Beyond Traditional Scoring Systems: Developing an AI- Powered Tool for Trauma Prognosis

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Note: Abstract based on unpublished work with University of South Alabama College of Medicine and recently published research with University of Cincinnati [1]

Introduction and Objective

Trauma is the leading cause of death in individuals under 45 in the U.S., requiring timely and accurate risk assessment. Traditional scoring systems like TRISS are limited by static variables and low specificity. Advances in machine learning and EHR interoperability present an opportunity for real-time, tailored prognostic tools.

Our objective was to develop and evaluate interpretable machine learning models predicting 48-hour mortality in polytrauma patients, using routine EHR data from two Level 1 trauma centers, to support early clinical decision-making in high-acuity trauma care.

Data and Methodology

We developed machine learning models using retrospective EHR data from two Level 1 trauma centers, totaling **11,800 polytrauma encounters**. Each dataset captured real-time clinical variables in **hourly snapshots** starting from patient admission.

Data Overview

- **Trauma Center 1:** 4,800 encounters, 4.5% mortality rate
- **Trauma Center 2:** 7,000 encounters, 7.0% mortality rate
  Common features included:
  - Glasgow Coma Scale (GCS)
  - Blood pressure
  - Lactate, BUN, potassium

Model Development

- **Model type:** XGBoost (chosen for interpretability and robustness to missing data)
- **Target outcome:** 48-hour mortality
- **Evaluation metric:** Precision at **80% recall**, chosen with clinician input
- **Train/test split:** Temporal split (80% training, 20% testing)
- **Feature engineering:**
  - Min/max/mean values from early vital signs and labs
  - PCA for reducing collinearity
  - Structured handling of missing data
- **Benchmarking:** Compared against a bivariate classifier that includes Base Excess and Lactate to approximate clinician gestalt (~10% precision at 80% recall)

