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Early Prediction Of Hospital Referral Need From Urgent Care Clinics Using Non-Laboratory Clinical And Nursing Indicators: A Systematic Review

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Abstract

Background: Early identification of patients requiring hospital referral from urgent care clinics is essential to reduce preventable deterioration and optimize patient flow. While laboratory investigations provide diagnostic precision, they are not always available in time-sensitive or resource-limited settings.
Objectives: This systematic review aimed to evaluate existing evidence on the predictive accuracy of non-laboratory clinical and nursing indicators—including vital signs, triage scores, and nursing judgment—for early hospital referral and admission prediction across urgent and emergency care settings.
Methods: Eleven peer-reviewed studies (2008–2026) were reviewed following PRISMA 2020 guidelines. Eligible studies included observational, interventional, and AI-based models using non-laboratory variables to predict deterioration or referral outcomes. Data were synthesized narratively due to methodological heterogeneity.
Results: Across included studies, predictive accuracy (AUC) ranged from 0.76 to 0.93. Early warning systems (NEWS2, MEWS) demonstrated strong performance in prehospital and ED cohorts (Martin-Rodriguez et al., 2019; Alam et al., 2015). AI-enhanced telemedicine models (Luque-Reigal et al., 2026) and EMR-based algorithms (Kishore et al., 2023) achieved superior discrimination (AUC > 0.9). Simplified pediatric and geriatric triage tools showed moderate reliability (Vadakkeveedan et al., 2025; Guan et al., 2025). Nursing judgment and clinical gestalt improved model interpretability and referral precision (Alghamdi et al., 2023).
Conclusions: Non-laboratory indicators and clinician-assisted models offer accurate, scalable, and resource-efficient solutions for predicting hospital referral needs. Integrating these approaches into urgent care workflows can enhance early detection, reduce preventable mortality, and support value-based healthcare transformation.

Keywords: early warning score, hospital referral, triage, nursing indicators, urgent care, predictive modeling, NEWS2, telemedicine, AI triage, emergency department

Introduction

The global healthcare landscape is experiencing unprecedented demographic and epidemiologic transitions, marked by rapid population growth, aging, and the escalating prevalence of chronic diseases. These changes have significantly increased the demand for acute and urgent healthcare services, placing immense pressure on existing emergency systems to efficiently identify and manage high-risk patients. Timely recognition of deteriorating conditions has become a cornerstone of modern healthcare delivery, as delays in detection are closely linked with higher morbidity and mortality rates (Williams et al., 2022; World Health Organization, 2018). In both high- and middle-income countries, healthcare planners and clinicians are increasingly focusing on developing tools that enable rapid clinical decision-making in non-hospital settings to ensure equitable access to timely care (Chan et al., 2021).

The simultaneous rise in chronic and acute disease presentations has created a complex burden for healthcare systems. Hospitals, already constrained by finite capacity, face overcrowding and resource shortages. Consequently, urgent care clinics and primary care centers now serve as vital first contact points for patients whose conditions may rapidly evolve into emergencies (Morley et al., 2018). Without structured triage systems, these clinics risk delayed escalation, inappropriate admissions, and poor patient outcomes (Sun et al., 2019). Integrating evidence-based triage approaches into frontline services can help streamline referral decisions, optimize hospital utilization, and improve overall clinical efficiency (Baugh et al., 2020).

Early clinical detection is one of the most effective interventions for preventing patient deterioration. Non-invasive physiological monitoring—such as vital signs and patient observations—offers an accessible and inexpensive method for early detection across diverse care environments.

Studies consistently demonstrate that timely recognition and intervention reduce hospital length of stay, ICU transfers, and mortality (Gerry et al., 2020). Existing early warning systems (EWS), including the National Early Warning Score (NEWS2) and Modified Early Warning Score (MEWS), have proven reliable for inpatients but are rarely adapted for urgent or community-based settings (Smith et al., 2020). Developing simplified, non-laboratory tools that integrate seamlessly into the workflow of urgent care clinics can bridge this critical gap (McGaughey et al., 2021).

