Implementing a Predictive Model to Reduce Hospital Readmissions in a Safety Net Healthcare System

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1. Introduction

Safety net health systems, healthcare delivery institutions committed to serving patients regardless of their insurance status or ability to pay, face the dual challenge of meeting pay-for-performance metrics without compromising patient outcomes. Hospital readmission reduction metrics often disproportionately penalize safety net health systems, despite risk-adjusted metrics (Ahmad et al., 2022; Figueroa et al., 2017) leading to reduced funding for health systems most in need.

Zuckerberg San Francisco General Hospital (ZSFG) is an urban, academic, safety net hospital within the San Francisco Health Network, which experienced elevated readmission rates before 2017. Failure to meet readmission reduction metrics imperiled $1.2 million per year of funding. A pivotal analysis revealed that heart failure (HF) accounted for over 40% of unplanned readmission events and that reducing all-cause 30-day HF readmission rates would enable the health system to meet overall readmission reduction metrics. Critical drivers of 30-day unplanned readmission in HF patients included:

1. Difficulty identifying patients at the highest risk of readmission
2. Lack of standardized HF care, contributing to substantial care variation driven by underlying treatment biases.

ZSFG postulated that a machine learning algorithm predicting unplanned 30-day readmission risk for HF would allow for the identification of patients at the highest risk of readmission. Though readmission risk stratification was thought to be necessary to reduce readmission rates, it was not felt to be sufficient in isolation. Therefore, the ML algorithm was incorporated into a broader, point-of-care, electronic health record integrated, logic-based HF decision-support tool that would surface readmission risk to physicians and provide *actionable* decision-support guidance.

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Model name: 30-day unplanned readmission risk prediction model

ZUCKERBERG SAN FRANCISCO GENERAL Hospital and Trauma Center

Summary:
This model uses electronic health record (EHR) data from heart failure (HF) patients at Zuckerberg San Francisco General Hospital. The model takes in 42 input features from the EHR to predict unplanned readmission risk within 30 days (based on CMS criteria) where high risk is any prediction exceeding 12%.

Mechanism:

Output	Predicted probability of unplanned readmission within 30 days
Target Population	Inpatient heart failure patients and outpatient heart failure patients who were admitted within the past 30 days
Input Data Source	Tabular data from Electronic Health Records
Time of Prediction	Predictions are updated once per day
Model Type	Gradient Boosted Tree
Feature Categories	Lab results, demographics, flowsheet values, and patient orders
Most Predictive Features	1) Number of previous emergency department encounters in the past year 2) The most recent lab value for B-Type Natriuretic Peptide 3) The most recent lab value for Lactate Dehydrogenase

Training Details:

Time Period	Aug 2019 - Mar 2024
Number of Unique Patients and Encounters	2,728 and 21,218
Gender Breakdown	Male: 63% Female: 37%
Age Breakdown	18-34: 3% 35-49:15% 50-64: 37% 65 and above: 45%
Demographics Breakdown	Asian:14% White:19% Black or African American: 33% Other: 34%

Performance:

	Test
AUC (90% CI)	.73 (.68, .77)
Positive Predictive Value	.19
Sensitivity	.62
Gender	Test AUC (90% CI)
Male	.73 (.67, .77)
Female	.73 (.62, .82)
Age	Test AUC (90% CI)
18-34	.70 (.4, .9)
35-49	.73 (.62, .82)
50-64	.70 (.63, .78)
65 and above	.73 (.66, .81)
Race	Test AUC (90% CI)
Asian	.78 (.68, .88)
White	.69 (.61, .77)
Black or African American	.78 (.70, .85)
Other	.67 (.57, .77)

Figure 1: Model card for readmission risk prediction

2. Methods

Development Team The Pioneering Research and Organizational Solutions to Promote Equitable Care (PROSPECT) Lab is a digital innovation taskforce with the mission of applying technology and digital tools to improve health outcomes and equity in underserved populations. The PROSPECT Lab has a multidisciplinary team composed of experts in clinical medicine, ML, data science, social determinants of health and was tasked with the development of the ML algorithm and decision support tool.

