Natural Resources for Human Health
eISSN: 2583-1194

Original Research

Received 14 June 2026
Revised 20 July 2026
Accepted 08 August 2026

Natural Resources for Human Health 2026, Vol. 6 (6): 744–753

KEYWORDS:
Prehospital triage, emergency patients, effectiveness, high-risk identification, EMS

Effectiveness of Prehospital Triage Systems in Identifying High-Risk Emergency Patients

Almutairi, Faisal Abdullah A[1], Nasser Mana Hamad Alamer[2], Hussain Ali Mutlaq Al Jumhur[3], Saad Mohammed Bin Omairah[4], Abdulrahman Ibrahim Alghurair[5], Altamemi, Abdullah Ibrahim H[6], Fawaz Mohammed Al Mousa[7], Rushud Mohammad Al Tamimi[8], Hayed Ibrahim Saad Al-Tamimi[9], Turki Abdurahman A Almusi[10]

[1]Emergency Medical Technician – Saudi Red Crescent Authority – Riyadh – Riyadh Region – Saudi Arabia
Email: al_997@hotmail.com
[2]Emergency Medical Services Technician – Saudi Red Crescent Authority – Wadi ad-Dawasir – Riyadh Region – Saudi Arabia
Email: srca07886@srca.org.sa
[3]Paramedic Technician – Saudi Red Crescent Authority – Hawtat Bani Tamim – Riyadh Region – Saudi Arabia
Email: ly7264363@gmail.com
[4]Emergency Medical Technician – Saudi Red Crescent Authority, Hawtat Bani Tamim Sector – Hawtat Bani Tamim – Riyadh Region – Saudi Arabia
Email: alsamr-959@hotmail.com
[5]Health Assistant – Emergency Medical Services (EMS) – Saudi Red Crescent Authority, Hawtat Bani Tamim – Riyadh Region – Saudi Arabia
Email: alghurair997@gmail.com
[6]Emergency Medical Technician – Saudi Red Crescent Authority – Riyadh – Riyadh Region – Saudi Arabia
Email: abboud.073@hotmail.com
[7]Emergency Medical Technician – Saudi Red Crescent Authority, Hawtat Bani Tamim – Riyadh Region – Saudi Arabia
Email: fawaz5653@outlook.sa
[8]Emergency Medical Technician – Saudi Red Crescent Authority, Hawtat Bani Tamim – Riyadh Region – Saudi Arabia
Email: alnagdi997@gmail.com
[9]Emergency Medical Technician – Al-Salamiyah Ambulance Center, Saudi Red Crescent Authority – Hawtat Bani Tamim – Riyadh Region – Saudi Arabia
Email: Hayd-1512@hotmail.com
[10]Emergency Medical Technician – Saudi Red Crescent Authority, Hawtat Bani Tamim – Riyadh Region – Saudi Arabia
Email: turki-997@hotmail.com

ABSTRACT: Prehospital triage systems are critical in emergency medical services (EMS) as they determine the priority of patient treatment and transport based on the severity of their conditions. These systems aim to rapidly identify high-risk emergency patients who may require immediate medical intervention, thereby improving outcomes and optimizing

resource deployment. Research has shown that effective triage can significantly impact survival rates, especially in traumatic events or during mass casualty incidents. By utilizing standardized protocols and trained personnel, EMS can ensure that patients with life-threatening conditions receive timely care, thereby reducing morbidity and mortality associated with critical emergencies. However, the effectiveness of prehospital triage systems can vary depending on factors such as system design, training of personnel, and the specific context of emergencies. Some studies have indicated that while certain triage scales, like the START (Simple Triage and Rapid Treatment) and the MCI (Mass Casualty Incident) triage systems, show promise in efficiently categorizing patients, limitations persist in their application during real-life scenarios. Variability in decision-making among EMTs and Paramedics, as well as challenges in communication and patient transport, can hinder the optimal functioning of these systems. Continuous evaluation and refinement of triage protocols, along with ongoing training for first responders, are essential for enhancing the identification of high-risk patients and ensuring that emergency medical resources are allocated effectively.

INTRODUCTION

The prehospital phase of emergency care constitutes a decisive interval in which the trajectory of a patient's outcome is often established. For time-critical conditions such as major trauma, stroke, acute coronary syndrome, sepsis, and respiratory failure, the decisions made by emergency medical services personnel in the field determine not only the destination facility but also the rapidity with which definitive care is initiated. Prehospital triage is the systematic process by which providers stratify patients according to acuity, prioritize life-saving interventions, and select the most appropriate receiving hospital. Its effectiveness is therefore not an abstract quality indicator but a direct determinant of survival and functional recovery [1].

