

Enhancing heart failure (HF) management—coupling predictive model with clinical insights using administrative data

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Background

- Many predictive HF models exist, but most have used only a small number of important clinical predictors to compute a risk score.
- While useful during individual patient-clinician encounters, these models have limited utility to inform and identify population-level interventions.

Objectives

• This study aimed to develop and internally validate predictive models of high-risk HF patients to identify a potential target population for intensified interventions or management adjustment in a large United States (U.S.) managed care population.

Methods

Data source

• The Healthcare Integrated Research Database (HIRD®) is a broad and geographically diverse repository of longitudinal medical and pharmacy claims data from Elevance Health affiliated health plans, representing over 65 million lives of commercially insured and Medicare Advantage members across the United States

Study cohort

- HF patients were identified as having ≥1 HF diagnosis after at least 6 months continuous health plan enrollment between January 1, 2016, and May 31, 2018.
- The index date was the first observed HF diagnosis after this initial 6 months of continuous
- Additional inclusion criteria: ≥12 months continuous health plan enrollment post-index date (or up to death if died within 12 months post-index), age ≥18 years on index date, and ≥1 procedure code for assessment of Left Ventricular Ejection Fraction (LVEF) within 12 months pre- or post-index date.

Outcomes

- Outcomes (HF hospitalization, total costs) were defined during the 12-month post-index period.
- HF hospitalization was defined as having HF diagnosis in the primary position on an inpatient
- Total cost of care was defined as the sum of all costs (plan paid, patient paid, and coordination of benefits).
- Patients were identified as top decile or top quartile cost cohort if their total monthly cost was in the top 10% or top 25% of total healthcare costs, respectively.

Predictors

- The potential predictor pools included 98 (for hospitalization model) and 99 (for cost models) predictor candidates defined during the 6-month pre-index period.
- Patient zip codes were linked to U.S. Census data to compute components to calculate socioeconomic status index.1
- Additionally, a claims-based frailty index was calculated.²

Model development and evaluation

- The cohort was randomly divided (7:3 ratio) into training and test datasets.
- Three predictive models were developed with the training dataset using least absolute shrinkage and selection operator (LASSO) logistic regression with 10-fold cross-validation to predict 1-year: HF hospitalization risk, top decile total costs, and top quartile total costs.
- The test dataset was used to assess model performance characteristics using receiver operating characteristics (ROC) and calibration.

Results

Table 1. Baseline demographics and comorbid conditions

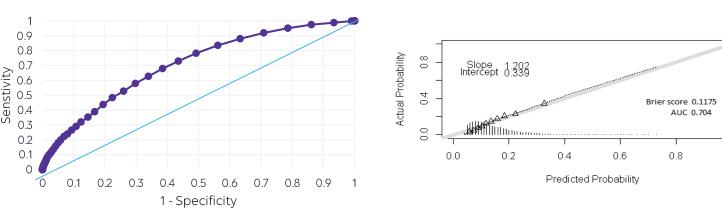
	Overall HF cohort			Top 10% monthly actual cost cohort			Top 11-25% monthly actual cost cohort		
	N/Mean	%/SD	Median	N/Mean	%/SD	Median	N/Mean	%/SD	Median
Total patients, (n, %)	70,926			7,092			10,639		
Demographics									
Age, years, (mean, SD, median)	67.5	14.0	68	62	12.8	61	67.2	13.2	67
Male, (n, %)	38,115	53.7%		4,143	58.4%		5,755	54.1%	
Comorbid conditions (n, %)									
QCI (mean, SD, median)	3.31	1.55	3	4.23	2.14	4	3.71	1.69	3
Coronary heart disease	34,070	48.0%		3,341	47.1%		5,612	52.7%	
Myocardial infarction	12,356	17.4%		1,388	19.6%		2,142	20.1%	
Cardiomyopathy / Idiopathic dilated cardiomyopathy	15,370	21.7%		1,729	24.4%		2,256	21.2%	
Renal failure	16,242	22.9%		2,619	36.9%		3,251	30.6%	
Heart transplant	236	0.3%		58	0.8%		47	0.4%	
Palliative care (n, %)									
Palliative care during 6- month pre-index period	1,863	2.6%		273	3.8%		414	3.9%	
Palliative care during 12- month post-index period	4,577	6.5%		955	13.5%		1,307	12.3%	
Post-index hospitalization (ı	n, %)								
≥ 1 all-cause hospitalization	28,795	40.6%		5,929	83.6%		8,233	77.4%	
≥1 HF-related hospitalization	10,417	14.7%		2,654	37.4%		3,254	30.6%	
Post-index costsª, \$, (mean,	SD, mediar	1)							
Total all-cause monthly costs	\$3,776	\$12,313	\$1,567	\$19,489	\$34,754	\$13,286	\$5,699	\$1,264	\$5,493
Total HF-related monthly costs	\$881	\$7,113	\$65	\$5,137	\$21,866	\$614	\$1,300	\$1,763	\$332

Figure 1. Model receiver operating characteristics (ROC) and calibration plots

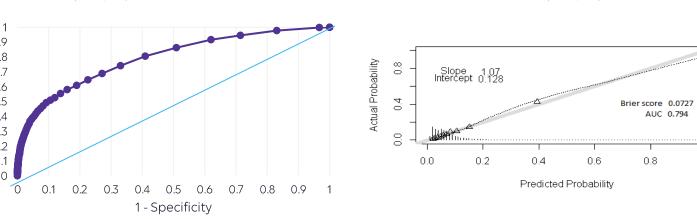
A. ROC curve for model predicting HF hospitalization

from test dataset (n=21,277)

test dataset (n=21,277)



