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Review Article

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Application of Artificial Intelligence in Trauma Diagnosis and Surgical Decision-Making: A Narrative Review

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Abstract

Trauma remains a major global health concern and continues to be a leading cause of morbidity and mortality worldwide. Due to the time-sensitive nature of traumatic injuries, rapid diagnosis and accurate surgical decision-making are essential for improving patient outcomes and reducing complications. In recent years, artificial intelligence (AI) has emerged as a promising technological approach in trauma medicine, with potential applications in various aspects of trauma management, including diagnostic assessment, surgical planning, and postoperative care. This narrative review aims to summarize the current applications of AI in trauma diagnosis and surgical decision-making while discussing its limitations and ethical considerations. Current evidence suggests that AI-based tools have the potential to improve diagnostic accuracy, support clinical decision-making, enhance patient triage, and assist surgeons in managing complex trauma cases. By providing advanced analytical capabilities, AI may contribute to more efficient and accurate decision-making processes in trauma care. Despite these promising applications, several challenges remain before the widespread clinical implementation of AI systems can be achieved. These challenges include heterogeneity in study designs, limited external validation of AI models, and the possibility of biases resulting from training datasets. Furthermore, appropriate policy development related to standardized protocols, clinical integration, and ethical oversight is necessary to ensure the safe, effective, and responsible adoption of AI technologies in trauma care. Future research should focus on comprehensive evaluation of AI-based approaches across diverse patient populations and clinical settings to determine their real-world effectiveness and facilitate their integration into routine trauma management..

Key words: Artificial intelligence (AI), Machine learning, Prognosis, Surgical procedures, Trauma

Introduction

Trauma remains one of the leading causes of death and disability worldwide, accounting for millions of hospital admissions and a substantial proportion of surgical emergencies each year. According to the WHO, traumatic injuries constitute a major global public health burden, responsible for approximately 8% of global deaths annually, predominantly affecting individuals under the age of 45 years. Road traffic injuries, falls, and interpersonal violence are the most common contributors to trauma-related morbidity and mortality, particularly among younger and economically productive populations (1). Trauma care is inherently time-sensitive, as even short delays in diagnosis and treatment may result in irreversible organ damage or death. Despite advances in surgical techniques and emergency care systems, early identification and accurate prioritization of treatment remain critical determinants of patient survival (2).

In recent years, rapid advances in digital technologies have increasingly influenced modern medical practice, with artificial intelligence (AI) emerging as a promising tool for analyzing complex clinical data with speed and computational efficiency (3,4). Key AI subfields, including machine learning (ML), deep learning (DL), and natural language processing, enable systems to learn from data, recognize patterns, and support clinical decision-making. In trauma care, these technologies can process large volumes of heterogeneous data

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derived from medical imaging, vital signs, laboratory findings, and electronic health records to assist in diagnosis, triage, and treatment planning (5).

Several studies have demonstrated AI applications in trauma medicine. In diagnostic imaging, deep convolutional neural networks (CNNs) have shown performance comparable to experienced radiologists in detecting fractures, internal bleeding, and organ injuries on computed tomography (CT) scans or radiographs (6,7). ML-based models have been developed to predict patient prognosis, intensive care unit (ICU) admission, and mortality risk, offering support for rapid triage and resource allocation in emergency departments (8). While these approaches highlight potential benefits in improving the speed and consistency of clinical decision-making, their effectiveness remains variable across different populations and clinical settings.

In surgical contexts, AI has been proposed as a supportive tool across the perioperative continuum. Preoperatively, AI systems may assist in surgical planning through three-dimensional imaging and simulation models. Intraoperatively, AI-assisted robotic platforms, such as the da Vinci Surgical System, enhance precision and reduce technical variability (9,10). Postoperatively, AI-driven monitoring systems can facilitate early detection of complications, including infection or hemorrhage, enabling timely interventions (11). Despite these advances, most AI applications remain confined to controlled or experimental environments.

