Managing Provider Capacity in a Growing Primary Care Practice

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June 1, 2024

Introduction

Effectively managing provider capacity is essential in the complex and dynamic primary care environment. This project aims to develop a predictive model to forecast optimal patient panel sizes for primary care providers. The model considers patient complexity, contact history, and projected patient volume growth to ensure equitable workload distribution among providers. This project is critical as it addresses the growing need to balance quality care, provider satisfaction, and operational efficiency. Healthcare administrators and clinic managers will find this model particularly beneficial for resource allocation and strategic planning.

Problem Statement

The challenge of determining the optimal patient panel size for primary care providers is not to be underestimated. It is a complex task due to the variance in patient needs and provider capacities. Finding the optimal panel size is crucial as it ensures that providers are not overburdened, thus preventing burnout and maintaining high-quality patient care. This problem is significant as it directly impacts patient outcomes, provider satisfaction, and the overall efficiency of healthcare delivery.

Data Selection

The data used for this project is a comprehensive set of ambulatory encounter records. These records span the past three years and come from sixty-three (63) providers across eight primary care practices within a single health system. Each record contains a wealth of information, including patient demographics, encounter type, visit duration, and multiple datetime stamps. This dataset is invaluable for understanding the patterns and demands on provider capacity and for developing predictive models.

Methods and Results

Data Preparation

The data preparation phase involved cleaning and filtering the dataset to focus on completed appointments, excluding non-credentialed providers, and creating new features such as provider visit types, patient no-shows, age groupings, and payor categories. The target feature, "Provider Effort Rating (PER)," was engineered to estimate the effort required for each patient based on age, payor type, and visit history.

Exploratory Data Analysis

Initial data visualizations revealed critical insights into the patient population and provider factors. The patient population is aging, with medium to high contact frequency. Provider factors showed significant variability in capacity and workload distribution. These visualizations helped identify the disparities in provider workload and informed the model-building process.

Model Building

Two primary models were developed: a baseline linear regression model and a more complex random forest model. The linear regression model initially understood the relationship between provider capacity and patient factors, while the random forest model captured more complicated patterns in the data. The random forest model showed better performance and was used for further analysis. See Chart 1 to examine feature importances in the random forest model.

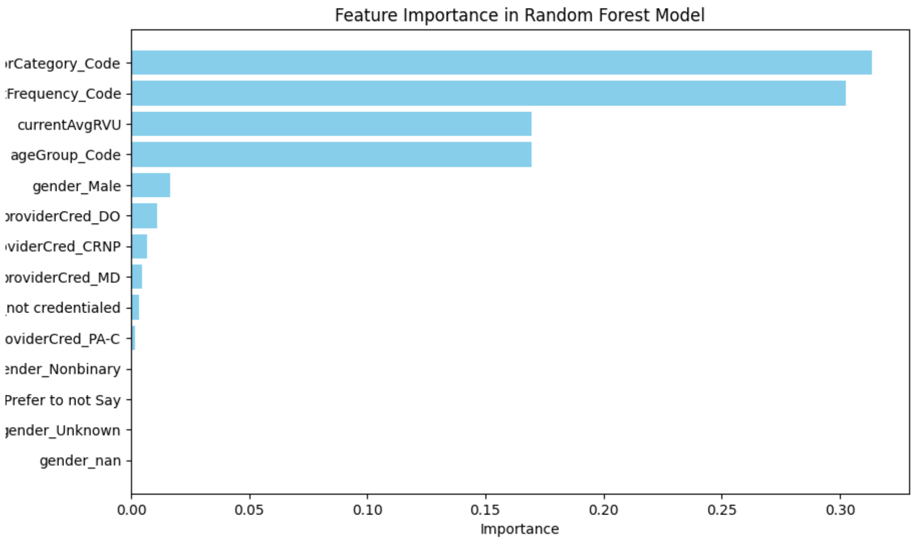

Chart 1 – Feature Importances for Random Forest Model

Linear Regression Results:

MSE: Moderate predictive error

R-squared: 36.6% variance explained

MAE: 29.4% of the mean

Random Forest Results:

MSE/RMSE: Lower in comparison

R-squared: 49.44% variance explained

MAE: 26.47% of the mean

Post-Result Visualizations

Visualizations were generated comparing initial and redistributed patient panels using the PER target feature, highlighting the improvements in workload distribution. The redistribution resulted in more uniform panel sizes and effort scores, indicating a fairer workload distribution among providers.

