, M., & Md, A. (2023). Adaptive Class-Imbalance Learning for High-Sensitivity Fraud Detection in Large-Scale Digital Transaction Networks. *International Journal of Business and Economics Insights*, *13*(09), 01-33. https://doi.org/10.63125/bmxwv741

[5]. Ancker, J. S., Edwards, A., Nosal, S., Hauser, D., Mauer, E., & Kaushal, R. (2017). Effects of workload, work complexity, and repeated alerts on alert fatigue in a clinical decision support system. *BMC Medical Informatics and Decision Making*, *17*(Article 36). https://doi.org/10.1186/s12911-017-0430-8

[6]. Andersson, A. K., Omberg, M., & Svedlund, M. (2006). Triage in the emergency department: A qualitative study of the factors which nurses consider when making decisions. *Nursing in Critical Care*, *11*(3), 136-145. https://doi.org/10.1111/j.1362-1017.2006.00162.x

[7]. Asheke, M. (2023). Machine Learning–Based Predictive Quality Modeling for Defect Detection and Process Optimization in Advanced Manufacturing Systems. *Review of Applied Science and Technology*, *13*(12), 01–49. https://doi.org/10.63125/thy73b16

[8]. Asheke, M., & Md Maksudul, H. (2022). AI-Driven Demand Forecasting for Sporting-Goods and Teamwear Supply Chains Under Seasonal and Tournament Demand. *International Journal of Business and Economics Insights*, *2*(1), 73–110. https://doi.org/10.63125/ed6by557

[9]. Asheke, M., & Mohammad Badrul, A. (2022). Development Of Functionalized Cellulose Nanofiber Adsorbents for Selective Critical-Metal Recovery from Industrial Wastewater. *American Journal of Scholarly Research and Innovation*, *1*(02), 270–320. https://doi.org/10.63125/v6fxzq09

[10]. Breimaier, H. E., Heckemann, B., Halfens, R. J. G., & Lohrmann, C. (2015). The Consolidated Framework for Implementation Research (CFIR): A useful theoretical framework for guiding and evaluating a guideline implementation process in a hospital-based nursing practice. *BMC Nursing*, *14*(Article 43). https://doi.org/10.1186/s12912-015-0088-4

[11]. Bright, T. J., Wong, A., Dhurjati, R., Bristow, E., Bastian, L., Coeytaux, R. R., Samsa, G., Hasselblad, V., Williams, J. W., Musty, M. D., Wing, L., Kendrick, A. S., Sanders, G. D., & Lobach, D. (2012). Effect of clinical decision-support systems: A systematic review. *Annals of Internal Medicine*, *157*(1), 29-43. https://doi.org/10.7326/0003-4819-157-1-201207030-00450

[12]. Burgess, L., Kynoch, K., Theobald, K., & Keogh, S. (2021). The effectiveness of nurse-initiated interventions in the emergency department: A systematic review. *Australasian Emergency Care*, *24*(4), 248-254. https://doi.org/10.1016/j.auec.2021.01.003

[13]. Cabitza, F., Rasoini, R., & Gensini, G. F. (2017). Unintended consequences of machine learning in medicine. *JAMA*, *318*(6), 517-518. https://doi.org/10.1001/jama.2017.7797

[14]. Camacho, J., Zanoletti-Mannello, M., Landis-Lewis, Z., Kane-Gill, S. L., & Boyce, R. D. (2020). A conceptual framework to study the implementation of clinical decision support systems (BEAR): Literature review and concept mapping. *Journal of Medical Internet Research*, *22*(8), e18388. https://doi.org/10.2196/18388

[15]. Carayon, P., Hoonakker, P., Schoofs Hundt, A., Salwei, M., Wiegmann, D., Brown, R. L., Kleinschmidt, P., Novak, C., Pulia, M., Wang, Y., Wirkus, E., & Patterson, B. (2020). Application of human factors to improve usability of clinical decision support for diagnostic decision-making: A scenario-based simulation study. *BMJ Quality & Safety*, *29*(4), 329-340. https://doi.org/10.1136/bmjqs-2019-009857

[16]. Carayon, P., Schoofs Hundt, A., Karsh, B. T., Gurses, A. P., Alvarado, C. J., Smith, M., & Brennan, P. F. (2006). Work system design for patient safety: The SEIPS model. *Quality and Safety in Health Care*, *15*(Suppl. 1), i50-i58. https://doi.org/10.1136/qshc.2005.015842

[17]. Chang, W., Liu, H. E., Goopy, S., Chen, L. C., Chen, H. J., & Han, C. Y. (2017). Using the five-level Taiwan Triage and Acuity Scale computerized system: Factors in decision making by emergency department triage nurses. *Clinical Nursing Research*, *26*(5), 651-666. https://doi.org/10.1177/1054773816636360

