# Machine Learning for Enhancing Quality and Safety in Trauma Care for Older Adults: A Conceptual Framework

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**Abstract:** Older adults face disproportionately high risks of Adverse Events (AEs) following trauma, including surgical complications, delirium, medication errors, and infections. As trauma care systems globally confront aging populations, Machine Learning (ML) offers significant potential to enhance safety and quality across all phases of care. This article proposes a conceptual framework that maps ML maturity onto the trauma care continuum to inform future research and implementation strategies. We review the current landscape of ML applications focused on older trauma patients, examine national data on age-specific AE trends and categories, and identify key challenges, such as data fragmentation, model bias, and limited clinical integration. Finally, we outline future priorities to support the safe, equitable, and effective use of ML in trauma care for older adults.

**Keywords:** trauma care, care quality, patient harm, machine learning, conceptual framework

## 1. Introduction

Older adults experience disproportionately high rates of in-hospital Adverse Events (AEs) following trauma, including medication-related conditions, healthcare associated infections, patient accidents, and procedure-related complications [1]. As population ages, trauma care systems face growing challenges in consistently delivering safe, high-quality care to older patients, who were often admitted with multimorbidity, frailty, and complex clinical needs.

Historically, surveillance and reporting of patient safety events have relied primarily on administrative data, such as hospital discharge abstracts [2]. While these datasets provide standardized, population-level coverage, they are inherently limited by their retrospective nature. Captured only at discharge, administrative records offer a single, cross-sectional view of the hospitalization, omitting crucial temporal patterns and often underreporting or misclassifying the occurrence and sequence of harms [3, 4].

In contrast, Electronic Medical Records (EMRs) offer longitudinal, high-resolution data across the clinical encounter. Over the past two decades, substantial investments in EMR infrastructure have transformed data availability in Canadian hospitals [5]. In Alberta, for example, the eCritical system collects real-time data from all adult intensive care units across the province, integrating bedside monitor readings, ventilator settings, laboratory results, and medication administration records [6]. In Nova Scotia, the One Patient One Record initiative has unified hospital-based EMRs under a single platform to support province-wide documentation [7]. Ontario has similarly adopted enterprise-scale EMR platforms such as Epic and Cerner across many acute care institutions, enabling integration of structured clinical data at scale [8].

Importantly, EMRs also capture large volumes of unstructured information, such as physician and nursing notes, diagnostic reports, and discharge summaries [9]. These narrative texts often include clinically details about symptom evolution, decision-making processes, and complications specific to individual patients. Such insights are typically unavailable in administrative data. Traditional statistical methods are not well equipped to analyze unstructured text, as they rely on predefined variables and cannot detect the semantic meaning, temporal relationships, or complex patterns present in free-text clinical documentation.

Advances in Machine Learning (ML) and Natural Language Processing (NLP) have introduced new capabilities for extracting, interpreting, and synthesizing information from both structured and unstructured EMR data [10, 11] (Fig. 1). ML models are particularly well suited to analyze high-dimensional clinical data, identifying nonlinear associations and detecting subtle, context-dependent signals of risk. In the trauma setting, ML can integrate inputs such as vital signs, medication profiles, surgical notes, and nursing documentation to predict adverse events, guide interventions, and inform personalized care plans [12]. Unlike traditional rules-based systems, ML approaches are adaptive, scalable, and capable of evolving with accumulating data, offering a pathway toward responsive, learning-oriented trauma care systems for older adults [13, 14].

