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REVIEW ARTICLE

Emergency Medical Services

Use of artificial intelligence to support prehospital traumatic injury care: A scoping review

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Abstract

Background: Artificial intelligence (AI) has transformative potential to support prehospital clinicians, emergency physicians, and trauma surgeons in acute traumatic injury care. This scoping review examines the literature evaluating AI models using prehospital features to support early traumatic injury care.

Methods: We conducted a systematic search in August 2023 of PubMed, Embase, and Web of Science. Two independent reviewers screened titles/abstracts, with a third reviewer for adjudication, followed by a full-text analysis. We included original research and conference presentations evaluating AI models—machine learning (ML), deep learning (DL), and natural language processing (NLP)—that used prehospital features or features available immediately upon emergency department arrival. Review articles were excluded. The same investigators extracted data and systematically categorized outcomes to ensure consistency and transparency. We calculated kappa for interrater reliability and descriptive statistics.

Results: We identified 1050 unique publications, with 49 meeting inclusion criteria after title and abstract review (kappa 0.58) and full-text review. Publications increased annually from 2 in 2007 to 10 in 2022. Geographic analysis revealed a 61% focus on data from the United States. Studies were predominantly retrospective (88%), used local (45%) or national level (41%) data, focused on adults only (59%) or did not specify adults or pediatrics (27%), and 57% encompassed both blunt and penetrating injury mechanisms. The majority used machine learning (88%) alone or in conjunction with DL or NLP, and the top three algorithms used were support vector machine, logistic regression, and random forest. The most common study objectives were to predict the need for critical care and life-saving interventions (29%), assist in triage (22%), and predict survival (20%).

Conclusions: A small but growing body of literature described AI models based on prehospital features that may support decisions made by dispatchers, Emergency Medical Services clinicians, and trauma teams in early traumatic injury care.

KEYWORDS
artificial intelligence, deep learning, emergency medical services, machine learning, natural language processing, prehospital care, traumatic injury

1 | INTRODUCTION

Prehospital traumatic injury care requires rapid decision-making based on limited and dynamic information. National guidelines from the American College of Surgeons (ACS) provide a framework for field triage of injured patients, which accounts for age, injury patterns, and physiologic assessment to determine a patient's risk for serious injury.[1] Training and scope of practice for Emergency Medical Services (EMS) clinicians has further expanded over the past decade, bringing advanced trauma care to the patient in the field.[2] Despite significant advances in prehospital trauma care, traumatic injury remains the leading cause of death in the United States for persons under 45 years and a major cause of death worldwide.[3,4]

In the past decade, artificial intelligence (AI) has shown significant potential as decision-support in the care of acute traumatic injuries.[5–7] AI, including machine learning (ML), deep learning (DL), and natural language processing (NLP), has the ability to generate predictions from structured (ie, vital sign parameters) or unstructured data (ie, text narratives or photos) without explicit human-operator programming. In the setting of traumatic injury care, AI can automatically extract a set of datapoints from dispatch narratives,[8] continuous vital sign monitoring,[9–11] or the electronic patient care record,[12] and rapidly analyze it to make predictions to support EMS clinicians. Prior scoping reviews have shown that AI may support prehospital care,[13] emergency care,[7] and early trauma care.[6,14] To date, no studies have assessed the extent of literature evaluating AI based on prehospital information to support early traumatic injury care.

We performed a scoping review to understand current advances in AI as decision-support for dispatchers, EMS clinicians, and trauma teams based on readily available prehospital information to guide early traumatic injury care.

2 | METHODS

2.1 | Study design

We performed a systematic search in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews guidelines[15] (Supporting Information Material A).

2.2 | Search strategy

A search was conducted on three databases including MEDLINE, Embase, and Web of Science in August 2023 and targeted articles focused on traumatic injury, AI (including ML, DL, NLP), and prehospital care. Search terms included "traumatic injury," "artificial intelligence," "machine learning," "deep learning," "natural language processing," and "emergency medical services." The full search criteria can be found in the Supporting Information Material B.