Growing enthusiasm surrounding AI in trauma care has raised concerns regarding potential overestimation of its readiness for routine clinical use. Many models are developed using retrospective or single-center datasets, increasing the risk of bias, overfitting, and limited generalizability across diverse patient populations and healthcare systems. Additional challenges include algorithm interpretability, ethical considerations related to data privacy and accountability, and variable acceptance among clinicians (12,13).

Given these opportunities and limitations, a critical synthesis of current evidence is essential. This narrative review aimed to summarize existing AI applications in trauma diagnosis and surgical decision-making, evaluate their benefits and limitations, and identify key gaps to guide future research and support safe and effective integration of AI technologies into trauma care systems.

Methods

This study was conducted as a narrative literature review aimed at providing a comprehensive overview of current applications of AI in trauma diagnosis and surgical decision-making. Narrative reviews allow for the synthesis of findings from diverse study designs, identification of emerging trends, and recognition of knowledge gaps within a specific research domain (14).

Search Strategy

A comprehensive literature search was performed in PubMed, Scopus, Web of Science, and Google Scholar to identify studies published between January 2015 and October 2025. Search terms were based on medical subject headings (MeSH) and supplemented with free-text keywords. Core concepts included AI, trauma, diagnosis, surgical decision-making, robotic surgery, and patient outcomes. Boolean operators (AND/OR) were applied to combine terms, and searches were restricted to Title/Abstract fields to enhance specificity. Additionally, reference lists of all included articles and relevant reviews were screened manually to identify further eligible studies.

Inclusion and Exclusion Criteria

The inclusion criteria included publication in English in peer reviewed journals, investigation of AI or ML applications in any domain of trauma care (including diagnosis, triage, prognosis, or surgical management), and reporting of quantitative or qualitative data on AI performance or associated clinical outcomes. The exclusion criteria included conference abstracts without accessible full texts, studies conducted outside the medical field, investigations focused exclusively on AI technology development without clinical implementation, and editorials, letters, or commentaries lacking original data (16).

Study Selection and Data Extraction

Full texts of potentially eligible studies were retrieved and assessed according to the inclusion and exclusion criteria. Data were extracted using a standardized extraction form, including: study design, AI technique, clinical application, patient population, outcomes, and key findings. Extracted data were organized thematically according to AI application areas: diagnosis, surgical decision-making, and postoperative monitoring.

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Results

Artificial Intelligence (AI) in Trauma Diagnosis

AI is increasingly being used in trauma imaging, with substantial benefits for both diagnostic speed and accuracy. The traditional radiological workflow may be adversely affected by large volumes and/or time-critical emergencies, particularly in trauma centers. Deep-learning systems, such as CNNs, have been tested for the detection of traumatic intracranial hemorrhage (ICH) on non-contrast head CT scans and have demonstrated pooled sensitivities of about 0.92 and specificities of about 0.94 in meta-analyses (18,19).

AI has also been applied to volumetric quantification in trauma imaging. In a pilot study, a deep-learning model was used to segment and quantify hemothorax on chest CT in trauma patients; the model showed good agreement with manual segmentation and predicted clinically relevant outcomes, such as massive transfusion and in-hospital mortality. There are also meaningful clinical implementations supporting their utility; AI triage systems for ICH have been integrated into emergency department workflows and have shown an impact on report prioritization and turnaround times (7, 21).

Despite these advances, there are still challenges to overcome: most studies are observational, external validation is limited, and generalizability across different populations and scanner protocols remains an obstacle for widespread adoption (7, 21).

Artificial intelligence (AI) in Surgical Decision Making

AI is increasingly considered a tool to enhance decision-making in acute care and trauma surgery, particularly under high-pressure conditions where rapid and accurate assessment can make a difference between life and death. In particular, machine-learning models predicting perioperative risks, complications, and surgical outcomes have been developed to help surgeons plan interventions more effectively.

A significant advance is the integration of AI in prehospital triage. For example, a Danish study used sequential vital-sign data collected during the first minutes of prehospital care to train neural network models that predict whether a trauma patient will require major surgery within 12 hours. The models achieved high performance; for example, the receiver operating characteristic-area under the curve (ROC-AUC) for predicting neurosurgery was high, indicating real potential to inform early surgical decision-making pathways.