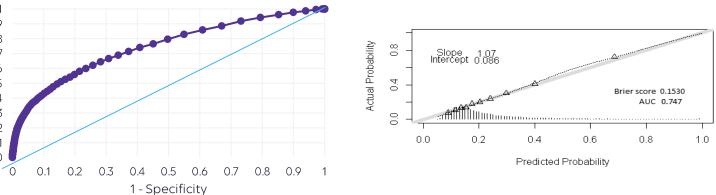




E. ROC curve for model predicting top cost quartile from F. LASSO regression model performance for top cost quartile from test dataset (n=21,277)

B. LASSO regression model performance for HF

hospitalization from test dataset (n=21,277)



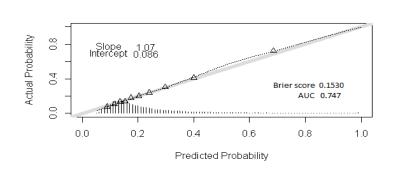
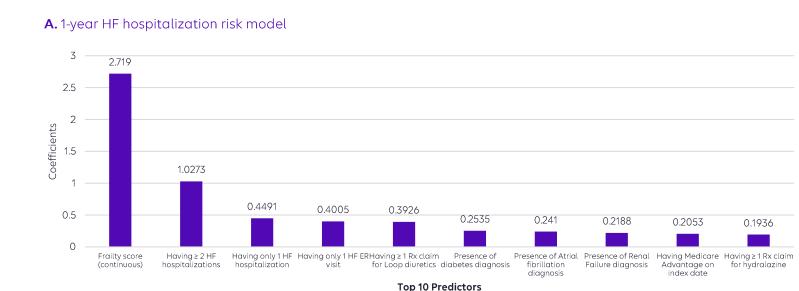
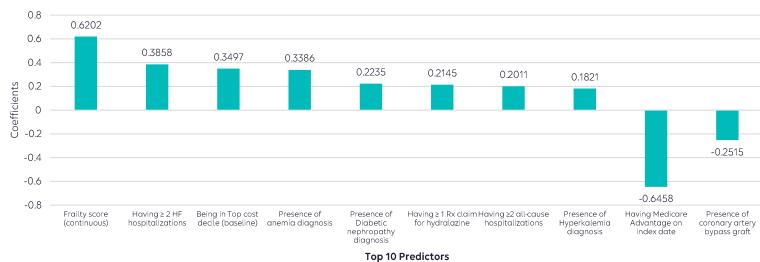


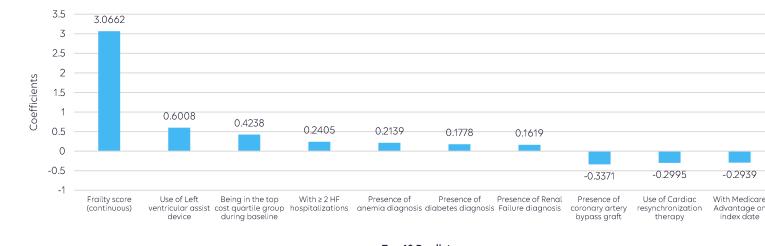
Figure 2. Top ten predictors by model







C. Top quartile total costs of care model



Top 10 Predictors

Limitations

model (Figure 2).

HF=heart failure, SD=standard deviation, QCI=Quan-Charlson Comorbidity Index

• The model could be missing some key predictors (i.e., clinical test results such as LVEF, HF severity, race/ethnicity, health literacy, rurality, social support). However, one study noted that while the inclusion of additional predictors from electronic medical records to a claims-based model improved prediction of HF hospitalization marginally, it offered no improvement in predicting high costs.³

• The study population of 70,926 adult HF patients was 53.7% male with a mean (SD) age of 67.5 (14.0) years (Table 1).

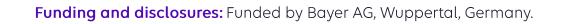
• Another limitation is the assumption of constant model predictive performance over time, which can be minimized by periodic model evaluation and retraining.

Discussion and Conclusions

- The top quartile total cost model was recommended for its balanced predictive performance and clinical relevance.
- While not all individuals in the top quartile cost cohort may be optimal for HF intervention, incorporating clinical insights based on the selected intervention may identify the most likely beneficiaries.
- A combination of advanced analytics with clinical insights tailored for a specific intervention maximizes the potential value of predictive modelling by better targeting the population most likely to benefit.

References

- 1. Bonito A, Bann C, Eicheldinger C, Carpenter L. Rockville, MD: Agency for Healthcare Research and Quality; January 2008. AHRQ publication 08-0029-EF.
- 2. Kim DH, Schneeweiss S, Glynn RJ, Lipsitz LA, Rockwood K, Avorn J. J Gerontol A Biol Sci Med Sci. 2018;73(7):980-987.
- 3. Desai RJ, Wang SV, Vaduganathan M, Evers T, Schneeweiss S. JAMA Netw Open. 2020;3(1):e1918962.





• All three models demonstrated good performance: area under the ROC curve (AUC) of 0.704, 0.794, and 0.747 for HF hospitalization, top decile, and top quartile total cost models, respectively (Figure 1).

• The frailty score was the strongest predictor for both the HF hospitalization and top quartile total cost models, while Commercial plan (vs. Medicare Advantage) was the strongest predictor for the top decile total cost