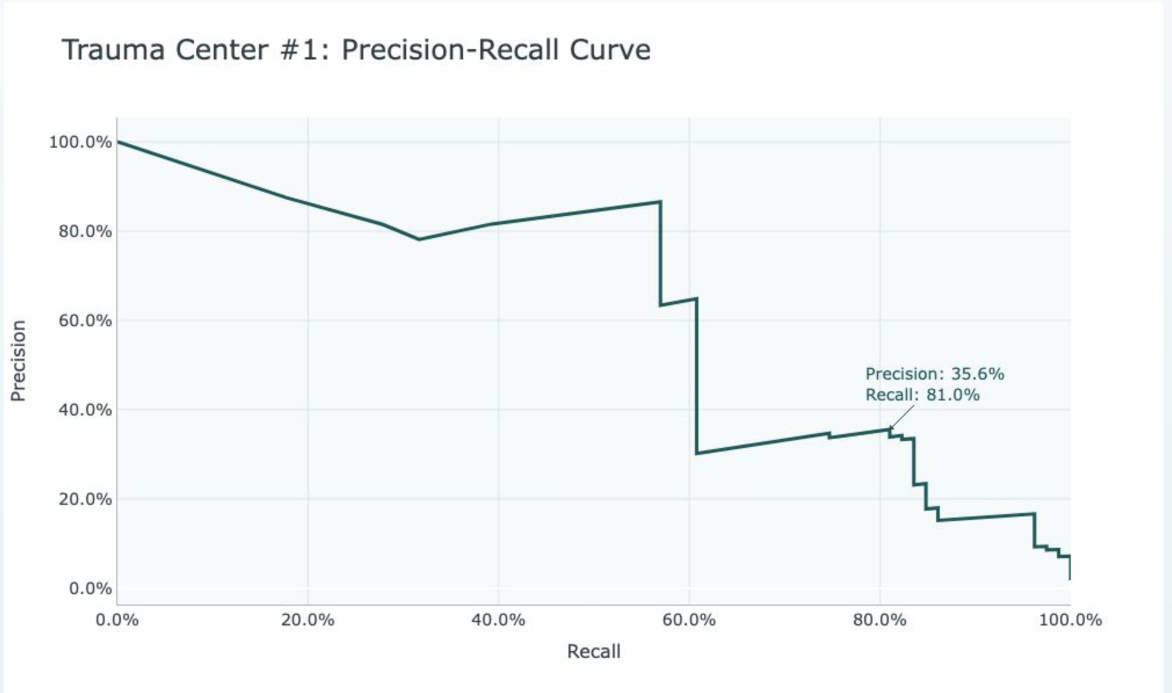
Results

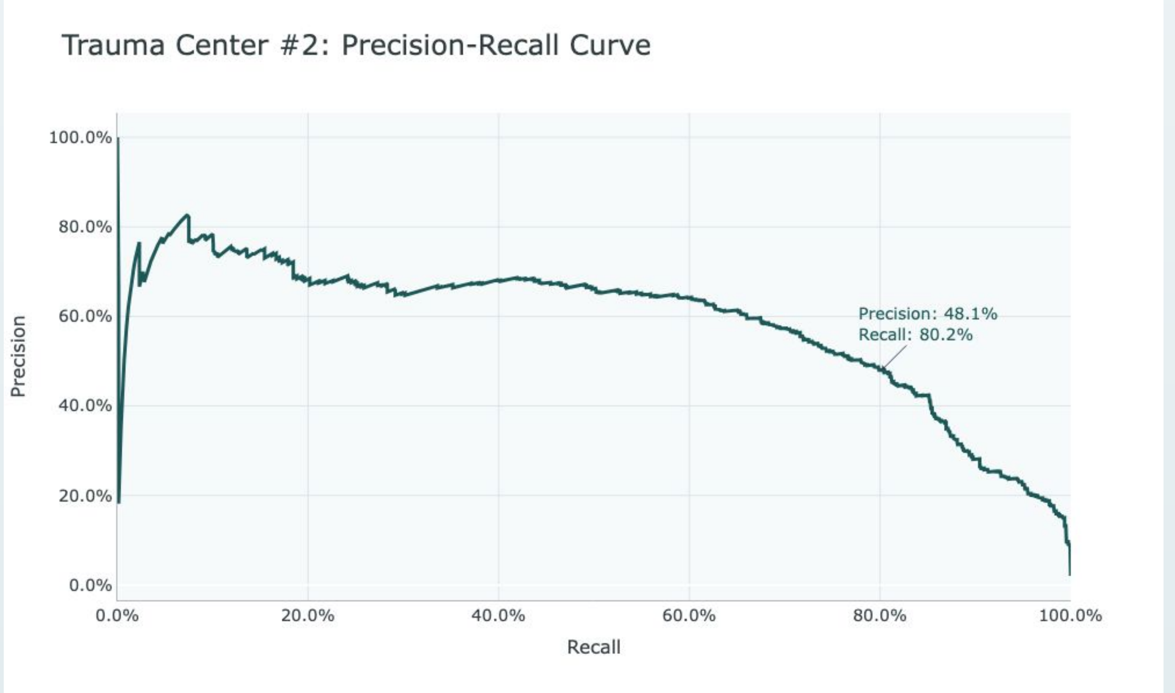
The machine learning models demonstrated strong performance in predicting 48-hour mortality across both trauma centers at the predefined threshold of **~80% recall**:

