MSR46

ADTs Drive Real-Time Readmission Prediction for Blue Cross and Blue Shield of Louisiana Members: A Model Evaluation

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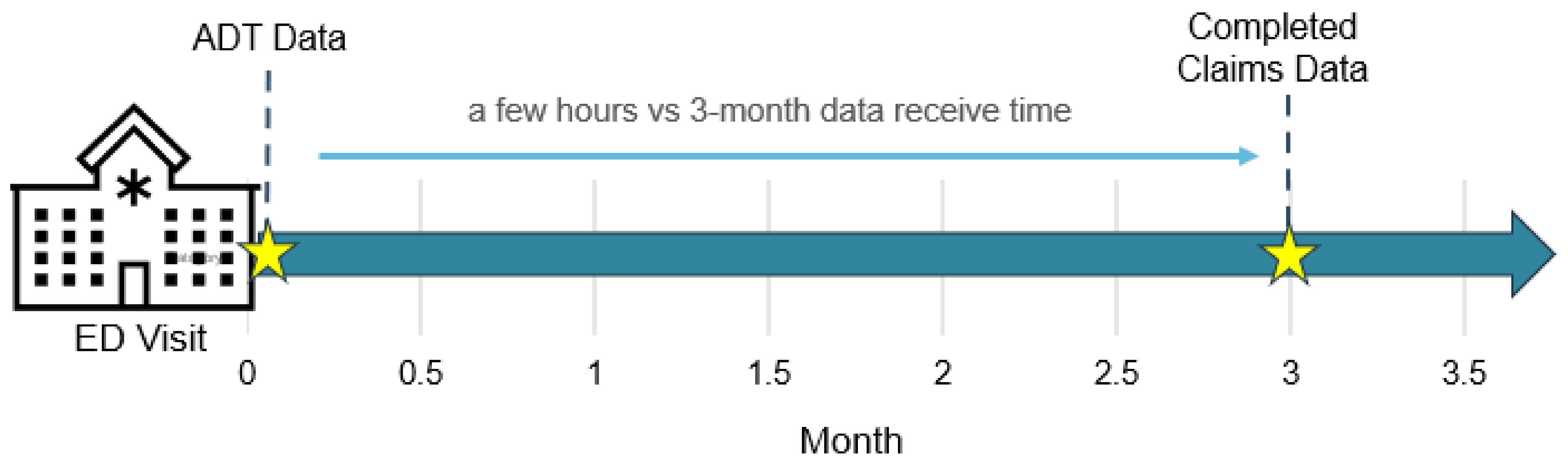
BACKGROUND

- The emergency department (ED) plays an important role in treating millions of patients each year. Some patients live with acute and chronic illnesses or experience accidents or injuries that require immediate care. However, the ED is expensive and inefficient for those visits where it is avoidable.
- Combining the use of admission-discharge-transfer (ADT) data and predictive modeling can improve the efficiency of ED use by quickly identifying patients at high risk of visiting. This study evaluates a Blue Cross and Blue Shield of Louisiana (BCBSLA) predictive model that identifies members at high risk of readmitting to the emergency department.

METHODS

- The traditional claims-based risk models meant to target these outcomes rely on completed claims data, which can take months to arrive. An alternative approach is to rely on ADT data, which is near real time and contains important patient medical information that is created at the start of a medical encounter.
- For this model, ADT records representing office visits, transfers, ED visits or hospital admissions serve as the index visit. These records are joined to internal sources containing data on a member's demographics, social determinants of health vulnerabilities, and prior healthcare utilization. Models are trained to predict a visit to the ED within 30 days.