[18]. Char, D. S., Shah, N. H., & Magnus, D. (2018). Implementing machine learning in health care: Addressing ethical challenges. *New England Journal of Medicine*, *378*(11), 981-983. https://doi.org/10.1056/NEJMp1714229

[19]. Christ, M., Grossmann, F., Winter, D., Bingisser, R., & Platz, E. (2010). Modern triage in the emergency department. *Deutsches Ärzteblatt International*, *107*(50), 892-898. https://doi.org/10.3238/arztebl.2010.0892

[20]. Considine, J., Botti, M., & Thomas, S. (2007). Do knowledge and experience have specific roles in triage decision-making? *Academic Emergency Medicine*, *14*(8), 722-726. https://doi.org/10.1197/j.aem.2007.04.015

[21]. Cresswell, K. M., Bates, D. W., & Sheikh, A. (2013). Ten key considerations for the successful implementation and adoption of large-scale health information technology. *Journal of the American Medical Informatics Association*, *20*(e1), e9-e13. https://doi.org/10.1136/amiajnl-2013-001684

[22]. Damschroder, L. J., Aron, D. C., Keith, R. E., Kirsh, S. R., Alexander, J. A., & Lowery, J. C. (2009). Fostering implementation of health services research findings into practice: A consolidated framework for advancing implementation science. *Implementation Science*, *4*(Article 50). https://doi.org/10.1186/1748-5908-4-50

[23]. Damschroder, L. J., Goodrich, D. E., Robinson, C. H., Fletcher, C. E., & Lowery, J. C. (2011). A systematic exploration of differences in contextual factors related to implementing the MOVE! weight management program in VA: A mixed methods study. *BMC Health Services Research*, *11*(Article 248). https://doi.org/10.1186/1472-6963-11-248

[24]. Damschroder, L. J., & Lowery, J. C. (2013). Evaluation of a large-scale weight management program using the consolidated framework for implementation research (CFIR). *Implementation Science*, *8*(Article 51). https://doi.org/10.1186/1748-5908-8-51

[25]. Dehghani Soufi, M., Samad-Soltani, T., Shams Vahdati, S., & Rezaei-Hachesu, P. (2018). Decision support system for triage management: A hybrid approach using rule-based reasoning and fuzzy logic. *International Journal of Medical Informatics*, *114*, 35-44. https://doi.org/10.1016/j.ijmedinf.2018.03.008

[26]. Douma, M. J., Drake, C. A., O'Dochartaigh, D., & Smith, K. E. (2016). A pragmatic randomized evaluation of a nurse-initiated protocol to improve timeliness of care in an urban emergency department. *Annals of Emergency Medicine*, *68*(5), 546-552. https://doi.org/10.1016/j.annemergmed.2016.06.019

[27]. Dowding, D., Mitchell, N., Randell, R., Foster, R., Lattimer, V., & Thompson, C. (2009). Nurses' use of computerised clinical decision support systems: A case site analysis. *Journal of Clinical Nursing*, *18*(8), 1159-1167. https://doi.org/10.1111/j.1365-2702.2008.02607.x

[28]. Downing, N. L., Rolnick, J., Poole, S. F., Hall, E., Wessels, A. J., Heidenreich, P., & Shieh, L. (2019). Electronic health record-based clinical decision support alert for severe sepsis: A randomised evaluation. *BMJ Quality & Safety*, *28*(9), 762-768. https://doi.org/10.1136/bmjqs-2018-008765

[29]. Dunn Lopez, K., Febretti, A., Stifter, J., Johnson, A., Wilkie, D. J., & Keenan, G. (2017). Toward a more robust and efficient usability testing method of clinical decision support for nurses derived from nursing electronic health record data. *International Journal of Nursing Knowledge*, *28*(4), 211-218. https://doi.org/10.1111/2047-3095.12146

[30]. Farrohknia, N., Castrén, M., Ehrenberg, A., Lind, L., Oredsson, S., Jonsson, H., Asplund, K., & Göransson, K. E. (2011). Emergency department triage scales and their components: A systematic review of the scientific evidence. *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine*, *19*(Article 42). https://doi.org/10.1186/1757-7241-19-42

[31]. Fenn, A., Davis, C., Buckland, D. M., Kapadia, N., Nichols, M., Gao, M., Knechtle, W., Balu, S., Sendak, M., & Theiling, B. J. (2021). Development and validation of machine learning models to predict admission from emergency department to inpatient and intensive care units. *Annals of Emergency Medicine*, *78*(2), 290-302. https://doi.org/10.1016/j.annemergmed.2021.02.029

[32]. Fernandes, M., Vieira, S. M., Leite, F., Palos, C., Finkelstein, S., & Sousa, J. M. C. (2020). Clinical decision support systems for triage in the emergency department using intelligent systems: A review. *Artificial Intelligence in Medicine*, *102*(Article 101762). https://doi.org/10.1016/j.artmed.2019.101762