2.3 | Selection of studies

After de-duplication, unique titles and abstracts were screened by two independent reviewers (J.T. and J.W.) based on study inclusion criteria. Original research and conference abstracts published from database inception up to the search date were eligible for inclusion. Conference abstracts were included in this review given the limited volume of peer-reviewed publications and to reduce the impact of publication bias. Reports were included if the study focused on human subjects suffering from traumatic injury. Studies must have utilized an AI model(s) (ie, DL, ML, and NLP) based on prehospital features (eg, input data) with a predicted outcome(s) that may support early traumatic injury care. Prehospital features were defined as any information available between 9-1-1 contact and emergency department (ED) transfer of care that may feasibly be collected by dispatchers and/or EMS clinicians. Additionally, models with features collected immediately upon ED arrival (ie, vital signs and Glasgow coma scale [GCS]) from simulated care that may feasibly be collected in the prehospital setting, from the military setting collected during field care and Role 1 care, and from mass casualty incidents (real or simulated) were also included. We excluded studies published in languages other than English, and those that used AI to augment community preparedness, or trauma system planning or surveillance. Lastly, we excluded review articles, study protocols, study datasets, case reports, and gray literature. Any disagreements during the title and abstract review phase were resolved through discussion and with a third reviewer (K.W.).

After title and abstract review, two independent reviewers (J.T. and J.W.) reviewed all full-text publications based on the same screening criteria stated above. Reasons for exclusion after full-text review were recorded. Disagreements were again resolved through discussion and with a third reviewer (K.W.) if needed. The screening and full-text review were performed using the web-based application Rayyan (Rayyan Systems Inc.).

2.4 | Data extraction and synthesis

Included studies were stored in the citation-manager Zotero (Version 6.0.23; Corporation for Digital Scholarship) and data were extracted by two independent reviewers (J.T. and J.W.) using a standardized form in Excel (Version 16.66.1; Microsoft Corp). Data were cross-checked after both independent reviewers extracted the data, and any disagreements regarding extracted values were resolved through discussion. Variables extracted included title, authors, publication year, country of training dataset origin, study type (original research or conference abstract), study design (retrospective or prospective), total sample size, data source, validation method (if performed), comparator to AI (if used), age demographic of population, mechanism of injury (blunt or penetrating), AI branch (ie, DL, ML, and NLP), AI algorithm (ie, logistic regression, and random forest), and feature types used (ie, heart rate [HR] and age). Total sample size was defined as the sum of both the training data set, and test and/or external validation data sets. Comparators to AI models were defined as any benchmark of performance including existing decision tools or human experts. Age demographics were broadly stratified into adult, pediatric, geriatric, or all ages based on age cut-offs as defined in each study. Feature inputs were extracted and categorized into general classes; for example, if a study described their feature input as "initial HR," "temporal HR variation," and "HR variability," these were all grouped under HR.

Outcome(s) of included studies were also extracted and two investigators (J.T. and J.W.) categorized these into broad groups. Studies with multiple outcomes were categorized into all appropriate groups. All study categories are described in Figure 4. Studies predicting triage category and injury severity were combined into a single group given that any attempt to stratify injury severity in the prehospital setting represents triage. Studies predicting the need for critical care and life-saving interventions were combined into a single group given that these actions are interdependent. Life-saving interventions were defined differently in each study and generally included one or more of the following: angioembolization, blood transfusion, cardioversion, cardiopulmonary resuscitation, cricothyrotomy, endotracheal intubation, needle decompression, pericardiocentesis, thoracotomy, tourniquet application, and tube thoracostomy. Studies solely predicting the need for any blood transfusion or massive transfusion were placed in a separate category.

Additional information was extracted to understand the number of studies with relevance to specific trauma and EMS sub-topics. These included 9-1-1 dispatch, mass casualty incidents, military involvement or sponsorship, and traumatic brain injury.

2.5 | Data analysis

We calculated Cohen's kappa for interrater reliability after title and abstract screening and descriptive statistics, including frequency and percentages, for extracted variables.