The evidence base supporting prehospital triage has expanded substantially, moving from descriptive accounts of individual tools to large-scale systematic reviews and multi-institutional validation studies. Structured triage systems, including stepwise algorithms, physiological scoring tools, and digital decision-support platforms, have been associated with reductions in trauma-related mortality ranging from 8% to 18%, alongside measurable improvements in scene time, transport time, and time to definitive care [1,2]. Triage accuracy across systems typically ranges from 62% to 89%, with artificial intelligence–supported models achieving accuracy above 90% in selected cohorts [1,3]. Yet these aggregate figures conceal considerable heterogeneity: performance is tool-dependent, population-dependent, and profoundly shaped by system-level factors such as provider training, geographic setting, and integration within coordinated trauma networks [2,4].

This article evaluates the effectiveness of prehospital triage systems in identifying high-risk emergency patients. It examines the principal triage paradigms, the diagnostic performance of physiological and anatomical tools, the role of mass casualty incident algorithms, the emerging contribution of artificial intelligence and telemedicine, and the outcome evidence linking triage accuracy to mortality, intensive care utilization, and healthcare efficiency [1,4]. Particular attention is devoted to persistent failure modes—under-triage and over-triage—and to the populations in which these failures are most consequential: older adults, pediatric patients, and those in resource-limited settings [5,6].

Conceptual Foundations and the Metrics of Triage Performance

Effective prehospital triage rests on two intertwined performance attributes: accuracy, defined as how well assigned categories reflect the true need for life-saving intervention, and timeliness, representing how quickly correct decisions are made. These attributes are operationalized through a standard set of diagnostic metrics. Sensitivity reflects the proportion of truly high-risk patients who are identified as such, while specificity reflects the proportion of low-risk patients correctly classified. The clinical consequences of misclassification are captured by under-triage and over-triage. Under-triage occurs when a severely injured or critically ill patient is assigned to a lower-acuity category or transported to a facility incapable of providing definitive care; it delays time-critical intervention and is consistently associated with excess mortality [1,5]. Over-triage occurs when a low-risk patient is assigned to a higher-acuity pathway; while less immediately dangerous for the individual patient, it consumes scarce

advanced resources, contributes to emergency department crowding, and can degrade system capacity during surge conditions [5,6].

The American College of Surgeons Committee on Trauma has established benchmark thresholds of under-triage below 5% and over-triage below 50% for mass casualty triage, while acknowledging that field triage protocols are rarely held to such stringent standards [5,6]. In practice, these benchmarks are seldom met by algorithm-based triage systems in prehospital and mass casualty contexts. A comparative analysis of 21 algorithm-based primary triage systems applied to a standardized casualty scenario found that no system achieved the under-triage threshold, and the most accurate system—START/JumpSTART—correctly categorized only 76.7% of casualties [5]. The Modified Physiological Triage Tool-24 and the National Health Service Major Incident Triage Tool demonstrated the best sensitivity–specificity balance but still failed to meet accepted criteria [5,6]. These findings underscore a fundamental tension: triage systems designed for rapid field use necessarily trade diagnostic precision for speed and simplicity, and the resulting error profile must be understood as an inherent characteristic of the tool rather than an isolated implementation failure [1,5].

Table 1 summarizes the principal performance benchmarks and the observed rates of misclassification across representative prehospital and mass casualty triage contexts.

Performance Domain	Accepted Benchmark	Observed in Prehospital and MCI Studies	Key Sources
Under-triage (trauma activation)	≤ 5% (ACS-COT)	Frequently exceeded; reported rates as high as 21.3% in critical care transport models and 62% in pediatric triage tape applications	[7,8]
Over-triage (trauma activation)	≤ 50% (ACS-COT)	Variable; some systems report 34.9%–63%, while others remain within threshold	[7,8]
Under-triage (MCI algorithms)	< 5% (ACS-COT)	None of 21 systems met threshold; START/JumpSTART accuracy 76.7%; Sacco Triage Method 40%	[5]
Overall triage accuracy	Not standardized	62%–89% across conventional tools; AI-supported models > 90%	[1,3]

Physiological and Anatomical Triage Tools: Comparative Performance

The physiological and anatomical scoring systems most widely deployed in prehospital trauma care include the Revised Trauma Score, the Glasgow Coma Scale–Age–Arterial Pressure score, the Mechanism–GCS–Age–Arterial Pressure score, the Shock Index, the New Early Warning Score 2, and the Trauma and Injury Severity Score. A systematic review synthesizing evidence across nine original studies reported high discriminative performance for mortality and early resuscitative needs: AUROC values reached 0.971 and 0.949 for MGAP in different cohorts, 0.949–0.935 for GAP, 0.967 for mREMS, and 0.934 for TRISS [2,4]. NEWS2 performed best for very early mortality but showed weaker discrimination over longer time horizons [4,9]. The Shock Index and its prehospital change predicted transfusion, intensive care admission, operative need, and short-term mortality signals in selected cohorts [1,2].

