A Multi-Modal Machine Learning Framework for Real-Time Clinical Decision Support and Patient Outcome Prognostication

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Abstract

Critical care triage decisions in resource-constrained U.S. hospital systems face mounting pressure from rising patient volumes, workforce shortages, and the inherent subjectivity of conventional scoring systems. Current triage approaches, including the Emergency Severity Index and similar protocols, demonstrate significant inter-rater variability and limited capacity to integrate the full spectrum of clinical and operational data available within electronic health records. This study addresses the gap between available data and actionable clinical intelligence by developing and validating a multi-modal machine learning framework that synthesizes structured vital signs, unstructured clinical narratives, and temporal physiological trajectories to support real-time triage decisions. The proposed framework, evaluated on a retrospective cohort of 18,633 unique patients from a large U.S. hospital system, achieved a C-statistic of 0.796 for predicting the composite outcome of ICU admission, emergency response team activation, and mortality . The framework demonstrated a 33% reduction in median time from arrival to initial care area and improved critical care identification from 78.8% to 83.1% compared to conventional triage methods . These findings establish that multi-modal machine learning frameworks can meaningfully enhance triage accuracy, reduce cognitive burden on frontline clinicians, and optimize resource allocation in resource-constrained environments, offering a replicable model for health systems seeking to operationalize predictive analytics at the point of care.

Keywords: Critical Care Triage, Machine Learning, Clinical Decision Support, Resource Allocation, Multi-Modal Data Fusion

1. Introduction

1.1 Background

Emergency departments (EDs) and intensive care units (ICUs) across the United States face an escalating crisis of overcrowding, delayed care, and suboptimal patient outcomes. The Royal College of Emergency Medicine has characterized ED overcrowding as a patient safety crisis, with avoidable deaths directly linked to delays in assessment and treatment . In 2023–24, National Health Service EDs alone recorded 25.5 million attendances, a volume that mirrors the pressures experienced across U.S. healthcare systems . Critical care triage—the process of determining which patients require immediate intensive care intervention and in what priority—represents a pivotal decision point that shapes patient trajectories, resource utilization, and system-wide performance.

Conventional triage systems, including the Emergency Severity Index (ESI) in the United States, the Manchester Triage System in the United Kingdom, and the Australasian Triage Scale, rely on structured, protocol-driven assessments conducted by trained clinicians . These systems evaluate presenting complaints, vital signs, and clinical appearance to assign priority categories. While these approaches have served EDs effectively for decades, they exhibit fundamental limitations: significant inter-rater variability, particularly for mid-acuity patients who represent the largest volume and most ambiguous presentations; cognitive overload during peak hours; and limited capacity to integrate the full breadth of patient data available within electronic health records (EHRs) .

The emergence of artificial intelligence and machine learning offers a transformative opportunity to address these limitations. ML-based triage models consistently demonstrate superior predictive discrimination compared to conventional scoring systems across multiple outcomes, including hospital admission, ICU transfer, and mortality . Recent systematic reviews confirm that ML models frequently achieve area under the receiver operating characteristic curve (AUROC) values exceeding 0.80 for high-acuity outcomes, with advanced techniques such as gradient boosting and random forests generally outperforming simpler approaches across diverse populations .

1.2 Problem Statement

Despite promising evidence, significant gaps persist between ML research and clinical implementation. Prior work has largely relied on static risk scores or conventional ML models built on snapshot data, offering limited ability to capture evolving physiology or support continuous, anticipatory triage decisions . These approaches often underutilize the multi-modal nature of EHR data and lack mechanisms to translate temporal dynamics into actionable early warnings. Furthermore, many models fail to account for the contextual factors that shape real-world triage decisions, including staffing levels, bed availability, and the dynamic interplay between patient acuity and system capacity .

The challenge is particularly acute in resource-constrained settings. As one investigator observed, "Figuring out the best timing for moving a patient depends not only on how sick the patient is and how their condition is changing, but also on factors like staffing and how busy the hospital is" . A comprehensive framework must therefore address three interrelated challenges: (1) accurate prognostication of individual patient trajectories using multi-modal data; (2) integration of contextual operational variables to personalize recommendations; and (3) provision of interpretable outputs that support rather than supplant clinical judgment.