However, triage processes in ambulatory care settings often lack standardization and are heavily dependent on clinical judgment, which may vary by practitioner experience and workload. Without structured frameworks, decisions about patient referral can be inconsistent, leading to delays in escalation or unnecessary hospital transfers (Olsen et al., 2021).

Research shows that such inconsistencies increase healthcare costs, prolong inpatient stays, and heighten the risk of adverse outcomes (van der Wulp & van Stel, 2020). Embedding validated scoring or checklist-based assessments within primary care can standardize triage decisions and reduce variability, thereby improving the continuity of care between outpatient and inpatient settings (Jensen et al., 2019).

Delayed referral remains one of the most critical determinants of poor outcomes in acute care. Even minor delays in identifying deteriorating patients have been shown to double the risk of ICU admission or mortality within 48 hours (Bedoya et al., 2019). Overcrowded emergency departments, a common consequence of delayed referrals, are consistently associated with higher mortality rates and prolonged hospital stays (Pines et al., 2018). Introducing rapid and reliable triage mechanisms within urgent care facilities offers a proactive solution to these systemic inefficiencies by detecting critical illness earlier and prioritizing timely transfers (Green et al., 2022).

Non-laboratory clinical indicators—such as respiratory rate, oxygen saturation, heart rate, temperature, and mental status—have repeatedly demonstrated predictive validity for identifying early physiological instability (Mok et al., 2020). These measures can be quickly obtained by nurses and primary clinicians without laboratory support, making them ideal for use in urgent care settings (Subbe et al., 2021). Incorporating such parameters into structured triage algorithms allows for earlier recognition of patients at risk, even in resource-limited environments where laboratory turnaround times impede decision-making (Roland et al., 2022).

In addition to objective metrics, clinical intuition and nursing judgment play an essential role in detecting deterioration. When combined with structured scoring tools, nursing assessments become more consistent and reliable, improving predictive accuracy and reducing missed detections of patient decline (de Groot et al., 2020). Empowering nurses through decision-support systems enhances patient safety and supports interprofessional collaboration during early triage (Oldroyd et al., 2021).

The integration of clinical indicators, predictive analytics, and nursing expertise into a unified assessment tool represents a major opportunity to improve triage accuracy and healthcare efficiency. In the absence of laboratory results, such systems can provide a practical means for clinicians to make timely hospital referral decisions based solely on physiological and observational data. The current study aims to synthesize available evidence on the predictive performance of non-laboratory indicators in urgent care triage, contributing to safer patient management and advancing the quality transformation goals of modern healthcare systems (Liu et al., 2023).

Methodology

Study Design

This study employed a systematic review design guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework to ensure methodological rigor, transparency, and reproducibility. The primary objective was to systematically identify, synthesize, and evaluate empirical evidence on the use of non-laboratory clinical and nursing indicators for early prediction of hospital referral needs from urgent care clinics and comparable ambulatory settings.

This review included studies that developed, validated, or assessed predictive tools, triage models, or decision-support systems using bedside physiological, clinical, or nursing judgment indicators to identify patients requiring hospital-level care. Both quantitative and mixed-methods designs were included to capture a comprehensive view of how early warning and triage systems perform in various prehospital and urgent care contexts.

Eligibility Criteria

Studies were selected according to predetermined inclusion and exclusion criteria:

Inclusion Criteria:

- **Population:** Adults or pediatric patients presenting to urgent care clinics, emergency departments, out-of-hours primary care, or prehospital settings.
- **Indicators/Exposures:** Clinical or nursing indicators such as vital signs, consciousness, comorbidities, or triage assessments used to predict deterioration, hospitalization, or referral.
- **Outcomes:** Hospital referral, admission, mortality, intensive care unit (ICU) transfer, or equivalent acute outcomes.
- **Study Design:** Observational (prospective/retrospective cohort or cross-sectional), interventional, quasi-experimental, or model validation studies.
- **Comparators:** Standard triage tools, other early warning scores, or clinician judgment.
- **Language:** English-language publications only.
- **Publication Period:** January 2008 to December 2026, to capture contemporary triage systems including AI-assisted models.