From the surgeons' point of view, AI adoption is promising but not without skepticism. In an international survey of 650 trauma and emergency surgeons from five continents, many expressed optimism about the potential of AI but raised concerns about issues of trust, transparency, and workflow integration. Despite high interest, a substantial portion reported limited familiarity with existing AI tools.

Furthermore, the gap in implementation remains one critical barrier. Although predictive models for surgical risk exist, few have made their way into routine clinical use because of challenges in external validation, data standardization, and real-time integration with surgical workflows. Ethically, AI-based decision support in surgery raises governance challenges related to accountability for algorithmic suggestions, bias, and the need for surgeons to maintain ultimate responsibility for decisions. Many call for frameworks that augment, rather than replace, surgical judgment, as well as for transparent models and rigorous clinical evaluation.

AI applications in trauma care have significant clinical implications with the potential to redefine practice, resource utilization, and patient outcomes. First, ML-based predictive models have shown promise in triage and early risk stratification: systematic reviews indicate that AI/ML/DL models outperform conventional triage tools in predicting mortality, hospitalization, and critical care admission among trauma patients (24). These gains could result in a more accurate distribution of trauma resources, a reduction in overtriage, and potentially lower rates of preventable morbidity or death.

In acute management, ML-powered decision-support systems have been developed to help determine which patients are at risk of hemorrhage, require transfusion, or need surgical intervention. A recent systematic review on ML systems in severely injured patients found that such tools have good predictive accuracy for outcomes, such as mortality and the need for interventions, but stressed that implementation at the bedside remains limited due to workflow integration challenges (25). This suggests that AI could improve clinician decision-making, especially under time pressures, but must be cautiously integrated to avoid disruption.

Another crucial implication is associated with the monitoring of perioperative risks and complications: AI-driven models can predict the development of post-surgical complications, such as acute kidney injury (AKI). By identifying high-risk patients undergoing trauma surgery pre- or intra-operatively,

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clinicians may provide more tailored monitoring and prevention strategies for better patient outcomes resulting in reduced postoperative morbidity. Ethical, operational, and trust-related issues create obstacles to clinical adoption. For example, surgeons cite problems related to transparency, accountability, and reliability of AI systems when AI guides high-stakes decisions (27). Despite promise in retrospective models, few AI decision support tools have been prospectively validated in multicenter trauma settings, and a "data-to-bedside" gap exists in real-world deployment (28). Finally, to ensure a beneficial clinical impact, AI tools must be paired with robust governance frameworks, structured clinical workflows, and clinician education regarding AI interpretation and limitations.

Artificial intelligence (AI) in Postoperative Monitoring and Outcome Prediction

AI has immense potential in the postoperative period to track patient progress, anticipate complications, and enable early interventions. Several ML models have been designed to predict postoperative AKI using intraoperative and perioperative data. For example, interpretable ML techniques, such as random forest and XGBoost, when applied to demographic, surgical, and laboratory data, have shown good accuracy for predicting AKI (29). Furthermore, predictive models using high-frequency intraoperative monitoring data, such as heart rate, perfusion index, and estimated blood loss, have demonstrated potential for dynamically estimating AKI risk. One study of surgical cases used elastic-net regression combined with ML to forecast AKI, highlighting the importance of real-time physiologic variables (29).

Beyond AKI, DL techniques have been utilized to predict healthcare-associated infections after surgery. Recurrent neural networks (RNNs), such as long short-term memory networks, that incorporate preoperative and intraoperative risk factors along with vital signs, have successfully forecasted postoperative infections with satisfactory performance (30). Despite these advances, clinical implementation of these tools still faces obstacles. Most studies remain retrospective, and integrating AI systems into clinical workflows demands thorough validation, transparency, and regulatory oversight. Ethical concerns around accountability, data protection, and algorithmic bias further complicate adoption. To fully translate this potential into clinical practice, real-world, prospective trials and seamless integration with electronic health records (EHRs) and monitoring systems are essential.