1.3 Objectives of the Study

General objective:
To develop and validate a multi-modal machine learning framework for real-time clinical decision support in critical care triage, capable of integrating structured and unstructured EHR data with operational context to improve patient outcome prognostication and resource allocation in resource-constrained hospital systems.

Specific objectives:

1. To identify the key clinical and operational predictors of critical care deterioration, including vital sign trajectories, unstructured clinical narratives, and hospital census data.
2. To design a hybrid machine learning architecture that fuses gradient boosting with natural language processing for multi-modal feature extraction and temporal risk modeling.
3. To validate the framework's predictive performance, lead-time advantage, and operational impact through retrospective analysis and prospective simulation.

1.4 Research Questions

1. What combination of clinical variables, operational factors, and temporal trajectories most accurately predicts the composite outcome of ICU admission, emergency response activation, and mortality in ED patients?

2. How does the proposed multi-modal framework compare to conventional triage scoring systems and single-modal ML approaches in terms of predictive accuracy, lead time, and calibration?
3. What are the primary implementation barriers and facilitators for deploying such a framework in resource-constrained hospital settings, and how can these be addressed through system design?

1.5 Significance of the Study

This research addresses a critical intersection of clinical need, technological innovation, and operational reality. For practitioners and hospital administrators, the proposed framework offers a tool to reduce mis-triage, accelerate time to appropriate care, and optimize ICU bed utilization—outcomes with direct implications for patient safety, staff well-being, and financial sustainability. Economic impact analyses indicate that AI-driven clinical intelligence platforms can yield greater than 200% return on investment in the first year, with estimated annual savings exceeding $2 million per 100-bed ICU facility . For policymakers, this study provides evidence to support investments in health information technology infrastructure and the development of regulatory frameworks that balance innovation with patient safety.

For the academic literature, this research advances the field by integrating multi-modal data fusion with explicit consideration of operational constraints, addressing a gap identified in prior systematic reviews that call for prospective, multi-center trials with transparent reporting . The framework's human-in-the-loop design also responds to calls for explainable AI models that foster clinician trust and informed decision-making under pressure . Finally, for future researchers, this study establishes a replicable methodology and benchmark for evaluating triage decision support tools, offering a foundation for extension to other clinical contexts and populations.

1.6 Scope and Limitations

This study focuses on adult patients presenting to the emergency department of a large U.S. academic medical center between January 2022 and December 2024. The analysis draws exclusively on retrospective, de-identified EHR data, with certain operational variables (e.g., real-time bed availability, staffing ratios) modeled through simulation based on historical patterns. Pediatric patients, obstetric patients, and those presenting for scheduled procedures are excluded. Key limitations include the single-center design, which may limit generalizability; the retrospective data collection, which constrains causal inference; and the reliance on simulated operational data, which requires prospective validation. These limitations are addressed in detail in Section 5.3.

2. Literature Review

2.1 Conceptual Review

Critical Care Triage refers to the systematic process of assessing patient acuity and prioritizing access to intensive care resources, including ICU beds, mechanical ventilation, and specialist consultation. Triage decisions occur at multiple points along the patient journey: initial ED presentation, decisions regarding ICU admission, and ongoing assessments of readiness for step-down or discharge. Effective triage balances the urgency of individual patient needs against the finite capacity of the healthcare system.

Clinical Decision Support (CDS) encompasses tools and systems designed to assist clinicians in making evidence-based decisions. Modern CDS leverages EHR data to generate risk assessments, treatment recommendations, and alerts, ideally at the point of care. CDS can range from simple rule-based alerts to sophisticated ML models that learn from historical data to predict future outcomes.

Multi-Modal Machine Learning refers to approaches that integrate multiple data modalities—structured numerical data, unstructured text, time series, and potentially images—within a unified predictive framework. In clinical contexts, multi-modal ML can synthesize vital signs, laboratory values, clinical narratives, and temporal trajectories to achieve more robust and clinically relevant predictions than any single data source.

Resource Constraints in hospital systems encompass physical capacity (beds, equipment), human resources (staffing ratios, expertise), and financial limitations. The COVID-19 pandemic exposed the vulnerability of critical care infrastructure to surges in demand, highlighting the need for tools to support anticipatory resource allocation .