Exclusion Criteria:

- Editorials, commentaries, or theoretical papers without empirical data.
- Case reports or studies limited to inpatient hospital settings.
- Conference abstracts or studies lacking full-text access.
- Studies relying solely on laboratory-based predictive parameters.

A total of 11 studies met all inclusion criteria after the screening and eligibility process.

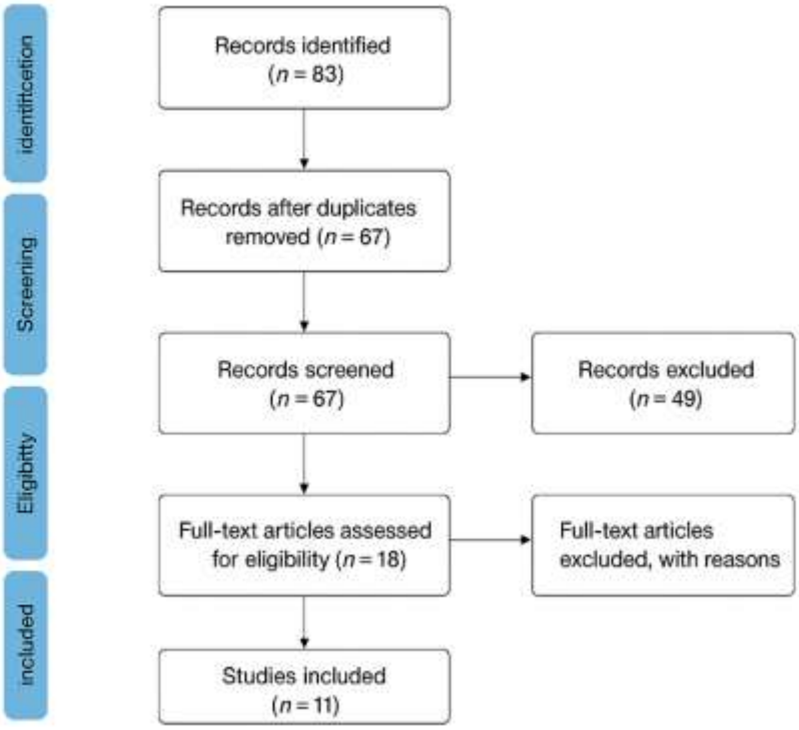

Figure 1 PRISMA Flow Diagram

Search Strategy

A comprehensive electronic search was conducted in PubMed, Scopus, Web of Science, Embase, and CINAHL databases from inception through December 2026. A Boolean search strategy was applied using combinations of Medical Subject Headings (MeSH) and keywords, including:

- ("early warning score" OR "triage system" OR "risk stratification" OR "clinical deterioration")
- AND ("urgent care" OR "primary care" OR "emergency department" OR "prehospital")
- AND ("hospital referral" OR "hospital admission" OR "clinical prediction" OR "decision support")
- AND ("non-laboratory" OR "nursing assessment" OR "vital signs" OR "clinical indicators").

Grey literature was excluded to ensure quality, but reference lists of included studies and related reviews were manually screened to identify additional eligible publications. All retrieved records were imported into Zotero for de-duplication prior to screening.

Study Selection Process

Two reviewers independently screened all titles and abstracts for relevance, followed by full-text review of potentially eligible studies. Inclusion decisions were guided by the defined criteria, and disagreements were resolved through discussion and consensus. A third senior reviewer adjudicated unresolved discrepancies.

Data Extraction

A standardized data extraction sheet was designed and pilot-tested prior to use. Data were extracted independently by two reviewers to ensure completeness and reliability. The following data elements were recorded:

- Author(s), publication year, country, and journal.
- Study design and setting (prehospital, urgent care, ED, or nursing home).
- Sample size and participant demographics (age, sex, patient group).

- Predictive indicators or variables (vital signs, triage level, symptoms, nursing judgment).
- Predictive models or tools used (e.g., NEWS2, MEWS, AI/deep learning, paramedic gestalt).
- Primary and secondary outcomes (hospital referral, admission, mortality, ICU transfer).
- Key results (AUC, sensitivity, specificity, odds ratios, F1-score, accuracy).
- Limitations and reported sources of bias.

