

Predicting Hospital Readmissions

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Agenda

01. BACKGROUND &
QUESTION

02. METHODS

03. RESULTS

04. DISCUSSION

01.

BACKGROUND & QUESTION



KEY NUMBERS



\$1.19 trillion

Spend on healthcare in the U.S.



33%

Healthcare expenditure on hospital
care



1 in 4

Patients hospitalized will have
readmission within 30-days






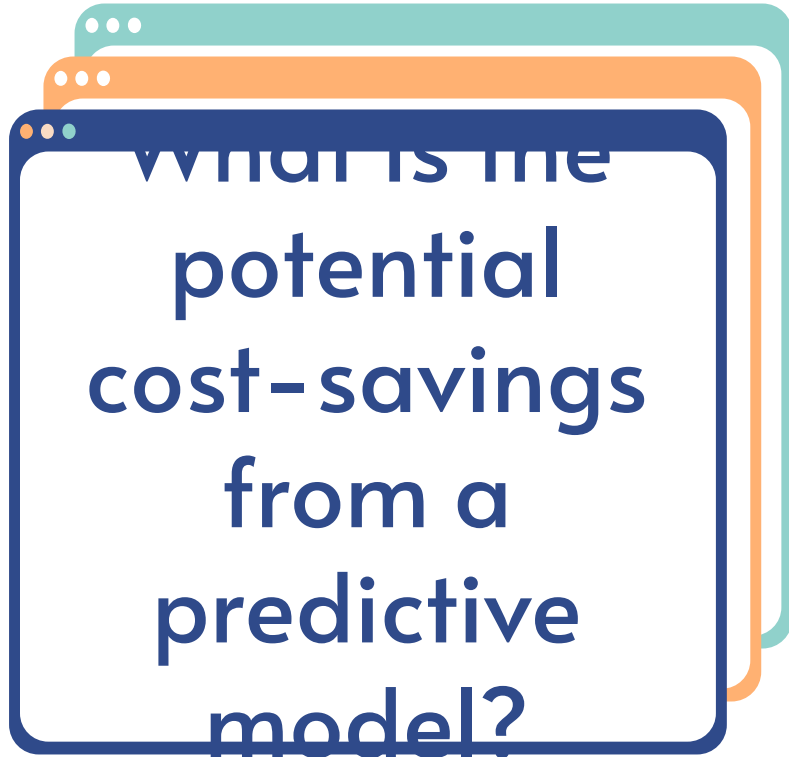
Readmissions

- Centers for Medicare and Medicaid Services (CMS) reduces payments to hospitals based on 30-day readmissions
- Many evidence-based programs to reduce hospital readmissions
- Limited resources available for these programs

Questions



Can we predict
readmissions
in patients
65+?



What is the
potential
cost-savings
from a
predictive
model?

02.

METHODS



Data Source



Annual survey administered by the Agency for Healthcare Research and Quality (AHRQ) of families, individuals, medical providers, and employers in the U.S.

Survey Components:

- Household
- Insurance/Employer
- Medical provider
- Nursing home (1996)

MEPS: Household Component

Collects person level information: 30,461 individuals (326,327,888 weighted) and 1,502 variables

- demographics
- health conditions
- health status
- use of medical services
- charges and source of payment
- access to care
- satisfaction with care
- health insurance coverage
- income
- employment

Predictor Variables Used in Analysis

Demographics

- Age
- Sex
- Marital Status

Chronic conditions

- Asthma
- Diabetes
- Coronary HD
- High BP
- Cancer
- Stroke
- Emphysema
- Stroke



Limitations

- Chronic
- Cognitive
- Health Status

Utilization

- Total Prescriptions
- Outpatient Visits
- ED Visits
- Dental Visits
- Home Care Day
- Inpatient Stay

Social determinants of health

- Family Income
- Years of Education
- Residence Region

Data Preparation

Data Subset:

- Population (65 and older)
- Independent Variables
 - Table 2 (23 variables)
- Dependent Variable
 - Readmissions
 - Discharges ≥ 2