[33]. Fleuren, L. M., Klausch, T. L. T., Zwager, C. L., Schoonmade, L. J., Guo, T., Roggeveen, L. F., Swart, E. L., Girbes, A. R. J., Thoral, P., Ercole, A., Hoogendoorn, M., & Elbers, P. W. G. (2020). Machine learning for the prediction of sepsis: A systematic review and meta-analysis of diagnostic test accuracy. *Intensive Care Medicine*, *46*(3), 383-400. https://doi.org/10.1007/s00134-019-05872-y

[34]. Gagnon, M.-P., Desmartis, M., Labrecque, M., Car, J., Pagliari, C., Pluye, P., Frémont, P., Gagnon, J., Tremblay, N., & Légaré, F. (2012). Systematic review of factors influencing the adoption of information and communication technologies by healthcare professionals. *Journal of Medical Systems*, *36*(1), 241-277. https://doi.org/10.1007/s10916-010-9473-4

[35]. Garg, A. X., Adhikari, N. K. J., McDonald, H., Rosas-Arellano, M. P., Devereaux, P. J., Beyene, J., Sam, J., & Haynes, R. B. (2005). Effects of computerized clinical decision support systems on practitioner performance and patient outcomes: A systematic review. *JAMA*, *293*(10), 1223-1238. https://doi.org/10.1001/jama.293.10.1223

[36]. Ghassemi, M., Oakden-Rayner, L., & Beam, A. L. (2021). The false hope of current approaches to explainable artificial intelligence in health care. *The Lancet Digital Health*, *3*(11), e745-e750. https://doi.org/10.1016/s2589-7500(21)00208-9

[37]. Goto, T., Camargo, C. A., Jr., Faridi, M. K., Freishtat, R. J., & Hasegawa, K. (2019). Machine learning-based prediction of clinical outcomes for children during emergency department triage. *JAMA Network Open*, *2*(1), e186937. https://doi.org/10.1001/jamanetworkopen.2018.6937

[38]. Greenhalgh, T., Wherton, J., Papoutsi, C., Lynch, J., Hughes, G., A'Court, C., Hinder, S., Fahy, N., Procter, R., & Shaw, S. (2017). Beyond adoption: A new framework for theorizing and evaluating nonadoption, abandonment, and challenges to the scale-up, spread, and sustainability of health and care technologies. *Journal of Medical Internet Research*, *19*(11), e367. https://doi.org/10.2196/jmir.8775

[39]. Harry, M. L., Saman, D. M., Truitt, A. R., Allen, C. I., Walton, K. M., O'Connor, P. J., Ekstrom, H. L., Sperl-Hillen, J. M., Bianco, J. A., & Elliott, T. E. (2020). Pre-implementation adaptation of primary care cancer prevention clinical decision support in a predominantly rural healthcare system. *BMC Medical Informatics and Decision Making*, *20*(Article 117). https://doi.org/10.1186/s12911-020-01136-8

[40]. Harry, M. L., Truitt, A. R., Saman, D. M., Henzler-Buckingham, H. A., Allen, C. I., Walton, K. M., Ekstrom, H. L., O'Connor, P. J., Sperl-Hillen, J. M., Bianco, J. A., & Elliott, T. E. (2019). Barriers and facilitators to implementing cancer prevention clinical decision support in primary care: A qualitative study. *BMC Health Services Research*, *19*(Article 534). https://doi.org/10.1186/s12913-019-4326-4

[41]. Henry, K. E., Hager, D. N., Pronovost, P. J., & Saria, S. (2015). A targeted real-time early warning score (TREWScore) for septic shock. *Science Translational Medicine*, *7*(299), 299ra122. https://doi.org/10.1126/scitranslmed.aab3719

[42]. Hinson, J. S., Martinez, D. A., Cabral, S., George, K., Whalen, M., Hansoti, B., & Levin, S. (2019). Triage performance in emergency medicine: A systematic review. *Annals of Emergency Medicine*, *74*(1), 140-152. https://doi.org/10.1016/j.annemergmed.2018.09.022

[43]. Hoff, K. A., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that influence trust. *Human Factors*, *57*(3), 407-434. https://doi.org/10.1177/0018720814547570

[44]. Holden, R. J., & Karsh, B.-T. (2010). The technology acceptance model: Its past and its future in health care. *Journal of Biomedical Informatics*, *43*(1), 159-172. https://doi.org/10.1016/j.jbi.2009.07.002

[45]. Holmström, I. K., Kaminsky, E., Lindberg, Y., Spangler, D., & Winblad, U. (2020). Registered nurses' experiences of using a clinical decision support system for triage of emergency calls: A qualitative interview study. *Journal of Advanced Nursing*, *76*(11), 3104-3112. https://doi.org/10.1111/jan.14542