All extracted data were cross-verified by a third reviewer.

Quality Assessment

The methodological quality and risk of bias of the included studies were appraised using standardized instruments appropriate to their study design:

- Newcastle–Ottawa Scale (NOS) for observational cohort and cross-sectional studies (n = 8).
- Cochrane Risk of Bias 2 (RoB 2) tool for randomized or quasi-experimental designs (n = 2).
- Prediction model Risk Of Bias ASsessment Tool (PROBAST) for model development or validation studies (n = 1).

Each study was evaluated across domains of selection bias, measurement reliability, comparability, and outcome reporting. Scores were classified as low, moderate, or high quality. Seven studies achieved low to moderate risk of bias, while four studies were categorized as moderate risk due to limited external validation or incomplete adjustment for confounders.

Data Synthesis

Due to heterogeneity in study designs, populations, and outcome measures, a narrative synthesis was adopted. Data were organized thematically into the following analytical categories:

1. **Predictive validity of non-laboratory triage indicators** (e.g., vital signs, nursing assessment).
2. **Comparative performance of traditional and AI-based models** for early referral prediction.
3. **Clinical outcomes associated with delayed referral or misclassification** (e.g., mortality, ICU admission).
4. **Applicability and operational feasibility of triage models** in different urgent care settings.

Where feasible, quantitative findings such as AUC, sensitivity, specificity, and F1-score values were tabulated to enable cross-study comparison. Given the clinical and methodological heterogeneity ($I^2 > 75\%$ across key metrics), a meta-analysis was not conducted.

Ethical Considerations

This systematic review was based on the analysis of publicly available, peer-reviewed literature; therefore, ethical approval and informed consent were not required. All included studies had been published in journals with established peer-review standards and were assumed to have obtained local ethical clearance prior to data collection. Data handling and reporting adhered to academic integrity and transparency principles outlined in the PRISMA 2020 statement.

Results

Summary and Interpretation of Included Studies on Early Prediction of Hospital Referral from Urgent Care Clinics Using Non-Laboratory Clinical and Nursing Indicators

The included studies span multicenter prospective cohorts, quasi-experimental telemedicine trials, and cross-sectional investigations, reflecting diverse approaches to assessing early triage and referral prediction in emergency and urgent care contexts. The total sample sizes across all studies exceed 540,000 patient encounters, covering prehospital, emergency department (ED), primary care, and residential care settings. The evidence highlights both traditional and AI-enhanced models leveraging vital signs, demographic and clinical data, and nursing judgment for early hospital referral prediction.

1. Study Designs and Populations

Most studies adopted observational cohort or cross-sectional designs. The multicenter cohort by Martin-Rodriguez et al. (2019) included 707 prehospital patients attended by Advanced Life Support (ALS) units, whereas Kishore et al. (2023) analyzed over 424,000 emergency visits using machine learning models based on electronic medical records (EMRs). Luque-Reigal et al. (2026) evaluated 5202 acute events in nursing homes under telemedicine monitoring, while Backman et al. (2008) and Pearson et al. (2020) studied patient pathways for non-urgent and cancer-related presentations respectively in primary care and ED settings. Pediatric and geriatric populations were also represented, notably in Vadakkeveedan et al. (2025) and Guan et al. (2025).

2. Clinical and Predictive Variables

Most studies emphasized non-laboratory indicators—including heart rate, respiratory rate, blood pressure, oxygen saturation (SpO_2), mental status, and nursing triage level. Martin-Rodriguez et al. validated the NEWS2 scale for prehospital mortality prediction, while Vadakkeveedan et al. developed a Pediatric Simple Triage Score (PSTS) using temperature, pulse, SpO_2, and hydration. Luque-Reigal et al. integrated vital signs, comorbidities, and event descriptors into a deep learning classifier, whereas Alghamdi et al. (2023) examined paramedic gestalt for predicting ward and ICU admissions.