Comparative analyses suggest that MGAP and GAP offer a favorable balance of sensitivity and specificity for identifying severe trauma and predicting unfavorable outcomes [2,4]. One prehospital study reported comparable AUROC values of 0.890 for GAP, 0.869 for MGAP, and 0.871 for RTS, with MGAP demonstrating the highest sensitivity [2]. A separate cohort evaluation focusing on resuscitative interventions within 24 hours found excellent discriminative performance, with AUROC values of 0.969 for T-RTS, 0.949 for GAP, 0.971 for MGAP, and 0.929 for NEWS-2 [4]. In this cohort, a GAP score below 19 yielded the highest accuracy for ruling out patients who did not require resuscitative interventions, with a specificity of 94.4% and a negative predictive value of 94.1% [4]. However, the apparent superiority of any single tool is contingent on the outcome against which it is evaluated [2,4]. When the outcome is mortality alone, differences between MGAP and GAP narrow considerably; when the outcome is the need for resuscitative interventions, MGAP demonstrates the highest discriminative ability, and GAP, MGAP, NEWS2, and T-RTS remain well calibrated with observed-to-expected ratios approaching unity [4].

Table 2 presents representative performance metrics for major physiological and anatomical triage tools across prehospital cohorts.

Triage Tool	Primary Components	Reported AUROC (Mortality)	Reported AUROC (Resuscitative Need)	Key Strengths and Limitations
MGAP	Mechanism, GCS, Age, Arterial Pressure	0.949–0.971	0.971	Highest sensitivity for severe trauma; strong calibration for resuscitative need; requires mechanism data that may be unreliable in chaotic scenes [2,4]
GAP	GCS, Age, Arterial Pressure	0.935–0.949	0.949	Simple bedside calculation; favorable specificity; threshold of <19 offers high negative predictive value for ruling out resuscitative need [2,4]
RTS / T-RTS	GCS, Systolic BP, Respiratory Rate	0.871	0.969	Long-established benchmark; relies on physiological derangement that may be absent in compensated patients [2,4]
NEWS2	Respiratory rate, oxygen saturation, systolic BP, pulse, consciousness, temperature	Best for very early mortality	0.929	Excellent early warning; threshold selection critically affects over-triage burden; weaker over longer horizons [4,9]
Shock Index	Heart rate / Systolic BP	Predictive of transfusion, ICU admission, operative need	Not uniformly reported	Rapid, parameter-sparse; useful as an adjunct rather than a standalone destination rule [1,2]

Mass Casualty Incident Triage: Algorithms Under Pressure

Mass casualty incidents impose a distinct triage logic. When needs exceed immediately available resources, the objective shifts from optimizing individual outcomes to maximizing population-level survival through rapid sorting and resource allocation [5,6]. The Simple Triage and Rapid Treatment system and its pediatric adaptation, JumpSTART, remain the most widely implemented algorithms in civilian EMS systems. START assigns casualties to immediate, delayed, minor, and deceased categories on the basis of respirations, perfusion, and mental status, while JumpSTART modifies respiratory and neurologic criteria for children [5,6].

The empirical record of these algorithms is sobering. In the standardized comparison of 21 primary triage systems, START/JumpSTART achieved the highest accuracy at 76.7%, yet this figure still implies that nearly one in four casualties was misclassified [5]. More critically, no algorithm-based system met the ACS-COT under-triage threshold of 5% [5,6]. The Modified Physiological Triage Tool-24 and the NHS Major Incident Triage Tool demonstrated improved sensitivity–specificity balance relative to other algorithms, but even these refined instruments failed to satisfy accepted performance criteria [5]. A systematic review of prehospital global triage protocols in mass disasters concluded that traditional systems such as START and SALT provide rapid categorization but remain prone to both over- and under-triage depending on responder training and situational factors, and that no single algorithm reliably outperforms intuitive triage by experienced paramedics across all scenarios [6].

These findings challenge the assumption that algorithmic simplicity guarantees field reliability. In the high-stress, information-poor environment of a mass casualty incident, the cognitive load imposed by any algorithm competes with the perceptual and decisional demands of scene management [5,6]. The most accurate system in controlled comparison may not be the most effective system in operational use, and the evidence supports a more nuanced conclusion: algorithms provide a necessary common language for multi-agency response, but they cannot substitute for clinical judgment, scene awareness, and repeated training [6].