3 | RESULTS

We identified a total of 1050 unique studies (Figure 1). After the title and abstract review (kappa 0.58), 108 studies underwent full review; after full-text review, 49 studies remained. Published studies increased annually from two in 2007 to 10 in 2022 (Figure 2A). Geographic analysis of the dataset country of origin found 18 countries represented and one study by Lammers et al. utilized combat registry data from an unspecified location[16]; 30 (61%) studies used data from the United States, seven (14%) from Europe, and five (10%) from Asia (Figure 2B). One study by Larsson et al. used data from both the United States and Sweden.[17]

Complete descriptive statistics are shown in Table 1. Of the 49 studies, most were retrospective (n = 43, 88%). The median sample size for retrospective and prospective studies was 9,447 subjects (interquartile range [IQR] 903, 54,292) and 32 subjects (IQR 17, 47), respectively. Many studies focused only on adults (n = 29, 59%) or did not specify a specific age demographic (n = 13, 27%); three (6%) focused on pediatric[18–20] and two (4%) focused on geriatric[21,22] populations. The majority focused on patients with both blunt and penetrating mechanisms of injury (n = 28, 57%). Data were primarily from local EMS providers or hospitals (n = 22, 45%) or from national registries (n = 20, 41%); the most common national registries were the ACS-Trauma Quality Improvement Program, ACS-National Trauma Data Bank (NTBD), and National Automotive Sampling Survey Crashworthiness Data Systems.

Forty-eight (98%) studies developed and/or validated an AI model(s); 38 (78%) performed internal validation via hold-out methods (ie, splitting the dataset into a training and test set) or cross-validation and 10 (20%) carried out external validation. Ting et al performed a study using principle component analysis to identify high value features and as such, validation does not apply to this study.[18] Many AI models used ML (n = 41) only or in combination with DL and/or NLP; four used DL alone, three used NLP alone, and one did not specify. Among the 41 models using ML, the top five algorithms used were support vector machine (n = 17, 41%), logistic regression (n = 16, 39%), random forest (n = 16, 39%), extreme gradient boosting (n = 7, 17%), and k-nearest neighbor (n = 7, 17%). The top five most common features selected as model inputs were systolic blood pressure (n = 25, 60%), HR (n = 23, 56%), age (n = 21, 51%), GCS (n = 21, 51%), and respiratory rate (n = 19, 46%) (Figure 3). Three studies utilized multidimensional vital sign parameter data (ie, patterns of variability and time-series).[9–11]

The different study outcomes are displayed in Figure 4. Fourteen (29%) predicted the need for critical care and life-saving interventions, of which five predicted the need for any life-saving interventions,[19,23–26] four predicted the need for any critical care,[27–31] one focused on prehospital airway management,[32] one focused on hospital mechanical ventilation,[29] one predicted intra-abdominal injuries requiring surgical intervention,[20] one predicted traumatic brain injury requiring neurosurgical intervention,[33] and one predicted any surgical procedures including orthopedic surgeries.[21]

Eleven studies (22%) predicted patient triage categories and injury severity. Among these, six were focused on injury severity prediction[18,22,31,34–36] and five were focused on triage category prediction.[17,19,37–39] While the majority of these models used features collected by EMS clinicians (ie, demographic and physiologic data), Chin