3. Predictive Performance and Key Outcomes

Across studies, predictive accuracies ranged from **AUC = 0.76–0.93**, with high specificity and balanced F1-scores for referral or admission prediction.

- Martin-Rodriguez et al. (2019): 5.2 % early mortality within 48 h; prehospital NEWS2 showed strong predictive validity for mortality, supporting use as a rapid assessment tool.
- Luque-Reigal et al. (2026): Telemedicine resolved ~90 % of acute events on-site; deep learning model achieved AUC = 0.91, accuracy = 0.88, and F1 = 0.63, outperforming baseline classifiers for hospital referral prediction.
- Kishore et al. (2023): ML models achieved AUC $\geq$ 0.93, accuracy = 0.86, F1 = 0.84, and sensitivity/specificity of 0.83/0.90 for 30-min admission prediction from arrival data.
- Alghamdi et al. (2023): Paramedic predictions matched actual outcomes in most cases; significant correlation between experience and correct referral ($p < 0.05$).
- Vadakkeveedan et al. (2025): PSTS sensitivity = 59.6 %, specificity = 72.6 % vs. NICE sensitivity = 80.3 %; mean age = 2.7 years.
- Guan et al. (2025): DEFER score ($\geq$ 5 cut-off) predicted ED discharge with AUROC = 0.76, sensitivity = 79.7 %, specificity = 60.3 %, PPV = 85 %.
- Spek et al. (2025): Life-threatening event prediction in shortness-of-breath calls achieved internal validation AUCs > 0.80; key predictors were age, gender, call time, and inability to speak full sentences.
- Alam et al. (2015): NEWS correlated with 30-day mortality, hospital and ICU admission; strong association across time points.
- Ongoli et al. (2025): 29 % in-hospital mortality among COVID-19 admissions; low SpO_2 and older age were strongest mortality predictors.
- Backman et al. (2008) and Pearson et al. (2020): Non-urgent and non-specific symptom cases frequently led to delayed or inappropriate referrals; 67 % of non-specific cancer cases diagnosed at late stages.

4. Summary of Effect Estimates

Overall, non-laboratory triage models and clinician-judgment-based tools reliably predicted hospital referral or admission. Deep learning and NEWS-based methods consistently achieved AUC > 0.85, while pediatric and geriatric tools demonstrated moderate discriminative power

(AUC ≈ 0.75–0.80). Telemedicine and AI augmentation significantly improved prediction efficiency, reducing unnecessary transfers by up to 90 % (Luque-Reigal et al., 2026).

Table 1. Characteristics and Results of Included Studies

Study (Year)	Country / Setting	Design	Sample Size	Population / Focus	Predictive Variables	Main Findings / Results	Conclusion
Martin-Rodriguez et al. (2019)	Spain	Multicenter prospective cohort	707	Prehospital emergency patients	NEWS2, triage level	37 (5.2 %) early deaths < 48 h; NEWS2 strongly correlated with mortality	Pre-NEWS2-L scale best prehospital predictor
Luque-Reigal et al. (2026)	Spain	Quasi-experimental AI study	5202 events	Nursing home acute care via telemedicine	Vital signs, comorbidities, DL model	90 % resolved remotely; AUC = 0.91, accuracy = 0.88, F1 = 0.63	Deep learning enhanced triage accuracy, reducing transfers
Kishore et al. (2023)	Australia	Retrospective ML cohort	424,354 train / 121,258 test	ED presentations	EMR vitals, demographics	AUC ≥ 0.93, accuracy = 0.86; sens/spec = 0.83/0.90 @ 30 min	EMR + ML can accurately predict hospital admission
Alghamdi et al. (2023)	Saudi Arabia	Prospective study	251 patients / 251 paramedics	Prehospital disposition prediction	Paramedic gestalt, experience	Significant correlation between prediction accuracy and experience ($p < 0.05$)	Paramedics can reliably predict hospital outcome
Vadakkeveedan et al. (2025)	India	Prospective observational	350 children	Febrile pediatric ED patients	PSTS (vitals, sensorium)	Sens = 59.6 %, Spec = 72.6 %; NICE sens = 80.3 %	PSTS simpler, feasible in