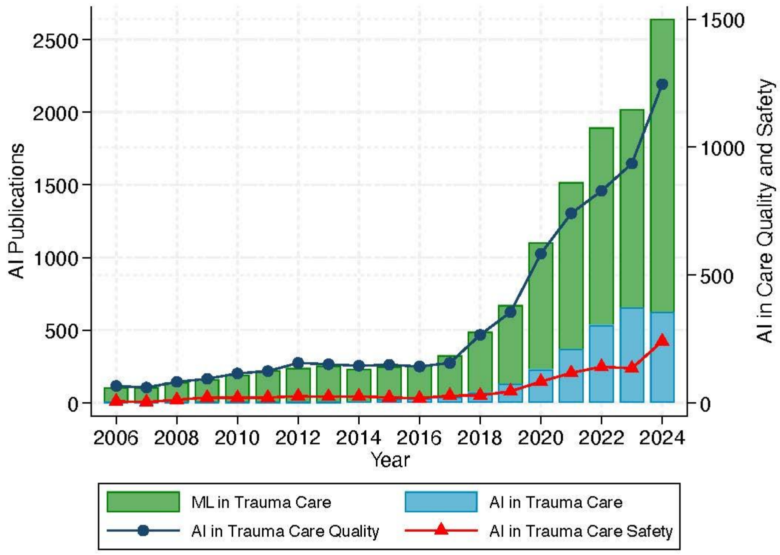



Fig. 1. Trends in AI and ML publications in trauma care, 2006–2025.

Stacked bars show annual AI-only and ML-only publication counts (left Y-axis). Lines indicate AI/ML publications focused on quality (circles) and safety (squares) (right Y-axis). Data were extracted from PubMed.

The growing interest in these applications is reflected in the increasing number of publications on AI and ML in trauma care over time (Fig. 1). Research has expanded across different clinical settings and applications, reflecting the broader use of ML throughout the trauma care continuum. Despite this growing body of research, the adoption of ML remains fragmented, and systematic evaluations of its impact are limited. This article presents a conceptual framework to support the integration of machine learning into trauma care for older adults. Using this framework, we examine current applications, identify key implementation challenges, and highlight opportunities to enhance safety, decision-making, and outcomes across all phases of trauma care.

## 2. Conceptual Framework: Mapping ML Maturity across the Trauma Care Continuum

We propose a three-dimensional conceptual framework through a synthesis of the existing literature on ML applications, trauma care, and clinical implementation. The framework integrates captures the technical evolution of machine learning tools (X-axis), the clinical trajectory of trauma care delivery (Y-axis), and the operational pipeline needed to translate ML insights into practice (Z-axis) (Fig. 2). The framework provides a structured approach for understanding the development and application of ML across the trauma care continuum. Unlike existing frameworks that primarily focus on model development, reporting, or implementation, our framework integrates these dimensions to provide a broader view of ML applications across the trauma care continuum.

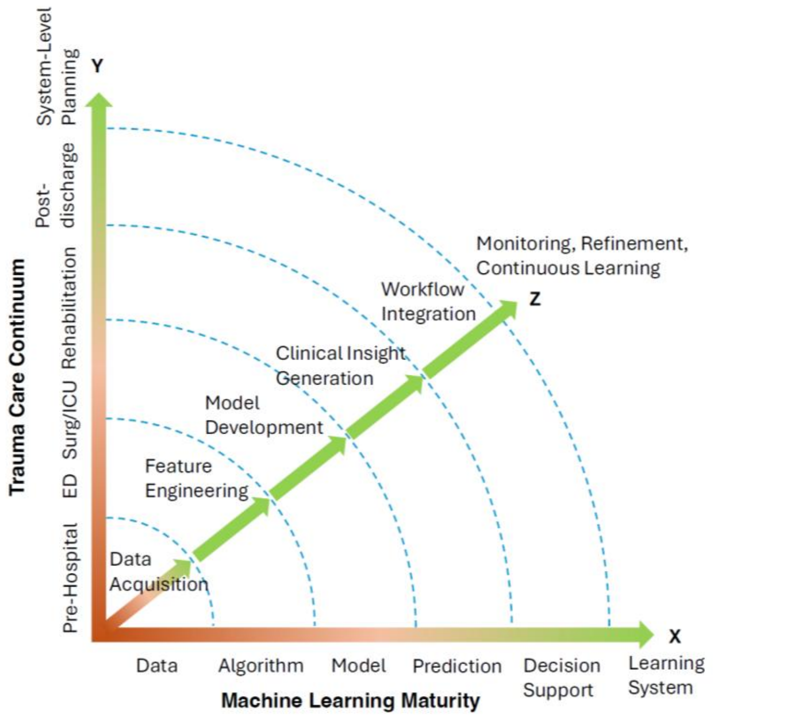



Fig. 2. Conceptual framework illustrating machine learning integration across the trauma care continuum.

