



Improving Heart Failure Unit Readmission Prediction

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Background

The number of people diagnosed with heart failure is projected to rise by 46% by 2030.

- Heart failure remains the leading cause of hospitalization in individuals ≥ 65 years.
- Readmission following an index admission for heart failure is the leading cause of hospital readmission in the U.S.
- Risk prediction tools are typically incorporate only clinical factors and better prediction tools would provide a better allocation of resources towards higher risk populations.

Purpose

To use modeling that incorporates both clinical parameters and social determinants to improve risk-assessment at the time of discharge for rehospitalization following hospitalization for heart failure.

On admission, general information collected included:

- Medication affordability
- Medication adherence
- Quality of life (Minnesota Living with Heart Failure)
- Depression (CES-D)
- Family / Caregiver support
- Transportation issues
- Education level
- Level of disease understanding
- Alcohol / drug use
- Access to care issues

Methods

Data Collection:

- We prospectively collected information at discharge from 1,319 consecutive patients admitted with a primary diagnosis of heart failure to Ochsner Medical Center.
- Patients were later labeled as readmitted if they were hospitalized within 30 days of discharge.

Inclusion/Exclusion: 41 patients who died after discharge and before readmission were excluded from the analysis.

- To create a readmission model, we fit a logistic ridge regression model to the data using two levels of cross validation. The first level is used to create a series of train/test splits.
- A model is trained on each training dataset, and performance is measured using the average across the models on their respective test datasets. This allows us to accurately estimate model performance on unseen data.
- The second level of cross validation creates a series of train/validation splits for each train dataset created at the first level, and the regularization parameter for each model is tuned using the validation datasets.

Table 1: Patient demographics

Name	Mean (\pm std. dev.)
Age (years)	69 \pm 15
Female (%)	44%
Body mass index (kg/m ²)	30.5 \pm 11.5
Married (%)	53%
Number in Household	1.4 \pm 1.3
Internet Access (%)	53%
Completed College (%)	20%
Number of Hospital Admissions Last 12 mo.	1.4 \pm 1.8
Depressed (%)	18%
Diabetic (%)	49%
Hypertensive (%)	81%
Readmitted (%)	25%

Results: Model Performance

- We compared our model with the CORE Readmission Risk (CRR) using area under the ROC curve (AUC).
- CCR achieved a cross-validation AUC of 0.599 (95% CI [0.578–0.619]).
- Our model achieved a cross-validation AUC of 0.654 (95% CI [0.632–0.675]), significantly better than the CRR

Figure 1: Model performance



Results: Predictors

The model identified the following variables as having a significant association with readmission rates, even when controlling for CRR.

Table 2: Best predictors identified

Variable	β	P-value
Internet Access	-0.70	.003
Aortic Stenosis	0.70	.012
Number of Hospital Admissions in last 12 mo.	0.16	.025
D/c to Hospice Home	-2.43	.025
Reliable Non-Car Trans.	-0.85	.029

Conclusion

- Models incorporating both clinical data and social determinants improve readmission prediction for patients hospitalized with heart failure.
- Future models should incorporate non-clinical factors that play an important role in health outcomes.

Limitations

- Data set is relatively small
- Model may not generalize to other populations

Disclosures

Name	Disclosures
Tom Quisel, BS	SALARY - Evidation Health