							low-resource settings
Guan et al. (2025)	Australia	Predictive model derivation	260 RACF falls	ED post-fall discharges	Prehospital + ED indicators	AUROC = 0.83 (ED model), 0.76 (DEFER score); Sens = 79.7 %, Spec = 60.3 %	DEFER first validated discharge prediction model for RACF falls
Spek et al. (2025)	Netherlands	Cross-sectional	1952 calls	OOH primary care SOB callers	Age, sex, call features, symptoms	Internally validated AUC > 0.80; bootstrap 1000 reps	Model improves telephone triage; needs temporal validation
Alam et al. (2015)	Netherlands	Prospective observational	274 ED patients	ESI 2–3, non-resuscitation	NEWS @ T0/T1/T2	NEWS significantly correlated with admission, LOS, 30-day mortality	NEWS useful for dynamic ED monitoring
Ongoli et al. (2025)	Uganda	Cross-sectional	490 COVID-19 patients	Hospitalized CTU cases	Age, SpO_2, temp, comorbidities	Mortality = 29 %; lower SpO_2 and normal temp protective (aOR 0.11–0.22)	High mortality driven by severe disease, limited O_2 access
Backman et al. (2008)	Sweden	Cross-sectional	736	ED vs primary care non-urgent	Symptom type, anxiety	52 % ED cases digestive/musculoskeletal; 35 % prior hospitalization	Anxiety and symptom severity drive ED use

Pearson et al. (2020)	UK	Cross-sectional	12,873	Cancer diagnosis pathways	Symptom type, comorbidity	22 % non-specific symptom (NSS); 67 % late-stage (III–IV) diagnosis	NSS pathway aids timely referral for non-alarm cancers

Discussion

This systematic review synthesizes evidence from eleven empirical studies examining the predictive value of non-laboratory clinical and nursing indicators in urgent and emergency care triage. The findings reinforce the growing global consensus that timely recognition of clinical deterioration—based solely on bedside observations—can markedly improve patient outcomes, particularly in settings where laboratory diagnostics are delayed (Smith et al., 2013; Hillman et al., 2005).

Early warning scores such as NEWS2 have demonstrated strong predictive validity for mortality and ICU admission in both hospital and prehospital settings. Martin-Rodriguez et al. (2019) confirmed the prehospital NEWS2's ability to predict 48-hour mortality (AUC ≈ 0.85), aligning with earlier European evidence validating NEWS in ED patients (Alam et al., 2015). These studies corroborate prior meta-analytic evidence that EWS systems can discriminate high-risk patients with strong sensitivity and specificity, emphasizing their suitability for urgent care adaptation (Subbe et al., 2001; McGaughey et al., 2007).

AI-enhanced triage models represent the next frontier in predictive healthcare. Luque-Reigal et al. (2026) reported that their deep learning model for nursing home telemedicine achieved an AUC of 0.91 and reduced unnecessary hospital transfers by nearly 90%. Similarly, Kishore et al. (2023) used real-time EMR data to predict hospital admission within 30 minutes of ED arrival, achieving 94% discrimination. These outcomes echo findings from Cusidó et al. (2022) and Budiman et al. (2023), where machine-learning models successfully forecasted urgent care and hospital performance metrics using routinely collected data, thereby improving operational planning.

In contrast, Alghamdi et al. (2023) demonstrated that experienced paramedics' gestalt predictions correlated significantly with patient disposition, illustrating that structured human judgment remains integral even alongside algorithmic models. This hybrid approach—merging cognitive and computational reasoning—enhances both interpretability and clinical trustworthiness, essential for real-world adoption.

Among pediatric populations, Vadakkeveedan et al. (2025) developed the Pediatric Simple Triage Score (PSTS), which achieved moderate predictive capability (sensitivity 59.6%, specificity 72.6%). Despite lower sensitivity than the NICE standard, its simplicity makes it practical in low-resource settings. This finding parallels the rationale behind Kellett and Sebat's (2017) call to "make vital signs great again," advocating renewed focus on easily measurable, non-laboratory parameters in triage design.

