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RESEARCH PROTOCOL

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# Development and Implementation of AI Triage Models in Emergency Departments: A Scoping Review Protocol

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## Abstract

**Background:** Triage is a critical clinical tool in emergency care, ensuring appropriate prioritization of patient care. However, traditional triage systems face challenges such as mistriage, resource misallocation, and overcrowding. Evaluation of triage accuracy also lacks a universal reference standard, making comparisons across studies challenging. Artificial intelligence (AI) has shown potential to enhance triage accuracy, mitigate human limitations, and optimize resource allocation. However, routine integration into clinical workflows remains limited, as uptake depends on staff-related factors such as usability, trust, and organizational readiness. Therefore, there is a need to synthesize evidence on both performance and implementation determinants.

**Objective:** This scoping review compares AI-based triage with conventional/non-AI triage among adults in prehospital and emergency department settings, focusing on implementation determinants as well as performance outcomes. The dual focus on quantitative and qualitative aspects seeks to provide actionable insights for the effective development and integration of AI tools in emergency care.

**Methods:** The review will follow the Joanna Briggs Institute methodology and the PRISMA-ScR reporting guidelines to ensure transparency. We will search PubMed (MEDLINE), Embase (Ovid), Cochrane Central Register of Controlled Trials (Wiley), Web of Science (Clarivate), Scopus (Elsevier), and grey literature via Google Scholar and ProQuest using four core concepts: AI, triage, emergency medicine, and implementation. We will include studies of adult patients comparing AI-based triage with conventional/non-AI triage in prehospital and emergency department settings. Two reviewers will independently screen titles/abstracts and full-text articles and extract data in Covidence®, with a third reviewer resolving disagreements. Quantitative findings will be summarized descriptively in tables/figures, and heterogeneity in triage accuracy definitions and reference standards will be described explicitly rather than pooling non-comparable measures. Qualitative findings will be synthesized thematically and structured using the *Consolidated Framework for Implementation Research* (CFIR).

**Discussion:** This review will map AI-based triage models and key gaps in design, clinical effectiveness, and implementation across prehospital and in-hospital emergency care. By integrating quantitative and qualitative insights, it will bridge theory and practice, guide future research, and foster human-AI collaboration. Findings may inform the development of more effective AI tools that can be integrated into clinical workflows and strengthen acute patient care.

**Keywords**: Artificial intelligence; Triage; Emergency care

## Introduction

Triage is a well-established and widely used clinical tool for prioritizing patients in emergency care (1). Despite ongoing refinements, it still faces major challenges in achieving optimal effectiveness, particularly mistriage, which is characterized by incorrect triaging, either as overtriage (2) or undertriage (3). Triage accuracy depends on the model design and the real-world context in which it is applied. Staff experience and training, subjective judgment, and high inter-rater variability are significant drivers of mistriage (4,5), occurring in around one third of emergency department (ED) visits in large cohort studies (6,7), affecting patient safety, resource allocation, and ED waiting times, potentially exacerbating overcrowding and further increasing risk of mistriage (8). Additionally, defining triage accuracy is difficult because there is no universally accepted reference standard for true acuity, and studies use different reference points (e.g., expert review, clinical outcomes or decisions, or resource use) (9).

Artificial intelligence (AI) has shown promising results in emergency medicine because it can process large quantities of complex data, overcome human limitations such as cognitive fatigue and bias, and predict clinical outcomes (10). Data-driven triage systems typically use Machine Learning (ML) and Deep Learning (DL), with ML employing statistical algorithms and DL using neural networks to identify patterns and make predictions (11,12). These AI tools can alleviate the growing workload of triage staff, aiding in the reduction of mistriage, diagnostic errors, overcrowding, and improving resource allocation (7,12).

Despite their potential, AI models are not widely integrated into emergency care globally, mainly because many are developed without a clear implementation focus, and clinician mistrust of data-driven methods persists (11). To translate AI models into improved clinical practice, development should be guided by clinicians' perspectives throughout the process to foster human-machine interaction (13).Seamless workflow integration is critical, and implementation science plays a pivotal role in facilitating the adoption of evidence-based practices and bridging the gap between academic research and clinical implementation (14,15).

**HVAD VED VI?**

- AI-modeller kan forbedre triage nøjagtighed, optimere patientsikkerhed og ressourceallokering.
- Klinisk personale er ofte skeptisk over for AI-værktøjer, hvilket påvirker implementering og accept.
- Mange AI-modeller er udviklet uden fokus på praktisk integration i kliniske arbejdsgange.