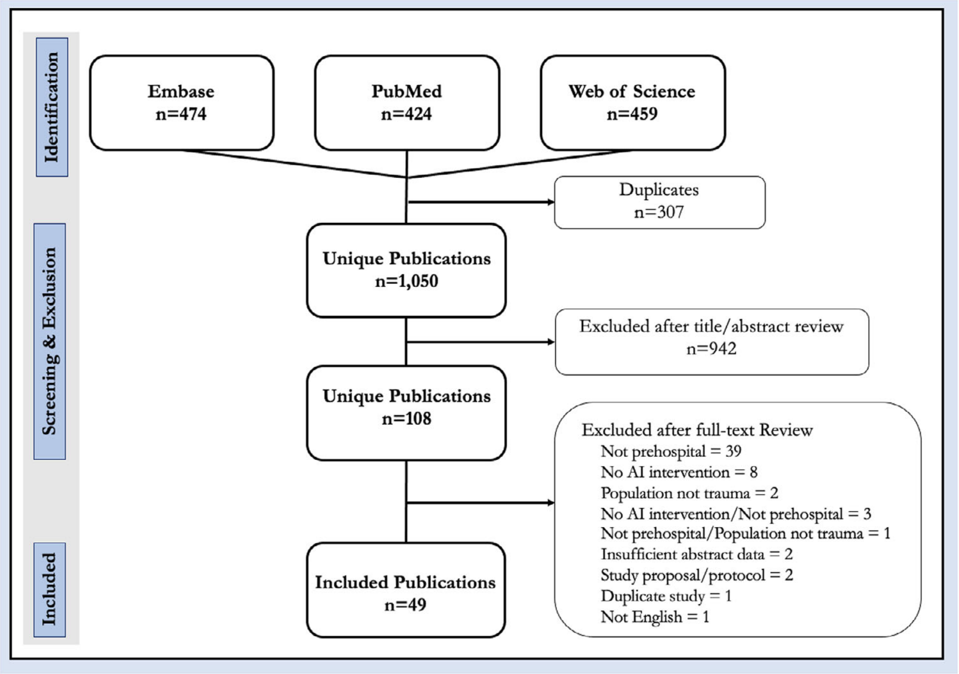

FIGURE 1 Flow diagram.

et al used NLP to carry out text mining from dispatcher audio to predict the need for prehospital major trauma activation[37] and Lu et al utilized images of victims collected from an unmanned aerial drone to predict injuries after a simulated mass casualty event.[39]

Ten studies (20%) predicted survival outcomes. Six predicted in-hospital survival outcomes,[18,27,35,40–42] two predicted survival at ED discharge,[43,44] and Taamneh and Taamneh predicted survival at 30 days.[31] One study did not specify a time period for survival prediction.[45] Finally, seven studies (14%) predicted the presence of traumatic hemorrhage requiring transfusion. Five predicted the need for transfusion of at least one unit of blood products,[9–11,46,47] while two predicted the need for massive transfusion.[16,26]

4 | LIMITATIONS

The following limitations should be considered. First, the search did not encompass databases including those specific to nursing and allied health professionals, engineering, and computer science. Citations of included articles were also not reviewed for additional studies not located in the primary search. However, we feel that our initial search across three databases was comprehensive enough to have identified most of all relevant publications. Second, this study did not include gray literature, which may be important given that the study of AI is an emerging field; however, we suspect that the risk of missing important non-peer reviewed publications evaluating AI models to support trauma care is small. Third, this review excluded AI models which utilized feature inputs that were obtained during the ED course including laboratory values. Nonetheless, some more advanced EMS systems may have field-based point-of-care testing or other advanced capabilities, and as such, the results of this review may not be representative of those systems. Lastly, only studies written in English were included, which may have resulted in bias.

5 | DISCUSSION

This scoping review identified a small but growing number of heterogenous studies evaluating the utilization of AI as decision-support for dispatchers, EMS clinicians, and trauma teams during the early phases of traumatic injury care. The dramatic 500% increase in annual publications during the study period aligns with advancements such as the digitalization of prehospital patient care reports, wider access to large trauma registries, and an emerging global interest in AI healthcare decision-support.[48] The studies we identified evaluated information captured from all stages of prehospital care from dispatch to ED arrival. Predictions generated from this early and critical care period have the potential to impact decisions in both prehospital and hospital settings, and reduce trauma patient morbidity and mortality.[49] To our knowledge, this is the first scoping review to comprehensively analyze the breadth of studies assessing AI-based primarily on prehospital information and aimed at supporting early traumatic injury care.

