

## Predicting Cardiac Decompensation and Cardiogenic Shock Phenotypes for Duke University Hospital Patients

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**Background:** The recognition and treatment of cardiogenic shock is difficult, as evidenced by a national in-hospital mortality rate of 27-51%<sup>1</sup>. Cardiologists at Duke identified an opportunity to reduce delayed identification of and intervention for cardiogenic shock, which also afflicts patients at Duke (21-30% in-hospital mortality), by considering the cardiac decompensation clinical phenotypes that lead to cardiogenic shock. Cardiac decompensation can quickly lead to cardiogenic shock without timely medical management<sup>2</sup>. Duke Heart Center and the Duke Institute for Health Innovation formed a transdisciplinary team to define outcomes and create predictive models for six clinical phenotypes within cardiac decompensation, using patient baseline and hospital stay data extracted in real-time from the EHR. These outcomes and models are currently being put into practice to support early intervention pilot workflows in the cardiology units at Duke.

**Methods:** Six clinical phenotypes that encompass cardiac decompensation definitions and outcomes were identified and refined on an inpatient data set. Hypotension evaluates low systolic blood pressure or mean arterial pressure data over a six-hour window. End organ dysfunction uses abnormal lab result data (creatinine, lactate, AST, ALT, bilirubin). Hypoperfusion is an aggregate of phenotypes 1 and 2 through the application of a 24-hour time window restriction on successive hypotension-then-end organ dysfunction events. New administration/escalation of vasopressors uses medication administration data. Respiratory decline uses an upper threshold of oxygen flow and a lower threshold of oxygen saturation as well as absolute and relative rate decreases for partial pressure of oxygen data. Respiratory intervention applies a hierarchical categorization of oxygen device and ventilator support documentation to identify a progression of oxygen support requirement. These six phenotypes, along with deterioration-intervention union outcomes for hypotension-vasopressors and respiratory decline-respiratory intervention, were applied to a retrospective cohort comprised of all adult Duke University Hospital (DUH) admissions during a 35-month timeframe from October 2015 to August 2018. We predict these outcomes within the next 12 and 24 hours, using 347 clinical data elements (e.g., patient labs, analytes, vitals, and comorbidities) to fit models using a light gradient boosted machine (LightGBM). The models were evaluated using a 90:10 test:train split, resulting in the area under the receiver operator characteristic (AUC) and area under the precision-recall curve (AUPRC). LASSO logistic regression, random forest, and XGBoost gradient boosted machine models were also experimented with; however, LightGBM delivered the best balance between training time and performance. Missing values for quantitative variables in the validation and test sets were imputed using means in the training set. The validation set was used to tune hyperparameters.

**Results:** The identified cohort totaled 108,697 unique encounters for 70,529 unique patients. Encounter-level prevalence was assessed for each phenotype outcome: hypotension (17.0%), end organ dysfunction (35.7%), hypoperfusion (6.6%), new vasopressors (8.7%), respiratory decline (25.1%), and respiratory intervention (13.5%). Model results:

Model	Hourly Prevalence	AUROC	AUPRC
hypotension_12	0.0159	0.8317	0.0712
hypotension_24	0.0268	0.8070	0.0924
end organ dysfunction_12	0.0323	0.8299	0.1238
end organ dysfunction_24	0.0519	0.8127	0.1489
hypoperfusion_12	0.0043	0.8421	0.0238
hypoperfusion_24	0.0072	0.7988	0.0292
new vasopressor_12	0.0071	0.8811	0.0643
new vasopressor_24	0.0117	0.8779	0.1016
respiratory decline_12	0.0363	0.8136	0.1475
respiratory decline_24	0.0627	0.8083	0.1968
respiratory intervention_12	0.0125	0.8978	0.1655
respiratory intervention_24	0.0212	0.8836	0.1669
hypotension_new vaso_12	0.0193	0.8555	0.0975
hypotension_new vaso_24	0.0319	0.8423	0.1493
Resp decline resp intervention_12	0.0381	0.8342	0.1500
Resp decline resp intervention_24	0.0646	0.8301	0.2247

**Evaluation and Implementation:** We have completed our retrospective analysis across cardiology and non-cardiology departments, and will couple this with prospective outcome evaluation for actionable recommendations to finalize the

pilot workflow. The phenotype algorithms have been constructed to run every hour and display results to clinicians via Tableau Dashboard. We will add the predictive model outputs and go live in pilot phase late summer 2020.

1. Diepen SV, Katz JN, Albert NM, et al. *Contemporary Management of Cardiogenic Shock: A Scientific Statement From the American Heart Association*. *Circulation*. 2017;136(16). doi:10.1161/cir.0000000000000525
2. Mebazaa, A., Tolppanen, H., Mueller, C. et al. Acute heart failure and cardiogenic shock: a multidisciplinary practical guidance. *Intensive Care Med* 42, 147–163 (2016).