## 2.1. Dimension 1 (X-axis): Maturity of Machine Learning Methodology

This dimension captures the technical evolution of machine learning in trauma care, from data preparation to adaptive systems that support continuous learning and improvement.

(1) **Data readiness:** Foundational efforts involve assembling structured and unstructured data from trauma registries, bedside monitors, and EMRs. Emphasis is placed on data completeness, standardization, and fidelity to clinical events.

(2) **Algorithm construction:** Initial analytical models are developed using approaches such as logistic regression, decision trees, and deep learning to identify patterns, infer associations, and support early hypothesis generation.

(3) **Model formalization**: Validated algorithms are operationalized into reproducible models that yield outputs such as risk scores, event probabilities, or classification labels, enabling structured interpretation of patient risk.

(4) **Predictive implementation**: Models are applied prospectively to identify patients at risk of adverse outcomes. These predictions inform triage, early intervention, and prioritization of care resources.

(5) **Decision support integration:** Models are incorporated into digital clinical environments through electronic records, dashboards, or alert systems. Integration is designed to enhance decision-making while preserving workflow efficiency.

(6) **Autonomous learning systems:** At full maturity, machine learning systems continuously update with

new data and outcomes. These tools support real-time recalibration, enabling learning health systems to adapt to clinical and population-level changes.

### 2.2. Dimension 2 (Y-axis): Trauma Care Continuum

This dimension reflects the sequence of clinical settings across the trauma care pathway where machine learning can inform diagnosis, risk assessment, and therapeutic planning for older adults.

(1) **Prehospital care:** Machine learning supports EMS-based triage, destination selection, and early stabilization decisions by synthesizing physiologic and geospatial data to assess injury severity and optimize transport.

(2) **Emergency department evaluation:** ML tools assist with rapid diagnostics, injury scoring, and resource prioritization. They may improve differentiation of clinical severity, anticipate procedural needs, and guide admission decisions.

(3) **Operative and critical care management:** Applications in perioperative and ICU settings include risk modeling, real-time physiologic monitoring, and early detection of complications such as hemorrhage, sepsis, or organ failure.

(4) **Rehabilitation planning:** ML models forecast recovery trajectories, tailor therapy intensity, and detect functional or cognitive decline. These tools support individualized rehabilitation strategies and timely reassessment.

(5) **Post-discharge follow-up:** Post-acute care may benefit from ML-enabled surveillance for readmissions, adverse drug events, or delayed complications. Predictive analytics aid in continuity of care and proactive outreach.

(6) **System-level coordination and planning**: At the population level, ML supports strategic planning by identifying trends in access, outcomes, and disparities. These tools can guide benchmarking, resource allocation, and trauma system optimization.

### 2.3. Dimension 3 (Z-axis): Machine Learning Operational Workflow

This dimension outlines the translational pipeline through which clinical data are transformed into usable tools that improve trauma care delivery and patient outcomes.

(1) **Data acquisition and harmonization:** Structured and unstructured data are extracted, standardized, and aligned across care settings. This process ensures interoperability and preserves the clinical fidelity required for modeling.

(2) **Feature engineering and representation:** Raw data are converted into meaningful variables using statistical techniques and natural language processing. Feature construction is tailored to reflect clinical relevance and improve interpretability.

(3) **Model development and** validation**:** Algorithms are trained and tested using robust internal and external validation strategies. Emphasis is placed on generalizability, fairness, and reproducibility, especially in heterogeneous trauma populations.

(4) **Clinical insight generation:** Model outputs are converted into actionable insights that align with clinical reasoning, such as alerts for sepsis risk, falls, or discharge readiness. Outputs are designed for interpretability and clinical trust.