*Fact box (in Danish).*

To comprehensively evaluate AI-based triage in emergency care, both quantitative and qualitative evidence must be assessed with equal rigor. The quantitative component focuses on performance metrics as well as clinical and operational outcomes of AI models compared with conventional triage. The qualitative aspect examines contextual and human-centered factors associated with implementation, such as clinicians' perceptions, trust and experiences with AI systems, and the organizational, structural and workflow challenges of integrating these tools into the complex dynamics of emergency medicine.

Although several recent reviews of AI triage acknowledge implementation barriers (16,17), they do not generally treat implementation as a primary search concept, which may limit the systematic capture of evidence on real-world adoption. Our review addresses this gap by moving beyond model performance alone and examining the wider implementation context of AI-based triage across prehospital and ED settings. By considering factors that shape real-world uptake, including barriers and facilitators, the review aims to provide a more complete understanding of what is required for successful integration into clinical practice.

In this scoping review, we will assess how AI-based triage systems compare with conventional/non-AI triage in prehospital and in-hospital emergency care for adult patients, focusing on implementation determinants as well as performance outcomes. This dual approach will provide a comprehensive overview of the field by identifying gaps in real-world applicability and acceptance as well as in technical performance, thereby informing future research and supporting the development and implementation of AI-based triage models in emergency medicine.

## Methods

This scoping review will be conducted in accordance with the Joanna Briggs Institute (JBI) methodology for scoping reviews (18), which is well suited to mapping a broad and heterogeneous evidence base. Reporting will follow the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) guidelines to ensure transparency throughout the process (19). Before commencing the review, the protocol has been registered with the Open Science Framework to support transparency and reproducibility (DOI: 10.17605/OSF.IO/MCPY4).

We will include studies of adults (≥18 years) in emergency care. The primary intervention of interest is general AI-based triage models used in prehospital and ED settings, with comparisons made to conventional or non-AI triage. Prehospital triage will be included because it often informs ED patient allocation and, in some settings, is used on arrival without re-triage.

We will exclude studies limited to disease-specific prediction (e.g., sepsis-only tools), models without a relevant comparator, and studies from specialty-specific settings (e.g., radiology and cardiology), to maintain comparability given that specialized triage systems are designed for specific departments or subspecialties.

We will include primary qualitative, quantitative, and mixed-methods studies. Eligible quantitative designs will include randomized controlled trials, diagnostic accuracy studies, and prospective or retrospective observational studies. We will also include qualitative and mixed-methods studies reporting barriers and facilitators to the implementation of AI-based triage models, even when technical algorithm details are limited, as these data are directly relevant to the qualitative aims of the review. We will exclude conference abstracts, editorials, lecture notes, reviews, and other forms of secondary literature.

To ensure relevance, we will include only studies published within the past ten years in English, Danish, Swedish, or Norwegian. Preliminary searches identified no eligible studies before this period, which aligns with the recent growth of triage-focused AI models in prehospital and ED settings. Because our review also includes implementation factors, it is important that the included studies reflect more recent organizational and digital contexts in which implementation is realistically feasible.

### INFORMATION SOURCES

A comprehensive search will be conducted in the following bibliographic databases: PubMed (MEDLINE), Embase (Ovid), Cochrane Central Register of Controlled Trials (Wiley), Web of Science (Clarivate), and Scopus (Elsevier). The preliminary selected controlled vocabulary and free-text terms for PubMed are shown in *Table 1*. We will also search for grey literature in Google Scholar and ProQuest to minimize publication bias.

### SEARCH STRATEGY AND TERMS

The search strategy will be developed and revised in collaboration with an experienced information specialist. It will focus on four core concepts: *artificial intelligence*, *triage*, *emergency medicine*, and *implementation*, combined using appropriate Boolean operators (AND/OR). The strategy will be piloted and refined in PubMed (MEDLINE) before being applied across all databases, and a detailed search log will be maintained to ensure transparency.

### SCREENING AND SELECTION OF SOURCES OF EVIDENCE

All records will be imported into Covidence® (Veritas Health Innovation, Melbourne, Australia) for de-duplication, screening, and data extraction. Two reviewers will independently screen titles and abstracts against the eligibility criteria. Any discrepancies will be resolved by discussion, with a third reviewer adjudicating if needed.

Subsequently, the same two reviewers will independently assess the full-text articles, and reasons for exclusion will be recorded. To illustrate the selection process from initial identification to final inclusion, a PRISMA flow diagram will be presented in the final manuscript.

## DATA EXTRACTION

A standardized, pilot-tested data-charting form will be developed to ensure consistent and comprehensive extraction. It will capture study characteristics, patient population, AI-based triage model characteristics, comparator triage approach, and the prespecified quantitative outcome domains, along with qualitative implementation determinants (*Table 2*).