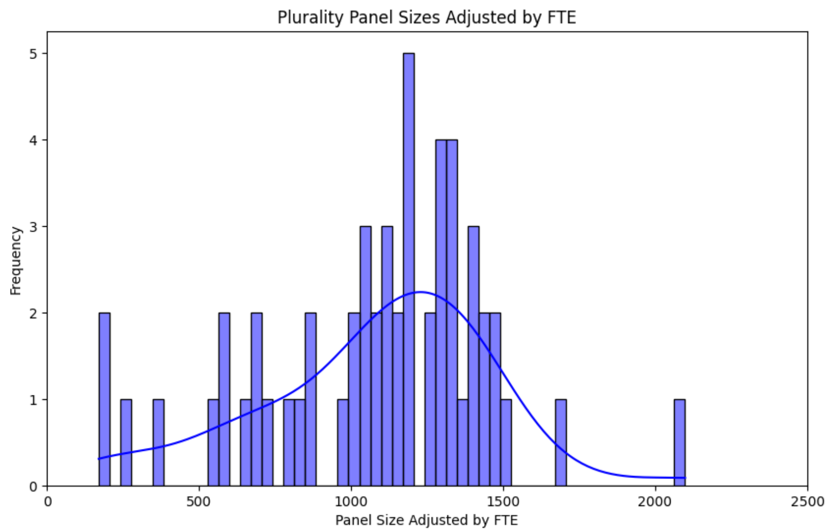

Chart 2 – Pre-Adjusted Panel Sizes

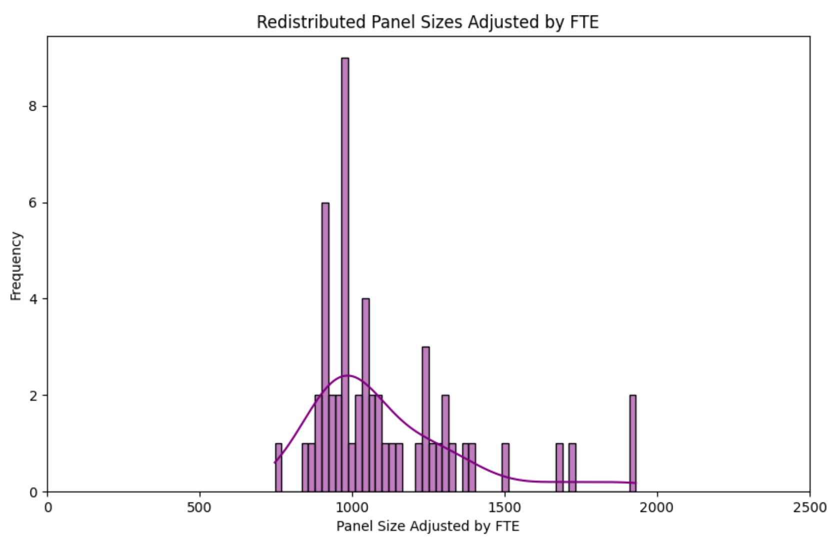

Chart 3 – Post-Adjusted Panel Sizes

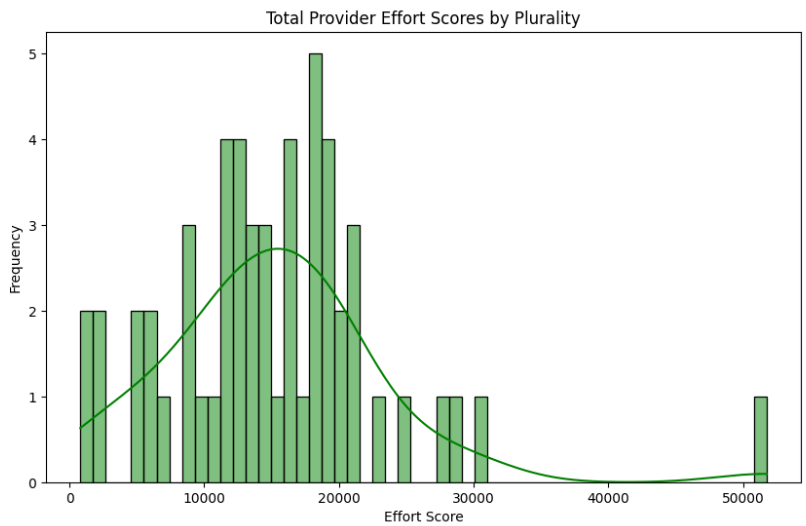

Chart 4 – Pre-Adjusted Effort Scores

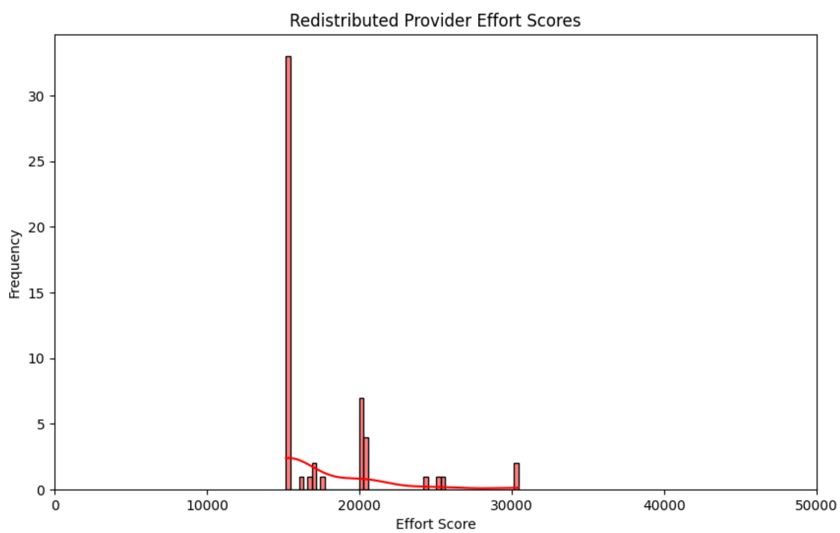

Chart 5 – Post-Adjusted Effort Scores

Conclusion

This project demonstrated the feasibility of using predictive analytics to manage provider capacity in primary care. The models developed provide a structured method for re-assigning patient panels, potentially enhancing operational efficiency and provider satisfaction. Before deployment, future recommendations include periodic redistribution algorithm refinement, policy adjustments based on quantified effort scores, and further research incorporating additional variables for a more profound impact.

Ethical Considerations

Ethical considerations include maintaining patient privacy and confidentiality, ensuring transparency in making predictions, and addressing potential biases in the data. Mitigating these concerns involves clear communication with stakeholders and monitoring the model's performance and impact.

Future Work

Future work includes refining the model with additional data, such as patient outcomes and provider satisfaction, and exploring other predictive applications within healthcare. The model is not yet ready for deployment but shows promise for practical use with further development and validation.

References

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