(5) **Workflow integration:** Tools are deployed within existing digital infrastructure, including EHR interfaces, dashboards, or point-of-care alerts. Design prioritizes usability, context sensitivity, and clinical efficiency.

(6) **Monitoring and refinement:** Post-implementation, model performance is continuously evaluated using real-world data. Ongoing updates address data drift, evolving practices, and feedback from frontline clinicians to maintain clinical relevance.

Together, these dimensions provide a structured framework to assess where machine learning is currently applied in trauma care, the maturity of these applications, where gaps remain, and how implementation can align with clinical context and technical readiness. The framework is intended to help researchers and health-system stakeholders identify gaps in current ML applications and guide future research and implementation across the trauma care continuum.

## 3. Adverse Events in Older Inpatients: How Serious is the Problem?

Adverse events in hospitalized patients represent a critical measure of safety and care quality. The Canadian Institute for Health Information (CIHI) classifies AEs into four principal categories: medication-related conditions, health care–associated infections, patient accidents, and procedure-associated complications [15]. Data for the temporal analysis were obtained from the Canadian Institute for Health Information (CIHI), Applying an Equity Lens to Patient Safety—Data Tables (2024), based on the Discharge Abstract Database (DAD). The DAD contains administrative, clinical, and demographic information on hospital discharges, including deaths, sign-outs, and transfers. The data used in this analysis covered 2014 to 2022 and included all provinces and territories except Quebec. Hospital harm was examined overall and, where applicable, among medical and surgical patients and across age groups.

CIHI reported age-standardized rates calculated using the direct method, with the 2011 Canadian population from the 2011 Census as the standard population and 5-year age groups for standardization. For the present analysis, denominators were derived from the reported case counts and crude rates (per 100 hospitalizations). Age-specific estimates were subsequently aggregated into two broader age groups (<65 and ≥65 years) using the corresponding number of hospitalizations as weights. For the combined age-group estimates, standard errors were derived from the 95% confidence intervals reported by CIHI, and corresponding 95% confidence intervals were calculated using the standard normal approximation.