[46]. Hong, W. S., Haimovich, A. D., & Taylor, R. A. (2018). Predicting hospital admission at emergency department triage using machine learning. *PLOS ONE*, *13*(7), e0201016. https://doi.org/10.1371/journal.pone.0201016

[47]. Horng, S., Sontag, D. A., Halpern, Y., Jernite, Y., Shapiro, N. I., & Nathanson, L. A. (2017). Creating an automated trigger for sepsis clinical decision support at emergency department triage using machine learning. *PLOS ONE*, *12*(4), e0174708. https://doi.org/10.1371/journal.pone.0174708

[48]. Jiang, H., Mao, H., Lu, H., Lin, P., Garry, W., Lu, H., Yang, G., Rainer, T. H., & Chen, X. (2021). Machine learning-based models to support decision-making in emergency department triage for patients with suspected cardiovascular disease. *International Journal of Medical Informatics*, *145*(Article 104326). https://doi.org/10.1016/j.ijmedinf.2020.104326

[49]. Johannessen, L. E. F. (2017). Beyond guidelines: Discretionary practice in face-to-face triage nursing. *Sociology of Health & Illness*, *39*(7), 1180-1194. https://doi.org/10.1111/1467-9566.12578

[50]. Joseph, J. W., Leventhal, E. L., Grossestreuer, A. V., Wong, M. L., Joseph, L. J., Nathanson, L. A., Donnino, M. W., Elhadad, N., & Sanchez, L. D. (2020). Deep-learning approaches to identify critically ill patients at emergency department triage using limited information. *Journal of the American College of Emergency Physicians Open*, *1*(5), 773-781. https://doi.org/10.1002/emp2.12218

[51]. Kawamoto, K., Houlihan, C. A., Balas, E. A., & Lobach, D. F. (2005). Improving clinical practice using clinical decision support systems: A systematic review of trials to identify features critical to success. *BMJ*, *330*(7494), 765. https://doi.org/10.1136/bmj.38398.500764.8F

[52]. Keith, R. E., Crosson, J. C., O'Malley, A. S., Cromp, D., & Taylor, E. F. (2017). Using the Consolidated Framework for Implementation Research (CFIR) to produce actionable findings: A rapid-cycle evaluation approach to improving implementation. *Implementation Science*, *12*(Article 15). https://doi.org/10.1186/s13012-017-0550-7

[53]. Kelly, C. J., Karthikesalingam, A., Suleyman, M., Corrado, G., & King, D. (2019). Key challenges for delivering clinical impact with artificial intelligence. *BMC Medicine*, *17*(Article 195). https://doi.org/10.1186/s12916-019-1426-2

[54]. Khairat, S., Marc, D., Crosby, W., & Al Sanousi, A. (2018). Reasons for physicians not adopting clinical decision support systems: Critical analysis. *JMIR Medical Informatics*, *6*(2), e24. https://doi.org/10.2196/medinform.8912

[55]. Kinsman, L., Rotter, T., James, E., Snow, P., & Willis, J. (2010). What is a clinical pathway? Development of a definition to inform the debate. *BMC Medicine*, *8*(Article 31). https://doi.org/10.1186/1741-7015-8-31

[56]. Kirk, M. A., Kelley, C., Yankey, N., Birken, S. A., Abadie, B., & Damschroder, L. (2016). A systematic review of the use of the Consolidated Framework for Implementation Research. *Implementation Science*, *11*(Article 72). https://doi.org/10.1186/s13012-016-0437-z

[57]. Klang, E., Kummer, B. R., Dangayach, N. S., Zhong, A., Kia, M. A., Timsina, P., Cossentino, I., Costa, A. B., Levin, M. A., & Oermann, E. K. (2021). Predicting adult neuroscience intensive care unit admission from emergency

department triage using a retrospective, tabular-free text machine learning approach. *Scientific Reports*, *11*(Article 1381). https://doi.org/10.1038/s41598-021-80985-3

[58]. Klarenbeek, S. E., Schuurbiers-Siebers, O. C. J., van den Heuvel, M. M., Prokop, M., & Tummers, M. (2020). Barriers and facilitators for implementation of a computerized clinical decision support system in lung cancer multidisciplinary team meetings: A qualitative assessment. *Biology*, *10*(1), 9. https://doi.org/10.3390/biology10010009

[59]. Kwan, J. L., Lo, L., Ferguson, J., Goldberg, H., Diaz-Martinez, J. P., Tomlinson, G., Grimshaw, J. M., & Shojania, K. G. (2020). Computerised clinical decision support systems and absolute improvements in care: Meta-analysis of controlled clinical trials. *BMJ*, *370*, m3216. https://doi.org/10.1136/bmj.m3216