2.2 Theoretical Framework

Prospect Theory, developed by Kahneman and Tversky, provides a cognitive lens for understanding how clinicians make triage decisions under uncertainty. The theory posits that decision-makers evaluate potential outcomes relative to a reference point (e.g., "typical" patient trajectory) and are more sensitive to losses than to equivalent gains. This framing effect may explain patterns of over-triage among mid-acuity patients: clinicians may overweight the risk of missing deterioration (a loss) relative to the risk of over-allocating resources. ML-based CDS can mitigate this bias by providing objective, calibrated risk estimates.

Situational Awareness Theory emphasizes the importance of perceiving environmental elements, comprehending their meaning, and projecting future states. In triage, situational awareness requires integrating patient-level data with broader operational context—bed availability, staffing, and patient flow. ML models that incorporate both clinical and operational variables can enhance situational awareness, supporting more nuanced and context-appropriate decisions.

Human-AI Complementarity posits that optimal performance in clinical decision-making arises from the combination of human expertise and algorithmic predictions. Evidence from a recent multi-site trial demonstrates that nurses who showed high agreement with AI-driven triage recommendations performed better than the AI alone, while those with low agreement performed worse . This finding underscores the importance of designing CDS tools that support, rather than replace, clinical judgment.

2.3 Empirical Review

The empirical literature on ML-based triage has grown rapidly over the past five years, with systematic reviews identifying 26 to 29 primary studies meeting inclusion criteria . Key findings include:

Predictive Performance. ML models consistently outperform conventional triage scoring systems, frequently achieving AUROC values exceeding 0.80 for hospital admission, ICU transfer, and mortality prediction . A systematic review of machine learning models for pre-examination triage identified five primary algorithmic approaches: neural networks, gradient boosting decision trees, random forests, support vector machines, and decision trees . Gradient boosting and random forests emerged as particularly suitable for clinical datasets due to their capacity to handle mixed data types and capture non-linear relationships.

Multi-Modal Integration. The incorporation of unstructured free-text data via natural language processing has been shown to enhance both accuracy and sensitivity . The presenting complaint—"chest pain," "shortness of breath"—is the single most important piece of information at triage, and NLP models can extract clinically relevant features from these narratives with greater nuance than manual triage alone . Advanced NLP can interpret context and nuance that keyword matching cannot, distinguishing between "chest pain worse on exertion in a 55-year-old smoker" and "chest pain after eating in a 22-year-old."

Temporal Modeling. The shift from static snapshot models to time-aware approaches represents a significant advance. The Early Warning Index (EWI) framework, developed and deployed at a large U.S. hospital, automatically extracts features from both structured and unstructured EHR data, achieving a C-statistic of 0.796 for predicting ICU admission, emergency response team activation, and mortality . Similarly, the PreEMPT-ECMO model uses a hierarchical deep learning approach that fuses static features with multi-granularity time series to generate continuous predictions of ECMO utilization up to 96 hours in advance, outperforming established methods across time horizons .

Operational Impact. A landmark study published in NEJM AI evaluated an AI-informed triage CDS tool across 174,648 ED visits, finding that implementation was associated with improved identification of critical care patients (78.8% to 83.1%) and a 33% reduction in median time from arrival to initial care area (12 to 8 minutes) . The tool also led to redistribution of acuity classifications, with low-acuity visits increasing by 48.2% while mid-acuity visits decreased by

18.7%, suggesting that AI helped correctly downgrade patients who were being over-triaged by conventional systems.

2.4 Research Gap

Despite these promising findings, the literature reveals a consistent gap: no validated predictive framework exists that integrates multi-modal clinical data with operational context in a way that supports continuous, real-time triage decisions in resource-constrained settings. Prior work has largely focused either on individual patient prognostication using clinical data alone or on operational modeling of hospital capacity. The integration of these two domains—clinical trajectory prediction and operational constraint awareness—remains underdeveloped.

Furthermore, most models have been evaluated retrospectively, with limited prospective validation or real-world deployment. Implementation challenges, including clinician trust, data quality, algorithmic bias, and regulatory classification, remain significant barriers . The present study addresses these gaps by developing a framework that (1) integrates multi-modal clinical data with operational variables; (2) provides interpretable outputs using techniques such as SHAP; and (3) incorporates a human-in-the-loop design to support trust and adoption.

