Machine Learning to Differentiate Congestive Heart Failure Onset Among High-Risk Patients Identified by the Framingham Risk Score

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Objective: To analyze the features which contribute to a machine learning model's prediction of which patients with the highest severity risk risk will develop CHF

Background

Risk scores derived from the Framingham Heart Study identify patients at elevated four-year risk for congestive heart failure (CHF), but do not explain why many high-risk individuals do not progress to CHF. This study aimed to (1) identify demographic, clinical, and care-delivery factors that differentiate high-risk patients who did versus did not develop CHF within four years, and (2) develop and validate a machine learning (ML) model to further stratify CHF risk within this high-risk population.

Methods

A retrospective cohort study used real-world data from individuals aged 45+ with coronary artery disease, hypertension, or valvular disease. Inclusion required ≥1 year baseline data (heart rate, blood pressure, height, weight, BMI) and ≥4 years follow-up. These data were used at the inputs fort eh FHS Risk score. "Severe Risk" defined as those with a CHF risk level in the 75th percentile or above, stratified by 3 groups to train our models: highest-risk males, highest-risk females, and highest-risk patients regardless of sex. A unique Xtreme Gradient Boosted Decision Tree model was developed for each group; one trained only on the highest risk males, a second on the highest risk females, and a third model with the highest-risk patients regardless of sex. The models were used to predict which of the highest risk for CHF patients would eventually progress to CHF. SHAPLEY Additive values for used as a method to identify key risk drivers.

Results

Among the highest-risk patients, those who developed CHF had higher cardiometabolic and renal comorbidity burden, greater baseline physiologic instability, and increased acute care use. Patients who did not progress to CHF were more likely to receive antihypertensive and cardioprotective drugs, show slower comorbidity progression, and engage earlier with cardiology specialists. Machine learning models excelled at CHF onset discrimination within the high-risk cohort. Feature analysis consistently identified comorbidity burden, long-term treatment exposure, and specialist care as key differentiators of CHF progression.

Conclusions

Within populations already classified as high risk, machine learning applied to real-world data can identify clinically meaningful heterogeneity in the progression of CHF. These findings suggest that modifiable treatment and care-delivery factors may mitigate CHF onset despite elevated baseline risk, supporting more targeted prevention strategies.

Figure 1. Severe CHF Risk Patients – Progression Rate to CHF from Qualifying Condition

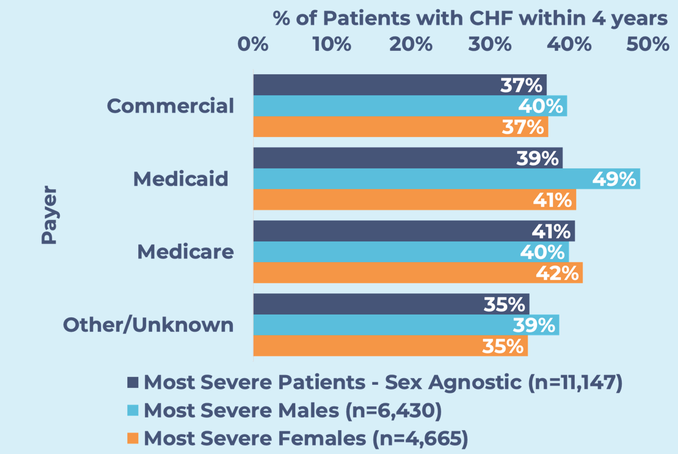

Figure 2. Model Testing
Model Types: eXtreme Gradient Boosted Trees
Models trained on up to 4 years of claims data per patient.

Most Severe Patients (A) (Sex Agnostic, n=3,025, precision:0.891, recall:0.806)		Predicted	
		Heart Failure Free	Heart Failure
Actual	Heart Failure Free	2,012	91
	Heart Failure	178	744

Most Severe Male Patients (B) (n=1,765, precision:0.715, recall:0.623)		Predicted	
		Heart Failure Free	Heart Failure
Actual	Heart Failure Free	1,010	148
	Heart Failure	225	372

Most Severe Female Patients (C) (n=1,335, precision:0.712, recall:0.613)		Predicted	
		Heart Failure Free	Heart Failure
Actual	Heart Failure Free	819	133
	Heart Failure	148	235

Figure 3. SHAPLEY Additive Values - Contributing Factors to Congestive Heart Failure