Continuous Monitoring and Early Warning Systems

Continuous monitoring of vital signs in postoperative patients, when paired with AI, offers a powerful means of detecting deterioration early and preventing adverse outcomes. ML models trained on continuous streams of physiological data, such as heart rate, blood pressure, respiratory rate, and oxygen saturation, have been developed to identify serious complications before clinical recognition.

For example, a study of 292 high-risk postoperative patients using wearable sensors found that random forest and boosted-ensemble models achieved area under the receiver operating characteristic curve (AUROC) values of around 0.65 for real-time prediction of major adverse outcomes (31). AI-enhanced wearable devices can significantly improve postoperative surveillance. A recent systematic review identified AI-powered wearables, including biosensors and smartwatches, that detect early signs of hypoxia, arrhythmias, hemodynamic instability, and other physiologic abnormalities in surgical patients, thus supporting early warning systems and minimizing avoidable complications (32).

Furthermore, continuous vital-sign monitoring on general wards (outside the ICU), with AI-based alert generation, has shown encouraging results. AI-assisted monitoring detects more vital-sign deviations than traditional manual checks and can reduce unnecessary alarms by filtering out irrelevant alerts (33). Recent innovations have even employed RNNs with wearable-based continuous sensor data to predict patient deterioration up to 24 hours in advance. In one such study, a wearable-based DL model predicted clinical alerts with an AUROC of approximately 0.89 (34).

Despite these technological leaps, several challenges persist for clinical implementation. Issues, such as data security, patient comfort and compliance, model interpretability, alert fatigue, and workflow integration, remain significant. Developing rigorous validation studies and deployment strategies that address these barriers will be crucial for translating AI-driven continuous monitoring into routine clinical practice.

Predictive Modeling of Outcomes

Predictive modeling through AI has become increasingly vital in trauma care, particularly for anticipating critical outcomes, such as mortality and

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the risk of complications. For instance, an ML model based on EHR data known as the Epic Deterioration Index predicted in-hospital mortality among trauma patients with an AUROC of 0.98, surpassing traditional scoring systems, such as the Injury Severity Score (ISS) and the New Injury Severity Score (NISS) (35).

Similarly, within ICU trauma populations, ML algorithms, such as random forest and XGBoost, achieved robust performance for mortality prediction, with AUCs reaching up to 0.99 (36). In polytrauma patients, studies using XGBoost and other ML methods successfully forecasted both mortality and patient complexity, outperforming standard trauma scoring tools (37).

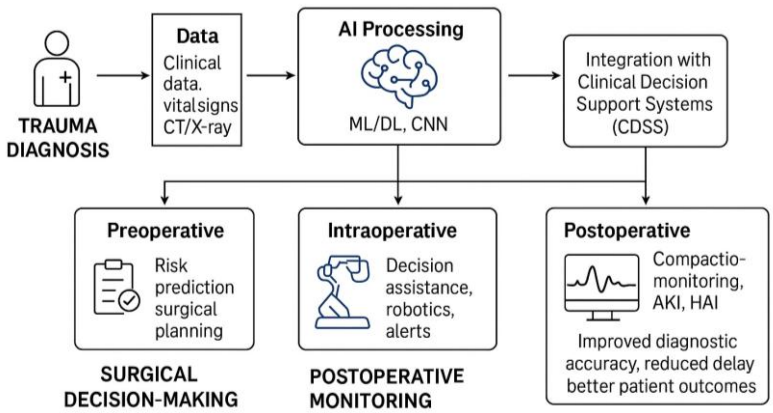
ML has also been applied to specific subgroups. For example, in traumatic brain injury cases, support vector machines and XGBoost models achieved AUCs between 0.85 and 0.86 for predicting in-hospital mortality (38). Additionally, ML systems have been used in ICU settings for early detection of hemorrhage. One model using logistic model trees and random forests predicted hemoglobin drops six hours before clinical detection in torso trauma patients, with an AUC of roughly 0.80 (39).