Time to Receive Data from ED Visit



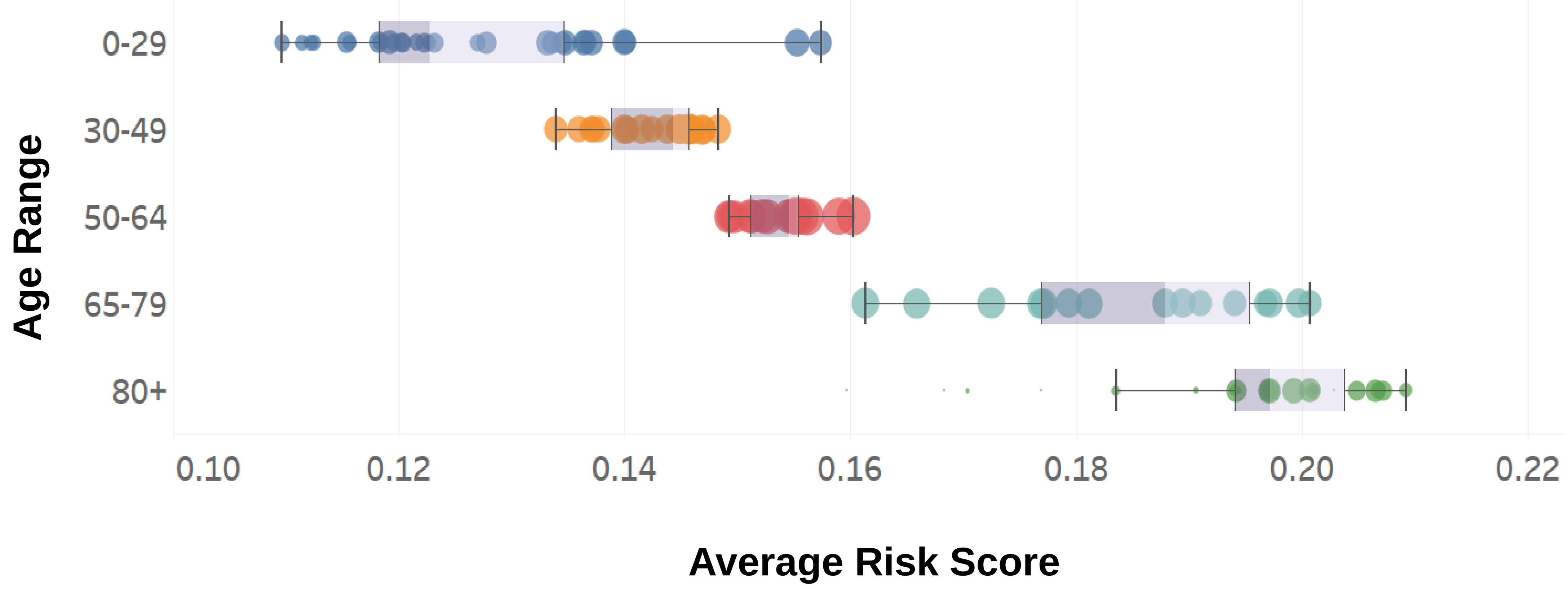
RESULTS

- The final model has an area under the curve statistic of 0.71 in the training and 0.72 in the testing sets.
- The precision or positive predictive value in the top 1%, 10% and 25% were 70%, 38%, and 28%, while the recall or sensitivity was 15%, 25% and 45%.

Table 1. ADT Member Demographics by Risk Category

Model Risk Category	Age	Female	ED Visits Per 1,000
Low Risk	38.9	51.2%	952
Medium Risk	31.7	57.9%	1,157
Medium High Risk	38.0	59.1%	1,655
High Risk	47.0	58.4%	2,100
Very High Risk	50.7	58.8%	4,270
Total	41.2	56.2%	1,361

Figure 1. Data Demographics



- The box plot shows the distribution of average risk scores for each age range.
- The boxes represent the middle 50% of the data, with the whiskers indicating the range of the data within 1.5 times the interquartile range.
- The darker shade within the box represents the middle 50% of the data (i.e., the interquartile range, or IQR).
- The lighter shade represents the entire range of the data outside of the IQR.