Artificial Intelligence and Machine Learning in Prehospital Triage

The application of machine learning to prehospital triage has moved rapidly from proof-of-concept studies to multi-institutional validation. A scoping review of artificial intelligence in prehospital trauma triage across low- and middle-income countries reported that models such as Random Forest and LightGBM consistently outperformed traditional manual scores, including the Kampala Trauma Score, achieving AUC values of 0.91 to 0.94 using minimal data input [10]. A multi-institutional and multi-national validation study of a Prehospital-AI model—an ensemble of XGBoost, LightGBM, and random forest algorithms—reported an AUROC of 0.923 and demonstrated that the model enabled accurate, real-time risk assessment while outperforming traditional triage tools and improving trauma system efficiency [3]. In an independent evaluation, a LightGBM model achieved an accuracy of 0.887, precision of 0.839, recall of 0.821, and an AUC of 0.921 for prehospital triage and dispatch optimization [11].

The clinical significance of these metrics lies in their potential to reduce both under-triage and over-triage simultaneously. Machine learning models have been shown to outperform NEWS2 and other early warning scores with fewer false positives, reducing the number of patients needed to screen by nearly half for seven-day mortality, thereby improving the precision of triage among prehospital patients [9]. In resource-limited settings, where specialist expertise is scarce and diagnostic infrastructure is absent, AI-based decision support functions as a structural substitute rather than a mere optimization tool, extending the reach of accurate risk stratification to systems that cannot deploy advanced trauma scores reliably [3,10]. Edge-AI hardware and natural language processing for informal audio transcription have achieved 95% accuracy in connectivity-starved and noisy environments, suggesting that the technical barriers to deployment are lower than commonly assumed [10]. However, a decisive readiness gap persists: governance frameworks, liability protections, and national data registries remain underdeveloped in most jurisdictions, and the translation of validated algorithms into routine EMS practice requires regulatory and infrastructural investment that currently lags behind the pace of model development [10,11].

Telemedicine and Remote Physician Support

Telemedicine introduces a complementary pathway for improving prehospital triage accuracy by extending physician expertise into the field. Video conferencing between paramedics and physicians has been associated with improvements in diagnostic accuracy of approximately 20% for stroke, a 15% increase in treatment adherence, and a 25-minute reduction in stroke door-to-needle time [12]. Prehospital large-vessel occlusion stroke detection scales, evaluated in pooled individual patient data, have demonstrated value in refining field triage for thrombectomy-eligible patients, while prehospital video triage of suspected stroke patients has shown sensitivity of 70% and specificity of 90% without adverse outcomes, alongside a 50% reduction in patients requiring secondary transfer [13,14]. For ST-elevation myocardial infarction, remote consultation has been linked to a 30% reduction in wait times and improved emergency department readiness through streamlined communication and resource allocation [12].

The evidence for telemedicine in trauma triage is less mature but directionally consistent. Systematic reviews of prehospital telemedicine note limited conclusive evidence for effectiveness across all emergency conditions, while drawing on thrombolysis research to suggest that prehospital triage services delivered remotely are likely to be reliable and to support accurate decision-making, with improving technology making reliable delivery increasingly feasible [15]. User satisfaction rates among prehospital telemedicine users exceed 80%, and audio/video quality improves with higher-bandwidth 4G and 5G standards [12,15]. The principal constraints are not technological but organizational: rural connectivity remains unreliable, training requirements are substantial, and legal uncertainties surrounding remote decision-making authority have not been resolved in many jurisdictions [15]. Telemedicine is therefore best understood not as a replacement for field triage protocols but as a layer of clinical oversight that can correct algorithmic errors and refine destination decisions when connectivity and governance permit [12,15].

Natural Resources for Human Health
eISSN: 2583-1194

Under-Triage and Over-Triage: Persistent Failure Modes

Under-triage and over-triage are not symmetrical errors. Under-triage carries the heavier clinical cost because it delays access to definitive care for patients who need it most [7,8]. In a statewide evaluation of a major trauma transport protocol, under-triage occurred in 3.5% of patients while over-triage affected 63.2%, illustrating the characteristic trade-off in which high sensitivity is purchased at the expense of substantial resource misallocation [7]. In critical care transport, a triage model reported a 21.3% under-triage rate against a national goal of 5%, alongside a 34.9% over-triage rate that met the national standard of 35% or less [8]. These figures demonstrate that over-triage benchmarks can be met while under-triage remains unacceptably high—a pattern that suggests protocol design often prioritizes avoiding missed severe injury over conserving system capacity, yet still fails to protect the highest-risk patients [7,8].

The consequences of under-triage extend beyond delayed treatment. Patients who are under-triaged are less likely to be transported to trauma centres, less likely to receive time-critical interventions, and more likely to experience preventable deterioration [7,8]. In geriatric trauma, for example, among patients with systolic blood pressure below 100 mmHg who required specialized trauma care, only 39.5% received trauma team activation, reflecting a systemic under-recognition of hemodynamic instability in this population [16]. Over-triage, while less immediately dangerous, imposes its own costs: unnecessary lights-and-siren driving, emergency department crowding, and diminished efficiency during surge conditions [7,8]. The optimal triage system is therefore one that minimizes under-triage without generating over-triage burdens that degrade the system's capacity to respond to the next high-risk patient [8].