EMS clinicians are challenged by a multitude of factors when delivering effective field trauma care. Out-of-hospital challenges include an information- and personnel-limited environment and situational elements such as bad weather, low lighting, and poor ergonomics. All these may influence EMS clinician care delivery and intensify cognitive burden. In trauma care, AI has the potential to decrease inter-provider decision-variability and improve decision accuracy. In an ideal setting, prehospital information (ie, vital signs) would be automatically

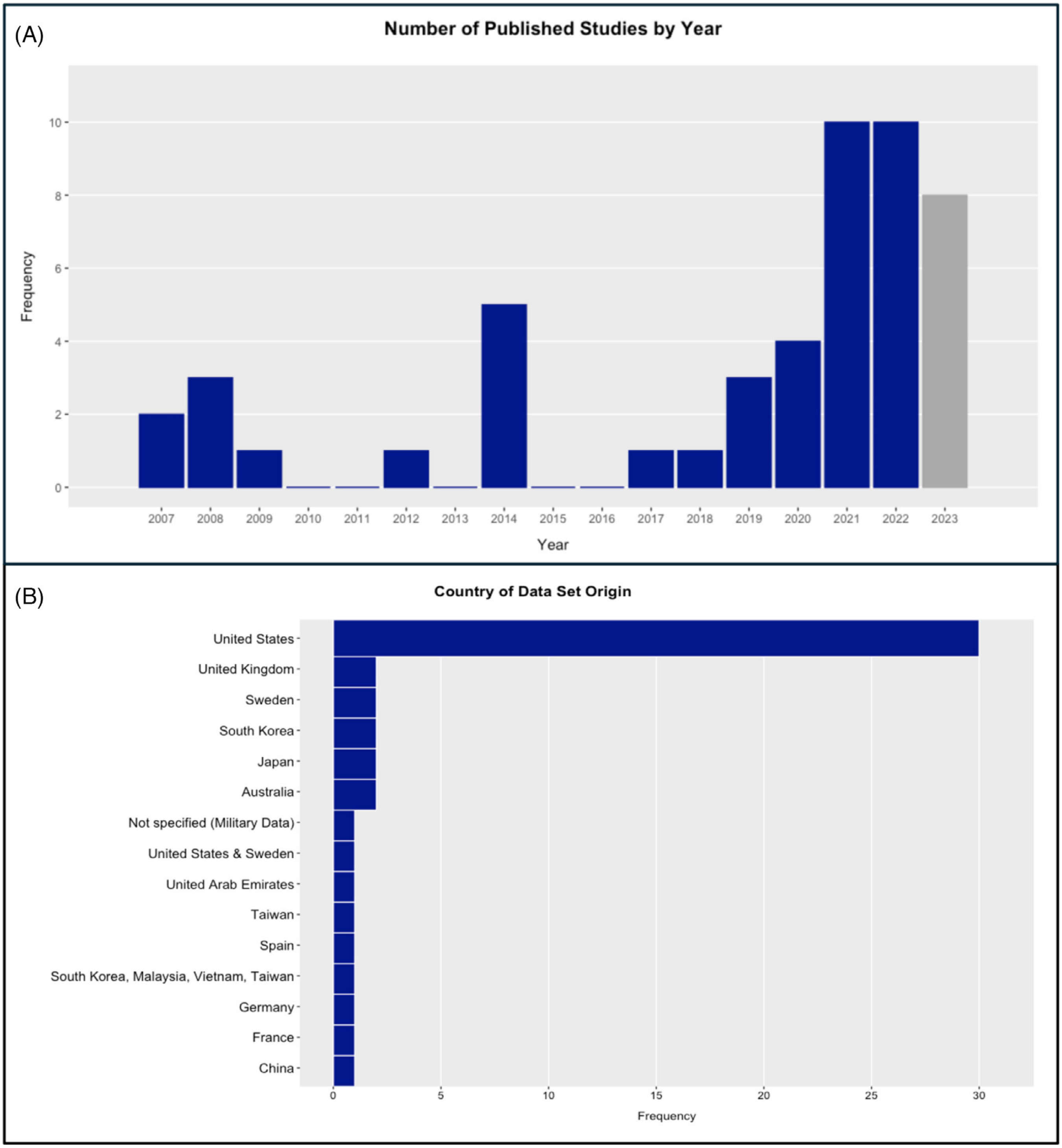

FIGURE 2 (A) Study Publications between 2007 and 2023. Data for the year 2023 was included up to August 2023. (B) Country of dataset origin.

collected and an autonomous algorithm would then suggest delivery of life-saving interventions, provide alerts about imminent decompensation, or give destination recommendations. All predictions would automatically be updated as additional information is available. Integrating AI decision-support with EMS clinician training and experience could drive improvements in care quality and patient outcomes. Nonetheless, it is critically important that available AI decision-support tools, including those that become commercially available, are supported by published research prior to routine use.