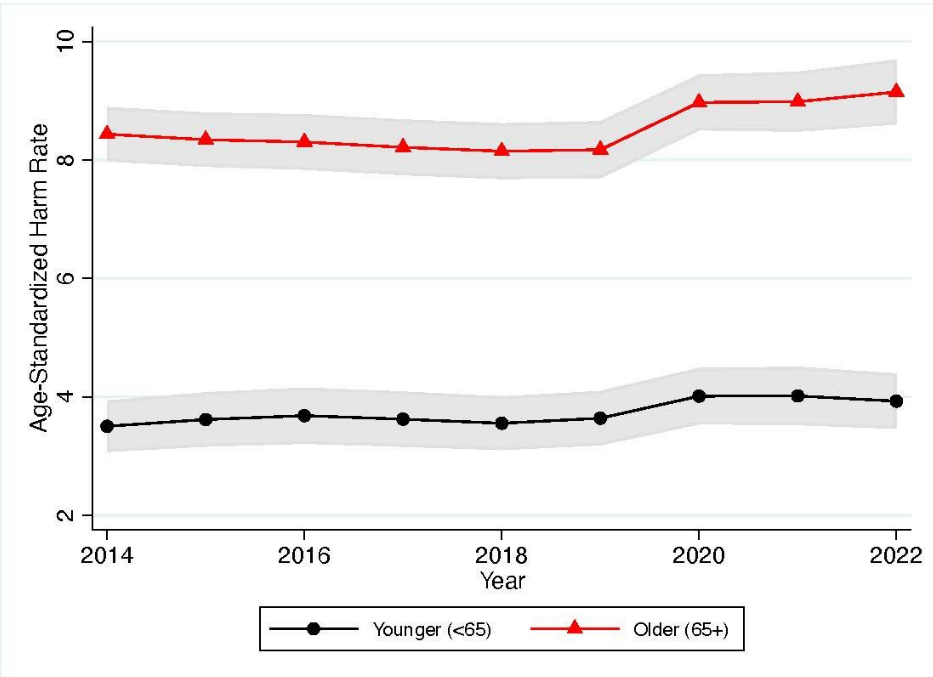
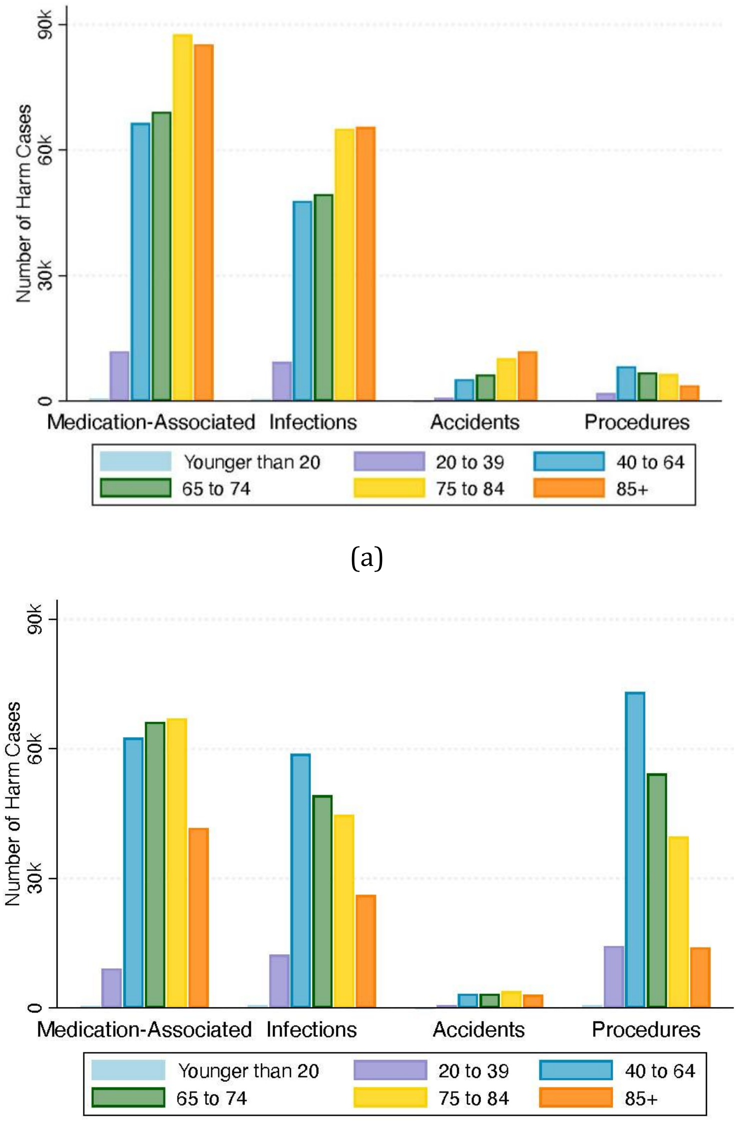



Fig. 3. Age-standardized harm rates in Canada, 2014–2022.

Using data from CIHI's Discharge Abstract Database, we examined national trends in AE rates across age groups. Between 2014 and 2022, the age-adjusted AE rate among hospitalized patients aged 65 years or older rose from 8.43 (95% CI, 7.9–8.89) to 9.15 (95% CI, 8.60–9.69) per 100 hospital admissions. In contrast, rates among younger adults remained substantially lower, increasing from 3.50 (95% CI, 3.07–3.93) to 3.93 (95% CI, 3.46–4.39) over the same period (Fig. 3).

Patients aged 75 years or older account for more than half of all hospital adverse events (Fig. 4). For patients aged 85 years or older, the rate of surgical AEs increased from 10.53 (95% CI, 10.23–10.83) in 2014 to 12.03 (95% CI, 11.72–12.34) in 2022. Rates of medical AEs in this group also rose from 4.27 (95% CI, 4.18–4.36) to 5.63 (95% CI, 5.53–5.74) per 100 admissions.