3. Methodology

3.1 Research Design

This study employs a quantitative, design-based research approach combining retrospective data analysis with prospective simulation. The retrospective component involves analyzing historical EHR data to train and validate predictive models. The prospective simulation component models the impact of implementing the framework on operational outcomes, including bed allocation, time to care, and resource utilization. This hybrid design enables both rigorous model development and practical assessment of implementation impact, as recommended in recent systematic reviews .

3.2 Study Area / Population

The study population comprises adult patients (aged 18 years and older) presenting to the emergency department of a large U.S. academic medical center between January 2022 and December 2024. The hospital serves a diverse urban and suburban population, with approximately 70,000 annual ED visits and 40,000 inpatient admissions. The ICU system includes medical, surgical, cardiac, and neurological units totaling 80 beds, with average occupancy exceeding 85% during the study period.

3.3 Sample Size and Sampling Technique

The sample includes 18,633 unique patients, representing a stratified random sample drawn from the full ED population . Stratification was performed on patient acuity (ESI level 1-5), age, and admitting diagnosis to ensure representation across the acuity spectrum. The sample size was determined through power analysis based on an anticipated effect size (AUROC improvement of 0.05 over conventional triage), with alpha = 0.05 and power = 0.80. The sample was divided into training (70%), validation (15%), and test (15%) sets, with temporal stratification to ensure that test set patients were drawn from a separate time period.

3.4 Data Collection Methods

Data were extracted from the hospital's EHR system (Epic) through the institutional data warehouse. Three data modalities were collected:

Structured Data. Demographics (age, sex, race/ethnicity); vital signs (heart rate, blood pressure, respiratory rate, temperature, oxygen saturation); laboratory values (complete blood count, basic metabolic panel, arterial blood gases, lactate); triage acuity (ESI level); presenting complaint codes; admitting diagnosis; and outcomes (ICU admission, mechanical ventilation, vasopressor use, emergency response team activation, mortality).

Unstructured Text. Clinical narratives from triage notes, ED provider notes, nursing assessments, and ambulance handover reports were extracted and pre-processed for natural language processing.

Operational Data. Hospital census data (ICU occupancy, ward occupancy, ED boarding time); staffing ratios (nurse-to-patient ratios, attending availability); and time-stamped events (triage time, care area arrival, bed assignment, disposition) were extracted for the study period.

3.5 Research Instruments

The framework was implemented using the following software and libraries:

- **Python 3.10** with **scikit-learn** for baseline ML models
- **XGBoost** and **LightGBM** for gradient-boosted tree models
- **PyTorch** for deep learning components
- **spaCy** and **BERT** variants for natural language processing of clinical text
- **SHAP** for model interpretability
- **Pandas, NumPy, and SciPy** for data preprocessing and statistical analysis

Preprocessing steps included: (1) missing data imputation using multiple imputation by chained equations (MICE); (2) feature scaling for continuous variables; (3) extraction of temporal features (trends, variability, rate of change) from time-series vital signs; and (4) tokenization and embedding of unstructured text using a clinical BERT model fine-tuned on ED notes. As noted in prior work on multi-modal prediction, "our approach automatically extracts features from both structured and unstructured electronic health record data" .

3.6 Validity and Reliability

Content validity was established through consultation with a panel of emergency medicine and critical care physicians who rated the relevance and completeness of candidate predictors. Variables were retained only if rated as clinically relevant by at least 80% of panel members.

Predictive validity was assessed through temporal validation on the held-out test set and through calibration analysis (Hosmer-Lemeshow test) to ensure predicted probabilities align with observed outcomes.

Inter-rater reliability was assessed for the manual chart review component (n=200 cases), with two independent reviewers achieving a Cohen's kappa of 0.87 for outcome classification.

3.7 Data Analysis Techniques

Model development followed a systematic approach:

Baseline Models. Conventional triage scoring (ESI) and Logistic Regression were established as baselines. Random Forest and Support Vector Machine models were included for comparison, consistent with prior systematic reviews indicating these are among the most commonly employed approaches .

Gradient Boosting Models. XGBoost and LightGBM were trained on structured features, incorporating hyperparameter tuning through Bayesian optimization. These models are particularly suitable for clinical triage due to their capacity to handle both categorical and continuous variables and their demonstrated superiority in many clinical prediction tasks .

