Abstract Title: Perioperative Risk Factors Associated with Unplanned Escalation of Care after Post-Anesthesia Care Unit Discharge

Presenting Author: Ryan L. Melvin, M.A., Ph.D., University of Alabama at Birmingham, Department of Anesthesiology and Perioperative Medicine

Co-Authors: Ryan Godwin, MS, PhD, University of Alabama at Birmingham, Department of Anesthesiology and Perioperative Medicine, Department of Radiology; Andrew B. Barker, M.D., University of Alabama at Birmingham, Department of Anesthesiology and Perioperative Medicine; Brant Wagener, M.D., Ph.D., University of Alabama at Birmingham, Department of Anesthesiology and Perioperative Medicine

Following Post-Anesthesia Care Unit (PACU) discharge, a number of patients require unexpected escalations in clinical care leading to transfer to intermediate care or the intensive care unit (ICU) setting. This study seeks to determine modifiable risk factors before PACU discharge and apply Artificial Intelligence/Machine Learning to predict patients that require escalations in clinical care to provide more effective patient care in the perioperative period.

We collected data from all non-cardiac surgical patients (n=58,931) discharged from the University of Alabama at Birmingham PACU between 2016 and 2019 in this single-site, retrospective study. Escalation of care was defined as patient transfer from the inpatient floor to either an intermediate care unit or ICU within three midnights of PACU discharge. A "credit scorecard" [1] modeling system was then applied as a set pre- and post-processing step layered on top of logistic regression. Continuous variables were binned into discrete categories and extant categorical variables were grouped using weight-of-evidence (WoE) binning [2]. Post-regression, WoE values were translated from model coefficients to scorecard points. Elastic-net regularized logistic regression served as both a variable selection method and hedge for colinear variables [3]. The final scorecard model range of values (0-100 points) was enforced upon the model by solving a mixed-integer programming problem.

Many of the top risk factors were simply the missingness of charted vital sign data within the last hour before discharge, suggesting immediately modifiable behavior that may improve patient outcomes. When applying the credit scorecard model to the clinical model, the best candidate model's predictive ability places it in the acceptable range (AUC of 0.75, see Figure 1) on holdout data. In holdout data, there was a statistically significant ($p<0.01$) relationship between the model's suggested score bins and the fraction of actual escalations that occurred for patients falling within those bins.

This model is intuitive in that the most important variables (by statistical significance and Shapley Additive Explanations [4,5]) match clinician intuition. Additionally, while there are too many variables to practically calculate by hand, the linear nature of a scorecard model makes it sufficiently simple and explainable that one could calculate the model's output using pencil and paper addition. The ability to understand the modifiable risk factors that lead to increased patient risk of an escalation of care with three midnights of PACU discharge may lead to improved perioperative optimization and bed utilization, translating to improved patient outcomes and more efficient bed flow.

Images:

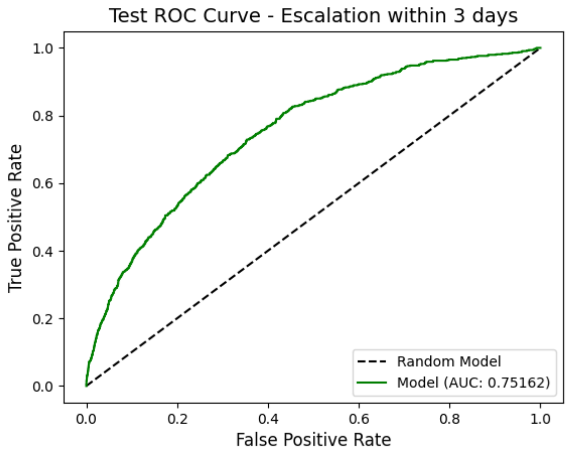

Figure 1: Receiver operating characteristic (ROC) curve is shown for the final model using holdout/ test data not used in model training. The corresponding area under curve (AUC) is presented in the figure legend. An AUC of 0.75 puts this model in an acceptable range of performance.

References

[1] Bailey, M. (2006). *Practical Credit Scoring: Issues and Techniques*. Bristol, United Kingdom: White Box Publishing.

[2] Zdravevski, E., Lameski, P., and Kulakov, A. (2011). Weight of Evidence as a tool for Attribute Transformation in the Preprocessing Stage of Supervised Learning Algorithms in: *The 2011 International Joint Conference on Neural Networks*, 181–188.

[3] Zou, H., and Hastie, T. (2005). Regularization and Variable Selection via the Elastic Net. *J. R. Stat. Soc B* 67 (2), 301–320. doi:10.1111/j.1467-9868.2005.00503.x

[4] Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. *Advances in neural information processing systems*, 30. 4765–774

[5] Aas, K., Jullum, M., & Løland, A. (2021). Explaining individual predictions when features are dependent: More accurate approximations to Shapley values. *Artificial Intelligence*, *298*, 103502.