Beyond predictive accuracy, real-world applications have been explored as well. A Korean study developed an AI-based risk calculator for predicting emergency department trauma mortality using over 6.5 million patient records, achieving an exceptional AUROC of approximately 0.997 (40). However, despite these promising results, several challenges persist. These include data variability, limited interpretability of complex models, lack of integration into existing clinical workflows, and the need for large-scale, prospective validation studies before routine implementation can be realized.

Integration with Decision Support Systems

AI is increasingly being incorporated into clinical decision support systems (CDSS) in trauma care to deliver patient-specific, real-time recommendations for both surgical and management decisions. One notable example is Trauma Flow, a workflow-based CDSS developed specifically for managing severe polytrauma cases. It provides real-time, guideline-driven decision support, personalized treatment recommendations and documentation assistance during resuscitation (41) (Fig. 1). Within the surgical domain, the implementation of AI-enabled CDSS models has demonstrated promise but also revealed a pronounced gap between development and practical application. While numerous models have been created and validated, only a small fraction has actually been integrated into bedside care. A recent review emphasized that this model-to-clinic transition frequently fails due to insufficient prospective evaluation, limited clinical integration and weak governance structures (42). From the clinician's perspective, attitudes toward AI decision-support tools are characterized by a blend of optimism and caution. A large international survey of trauma surgeons revealed widespread enthusiasm about the potential of AI-driven support but also raised concerns regarding trust, usability, and compatibility with existing clinical workflows (43).

Broader research on AI-based CDSS reinforces their promise. Systematic reviews show that AI-powered decision support systems can improve diagnostic accuracy, minimize medical errors, and enhance the overall quality of care when effectively embedded into clinical infrastructures (44). However, despite these opportunities, significant barriers persist to their real-world adoption. Key challenges include issues of data security and privacy, lack of interoperability with current EHR systems, limited transparency in AI-generated recommendations, and the pressing need for robust standardized implementation frameworks (45).



Figur 1: Application of Artificial Intelligence (AI) in Trauma Diagnosis

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Discussion

The findings of this narrative review highlight the expanding and increasingly sophisticated role of AI in trauma diagnosis, surgical decision-making, and postoperative management. Across the trauma care continuum, AI applications demonstrate potential to enhance clinical decision-making, predictive modeling, and the optimization of patient outcomes. Evidence suggests that ML models can improve risk stratification for mortality, major hemorrhage, and long-term complications; however, substantial barriers continue to limit their widespread clinical implementation (35, 39, 46, 47).

Artificial Intelligence (AI) in Prognostication and Risk Stratification

ML-based prognostic models frequently outperform traditional scoring systems due to their ability to integrate high-dimensional data and identify complex, non-linear relationships between variables. For example, a large retrospective analysis using data from the National Trauma Data Bank demonstrated strong predictive performance (AUC of 0.86) for in-hospital mortality using ML models incorporating demographic characteristics, vital signs, comorbidities, and transfer status (46). Similarly, the Epic Deterioration Index achieved superior predictive accuracy compared with conventional scoring tools, such as the ISS and the NISS, with reported AUC values approaching 0.98 (35). These findings underscore AI's potential to enable real-time risk stratification and personalized prognostication in high-acuity trauma settings. Beyond mortality prediction, AI has demonstrated value in anticipating clinical deterioration. In ICU-admitted torso trauma patients, random forests and logistic model tree algorithms successfully predicted hemoglobin decline several hours before clinical recognition, with AUC values exceeding 0.80 (39). Such early warning systems may facilitate proactive intervention, optimize blood product utilization, and potentially reduce mortality. Despite these encouraging findings, translation into real-world practice remains limited. Systematic reviews reveal substantial heterogeneity in study design, inconsistent reporting of calibration metrics, limited external validation, and variability in feature selection strategies (47). These methodological inconsistencies raise concerns regarding generalizability across diverse healthcare systems and patient populations.