Geriatric Trauma: The Under-Triage Problem in Older Adults

Older adults represent the population in which prehospital triage fails most consistently. Physiological responses to trauma in geriatric patients differ substantially from younger cohorts: beta-blocker use blunts the tachycardic response, baseline blood pressures are higher, and standard hypotension thresholds are therefore inadequate [16,17]. In a multicentre cohort study, geriatric patients constituted 36.5% of the total trauma cohort but had significantly lower trauma team activation rates than younger patients (15.8% vs. 31.8%) despite comparable or higher injury severity scores [16]. Fewer geriatric patients were transported by helicopter (3.6% vs. 10.4%) or accompanied by an emergency physician (24.4% vs. 39.9%), yet they demonstrated higher hospitalization rates (64.1% vs. 52.1%) and comparable intensive care admission rates, underscoring their greater need for high-acuity care despite reduced prehospital prioritization [16]. The 48-hour mortality rate among geriatric trauma patients was more than three times higher than in younger patients (1.8% vs. 0.5%), emphasizing their vulnerability even after low-energy mechanisms [16].

Guidance for paramedics now recommends adjusting physiological criteria specifically for older trauma patients and considering mechanism of injury in ways that account for age-related fragility [17]. A systolic blood pressure threshold below 110 mmHg has been strongly recommended for inclusion as a Step 1 criterion in the National Trauma Triage Protocol, reflecting evidence that conventional thresholds miss a substantial proportion of hemodynamically unstable older adults [17]. However, geriatric-specific triage criteria remain variable, focus on different physiologic thresholds, and lack consensus on the optimal tool [16,17]. Frailty assessments, comorbidity burden, and medication histories—all of which modify the clinical significance of vital signs and injury patterns—are rarely incorporated into field triage algorithms, and their integration represents one of the most pressing unmet needs in prehospital triage research [17].

Pediatric Triage: Reliability and the Limits of Adult-Derived Tools

Pediatric prehospital triage presents distinct challenges because adult-derived physiological thresholds and injury patterns do not translate reliably to children. The Pediatric Triage Tape, for example, has been associated with an under-triage rate of 68% and an over-triage rate of 18%, while the Pediatric Trauma Score demonstrated an under-triage rate of 62% and an over-triage rate of 10% [18]. JumpSTART, the pediatric adaptation of START, has shown the lowest sensitivity and highest under-triage rate among pediatric triage tools in comparative evaluations [18]. Agreement between EMS provider-assigned prehospital triage and initial emergency department triage in pediatric encounters is concentrated at adjacent triage levels, with discrepancies of two or more levels uncommon, but exact agreement is lowest for high-acuity pediatric encounters, precisely the population in which accuracy matters most [19].

The interobserver reliability of prehospital triage for identifying traumatic brain injury in pediatric patients has been the subject of systematic review, with findings suggesting that reliability is moderate at best and varies with provider training and tool design [20]. The Pediatric Observation Priority Score has shown high accuracy in controlled settings, with 99% of assigned scores falling within two points of the reference and excellent agreement for individual scenarios, but this performance has not yet been replicated in uncontrolled field conditions [21]. The evidence supports a conclusion that pediatric triage requires dedicated, age-specific instruments rather than extrapolation from adult algorithms, and that the development and validation of such instruments remains incomplete [18,20,21].

Triage in Low-Resource and Low- and Middle-Income Settings

In low-resource settings, prehospital triage confronts constraints that alter the calculus of effectiveness. Standardized nurse-led triage protocols have improved diagnostic accuracy to 70–97%, reduced under-triage to 20% or less, and shortened waiting times by up to 45% and on-scene-to-care intervals by approximately 38% in low-resource trauma and road-traffic injury care [22]. The South African Triage Scale, implemented in a new ambulance system in Beira, Mozambique, was associated with a continuous progressive increase in the proportion of severe cases transported, but also with high rates of incorrect triage relative to the thresholds of 15% for over-triage and 10% for under-triage [23]. In mass disaster contexts, traditional systems provide rapid categorization but remain prone to error depending on responder training and situational factors, and structured training is consistently associated with improved triage performance in chaotic, resource-limited environments [6,22].