Trauma Center	Mortality Rate	Precision
#1	4.5%	**35.6%**
#2	7.0%	**48.1%**

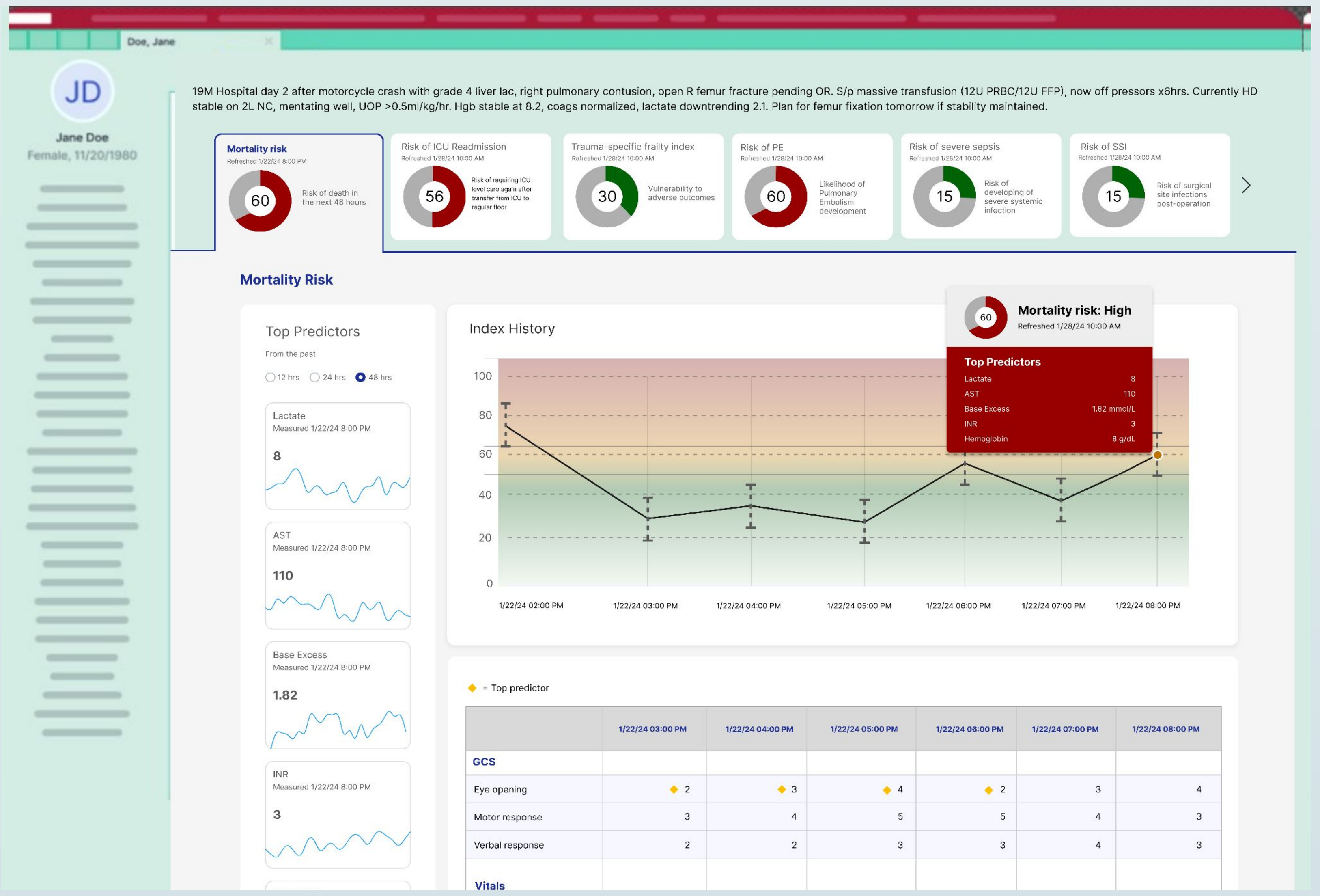
- Both models operated using EHR data available within the **first hour of admission**, supporting early clinical decision-making.
- **Top predictors** differed by site, reflecting local data characteristics:
  - **Center 1:** GCS, lactate, systolic blood pressure
  - **Center 2:** GCS, BUN, potassium
- Differences in performance may reflect **variability in patient populations, data availability, and institutional workflows.**

These results support the potential for AI-driven tools to identify high-risk patients early in trauma workflows using routinely collected EHR data.





Turning Data into Clinical Stories



Clinicians don't make decisions from numbers alone—they rely on clear narratives to act swiftly and decisively. With direct input from trauma surgeons and critical care nurses, we designed our user interface to transform complex AI-driven predictions into clear, intuitive visual narratives.

Clinicians instantly grasp a patient's evolving clinical story, highlighting critical risks and urgent priorities, ensuring timely and informed interventions when every moment counts.

Less complexity. Clearer narratives. Better decisions.

Conclusion

This study demonstrates the feasibility of building high-performing, real-time machine learning models to predict early mortality in polytrauma patients. Importantly, by grounding model development in clinical feedback and workflow compatibility, we improved interpretability and utility at the point of care.

Performance across two institutions validates the adaptability of our approach, and the models significantly outperform clinician-estimated baselines for mortality risk assessment.

Future Work

Ongoing work includes:

- **EHR Integration:** Embedding models into trauma workflows using SMART on FHIR and FHIR API standards
- **Prospective Validation:** Assessing model impact on clinical decision-making, care prioritization, and patient outcomes
- **Scalability:** Expansion to additional trauma centers and inclusion of transfer patients to improve generalizability

References

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