Model Development and Deployment Pipeline Through the collaboration between the PROSPECT lab and analysts at ZSFG, we extracted EHR tables with information on patient demographics, insurance, lab results, diagnosis codes, etc. Initially all the EHR features for HF patients, across both inpatient and outpatient settings, were used to train several models such as logistic regression, random forests, and gradient boosted trees. These features were pared down to meet model deployment requirements and improve model transparency. The final model selected was a gradient boosted tree with 47 features. A model card summarizing the algorithm's training procedure and evaluation performance can be found in Fig 1.

The model was deployed using Epic's Nebula cloud platform, which interfaces directly with live EHR data through the Chronicles database used in Epic. The cloud platform allows for the model code and outputs to be bundled through a docker container which is used for secure deployment into SFHN's Epic platform. While in clinical use, a monitoring pipeline is setup to verify the ML model is aligned with the true readmission rate and accurately predicts the readmission risk for patients.

Clinical Interface As prior research in HF risk prediction has demonstrated that surfacing a prediction without actionable guidance does not improve outcomes (Joynt and Jha, 2013) significant attention was given to linking ML predictive outputs with actionable decision support. We built a point-of-care decision support tool housed within a custom-built user interface. This tool surfaced patient-specific guideline-based recommendations about HF care to inpatient providers and guided them to place high-priority follow-up referrals to a specialized HF clinic for patients in the highest quartile of predicted readmission risk. In this way, HF care was standardized; however, the patients at the highest risk of readmission were rapidly triaged to a HF specialist.

3. Results

At ZSFG an interrupted time series analysis revealed that HF readmission rates declined from 27.9% in the pre-implementation period to 23.9% in the post-implementation period ($p < 0.004$) by the end of 2023. In comparison to five peer hospitals, the odds of 30-day readmission were significantly higher at ZSFG in the pre-implementation period (OR 1.58 [CI 1.21-2.06], $p < 0.001$), and readmission odds trended upwards over time before implementation (OR 1.06 [CI 1-1.13]/year, $p = 0.065$). The decline in readmission odds following program implementation was significantly higher at ZSFG compared to peer hospitals (OR 0.91 [CI 0.84-0.98]/year, $p = 0.015$)

Cox proportional hazards models adjusted for age, sex, Charlson Comorbidity Index, and social deprivation index revealed a significant reduction in risk of mortality in HF patients in the post-implementation period in comparison to the HF patients in the three years before implementation (OR 0.82[CI 0.68-0.99], $p = 0.037$)

The ML algorithm is applied to the entire HF population in the SFHN. Over 200 providers have used the decision support tool during 2,130 inpatient encounters. The model has a test AUC of .73 and performs consistently across various subgroups (Fig 1).

4. Discussion

This health system-wide performance improvement initiative in a safety net health system demonstrates the feasibility of utilizing machine learning prediction models to meet readmission reduction metrics while simultaneously improving mortality. Furthermore, the success of this tool led the health system to retain over 7.2 million dollars of at-risk pay for performance funding.

Despite these successes, we encountered several hurdles during the implementation of this program. First, general interaction rates with EHR-based decision support aids across our health system were meager. To ensure usage, we conducted workshops with providers utilizing the digital tool to integrate their design feedback and encourage buy-in to the tool's success. Current metrics show that providers interact with the tool for decision support in 56-75% of inpatient HF patients. Further, deploying our custom model through Epic Nebula presented significant challenges. Each EHR feature required individual mapping as an input to the model, a time-intensive, manual process that restricted us to a maximum of 50 features from over 3,000 features in the EHR data. This limitation meant important engineered features could not be used for our deployed model leading to a decrease in accuracy.

Though outcomes have improved via deployment of the decision support tool and ML model, in the outpatient setting we believe further improvement in outcomes is possible by focusing on outpatient care. Therefore, the decision support tool and ML model have been adapted to the outpatient setting and are currently being deployed in a step wedge, cluster randomized trial to evaluate the effect on HF medication prescription rates, readmission rates, and mortality.

References

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