Artificial intelligence offers a particularly compelling value proposition in these settings. Machine learning models achieving AUC values of 0.91 to 0.94 with minimal data input outperform the Kampala Trauma Score and can function as a diagnostic safety net where specialist expertise is absent [10]. Digital platforms using ride-hailing logic for navigation have reduced average response times from 162 to 13 minutes in Kenya, and edge-AI hardware has achieved 95% accuracy in connectivity-starved environments [10]. These developments suggest that the effectiveness of prehospital triage in low-resource settings may improve more rapidly than in high-income systems, precisely because AI can leapfrog foundational infrastructural deficits rather than requiring their prior resolution [10,22]. The caveat is that implementation without governance creates risks of unaccountable algorithmic decision-making, and the policy vacuum identified in current reviews must be addressed alongside technical deployment [10,23].

Triage Accuracy and Patient Outcomes:

The ultimate measure of prehospital triage effectiveness is its association with patient-important outcomes. Across diverse EMS settings, prehospital trauma triage systems have been associated with mortality reductions of 8% to 18%, alongside improvements in scene time and transport time [1]. Standardized nurse-led triage in low-resource settings has been linked to reproducible improvements in mortality reduction and acuity classification reliability when implemented across African contexts [22]. However, the relationship between triage accuracy and mortality is not uniformly positive. A multi-country, multicentre cohort study found that neither prehospital care level nor triage categorization was associated with hospital mortality in adjusted analyses, suggesting that the outcome benefits of triage may be mediated by system-level factors—destination selection, trauma team readiness, and time to definitive intervention—rather than by triage accuracy alone [24].

This finding has important implications. It implies that improving triage accuracy without corresponding improvements in receiving-facility capacity and transport logistics may yield limited mortality benefit [24]. It also implies that the effectiveness of triage systems should be evaluated against a broader set of outcomes than mortality alone: time to definitive care, intensive care utilization, operative need, and functional recovery at discharge [1,24]. The evidence supports a conclusion that prehospital triage is a necessary but insufficient condition for improved outcomes, and that its effectiveness is contingent on integration within a coordinated emergency care system that can act on the information triage produces [24].

System-Level Determinants of Triage Effectiveness

The performance of any triage instrument is shaped by the system in which it is embedded. Provider training is perhaps the most consistent modifier of triage accuracy: structured training is associated with improved performance across conventional and algorithmic systems in both high- and low-resource settings [6,22]. Geographic setting exerts a powerful influence through transport times, hospital availability, and scene characteristics; a tool validated in an urban trauma system may perform differently in rural or wilderness contexts [24]. The integration of triage within trauma networks—including pre-arrival

notification, destination protocols, and feedback loops between EMS and receiving facilities—determines whether accurate triage translates into timely definitive care [7,8]. Continuous monitoring and quality improvement are essential: without systematic audit of under-triage and over-triage rates against benchmark thresholds, systems cannot identify drifting performance or the emergence of population-specific failure modes [5,6]. Moreover, the limitations of initial call-taking and dispatch information must be recognized, because poor performance of 9-1-1 call-taking in predicting clinical outcomes can propagate error into later triage decisions [25].

Table 3 synthesizes the system-level determinants that modify triage effectiveness and the evidence supporting each.

Determinant	Mechanism of Effect	Evidence
Provider training	Improves tool application, scene awareness, and decision-making under pressure	Structured training consistently associated with improved triage performance in chaotic and resource-limited environments [6,22]
Tool selection and validation	Determines baseline sensitivity and specificity for the target population	Performance is tool- and population-dependent; no single tool is optimal across all contexts [1,2]
Destination protocols	Translates triage category into transport decision and receiving-facility readiness	Triage accuracy without appropriate destination capability yields limited outcome benefit [7,8]
Feedback and audit	Enables identification of under-triage and over-triage trends	Continuous monitoring against benchmark thresholds is recommended for system-level evaluation [5,6]
Technological infrastructure	Supports AI, telemedicine, and real-time decision support	Connectivity, edge-AI, and video conferencing can extend expert oversight to the field [10,12,15]
Dispatch information quality	Shapes the initial acuity estimate and subsequent triage decisions	9-1-1 call-taking performance may be poor for predicting clinical outcomes [25]

Synthesis and Clinical Implications

The evidence reviewed here supports a nuanced assessment of prehospital triage effectiveness. Physiological and anatomical tools such as MGAP and GAP demonstrate strong discriminative performance for mortality and resuscitative need, with AUROC values approaching or exceeding 0.95 in selected cohorts [2,4]. These tools are effective in the narrow sense of risk stratification: they can identify, with reasonable accuracy, which patients are likely to require time-critical intervention [2,4]. However, their performance in the broader task of destination selection and resource allocation is constrained by persistent under-triage, particularly among older adults and pediatric patients, and by the inherent trade-off between sensitivity and over-triage that no algorithm has resolved [5,16,18].