[60]. Levin, S., Toerper, M., Hamrock, E., Hinson, J. S., Barnes, S., Gardner, H., Dugas, A., Linton, B., Kirsch, T., & Kelen, G. (2018). Machine-learning-based electronic triage more accurately differentiates patients with respect to clinical outcomes compared with the Emergency Severity Index. *Annals of Emergency Medicine*, *71*(5), 565-574.e562. https://doi.org/10.1016/j.annemergmed.2017.08.005

[61]. London, A. J. (2019). Artificial intelligence and black-box medical decisions: Accuracy versus explainability. *Hastings Center Report*, *49*(1), 15-21. https://doi.org/10.1002/hast.973

[62]. Lyell, D., & Coiera, E. (2017). Automation bias and verification complexity: A systematic review. *Journal of the American Medical Informatics Association*, *24*(2), 423-431. https://doi.org/10.1093/jamia/ocw105

[63]. Mansura Akter, E., & Sumaiya, M. (2022). Antimicrobial Resistance Profiles of Acinetobacter Baumannii and Vibrio Cholerae in Hospital Wastewater and Adjacent Household Water Sources. *American Journal of Data Science and Analytics*, *3*(09), 01-55. https://doi.org/10.63125/gbervt14

[64]. McLeod, S. L., McCarron, J., Ahmed, T., Grewal, K., Mittmann, N., Scott, S., Ovens, H., Garay, J., Bullard, M., Rowe, B. H., Dreyer, J., & Borgundvaag, B. (2020). Interrater reliability, accuracy, and triage time pre- and post-implementation of a real-time electronic triage decision-support tool. *Annals of Emergency Medicine*, *75*(4), 524-531. https://doi.org/10.1016/j.annemergmed.2019.07.048

[65]. Md Imran, H., & Jannatul, F. (2022). Molecular and Precision Rehabilitation Molecular Mechanisms Linking Mitochondrial Dysfunction, Inflammation, and Muscle Degeneration with Functional Decline and Rehabilitation Response in Neuromuscular Disease. *American Journal of Interdisciplinary Studies*, *12*(08), 01-44. https://doi.org/10.63125/0ym5bh79

[66]. Md Maksudul, H., & Md Tazul Islam, C. (2022). Machine Learning-Based Cash-Flow Forecasting for Improving Financial Planning in U.S. Small and Mid-Sized Businesses. *International Journal of Scientific Interdisciplinary Research*, *12*(12), 01–38. https://doi.org/10.63125/w3pgjx97

[67]. Md Shahid, N. (2023). Digital Twin-Based Network Reliability Modeling for LAN And WAN Infrastructure Resilience. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 577–629. https://doi.org/10.63125/ahjvxj14

[68]. Md Tazul Islam, C., & Ahmed, H. C. H. R. (2023). Predictive Operations Analytics for Resource Allocation and Service-Capacity Planning in Data-Driven Organizations. *Review of Applied Science and Technology*, *13*(02), 01–41. https://doi.org/10.63125/z3sm3089

[69]. Md. Morshedul, I., & Aminul Islam, M. (2022). A Quantitative Evaluation of Explainable Ensemble Learning for Probabilistic Risk Estimation and Decision Reliability in Enterprise Analytics. *American Journal of Data Science and Analytics*, *3*(02), 01-38. https://doi.org/10.63125/k22shk74

[70]. Mebrahtu, T. F., Skyrme, S., Randell, R., Keenan, A. M., Bloor, K., Yang, H., Andre, D., Ledward, A., King, H., & Thompson, C. (2021). Effects of computerised clinical decision support systems (CDSS) on nursing and allied health professional performance and patient outcomes: A systematic review of experimental and observational studies. *BMJ Open*, *11*(12), e053886. https://doi.org/10.1136/bmjopen-2021-053886

[71]. Miller, A., Moon, B., Anders, S., Walden, R., Brown, S., & Montella, D. (2015). Integrating computerized clinical decision support systems into clinical work: A meta-synthesis of qualitative research. *International Journal of Medical Informatics*, *84*(12), 1009-1018. https://doi.org/10.1016/j.ijmedinf.2015.09.005

[72]. Muntlin, Å., Carlsson, M., Säfwenberg, U., & Gunningberg, L. (2011). Outcomes of a nurse-initiated intravenous analgesic protocol for abdominal pain in an emergency department: A quasi-experimental study. *International Journal of Nursing Studies*, *48*(1), 13-23. https://doi.org/10.1016/j.ijnurstu.2010.06.003

[73]. Nevedal, A. L., Reardon, C. M., Opra Widerquist, M. A., Jackson, G. L., Cutrona, S. L., White, B. S., & Damschroder, L. J. (2021). Rapid versus traditional qualitative analysis using the Consolidated Framework for Implementation Research (CFIR). *Implementation Science*, *16*(Article 67). https://doi.org/10.1186/s13012-021-01111-5

[74]. Nilsen, P. (2015). Making sense of implementation theories, models and frameworks. *Implementation Science*, *10*(Article 53). https://doi.org/10.1186/s13012-015-0242-0