These findings highlight the escalating safety risks among older adults and underscore the need for advanced technologies to improve surveillance and guide prevention strategies.




(b)

Fig. 4. Frequency of (a) medical; (b) surgical harms by age group in Canada, 2014–2022.

## 4. Applying Machine Learning across the Trauma Care Continuum

Mapping machine learning capabilities onto the trauma care continuum highlights specific opportunities to enhance patient safety, support clinical decision-making, and improve outcomes among older adults. Table 1 summarizes key applications across adverse event types, data sources, algorithm classes, and clinical contexts.

Table 1. Machine Learning Applications for Adverse Events in Trauma Patients

| AE Type | Study Design | Setting / Data Source | Algorithm | Model Performance | Clinical Impact | Level of Evidence |
| --- | --- | --- | --- | --- | --- | --- |
| Delirium [16] | Retrospective observational study | Single center/ EMR | Logistic regression, SVM, neural network, kNN, RF, AdaBoost, GBM, LDA, naïve Bayes, decision tree | Best AUCs: Logistic regression (0.906), SVM (0.897), kNN (0.894) | Vital signs and lab data enabled high-performing early prediction of delirium in burn ICU patients | L3 |
| Falls [17] | Retrospective cohort study | Eight hospitals/ EMR | Logistic regression with model-based imputation | Training AUC: 0.713 (95% CI, 0.701–0.725); Testing AUC: 0.808 (95% CI, 0.740–0.876) | Robust prediction of fall severity using integrative ML across multi-source clinical data | L2 |
| Hemorrhage [18] | Prospective observational study | Trauma base registry | CART, RF, XGBoost, CatBoost | ML: LR+ 4.01 (95% CI, 3.43–4.70); LR: 0.35 (95% CI, 0.38–0.44) | ML outperformed clinicians in detecting hemorrhage control needs; supports early intervention decisions | L1 |
| Sepsis [19] | Retrospective cohort study | MIMIC-IV database | XGBoost, logistic regression | AUC: 0.83–0.88 for 4–24 h prediction window; predicted 91% of sepsis events with 9:1 false alert ratio | Early prediction of sepsis in trauma patients with high discrimination and clinical usefulness | L3 |
| Readmissions [20] | Observational cohort study | Single center/ EMR, MIMIC-III | Gradient boosted machine | AUC: 0.73 (early), 0.77 (late), 0.76 (overall) | More accurate than prior models in predicting ICU readmissions; supports discharge and monitoring | L3 |
| Various outcomes [21] | Retrospective prognostic study | National Trauma Data Bank | Not specified | AUC: 0.86 for adults and children; consistent generalizability across U.S. trauma settings | ML models generalize across trauma populations, enabling scalable decision support | L2 |
| Various outcomes [22] | Retrospective cohort study | NHAMCS Emergency Department data | Lasso regression, RF, GBDT, deep neural network | AUC for critical care outcome: DNN 0.86; for hospitalization outcome: GBDT 0.82 | ML enhanced ED triage precision, optimizing critical care and hospitalization decisions | L2 |

Notes: Evidence level: L1—prospective multicenter evidence; L2—multicenter retrospective evidence; L3—single-center retrospective evidence; L4—model development or exploratory evidence.

**Abbreviations**: AE, adverse event; AUC, area under the curve; CI, confidence interval; DNN, deep neural network; EMR, electronic medical record; GBDT, gradient-boosted decision tree; ICU, intensive care unit; kNN, k-nearest neighbor; LR, likelihood ratio; ML, machine learning; NHAMCS, National Hospital Ambulatory Medical Care Survey; RF, random forest; SVM, support vector machine.

In prehospital and emergency department settings, ML models have improved triage precision and risk stratification [22]. Gradient-boosted trees and deep neural networks applied to emergency department data have achieved high predictive accuracy for critical care and hospitalization outcomes, with Area under the Receiver Operating Characteristic Curve (AUROC) values as high as 0.86. These tools support timely interventions and more efficient resource allocation.