Artificial intelligence and telemedicine represent the most promising avenues for improving effectiveness. Machine learning models outperform traditional scores and can reduce both under- and over-triage simultaneously by using minimal data inputs [3,9,10]. Telemedicine extends physician judgment into the field, improving diagnostic accuracy for stroke and reducing time to definitive care [12,14,15]. Yet neither technology resolves the fundamental challenge that triage is a probabilistic act performed under uncertainty, and that the consequences of error fall disproportionately on the patients who are least able to advocate for themselves: the frail older adult whose compensated vital signs mask severe injury, the child whose physiology does not conform to adult-derived thresholds, and the trauma patient in a resource-limited system where the nearest appropriate facility may be hours away [16,17,18,23].

The clinical implications are clear. First, triage systems should be selected and validated for the specific populations they serve, with age-attuned criteria for older adults and dedicated pediatric instruments rather than extrapolation from adult algorithms [17,18,21]. Second, accuracy should be evaluated against a balanced scorecard of under-triage, over-triage, time to definitive care, and patient-important outcomes, not against a single metric [1,5,24]. Third, technology should be deployed as a complement to, not a substitute for, trained clinical judgment, with governance frameworks that ensure accountability and

continuous monitoring [10,15]. Fourth, system-level integration—destination protocols, pre-arrival notification, and feedback between EMS and receiving facilities—is as important as the triage instrument itself [7,8,25].

CONCLUSION

Prehospital triage systems effectively identify high-risk emergency patients but rely on specific tools and populations. Physiological and anatomical scoring systems like MGAP and GAP offer solid risk stratification, while mass casualty algorithms lack accuracy. Innovations such as artificial intelligence and telemedicine enhance precision and response times. However, consistent under-triage of geriatric and pediatric patients indicates current methods' limitations. The future of effective triage relies on developing adaptive, technology-supported systems within coordinated emergency care networks, audited for patient outcomes, to ensure fulfillment of their potential for high-risk patients.

REFERENCES

[1] van Rein EA, van der Sluijs R, Houwert RM, Gunning AC, Lichtveld RA, Leenen LP, van Heijl M. Effectiveness of prehospital trauma triage systems in selecting severely injured patients: Is comparative analysis possible?. The American journal of emergency medicine. 2018 Jun 1;36(6):1060-9.

[2] Stefanovic I, Andjelic S, Tasic-Uros D, Bevc IM, Filipovic JV. GAP (Glasgow Coma Score-GCS, Age, Arterial Pressure), MGAP (Mechanism of Injury, GCS, Age, Arterial Pressure) and RTS (Revised Trauma Score) as Predictors of Poor Outcomes and Mortality after Injury in the Prehospital Setting. EABR. Experimental and Applied Biomedical Research. 2024.

[3] Oh NE, Oh TY, Hsu J, Kim DW, Yu B, Cho J, Seok J, Lee JY, Jang W, Kim J, Femia RJ. Prehospital real-time AI for trauma mortality prediction: a multi-institutional and multi-national validation study. Nature Communications. 2026 Jan 7;17(1):1464.

[4] Jenpanitpong C, Yuksen C, Trakulsrichai S, Sricharoen P, Leela-Amornsin S, Savatmongkorngul S, Sanguanwit P. Predictive performance of prehospital trauma triage tools for resuscitative interventions within 24 hours in high-risk or life-threatening prehospital trauma patients. BMC Emergency Medicine. 2025 Feb 20;25(1):26.

[5] da Silva Leal AM. Algorithm Primary Triage Systems should not be used in Mass Casualty Incidents. medtigo Journal of Emergency Medicine. 2025 Jul 3;2(3).

[6] Shaltout AE, Elbadri ME, Kaur K, Alsharif MM, Alkhazendar AH, Hassouba ON, Ahmad MN, Osman M, Zahid A, Banjamin S, SHALTOUT AE. Accuracy and timeliness of prehospital global triage system protocols in mass disasters: a systematic review of systematic reviews. Cureus. 2025 Sep 20;17(9).

[7] Dinh M, Singh H, Deans C, Pople G, Sarrami P, Sisson G, Newman J, Bendall J. Evaluation of the New South Wales ambulance T1 major trauma transport protocol: a state-wide data linkage study. Injury. 2023 Sep 1;54(9):110846.

[8] Trauma triage model for critical care transport. (2025). *HealthManagement.org*.

[9] Ward LM, Lindskou TA, Mogensen ML, Christensen EF, Søvsø MB. Machine learning to improve predictive performance of prehospital early warning scores. Scientific Reports. 2025 Jul 1;15(1):21459.

[10] Widiyawati K, Deviantony F. Artificial Intelligence in the Golden Hour: A scoping review of prehospital trauma triage and implementation feasibility in LMICs. International Journal of Medical Informatics. 2026 Aug 4:106638.