The time-sensitive need for critical interventions in trauma care necessitates rapid decision-making; it is thus unsurprising that most AI in this review focused on predicting triage categories and the need for

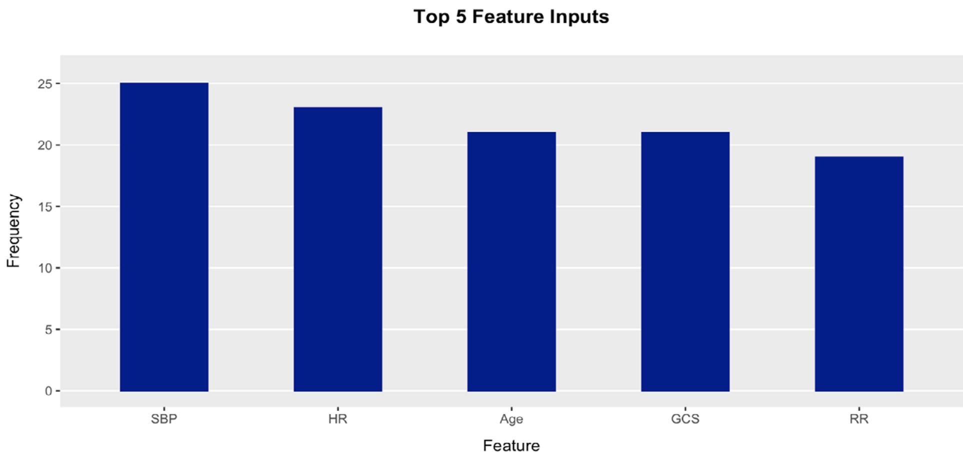

FIGURE 3 Top five most common features. GCS, Glasgow Coma Scale; HR, heart rate; RR, respiratory rate; SBP, systolic blood pressure.