Barriers to Clinical Implementation

Although AI models demonstrate promising performance metrics, their integration into routine trauma practice faces multidimensional challenges.

Technical Barriers

Technical challenges include data heterogeneity, missing or incomplete clinical data, and limited interoperability between EHR systems. Variability in imaging protocols, laboratory measurements, and documentation standards may compromise model reproducibility. Additionally, model drift, in which algorithm performance degrades over time due to changes in clinical practice or population characteristics, poses a significant concern in dynamic trauma environments. Continuous model updating and monitoring frameworks are therefore essential.

Human and Organizational Factors

Successful implementation also depends on clinician trust, usability, and workflow integration. Trauma care operates under extreme time pressure; therefore, AI tools must provide interpretable, actionable outputs without disrupting established clinical pathways. Resistance may arise if clinicians perceive AI systems as opaque or misaligned with clinical judgment. Structured training programs and human-centered interface design are necessary to foster adoption.

Ethical and Legal Considerations

Ethical and legal challenges further complicate implementation. Algorithmic bias may disproportionately affect vulnerable populations if training datasets lack diversity. Questions regarding accountability, particularly in cases of incorrect predictions, remain unresolved. Ensuring transparency, explainability, and compliance with data privacy regulations is critical for responsible AI deployment. Clear regulatory frameworks and governance policies are needed to balance innovation with patient safety.

Future Directions

Future efforts should focus on developing AI systems capable of integrating real-time multimodal data, including imaging, physiologic monitoring, laboratory results, and clinical documentation, into unified predictive platforms for dynamic risk assessment. Emphasis should be placed on interpretable and explainable AI frameworks to enhance clinician confidence and support shared decision-making. AI-driven tools, such as simulation models and 3D reconstruction software,

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may enable personalized surgical planning tailored to patient-specific anatomy and injury patterns. Robust external validation through prospective, multicenter studies is essential to ensure generalizability across diverse healthcare settings. Furthermore, embedding AI within existing CDSS can facilitate seamless alerts and recommendations without disrupting workflow. Finally, comprehensive ethical and regulatory frameworks must accompany technological advancements to address bias mitigation, accountability, transparency, and data governance. Collectively, these measures will help bridge the gap between retrospective model development and bedside implementation, ensuring safe and effective integration of AI into trauma care.

Strengthened Synthesis

Overall, AI applications in trauma care demonstrate strong potential to enhance diagnostic precision, accelerate decision-making, and improve resource allocation. However, performance metrics, such as AUC and sensitivity, while encouraging, do not alone guarantee clinical benefit. True impact must be measured in terms of improved survival rates, reduced complication burden, shorter ICU stays, and optimized system-level efficiency. Bridging the gap between retrospective model development and bedside implementation requires rigorous validation, interdisciplinary collaboration, and governance structures that prioritize patient safety. AI should be viewed not as a replacement for clinical expertise but as a decision-support adjunct that augments human judgment in high-stakes trauma scenarios.

Conclusion

AI-driven predictive models in trauma medicine hold substantial potential to improve prognostication, risk assessment, and early clinical intervention. Nevertheless, successful translation into routine clinical practice requires robust external validation, enhanced interpretability, seamless workflow integration, and comprehensive ethical oversight. If these challenges are systematically addressed, AI may significantly improve patient outcomes and operational performance across the trauma care continuum.

Ethics Approval and Consent to Participate

Not applicable, as this is a narrative review of existing literature and does not involve human participants or original data collection.

Consent for Publication

Not applicable.

Data Availability Statement

No datasets were generated or analyzed during the current study.

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Not applicable.

Authors' Contributions

MF contributed to conceptualization, study design, literature search, and resource collection, as well as writing, reviewing, and editing the original drafts.

Conflict of Interest

The authors declared no conflicts of interest.

Declaration of Generative Artificial Intelligence (AI) in Scientific Writing

AI tools were used solely for text paraphrasing and editorial purposes. All scientific content, reasoning, and conclusions presented in this manuscript are solely the responsibility of the authors.

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