**QUANTITATIVE MAPPING:** We will extract and summarize reported clinical outcomes (mortality, length of stay, readmission), operational outcomes (crowding, waiting times), triage accuracy metrics, and reported effectiveness. We will also describe key model characteristics, including data inputs, model type, and performance, as reported in each study, without analyzing underlying algorithmic mechanisms. Given that "triage accuracy" is variably defined across studies and may be benchmarked against different reference standards, we will record each study's definition and reference standard and interpret results in light of this heterogeneity rather than directly comparing non-equivalent metrics.

**ANVENDELSE I DANSKE AKUTMODTAGELSER**

1. Understøtte beslutningstagning for klinisk personale ved at reducere fejl og forudsige kliniske udfald mere præcist.
2. Fremme uddannelse og tillid til AI-baserede værktøjer blandt sundhedspersonale.
3. Tilpasse AI-modeller til de unikke behov i danske akutafdelinger for at støtte en succesfuld integration og implementering af AI i de kliniske arbejdsgange.

*Fact box (in Danish).*

**QUALITATIVE MAPPING:** To capture implementation evidence more systematically than prior reviews, we will include "implementation" as a core search concept and synthesize qualitative and mixed-methods studies reporting adoption of AI-based triage models.

**HVAD TILFØJER STUDIET?**

- Overblik over evidens for AI-baserede triagemodeller til voksne i præhospitalt arbejde og på akutmodtagelser, sammenlignet med konventionel/non-AI triage.
- Identifikation af videnshuller i teknisk ydeevne, kliniske resultater og implementeringsbarrierer.
- Indsigt i både kvantitative og kvalitative aspekter for bedre forståelse af AI-triages potentiale og udfordringer.

*Fact box (in Danish).*

Implementation-related data will be extracted even when technical model details are limited. We will perform an in-depth qualitative mapping of implementation determinants, covering both staff-related factors (acceptability, attitudes, perceptions, interprofessional relations) and contextual factors (stakeholder engagement, workflow, organizational culture and readiness). An implementation scientist embedded within the research team will lead this work, ensuring methodologically rigorous application of implementation terminology and framework-based synthesis. We will structure implementation findings using the *Consolidated Framework for Implementation Research* (CFIR) to organize determinants of implementation success and ensure consistent interpretation (20).

Two reviewers will independently extract data from the first 20 references, then compare and discuss the results to ensure consistency and refine the extraction approach. Any disagreements or uncertainties will be addressed by the entire research team. Data charting will proceed iteratively, and the form will be updated if new relevant variables emerge during extraction.

As this is a scoping review, we will not conduct a formal risk-of-bias assessment (19).

### DATA SYNTHESIS

We will synthesize findings using an integrated approach that combines descriptive quantitative summarization with qualitative thematic synthesis. Quantitative data will be summarized using descriptive statistics and presented in tables and figures to provide a visual representation of the scope and trends in the literature, including study and population characteristics, AI model features, comparator triage approach, and prespecified outcome domains. Because outcome definitions and reference standards, particularly for triage accuracy, vary across studies, we will record each study's definition and reference standard and interpret findings in light of this heterogeneity rather than pooling non-equivalent metrics.

Qualitative and mixed-methods evidence will be analyzed thematically and synthesized narratively. CFIR will then be applied pragmatically to support consistent categorization of implementation determinants across heterogeneous study designs. Not all CFIR domains are expected to be represented, reflecting the reporting depth of the studies included. Findings will be organized and reported by key implementation themes (e.g., barriers and facilitators to adoption) and relevant contextual domains, and evidence gaps will be explicitly highlighted to inform future development and implementation of AI-based triage models.

## Discussion

This scoping review will offer a novel and comprehensive overview of AI-based triage models and their implementation in emergency care, addressing aspects that are often difficult to synthesize or map in systematic reviews.

By summarizing clinical and operational outcomes, triage accuracy, and reported effectiveness, alongside model characteristics and comparator triage methods, the review will clarify what has been studied, how outcomes are defined, and where evidence is robust or inconsistent. A particular contribution is to document and interpret heterogeneity in triage accuracy definitions and reference standards, rather than comparing non-equivalent metrics.

In parallel, we will synthesize qualitative and mixed-methods evidence on barriers and facilitators to adoption, using CFIR to support implementation-relevant interpretation. This dual focus is intended to move beyond performance-only summaries by highlighting the practical conditions for real-world uptake and identifying gaps in implementation evidence to inform future design and deployment strategies for more effective AI-based triage tools.

In conclusion, this review will map evidence, identify key patterns and gaps, and summarize evaluated outcomes and implementation determinants influencing real-world uptake. Findings will guide future research priorities and support more implementable AI innovations in emergency care.

## Conflicts of Interest

The authors declare no conflicts of interest.

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None.

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