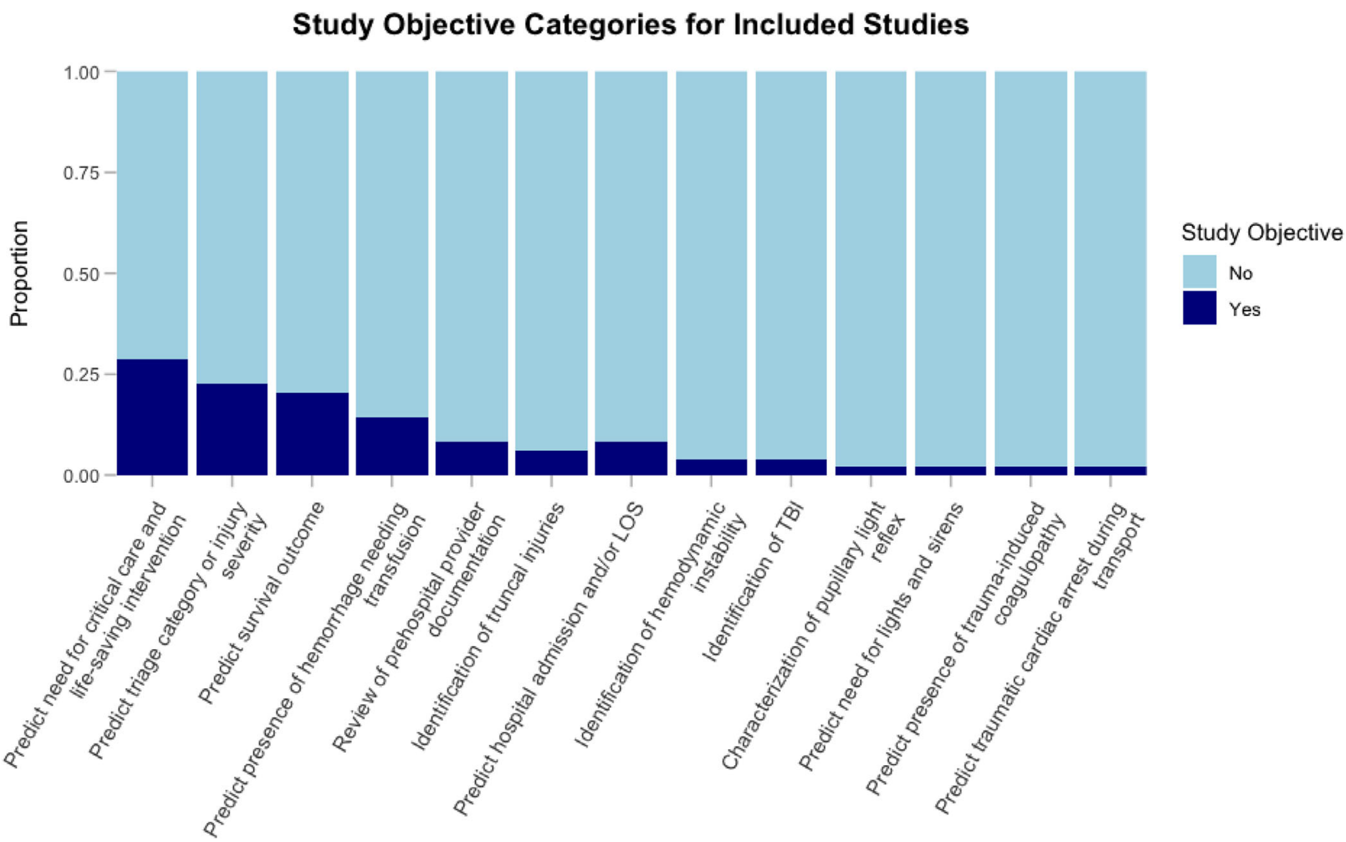

FIGURE 4 Categorization of study objectives for included studies. Some studies may have had more than one study objective.

life-saving interventions. Larsson et al. used the NTBD and SweTrau (a National Swedish Trauma Registry) to develop ML which predicted over- and under-triage rates based on similar parameters.[17] While ML demonstrated appropriate over-triage rates at 32%, an under-triage rate of 31% far exceeded the 5% cutoff recommended by the ACS Committee on Trauma.[50] Among studies identifying patients who may require critical care and life-saving interventions, Kang et al performed the largest using Korean trauma data to develop and externally validate a DL model which predicted intensive care unit admission with high predictive performance.[30] Models predicting the need for critical care and surgical intervention could better inform trauma teams and hospital resource mobilization as well as indicate cases that would benefit from online medical direction (ie, remote consultation of a physician or mobile intensive care nurse). These studies underscore the numerous potential implementations of AI to support clinicians early in the continuum of trauma care.

TABLE 1 Descriptive statistics ($n = 49$).

Characteristic	Frequency	Percentage
Type		
Conference abstracts	11	22
Original research	38	78
Study design		
Retrospective	43	88
Prospective	6	12
Population		
Adult	29	59
Pediatric	3	6
Geriatric	2	4
All ages	2	4
Not specified	13	27
Mechanism of injury		
Blunt	14	29
Penetrating	4	8
Both	28	57
Not applicable	3	6
Focused on traumatic brain injury	5	10
Focused on mass casualty incidents	4	8
Military involvement/sponsorship	7	14
Involved dispatch-level data	4	8
Data source		
Local provider/hospital data	22	45
Military registry	1	2
Multi-national registry	1	2
National registry	20	41
Simulation/lab	5	10
Branch of artificial intelligence		
DL	9	–
ML	41	–
NLP	6	–
Not specified	1	–
Top 5 classification algorithms		
Support vector machine	17	–
Logistic regression	16	–
Random forest	16	–
Extreme gradient boosting	7	–
K-nearest neighbors	7	–

Abbreviations: DL, deep learning; ML, machine learning; NLP, natural language processing.