In inpatient and intensive care settings, ML has demonstrated utility in forecasting complications. For example, ensemble models trained on vital signs, laboratory values, and EMR data achieved AUROCs between 0.83 and 0.88 for early prediction of sepsis [19]. Similarly, models using structured clinical data have predicted fall severity and delirium risk, with performance metrics exceeding 0.80 in most cases [17]. These applications enable earlier recognition and more tailored preventive strategies.

During postoperative and post-acute phases, ML models have supported discharge planning and longitudinal care coordination [20]. Gradient-boosted models using EMR and trauma registry data have predicted ICU readmissions with AUROCs ranging from 0.73 to 0.77, outperforming traditional approaches. In rehabilitation settings, such tools may assist in identifying patients at elevated risk of complications or functional decline [23].

In procedural care, ML has demonstrated potential in augmenting clinical judgment [18]. A prospective study using tree-based models to detect patients in need of hemorrhage control showed higher diagnostic accuracy than clinicians alone, reinforcing the value of ML as a decision-support adjunct.

Machine learning has been increasingly applied across trauma care to support risk prediction, early intervention, and clinical decision-making [13, 14]. Despite growing evidence of utility, applications remain uneven across care stages and event types. An important gap remains between demonstrating predictive performance and demonstrating clinical benefit. Few studies have evaluated whether ML tools can be sustainably integrated into routine clinical workflows, influence clinician actions, or improve patient outcomes. Addressing this gap requires prospective implementation studies that assess workflow integration, clinician uptake, unintended consequences such as alert burden, and downstream patient outcomes. The proposed framework offers a structured approach to identify existing gaps, prioritize areas for development, and guide the alignment of future machine learning efforts with the clinical and operational demands of trauma care.

## 5. Challenges and Future Directions

Despite its promise, machine learning faces critical challenges that must be addressed to ensure safe, effective, and equitable integration into trauma care [11, 24]. First, clinical data remain fragmented across care settings, including emergency medical services, acute care, and post-acute rehabilitation, limiting data completeness, standardization, and interoperability. This undermines model generalizability and restricts multicenter validation. Second, algorithmic bias remains a concern, as older adults may be underrepresented or differently represented in ML training datasets because of multimorbidity, complex care trajectories, and variation in clinical documentation, potentially resulting in suboptimal model performance and exacerbating existing disparities in care delivery. Third, the lack of interpretability in complex models, such as deep neural networks, poses challenges to clinical integration, especially when outputs cannot be readily aligned with physician reasoning or clinical heuristics. Fourth, ethical considerations related to informed consent and the privacy and security of patient data must be addressed throughout ML development and deployment [25]. Fifth, although the CIHI data provide a national perspective on adverse events among older adults in Canada, these findings may not be directly generalizable to other health systems. The ML studies reviewed included diverse populations, clinical settings, and data sources, which may limit the transferability of their findings across populations and healthcare systems [26].

The framework proposed in this study offers a structured approach to align machine learning maturity with stages of trauma care, facilitating targeted application and evaluation. Future efforts should prioritize standardizing data systems and improving interoperability to enable seamless integration across trauma care settings. Ensuring fairness and transparency through bias mitigation, explainable AI, and subgroup validation is essential. Embedding machine learning tools into clinical workflows using user-centered design and clinician engagement will promote adoption. Additionally, investment in infrastructure to support real-time performance monitoring, federated learning, and iterative model refinement is critical. Together, these strategies will bridge the gap between innovation and clinical implementation, advancing trauma care quality and safety for older adults.

## 6. Conclusion

Machine learning offers substantial promise for improving trauma care in older adults through earlier detection, precise interventions, and continuous quality improvement. The proposed framework demonstrates how machine learning capabilities can be systematically aligned with stages of care and operational needs. By identifying gaps in current applications and guiding future research priorities, this framework can help translate technical advances into scalable, equitable, and clinically applicable solutions for high-risk trauma populations.

### Conflict of Interest

The author declares no conflict of interest.

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