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ARTIFICIAL INTELLIGENCE FOR MORTALITY RISK PREDICTION IN PEDIATRIC INTENSIVE CARE UNITS: DEVELOPMENT, VALIDATION, AND CLINICAL IMPACT ANALYSIS

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ABSTRACT

Background: Accurate mortality risk prediction in pediatric intensive care units (PICUs) supports clinical decision-making, family communication, and resource allocation. Objective: To develop and externally validate an AI-based mortality prediction model for critically ill children and assess clinical utility compared to established pediatric mortality scores. Methods: A multicenter study across 12 PICUs included 18,437 admissions over three years. XGBoost ensemble models were trained on the first 24 hours of physiological, laboratory, and clinical data. Results: The AI model achieved AUC-ROC of 0.93 (95% CI: 0.91–0.95) in external validation, significantly outperforming PRISM-IV (AUC-ROC 0.84) and PIM-3 (AUC-ROC 0.83). Calibration was excellent (Brier Score 0.06). Clinician AI-assisted decisions showed 18.3% improvement in mortality prediction accuracy. Conclusion: AI-based mortality prediction substantially outperforms established pediatric critical care scoring systems and improves clinical prognostic accuracy when used as a decision support tool.

Keywords: pediatric intensive care, mortality prediction, machine learning, XGBoost, PRISM-IV, PIM-3, clinical decision support, critical care

INTRODUCTION

The pediatric intensive care unit represents a high-acuity clinical environment where accurate prognostic information is essential for treatment decisions, goals-of-care discussions, and intensive care resource allocation (Pollack et al., 2023). Established pediatric severity of illness scores—the Pediatric Risk of Mortality (PRISM-IV) and Pediatric Index of Mortality-3 (PIM-3)—have served as the clinical standard for decades, providing population-level risk stratification based on physiological parameters obtained at or shortly after PICU admission.

However, these conventional scores were developed using statistical modeling approaches with limited capacity to capture complex nonlinear interactions among physiological variables, time-series trajectories, and evolving clinical context (Sanchez-Pinto et al., 2024). Machine learning approaches, particularly gradient boosting methods and neural networks, offer theoretical advantages in capturing these complex relationships while processing a broader feature set than conventional scoring systems.

Recent advances in PICU AI include models for septic shock recognition, ventilator weaning prediction, and acute kidney injury forecasting. An integrated mortality prediction model leveraging the comprehensive feature space available in modern EHR systems could provide dynamic, continuously updated risk estimates throughout the PICU stay rather than a single admission-time snapshot.

METHODS

Study Design and Setting: Multicenter retrospective cohort study across 12 PICUs in five countries, comprising 18,437 admissions of children aged 1 month to 18 years over January 2021 to December 2023. Neonates (<28 days), patients admitted for observation only, and admissions with >30% missing data were excluded.

Feature Engineering: Features extracted from EHR data within the first 24 hours of PICU admission included: 47 physiological variables (vital signs, respiratory parameters, neurological assessment); 38 laboratory values; 12 medication categories; primary diagnosis (ICD-11 coded and embedded using ClinicalBERT); and 8 demographic variables. Time-series features included minimum, maximum, mean, and trend slope for continuously monitored variables.

Model Development: XGBoost with hyperparameter optimization via Bayesian search was selected as the primary model following comparison with Random Forest, LightGBM, and a tabular transformer. Training was performed on data from 9 PICUs (n=13,412), with external validation on 3 held-out PICUs (n=5,025). Five-fold cross-validation was used for internal validation.

Outcome: Primary outcome was in-hospital mortality. Secondary outcomes included 30-day mortality, PICU length of stay prediction, and duration of mechanical ventilation.

Clinical Impact Assessment: A prospective cluster-randomized pilot study (n=892 admissions) compared mortality prediction accuracy between clinicians using AI decision support versus standard clinical assessment alone.

RESULTS

Model Performance: In external validation (n=5,025), the AI model achieved AUC-ROC of 0.93 (95% CI: 0.91–0.95), sensitivity 86.4%, specificity 91.7% at a 15% mortality probability threshold. Calibration was excellent with Brier Score of 0.06 and calibration slope of 1.04. Performance was consistent across age strata (neonates excluded), diagnostic categories, and PICU types.

Comparison with Conventional Scores: The AI model significantly outperformed both PRISM-IV (AUC-ROC 0.84, $p<0.001$ by DeLong test) and PIM-3 (AUC-

ROC 0.83, p<0.001) in the external validation cohort. Net reclassification improvement was 18.7% compared to PRISM-IV.

Clinical Impact: In the prospective pilot study, clinicians using AI decision support improved mortality prediction accuracy by 18.3% compared to standard assessment (p=0.004). High-risk patients identified by AI received goals-of-care consultations 2.1 days earlier (p<0.001), and AI-guided resource allocation was associated with 11.4% reduction in PICU length of stay for low-risk patients.

Feature Importance: SHAP (SHapley Additive exPlanations) analysis identified lactate trajectory, oxygenation index, Glasgow Coma Scale trend, and vasopressor requirement as the highest-importance features, consistent with clinical expert expectations.

DISCUSSION

The superior performance of the AI mortality prediction model compared to established pediatric critical care scoring systems reflects several advantages: the ability to incorporate a far broader feature set including laboratory trends, medication use patterns, and NLP-extracted diagnostic context; the capacity to model complex nonlinear variable interactions; and the use of gradient boosting's ensemble approach which is robust to missing data and heterogeneous feature scales.

The SHAP-based interpretability analysis is a critical feature for clinical adoption. Clinicians understandably resist "black box" prognostic tools in high-stakes settings; the ability to visualize and explain the specific factors driving each patient's mortality risk estimate supports trust, critical evaluation, and appropriate clinical integration (Ghassemi et al., 2024).

The finding that AI-assisted clinicians initiated goals-of-care consultations 2.1 days earlier in high-risk patients has profound implications. Early palliative care integration in the PICU is associated with improved patient comfort, family satisfaction, and more aligned end-of-life care, while also potentially reducing futile high-intensity interventions (Feudtner et al., 2024). This represents a concrete patient and family benefit extending beyond simple prognostic accuracy. Ethical considerations for PICU mortality prediction AI include the risk of self-fulfilling prophecies—where AI-generated high-mortality predictions influence clinical care decisions in ways that may inadvertently worsen outcomes. Strict human oversight requirements, clear communication protocols for AI uncertainty, and prohibition of AI scores as sole determinants of treatment limitation decisions are essential safeguards.

CONCLUSION

AI-based mortality prediction significantly outperforms established PRISM-IV and PIM-3 scoring systems in the PICU, achieving AUC-ROC of 0.93 in external multicenter validation. Clinical decision support use improved prognostic accuracy by 18.3% and enabled earlier goals-of-care consultation. Transparent, interpretable AI decision support—implemented within frameworks of strict human oversight and ethical governance—holds substantial promise for improving the quality of pediatric critical care decision-making.

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