Comparing trauma-focused AI models with conventional predictive instruments is essential in validating AI's capabilities and ensuring clinical readiness. Three studies compared the Revised Trauma Score (RTS)[51,52] to AI and, in general, AI outperformed the RTS.[43–45] Other studies compared AI to the Trauma Score and Injury Severity Score (TRISS) or Injury Severity Score (ISS); these scores represent an injury classification benchmark and neither can be feasibly calculated in the prehospital setting.[53] Four studies compared TRISS and/or ISS to AI and found that AI performed at least as well.[40,41,43,45] Kang et al compared an AI triage model to the National Early Warning Score and Emergency Severity Index,[30] while Chernbumroong et al. compared a pediatric AI triage model to the Pediatric Triage Tape and JumpSTART.[19] These comparisons represent an initial step toward understanding the potential impact that AI may have on trauma care in specific populations.

Additional studies compared AI to human decision-making. Two studies evaluated the use of AI models at the dispatch level in comparison to human-operators.[27,37] Chin et al found that AI did not outperform humans in dispatching the appropriate resources in routine traumatic injury cases, but had higher accuracy when dispatchers were less certain of their judgements.[37] Spangler et al found that AI outperformed dispatchers in predicting call priority.[27] Outside of dispatch, Marsden et al prospectively compared the performance of air ambulance EMS clinicians versus AI in estimating the risk of trauma-induced coagulopathy; the AI outperformed clinicians.[54] This small subset of studies support the notion that AI may support complex clinical decision-making for both experienced and non-experienced EMS clinicians alike.

When developing trauma-focused models, selection of the number and set of features using AI has demonstrated advantages. ML and DL algorithms have the capability to automatically identify and extract important features from large, multidimensional databases without the need for explicit human programming. Ting et al utilized principal component analysis, a technique used to reduce dimensionality in large data sets and identify key variables, and found that prehospital GCS and RTS were most correlated with trauma injury severity, length of stay, and mortality.[18] Other investigators utilized ML algorithms, such as random forest or gradient boosting, to automatically assess feature importance in a dataset.[12,21,25,27,29,32,33,35,38,42–44,47,55] Studies have also found that increasing the number of features did not significantly improve model performance.[12,34] Abe et al used Japanese trauma data to predicted traumatic intracranial hemorrhage and found that a reduction from 18 to five features showed similar performance.[12] Through careful feature selection, this reduces the chance of overfitting that occurs when a model is trained to predict training data too well but has poor performance on external data. When developing models, use of AI to support appropriate feature selection will enable timely, accurate, and actionable prehospital predictions while limiting the possibility of missing data from the prehospital setting.

Finally, this review identified gaps in current literature including a lack of externally validated models, prospective investigations, and pediatric-focused studies. External validation, which may be conducted retrospectively or prospectively, and prospective investigations are crucial to evaluate for generalizability and overfitting. In this review, only six small prospective studies were identified, nearly all of which were simulation studies.[39,54,56–59] Only 11 studies conducted external validation.[8,19,27,40,42,44,55,60–62] Further, only three studies focused specifically on pediatrics.[18–20] Detection of decompensation in pediatrics is often more difficult due to increased compensatory reserves and by environmental stressors (ie, emotional parents and non-accidental trauma) that may cloud clinician judgment. As such, real-time AI decision-support in pediatric trauma care represents an area that is ripe for innovation. Unfortunately, a lack of large pediatric focus trauma databases has likely hindered development. Identifying these gaps not only directs future research efforts but also underlines the urgency for developing future AI models tailored for pediatric and other specialized trauma care needs.

6 | CONCLUSION

A small but growing body of literature exists describing AI using prehospital features to make predictions that may support dispatchers, EMS clinicians, and trauma teams in early traumatic injury care. The study outcomes identified in this review were heterogeneous; the most common models aimed to predict the need for critical care and life-saving interventions, assist in triage and injury severity classification, and predict survival. Additionally, there was a lack of prospective investigations and pediatric-focused studies. While the results of this review demonstrate the potential of AI to support early traumatic injury care, there is significant opportunity for future investigations to standardize outcome prediction, externally validate models, and understand the barriers associated with real-time implementation.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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