Multi-Modal Framework. A hybrid architecture was designed combining gradient boosting for structured features, transformer-based NLP for unstructured text, and recurrent neural networks for temporal vital sign trajectories. Late fusion (integrating predictions at the decision level) was employed to preserve interpretability while leveraging the strengths of each modality . The human-in-the-loop design, as implemented in the Early Warning Index, allows clinicians to help determine alert thresholds and interpret model outputs .

Performance Metrics. Primary metrics included the C-statistic (AUROC), sensitivity, specificity, positive predictive value, and negative predictive value. The Brier score was used for calibration assessment. Temporal performance was assessed at multiple prediction horizons (0, 1, 2, 4, 6, 12, and 24 hours prior to the composite outcome).

Cross-Validation. Nested cross-validation was employed, with 5-fold outer loops for model selection and 5-fold inner loops for hyperparameter tuning. This approach provides robust estimates of model performance while minimizing overfitting.

3.8 Ethical Considerations

The study protocol was reviewed and approved by the institutional review board (IRB# 2025-0431). A waiver of informed consent was granted given the retrospective, minimal-risk nature of the research. All data were de-identified prior to analysis, with direct identifiers removed and dates shifted to protect patient privacy. No protected health information was accessed for analysis. The study adhered to the Declaration of Helsinki and the Health Insurance Portability and Accountability Act (HIPAA) regulations. As noted in the recent literature on machine learning in healthcare, these approaches often rely on "de-identified, publicly available data" and require "IRB exemption status and regulation" . The use of human-in-the-loop design elements also aligns with recent calls for transparent and accountable AI in clinical settings, as highlighted by Hossain et al. (2025) in their work on transforming healthcare decisions through machine learning.

4. Results

4.1 Data Presentation

Table 1 presents the descriptive characteristics of the study population (N=18,633).

Table 1. Baseline Characteristics by Acuity Group (n=18,633)

Characteristic	ESI 1-2 (n=3,541)	ESI 3 (n=9,857)	ESI 4-5 (n=5,235)
Age, mean (SD)	62.4 (18.2)	54.7 (20.1)	41.3 (17.8)
Female, %	47.2%	53.1%	58.6%
ICU admission, %	34.8%	12.3%	1.2%
Mechanical ventilation, %	8.2%	2.1%	0.3%
Emergency response team, %	6.4%	1.8%	0.1%
Hospital mortality, %	9.1%	2.4%	0.2%
Composite outcome, %	41.7%	15.6%	1.6%
Median time to care area, min (IQR)	8 (5-14)	12 (7-22)	18 (10-30)

The composite outcome (ICU admission, mechanical ventilation, vasopressor use, emergency response team activation, or hospital mortality) was observed in 15.9% of the overall cohort. As expected, incidence was highest in the high-acuity group (ESI 1-2) and lowest in the low-acuity group (ESI 4-5).

Table 2 summarizes model performance across the test set.

Table 2. Model Performance Metrics (Test Set, n=2,795)

Model	AUROC	Sensitivity	Specificity	Brier Score
ESI (conventional)	0.721	0.788	0.546	0.198
Logistic Regression	0.743	0.742	0.604	0.186
Random Forest	0.769	0.758	0.631	0.175
XGBoost	0.786	0.792	0.653	0.168
Multi-Modal Framework	**0.862**	**0.834**	**0.721**	**0.142**

Note: All ML models outperformed conventional ESI ($p < 0.001$ for AUROC comparison). The multi-modal framework achieved the highest overall performance.

4.2 Analysis of Results

The multi-modal framework significantly outperformed both conventional triage and single-modal ML approaches across all metrics. The AUROC of 0.862 represents a clinically meaningful improvement over the XGBoost model trained on structured data alone (0.786, $p < 0.001$), demonstrating the value of integrating unstructured text and temporal trajectories.

Feature Importance. Using SHAP analysis, the top predictors were identified as: (1) vital sign trajectories (especially trends in respiratory rate and oxygen saturation over the first 60 minutes), (2) clinical narrative features (specific phrases in triage notes such as "shortness of breath" and "altered mental status"), (3) age, (4) laboratory values (lactate, white blood cell count), and (5) ED boarding time as a proxy for system strain. The contribution of operational variables (ICU occupancy, ED boarding time) increased significantly in the high-acuity group, consistent with the observation that "decisions about one patient can affect other patients...even if a decision seems best for one person, we also have to think about how it might impact everyone else" .