Table 2: Predictor Variables Included in Analysis

Predictor variable	MEPS Name	Variable type
Prescribed Medications	RXTOT18	Continuous
Age	AGE18X	Continuous
Sex	SEX	Binary
Household income	FAMINC18	Categorical
Perceived health status	RTHLTH31	Categorical
Geographic location	REGION18	Categorical
Education	EDUCYR	Categorical
Marital status	MARRY18X	Binary
Cognitive limitation	COGLIM31	Binary
Physical limitation	WLKLIM31	Binary
# ER Visits	ERTOT18	Continuous
# Dental Visits	DVTOT18	Continuous
# Home Care Days	HHTOTD18	Continuous
# Outpatient Visits	OPTOTV18	Continuous
# Inpatient Days	IPNGTD18	Continuous
Cancer Diagnosis	CANCERDX	Binary
Arthritis Diagnosis	ARTHDX	Binary
Coronary HD Diagnosis	CHDDX	Binary
Diabetes Diagnosis	DIABDX_M18	Binary
Stroke Diagnosis	STRKDX	Binary
Asthma Diagnosis	ASTHDX	Binary
High BP Diagnosis	BPMLDX	Binary
Emphysema Diagnosis	EMPHDX	Binary



Simple Models

- k Nearest Neighbor
- Naive Bayes
- Logistic Regression
- Classification Tree



Ensemble Models

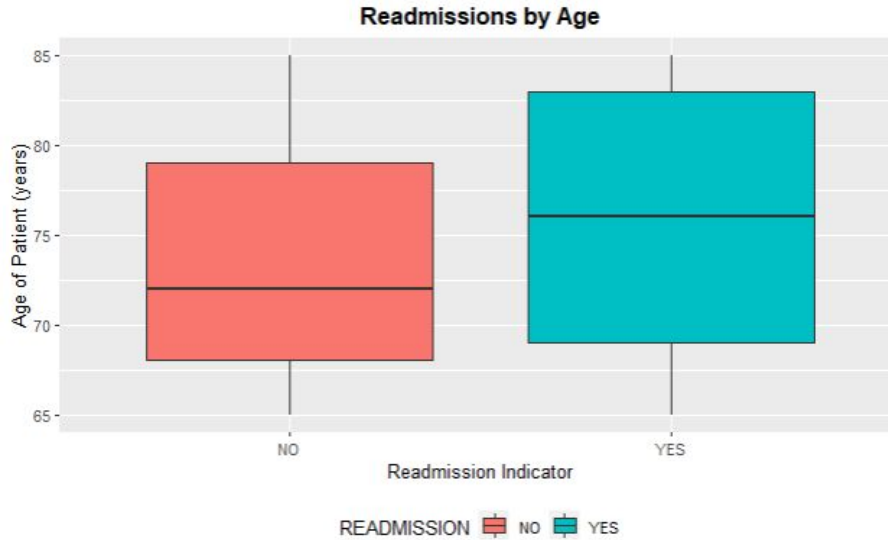
- Random Forest
- Bagging
- Boosting
- XG Boosting

03.

Results



Exploratory Analysis



Total Patients: 3,394 | W/Readmission: 162 | Average Age: 74 | Female: 54.4%

Model Performance

Table 3 :Performance Metrics by Model

		Model Type	Accuracy	Sensitivity	Specificity
Simple		Logistic Regression	96.2%	42.6%	99.1%
		K-nearest neighbor	96.7%	27.5%	99.6%
		Naive bayes	93.1%	30.8%	98.3%
		Classification tree	97.1%	42.4%	99.6%
Ensemble		Bagging	96.7%	57.1%	98.6%
		Random Forest	97.0%	63.3%	98.9%
		Boosting	96.6%	63.9%	98.3%
		XG Boosting	96.8%	60.2%	98.9%