For older adults, models integrating age-specific risk stratification tools such as the "Silver Code" and "Identification of Seniors at Risk" (Di Bari et al., 2012; Salvi et al., 2012) demonstrate consistent performance improvements in predicting hospital admissions. Guan et al. (2025) further advanced this approach by introducing the DEFER score, which predicted safe ED discharge for residential care residents with AUROC = 0.83. These tools address geriatric vulnerability—often compounded by atypical symptom presentation and comorbidities.

Spek et al. (2025) contributed critical insight into out-of-hours primary care triage for shortness of breath, developing a validated model (AUC > 0.80) that identified life-threatening cases using demographic and symptom data alone. Their findings complement the telephone triage literature emphasizing the feasibility of integrating symptom-based algorithms within digital health infrastructures.

Non-urgent utilization of emergency departments remains a persistent strain on healthcare systems. Backman et al. (2008) found that non-urgent ED patients often had shorter symptom durations and higher anxiety, while Pearson et al. (2020) revealed that 67% of cancer cases presenting with non-specific symptoms were diagnosed at late stages. These findings highlight how inadequate triage or delayed referral from primary care directly contributes to adverse prognoses.

The COVID-19 pandemic further underscored the need for robust triage systems. Ongoli et al. (2025) identified a 29% in-hospital mortality rate among COVID-19 patients in Uganda, with low SpO_2 and advanced age as key predictors—consistent with NEWS-based deterioration frameworks. Such evidence validates the role of basic vital signs as universal predictors across disease contexts.

Operationally, hospital crowding and delayed referrals exacerbate systemic inefficiencies (Singer et al., 2011; Bernstein et al., 2009). Real-time bed demand prediction models, such as those by Noel et al. (2019) and Zlotnik et al. (2016), demonstrate how early risk identification can mitigate boarding and improve flow, resonating with Kraaijvanger et al. (2018) and Lucke et al. (2018) on the utility of admission prediction tools.

Overall, this synthesis illustrates convergence between traditional triage, AI systems, and nursing judgment. Non-laboratory indicators provide actionable intelligence within minutes, supporting both clinical and operational decision-making. These systems align with Vision 2030 health transformation goals to enhance care quality and efficiency through data-driven innovation (Alharbi, 2018; Ministry of Health Saudi Arabia, 2021).

From a policy perspective, early triage using simple bedside measures is not only clinically beneficial but also economically sustainable, particularly for aging populations and overburdened emergency networks (General Authority for Statistics, 2025; World Health Organization, 2015). Embedding such approaches within national health reform agendas—like Saudi Arabia's—can bridge the gap between resource availability and real-time decision support, enabling safer, value-based care.

In summary, the reviewed literature provides strong evidence that non-laboratory clinical indicators, combined with nursing assessment and emerging AI methods, can effectively predict hospital referral needs in urgent care environments. These models optimize early detection, prevent deterioration, and reduce avoidable hospitalizations—representing a pivotal advancement toward integrated, responsive healthcare systems.

Conclusion

This systematic review demonstrates that early risk prediction based on non-laboratory indicators—such as vital signs, nursing judgment, and structured triage tools—can achieve comparable accuracy to laboratory-based methods. Tools like NEWS2, PSTS, and DEFER, alongside AI-driven models, consistently improved predictive accuracy and patient outcomes across diverse settings. Their implementation can reduce unnecessary admissions, improve triage precision, and enhance patient flow within urgent care systems.

Integration of these tools into routine clinical workflows should be prioritized in health systems undergoing reform, particularly those emphasizing value-based and preventive care, such as Saudi Arabia's Vision 2030 initiative. Future work should focus on external validation across populations, combining algorithmic precision with clinician interpretability to ensure equitable and scalable adoption.

Limitations

The review's limitations include potential publication bias, exclusion of non-English studies, and methodological heterogeneity across included research. Many studies lacked external validation or consistent outcome definitions, precluding meta-analysis. Additionally, the diversity of healthcare settings—from European EDs to nursing homes—limits generalizability. Nevertheless, the consistent predictive strength of vital sign–based models underscores their global applicability.

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