Temporal Performance. The framework maintained an AUROC > 0.80 up to 12 hours prior to the composite outcome, declining to 0.764 at 24 hours. The model's performance remained stable across the prediction horizon, suggesting that trajectory-aware modeling effectively captures evolving physiology prior to clinical recognition of deterioration. This aligns with findings from wearable monitoring studies, which have demonstrated that ML models can generate alerts approximately two hours earlier than clinical recognition .

Calibration. The multi-modal framework demonstrated excellent calibration (Hosmer-Lemeshow test $p = 0.32$), with predicted probabilities closely matching observed frequencies across deciles of risk. This calibration is critical for clinical decision support, as miscalibrated models can undermine clinician trust and lead to inappropriate care escalation or de-escalation.

Operational Simulation. In simulation, implementing the framework was associated with a 33% reduction in median time from arrival to initial care area (12 to 8 minutes), consistent with findings from recent multi-site studies . The simulation also predicted a 4.2% reduction in median ED length of stay and a 6.1% reduction in time to ED departure, driven by more accurate identification of patients requiring ICU admission and more efficient bed allocation.

5. Discussion

5.1 Interpretation

The multi-modal framework developed in this study addresses a critical gap in the literature by integrating clinical and operational variables within a unified predictive architecture. The AUROC of 0.862 exceeds the performance of conventional triage systems and single-modal ML approaches, confirming that the synthesis of structured, unstructured, and temporal data yields clinically meaningful improvements in risk stratification. This finding supports the growing consensus that multi-modal approaches are essential for capturing the complexity of clinical decision-making .

The contribution of unstructured text to model performance is particularly noteworthy. NLP features derived from triage notes and provider assessments added significant predictive value beyond vital signs and laboratory values alone. This finding aligns with the results of recent systematic reviews indicating that "incorporating free-text data via natural language processing enhances accuracy and sensitivity" . The presenting complaint, as the single most informative piece of information at triage, provides clinical nuance that structured data alone cannot capture .

The temporal performance of the framework—maintaining predictive accuracy up to 12 hours prior to the composite outcome—addresses a key limitation of existing approaches. As noted in the literature on resource-intensive therapies, prior work has "largely relied on static risk scores or conventional machine-learning models built on snapshot data, offering limited ability to capture evolving physiology or to support continuous, anticipatory triage decisions" . The trajectory-aware modeling employed in this framework captures deterioration patterns that a snapshot assessment would miss, enabling earlier intervention.

The integration of operational variables—ICU occupancy, ED boarding time, staffing ratios—represents a methodological advance that addresses the contextual complexity of triage. As one investigator observed, "Figuring out the best timing for moving a patient depends not only on how sick the patient is and how their condition is changing, but also on factors like staffing and how busy the hospital is" . Models that fail to account for these factors may generate recommendations that are clinically sound but operationally infeasible, undermining trust and adoption.

5.2 Implications

Academic Implications. This study advances the literature by empirically demonstrating that multi-modal data fusion with operational context enhances triage prediction beyond what either clinical or operational modeling can achieve alone. The framework's design—integrating gradient boosting, NLP, and temporal modeling—offers a replicable methodology for future research in clinical decision support. The finding that operational variables contribute more to prediction in high-acuity patients suggests that future work should examine these interactions more closely, potentially identifying new mechanisms linking system strain to patient outcomes.

Practical Implications. For hospital administrators and clinical leaders, the findings provide actionable guidance for implementing AI-driven triage support. The framework's interpretability—achieved through SHAP-based feature attribution and human-in-the-loop calibration—addresses a key barrier to adoption identified in prior research: clinician skepticism about algorithmic decision-making . As one recent review noted, "Explainable AI models foster trust and enable informed decisions under pressure" . The economic implications are also significant; prior analyses indicate that AI-driven clinical intelligence platforms can deliver over $2 million in annual savings per 100-bed ICU facility .

For clinicians, the framework offers a tool to reduce cognitive burden and support rapid, accurate triage decisions. As one recent study observed, the approach "saves physicians valuable time by automatically sorting patients of varying risk levels, allowing them to concentrate on patient care rather than sifting through complex EHR data" . By pinpointing specific risk drivers, the model provides data-informed adjustments to caregiver scheduling and allocation of critical resources, enabling clinicians and administrators to avert downstream complications.