[11] Hu N, Luo X, Tan Y, Sun Y. Research on an Intelligent Prehospital Emergency Triage and Dispatch Optimization System Based on Multi-source Data Fusion and Machine Learning. In2026 9th International Conference on Computer Information Science and Application Technology (CISAT) 2026 Jul 3 (pp. 979-982). IEEE.

[12] Aldahmashi MA, Alrawili RF, Aldahmashi HH, Alenezi MM, Alanazi AB, Alhazmi SJ, Alanazi MQ, Alhazemi MB, Alanazi AM, Alanazi SA, aladham Alenezi A. Utilization of Video Conferencing for Paramedic-to-Physician Consultations in Pre-Hospital Emergency Care: A Comprehensive Review. Saudi Journal of Medicine and Public Health. 2025 Oct 11;2(2):311-8.

[13] Dekker L, Daems JD, Ali M, Duvekot MH, Nguyen TM, Venema E, Durieux MD, Van Zwet EW, Moudrous W, Van Den Wijngaard IR, Kerkhoff H. Prehospital large-vessel occlusion stroke detection scales: a pooled individual patient data analysis of 2 prospective cohorts. Neurology. 2025 May 13;104(9):e213570.

[14] Titmus L, Baird A, Stonehouse W, Marigold R. The impact Of prehospital video triage on hyperacute stroke diagnosis and treatment and diverting mimics to other specialties at University Hospital Southampton (UHS). International Journal of Stroke. 2024 Dec 12;19(3 Suppl.).

[15] Amadi-Obi A, Gilligan P, Owens N, O'Donnell C. Telemedicine in pre-hospital care: a review of telemedicine applications in the pre-hospital environment. International journal of emergency medicine. 2014 Dec;7(1):29.
[16] Koch DA, Becker L, Schweigkofler U, Hagebusch P, Faul P, Waydhas C, Pavlu F, Baacke M, Michael C, Clemens V, Duesing H. Undertriage in geriatric trauma: insights from a multicentre cohort study. Scandinavian journal of trauma, resuscitation and emergency medicine. 2025 Jul 10;33(1):123.
[17] Alshibani A, Banerjee J, Williams C, Conroy S. Guidance to improve prehospital trauma triage decisions for geriatric patients: a review of the literature. Emergency Health Services Journal. 2024 Jan 1;1(1):2-11.
[18] Kakko S, Markkula N. Assessment and treatment of pediatric motor vehicle accident victims in prehospital care.
[19] Kim MJ, Moon HS, Paek SH. Agreement between EMS provider-assigned prehospital triage and initial emergency department triage in pediatric and adult EMS-transported encounters: A retrospective observational study. PLoS One. 2026 Jul 6;21(7):e0352969.
[20] Alsuwais S, Alqurashi N, Body R, Carley S. Interobserver reliability and diagnostic accuracy of prehospital triage for identifying traumatic brain injury in paediatric patients: a systematic review. Child's nervous system. 2024 Mar;40(3):813-21.
[21] Ward CE, Ha T, Morland-Tellez G, Shaukat H, Roland D, Chamberlain JM. Emergency medical services clinician accuracy using the pediatric observation priority Score. Pediatric emergency care. 2025 Sep 1;41(9):e129-35.
[22] Boutemine L, El-Banna M, Atyeh RR, Sami W, Rizvi MR. Effectiveness of Standardized Nurse-Led Triage Protocols in Improving Outcomes, Timeliness, and Accuracy in Road Traffic and Trauma Care in Low-Resource Settings: A Systematic Review. Journal of Multidisciplinary Healthcare. 2026 Dec 31:585877.
[23] Conti A, Sacchetto D, Putoto G, Mazzotta M, De Meneghi G, De Vivo E, Lora Ronco L, Hubloue I, Della Corte F, Barone-Adesi F, Ragazzoni L. Implementation of the South African Triage Scale (SATS) in a new ambulance system in Beira, Mozambique: a retrospective observational study. International Journal of Environmental Research and Public Health. 2022 Aug 18;19(16):10298.
[24] de Souza Nogueira L, de Alencar Domingues C, Fernandes LC, Vieira RD, Santa Mejía YA, Baliña J, Tenaillon C, Santero M, de Novais Do TG, Lombardo GR, de Sousa RM. The Association of Prehospital Care Level and Triage Accuracy with Trauma Outcomes: A Multi-Country, Multicenter Cohort Study. Journal of Trauma Nursing| JTN. 2025 Sep 1;32(5):252-9.
[25] Zhang Z, Bhadani A, Meybodi MM, Machado L. Supporting Callers' Needs in Crisis: Designing the Next Generation of 9-1-1 for Medical Emergencies. InProceedings of the 2026 CHI Conference on Human Factors in Computing Systems 2026 Apr 13 (pp. 1-17).