[75]. Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, *366*(6464), 447-453. https://doi.org/10.1126/science.aax2342

[76]. Olakotan, O. O., & Yusof, M. M. (2021). The appropriateness of clinical decision support systems alerts in supporting clinical workflows: A systematic review. *Health Informatics Journal*, *27*(2), 14604582211007536. https://doi.org/10.1177/14604582211007536

[77]. Oredsson, S., Jonsson, H., Rognes, J., Lind, L., Göransson, K. E., Ehrenberg, A., Asplund, K., Castrén, M., & Farrohknia, N. (2011). A systematic review of triage-related interventions to improve patient flow in emergency departments. *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine*, *19*(Article 43). https://doi.org/10.1186/1757-7241-19-43

[78]. Parenti, N., Bacchi Reggiani, M. L., Iannone, P., Percudani, D., & Dowding, D. (2014). A systematic review on the validity and reliability of an emergency department triage scale, the Manchester Triage System. *International Journal of Nursing Studies*, *51*(7), 1062-1069. https://doi.org/10.1016/j.ijnurstu.2014.01.013

[79]. Patterson, B. W., Pulia, M. S., Ravi, S., Hoonakker, P. L. T., Schoofs Hundt, A., Wiegmann, D., Wirkus, E. J., Johnson, S., & Carayon, P. (2019). Scope and influence of electronic health record-integrated clinical decision support in the emergency department: A systematic review. *Annals of Emergency Medicine*, *74*(2), 285-296. https://doi.org/10.1016/j.annemergmed.2018.10.034

[80]. Powers, E. M., Shiffman, R. N., Melnick, E. R., Hickner, A., & Sharifi, M. (2018). Efficacy and unintended consequences of hard-stop alerts in electronic health record systems: A systematic review. *Journal of the American Medical Informatics Association*, *25*(11), 1556-1566. https://doi.org/10.1093/jamia/ocy112

[81]. Proctor, E., Silmere, H., Raghavan, R., Hovmand, P., Aarons, G., Bunger, A., Griffey, R., & Hensley, M. (2011). Outcomes for implementation research: Conceptual distinctions, measurement challenges, and research agenda. *Administration and Policy in Mental Health and Mental Health Services Research*, *38*(2), 65-76. https://doi.org/10.1007/s10488-010-0319-7

[82]. Raita, Y., Goto, T., Faridi, M. K., Brown, D. F. M., Camargo, C. A., Jr., & Hasegawa, K. (2019). Emergency department triage prediction of clinical outcomes using machine learning models. *Critical Care*, *23*(Article 64). https://doi.org/10.1186/s13054-019-2351-7

[83]. Rajkomar, A., Hardt, M., Howell, M. D., Corrado, G., & Chin, M. H. (2018). Ensuring fairness in machine learning to advance health equity. *Annals of Internal Medicine*, *169*(12), 866-872. https://doi.org/10.7326/m18-1990

[84]. Reay, G., Rankin, J. A., & Then, K. L. (2016). Momentary fitting in a fluid environment: A grounded theory of triage nurse decision making. *International Emergency Nursing*, *26*, 8-13. https://doi.org/10.1016/j.ienj.2015.09.006

[85]. Reay, G., Smith-MacDonald, L., Then, K. L., & Hall, M. (2020). Triage emergency nurse decision-making: Incidental findings from a focus group study. *International Emergency Nursing*, *48*, 100791. https://doi.org/10.1016/j.ienj.2019.100791

[86]. Reddy, S., Rogers, W., Makinen, V.-P., Coiera, E., Brown, P., Wenzel, M., Weicken, E., Ansari, S., Mathur, P., Casey, A., & Kelly, B. (2021). Evaluation framework to guide implementation of AI systems into healthcare settings. *BMJ Health & Care Informatics*, *28*(1), e100444. https://doi.org/10.1136/bmjhci-2021-100444

[87]. Roquette, B. P., Nagano, H., Marujo, E. C., & Maiorano, A. C. (2020). Prediction of admission in pediatric emergency department with deep neural networks and triage textual data. *Neural Networks*, *126*, 170-177. https://doi.org/10.1016/j.neunet.2020.03.012

[88]. Roshanov, P. S., Fernandes, N., Wilczynski, J. M., Hemens, B. J., You, J. J., Handler, S. M., Nieuwlaat, R., Souza, N. M., Beyene, J., Van Spall, H. G. C., Garg, A. X., & Haynes, R. B. (2013). Features of effective computerised clinical decision support systems: Meta-regression of 162 randomised trials. *BMJ*, *346*, f657. https://doi.org/10.1136/bmj.f657