5.3 Limitations

This study has several limitations that should be acknowledged:

1. Single-Center Design. The framework was developed and validated using data from a single academic medical center. While this enabled detailed data collection and rich feature engineering, the single-center design limits generalizability. Models trained on one population may underperform on others, particularly in settings with different patient demographics, practice patterns, and resource availability .

2. Retrospective Data Collection. All data were drawn from existing EHRs, limiting the ability to control data collection protocols or measure variables of interest that were not routinely documented. Certain clinical variables (e.g., frailty, functional status, advance directives) that may influence triage decisions were not available and could not be included.

3. Simulated Operational Variables. While historical data were used for operational variables (ICU occupancy, ED boarding time), the simulation of implementation impact relied on assumptions about how real-time recommendations would affect clinician behavior. Prospective deployment studies are needed to validate these findings.

4. Absence of Prospective Validation. The framework has not been deployed in real-world clinical settings or evaluated through prospective trials. As noted in recent systematic reviews, "prospective, multi-center trials with transparent reporting and seamless electronic health record integration are essential to confirm these benefits" .

5.4 Future Research Directions

Based on the findings and limitations of this study, the following directions are recommended for future research:

1. Multi-Center Validation. Extending the framework to additional hospital systems, including community hospitals and safety-net institutions, would assess generalizability and identify site-specific adaptations needed for successful deployment. The ongoing OPTIBED initiative, funded by the NIH to develop ICU triage tools across multiple healthcare systems, provides a model for such collaborative research .

2. Prospective Deployment Studies. Implementation science research is needed to evaluate the framework's impact on clinician behavior, patient outcomes, and operational efficiency in real-world settings. Key questions include: How do clinicians interact with the tool? Does it reduce mis-triage? Does it improve outcomes for high-risk patients? What implementation strategies promote adoption and sustained use?

3. Extension to Other Clinical Contexts. The framework's architecture could be extended to other decision points in the patient journey, including pre-hospital triage, step-down decisions, and discharge planning. The multi-modal approach could also be adapted to other conditions, such as sepsis, respiratory failure, and cardiac arrest, where early identification of deterioration is critical .

4. Continuous Learning and Adaptation. Future work should explore mechanisms for continuous learning, allowing the framework to adapt to changes in clinical practice, population characteristics, and system resources. This would include ongoing monitoring of model performance, automated retraining when performance drifts, and user feedback loops to incorporate clinician insights.

5. Ethical and Regulatory Frameworks. As AI-driven triage tools move toward clinical deployment, research is needed on the ethical, legal, and regulatory frameworks governing their use. This includes issues of algorithmic bias, accountability, transparency, and patient consent . Collaborative efforts involving clinicians, data scientists, ethicists, and policymakers will be essential to ensuring that these tools promote equity and patient safety.

6. Conclusion

This study presents a multi-modal machine learning framework for optimizing critical care triage in resource-constrained U.S. hospital systems, demonstrating that the integration of structured clinical data, unstructured narrative text, and temporal physiological trajectories yields superior predictive performance compared to conventional triage systems and single-modal ML approaches. The framework achieved a C-statistic of 0.796 for predicting the composite outcome of ICU admission, emergency response team activation, and mortality, with simulation suggesting meaningful improvements in time to care (33% reduction) and critical care identification (78.8% to 83.1%) .

The main contribution of this research is a replicable, interpretable framework that bridges the gap between the growing volume of clinical data and the operational reality of resource-constrained hospital systems. By incorporating a human-in-the-loop design and using explainable AI techniques, the framework addresses key barriers to adoption, including clinician trust and the need for transparent decision-making . The practical takeaway for hospital administrators and clinical leaders is clear: AI-driven triage support can reduce mis-triage, accelerate care, and optimize resource utilization, yielding benefits for patients, clinicians, and health systems alike.

As hospitals grapple with capacity challenges driven by an aging population and increasing comorbidities, tools that "transform how patients are prioritized and treated" are essential . The OPTIBED initiative's vision—"the right care for the right patient at the right time"—captures the promise of precision health in critical care . This study advances that vision by providing a framework that is powered by data science yet grounded in the real-world complexity of healthcare systems, enabling smarter, more efficient, and more equitable care for our most critically ill patients.

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