Figure 2. Final Model Performance

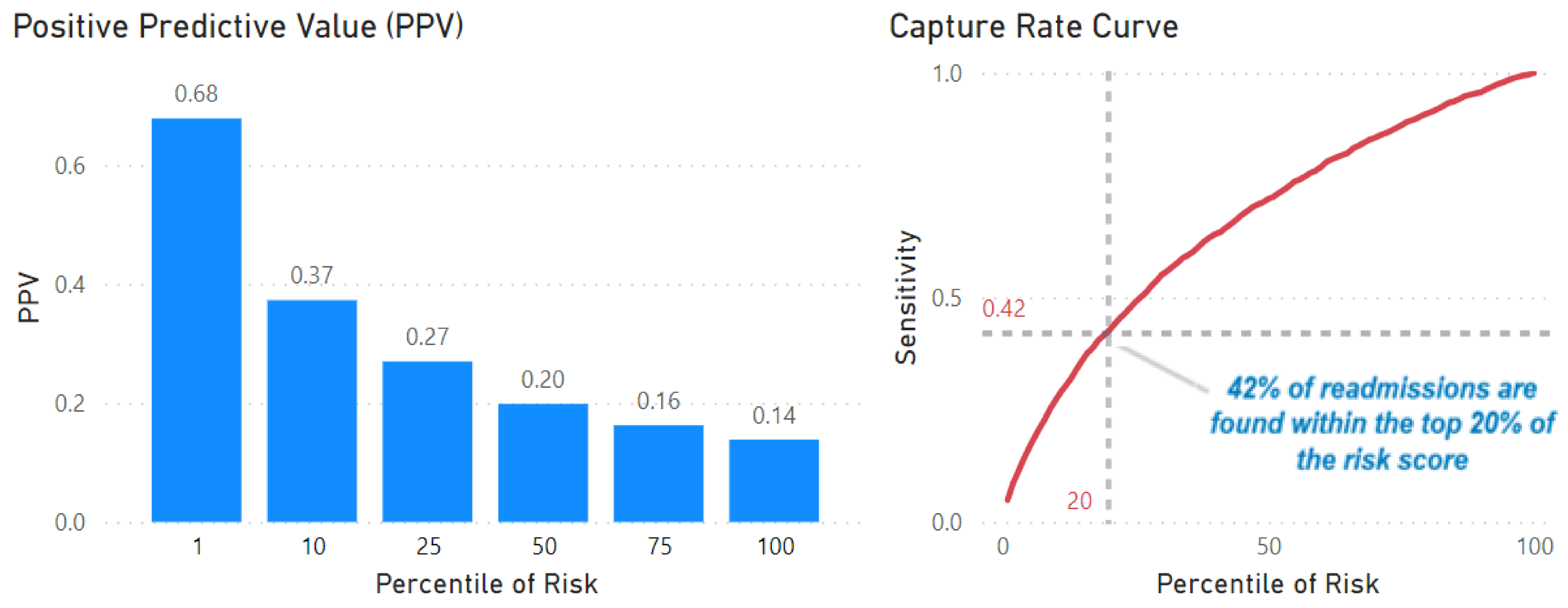


Figure 3. Feature Importance Breakdown

Comparing the mean values of the top-ranking features for the high and low risk groups of the risk-evaluated population provides insight into their predictive power.

Rank	Features	Very High Risk	High Risk	Medium to Low Risk
1	Previous ED Visits	5.65	2.50	1.26
2	Age at Event	54.93	48.97	39.86
3	Hospital Service: Medical	0.40	0.11	0.04
4	Congestive Heart Failure	0.09	0.01	0.00
5	Hospital Service: Surgery	0.09	0.03	0.02
6	Discharge Disposition: Left Against Medical Advice	0.02	0.01	0.01
7	Diabetes with Chronic Complications	0.13	0.06	0.01
8	Cirrhosis of Liver	0.15	0.01	0.00
9	Diabetes without Complication	0.09	0.07	0.01
10	Specified Heart Arrhythmias	0.08	0.02	0.00

CONCLUSIONS

- Using this predictive model and relying on incoming ADTs as a critical source of real-time data, BCBSLA can quickly identify patients at risk for a readmission of ED visit.
- This speed of identification allows the BCBSLA Care Management team to offer timely intervention leading to improved health outcomes for members.

Louisiana