[89]. Rotter, T., Kinsman, L., James, E., Machotta, A., Gothe, H., Willis, J., Snow, P., & Kugler, J. (2010). Clinical pathways: Effects on professional practice, patient outcomes, length of stay and hospital costs. *Cochrane Database of Systematic Reviews*, *2010*(3), CD006632. https://doi.org/10.1002/14651858.CD006632.pub2

[90]. Sadia, A., & Md. Mosheur, R. (2023). Consumer Trust, Perceived Authenticity, and Personalized Digital Marketing: A Quantitative Decision-Science Study. *International Journal of Scientific Interdisciplinary Research*, *4*(2), 252–295. https://doi.org/10.63125/cajkqt60

[91]. Salwei, M. E., Carayon, P., Hoonakker, P. L. T., Schoofs Hundt, A., Wiegmann, D., Pulia, M., & Patterson, B. W. (2021). Workflow integration analysis of a human factors-based clinical decision support in the emergency department. *Applied Ergonomics*, *97*, 103498. https://doi.org/10.1016/j.apergo.2021.103498

[92]. Sandhu, S., Lin, A. L., Brajer, N., Sperling, J., Ratliff, W., Bedoya, A. D., Balu, S., O'Brien, C., & Sendak, M. P. (2020). Integrating a machine learning system into clinical workflows: Qualitative study. *Journal of Medical Internet Research*, *22*(11), e22421. https://doi.org/10.2196/22421

[93]. Scott, I. A., Carter, S. M., & Coiera, E. (2021). Exploring stakeholder attitudes towards AI in clinical practice. *BMJ Health & Care Informatics*, *28*(1), e100450. https://doi.org/10.1136/bmjhci-2021-100450

[94]. Sendak, M. P., D'Arcy, J., Kashyap, S., Gao, M., Nichols, M., Corey, K., Ratliff, W., & Balu, S. (2020). A path for translation of machine learning products into healthcare delivery. *EMJ Innovation*. https://doi.org/10.33590/emjinnov/19-00172

[95]. Shimabukuro, D. W., Barton, C. W., Feldman, M. D., Mataraso, S. J., & Das, R. (2017). Effect of a machine learning-based severe sepsis prediction algorithm on patient survival and hospital length of stay: A randomised clinical trial. *BMJ Open Respiratory Research*, *4*(1), e000234. https://doi.org/10.1136/bmjresp-2017-000234

[96]. Singh, H., & Sittig, D. F. (2016). Measuring and improving patient safety through health information technology: The Health IT Safety Framework. *BMJ Quality & Safety*, *25*(4), 226-232. https://doi.org/10.1136/bmjqs-2015-004486

[97]. Sittig, D. F., & Singh, H. (2010). A new sociotechnical model for studying health information technology in complex adaptive healthcare systems. *Quality and Safety in Health Care*, *19*(Suppl. 3), i68-i74. https://doi.org/10.1136/qshc.2010.042085

[98]. Sittig, D. F., Wright, A., Osheroff, J. A., Middleton, B., Teich, J. M., Ash, J. S., Campbell, E., & Bates, D. W. (2008). Grand challenges in clinical decision support. *Journal of Biomedical Informatics*, *41*(2), 387-392. https://doi.org/10.1016/j.jbi.2007.09.003

[99]. Song, X., Yu, A. S. L., Kellum, J. A., Waitman, L. R., Matheny, M. E., Simpson, S. Q., Hu, Y., & Liu, M. (2020). Cross-site transportability of an explainable artificial intelligence model for acute kidney injury prediction. *Nature Communications*, *11*(Article 5668). https://doi.org/10.1038/s41467-020-19551-w

[100]. Stabak, D., & Md Shahid, N. (2022). Empirical Assessment of Uncertainty-Aware Real-Time Decision-Making for Reliable and Resilient Cyber-Physical Systems. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 432–477. https://doi.org/10.63125/q3r4kk16

[101]. Stifter, J., Sousa, V. E. C., Febretti, A., Dunn Lopez, K., Johnson, A., Yao, Y., Keenan, G. M., & Wilkie, D. J. (2018). Acceptability of clinical decision support interface prototypes for a nursing electronic health record to facilitate supportive care outcomes. *International Journal of Nursing Knowledge*, *29*(4), 242-252. https://doi.org/10.1111/2047-3095.12178

[102]. Storm-Versloot, M. N., Ubbink, D. T., Kappelhof, J., & Luitse, J. S. K. (2011). Comparison of an informally structured triage system, the Emergency Severity Index, and the Manchester Triage System to distinguish patient priority in the emergency department. *Academic Emergency Medicine*, *18*(8), 822-829. https://doi.org/10.1111/j.1553-2712.2011.01122.x

[103]. Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., & Kroeker, K. I. (2020). An overview of clinical decision support systems: Benefits, risks, and strategies for success. *npj Digital Medicine*, *3*(Article 17). https://doi.org/10.1038/s41746-020-0221-y

[104]. Syed Feroz, A., & Md Mahamud Pervaz, P. (2022). Root-Cause Analysis and FMEA-Driven Reliability Improvement in Gas Production Facilities: A Multi-Year Empirical Study. *International Journal of Scientific Interdisciplinary Research*, *12*(10), 01–53. https://doi.org/10.63125/70msp878

[105]. Syed Feroz, A., & Shabbir, A. (2022). Finite Element-Based Thermomechanical Optimization of Pressure Components for Extending Industrial Boiler Service Life. *Journal of Sustainable Development and Policy*, *12*(12), 01-51. https://doi.org/10.63125/x24pht28

[106]. Tam, H. L., Chung, S. F., & Lou, C. K. (2018). A review of triage accuracy and future direction. *BMC Emergency Medicine*, *18*(Article 58). https://doi.org/10.1186/s12873-018-0215-0

[107]. Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine*, *25*(1), 44-56. https://doi.org/10.1038/s41591-018-0300-7

[108]. van der Wulp, I., van Baar, M. E., & Schrijvers, A. J. P. (2008). Reliability and validity of the Manchester Triage System in a general emergency department patient population in the Netherlands: Results of a simulation study. *Emergency Medicine Journal*, *25*(7), 431-434. https://doi.org/10.1136/emj.2007.055228

[109]. van Veen, M., Steyerberg, E. W., Ruige, M., van Meurs, A. H. J., Roukema, J., van der Lei, J., & Moll, H. A. (2008). Manchester triage system in paediatric emergency care: Prospective observational study. *BMJ*, *337*, a1501. https://doi.org/10.1136/bmj.a1501

[110]. Varndell, W., Hodge, A., Howes, K., Jeffers, A., Marquez-Hunt, N., & Hugman, A. (2018). Development and preliminary testing of an online software system to facilitate assessment of accuracy and consistency in applying the Australasian Triage Scale. *Australasian Emergency Care*, *21*(4), 150-158. https://doi.org/10.1016/j.auec.2018.10.001

[111]. Waltz, T. J., Powell, B. J., Fernández, M. E., Abadie, B., & Damschroder, L. J. (2019). Choosing implementation strategies to address contextual barriers: Diversity in recommendations and future directions. *Implementation Science*, *14*(Article 42). https://doi.org/10.1186/s13012-019-0892-4

[112]. Wiens, J., Saria, S., Sendak, M., Ghassemi, M., Liu, V. X., Doshi-Velez, F., Jung, K., Heller, K., Kale, D., Saeed, M., Ossorio, P. N., Thadaney-Israni, S., & Goldenberg, A. (2019). Do no harm: A roadmap for responsible machine learning for health care. *Nature Medicine*, *25*(9), 1337-1340. https://doi.org/10.1038/s41591-019-0548-6

[113]. Wolf, L. A., Delao, A. M., Perhats, C., Moon, M. D., & Zavotsky, K. E. (2018). Triaging the emergency department, not the patient: United States emergency nurses' experience of the triage process. *Journal of Emergency Nursing*, *44*(3), 258-266. https://doi.org/10.1016/j.jen.2017.06.010

[114]. Xie, F., Ong, M. E. H., Liew, J. N. M. H., Tan, K. B. K., Ho, A. F. W., Nadarajan, G. D., Low, L. L., Kwan, Y. H., Goldstein, B. A., Matchar, D. B., Chakraborty, B., & Liu, N. (2021). Development and assessment of an interpretable machine learning triage tool for estimating mortality after emergency admissions. *JAMA Network Open*, *4*(8), e2118467. https://doi.org/10.1001/jamanetworkopen.2021.18467

[115]. Yao, L. H., Leung, K. C., Tsai, C. L., Huang, C. H., & Fu, L. C. (2021). A novel deep learning-based system for triage in the emergency department using electronic medical records: Retrospective cohort study. *Journal of Medical Internet Research*, *23*(12), e27008. https://doi.org/10.2196/27008

[116]. Yin, J., Ngiam, K. Y., & Teo, H. H. (2021). Role of artificial intelligence applications in real-life clinical practice: Systematic review. *Journal of Medical Internet Research*, *23*(4), e25759. https://doi.org/10.2196/25759

[117]. Zachariasse, J. M., Seiger, N., Rood, P. P. M., Alves, C. F., Freitas, P., Smit, F. J., Roukema, G. R., & Moll, H. A. (2017). Validity of the Manchester Triage System in emergency care: A prospective observational study. *PLOS ONE*, *12*(2), e0170811. https://doi.org/10.1371/journal.pone.0170811

[118]. Zachariasse, J. M., van der Hagen, V., Seiger, N., Mackway-Jones, K., van Veen, M., & Moll, H. A. (2019). Performance of triage systems in emergency care: A systematic review and meta-analysis. *BMJ Open*, *9*(5), e026471. https://doi.org/10.1136/bmjopen-2018-026471