ROC Curve: Top Five Models

Figure 1: ROC Curve Model Comparison: Top Five Models

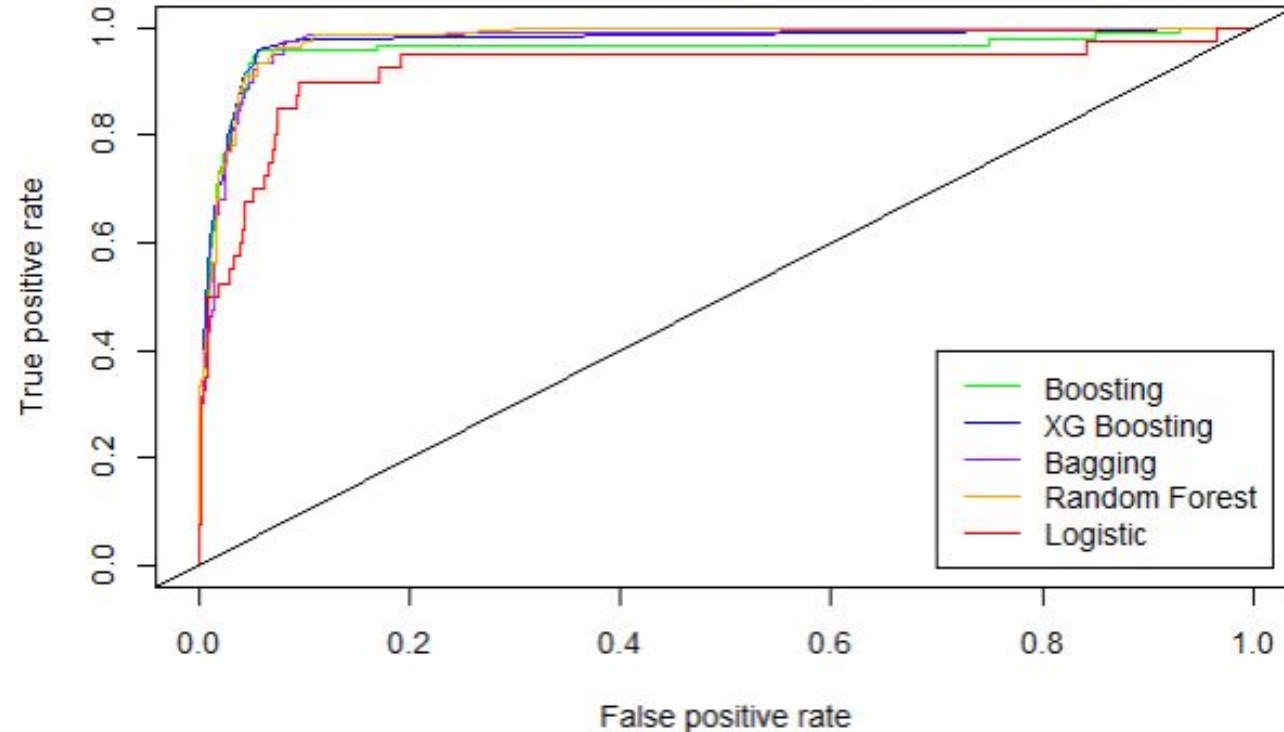


Table 4: Area Under Curve

Model	AUC
Boosting	95.8%
XG Boosting	97.4%
Bagging	97.5%
Random Forest	98.0%
Logistic	92.1%

Comparative Cost Analysis by Model (\$)

Table 5: Comparative Cost Analysis by Model (Annual)

Actual	Predicted	
	TP	FN
	135	27
	FP	TN
	26	3,206
Actual	Predicted	
	TP	FN
	109	53
	FP	TN
	35	3,197
Actual	Predicted	
	TP	FN
	129	33
	FP	TN
	18	3,214
Actual	Predicted	
	TP	FN
	64	98
	FP	TN
	28	3,204

Model	Expected Cost (\$)	
	Total	Per Capita
Boosting	\$ 423,400.00	\$ 124.75
XG Boosting	\$ 823,100.00	\$ 242.52
Random Forest	\$ 510,600.00	\$ 150.44
Logistic	\$ 1,503,600.00	\$ 443.02
Current State	\$ 2,462,400.00	\$ 725.52
Cost Averted (max)	\$ 2,039,000.00	\$ 600.77

* Calculated by applying national average cost per readmission (\$15,200) in 2018 to False Negatives and a \$500 case management cost per capita to False Positives.

HCUP, 2021

04.

Discussion



Strengths and Limitations

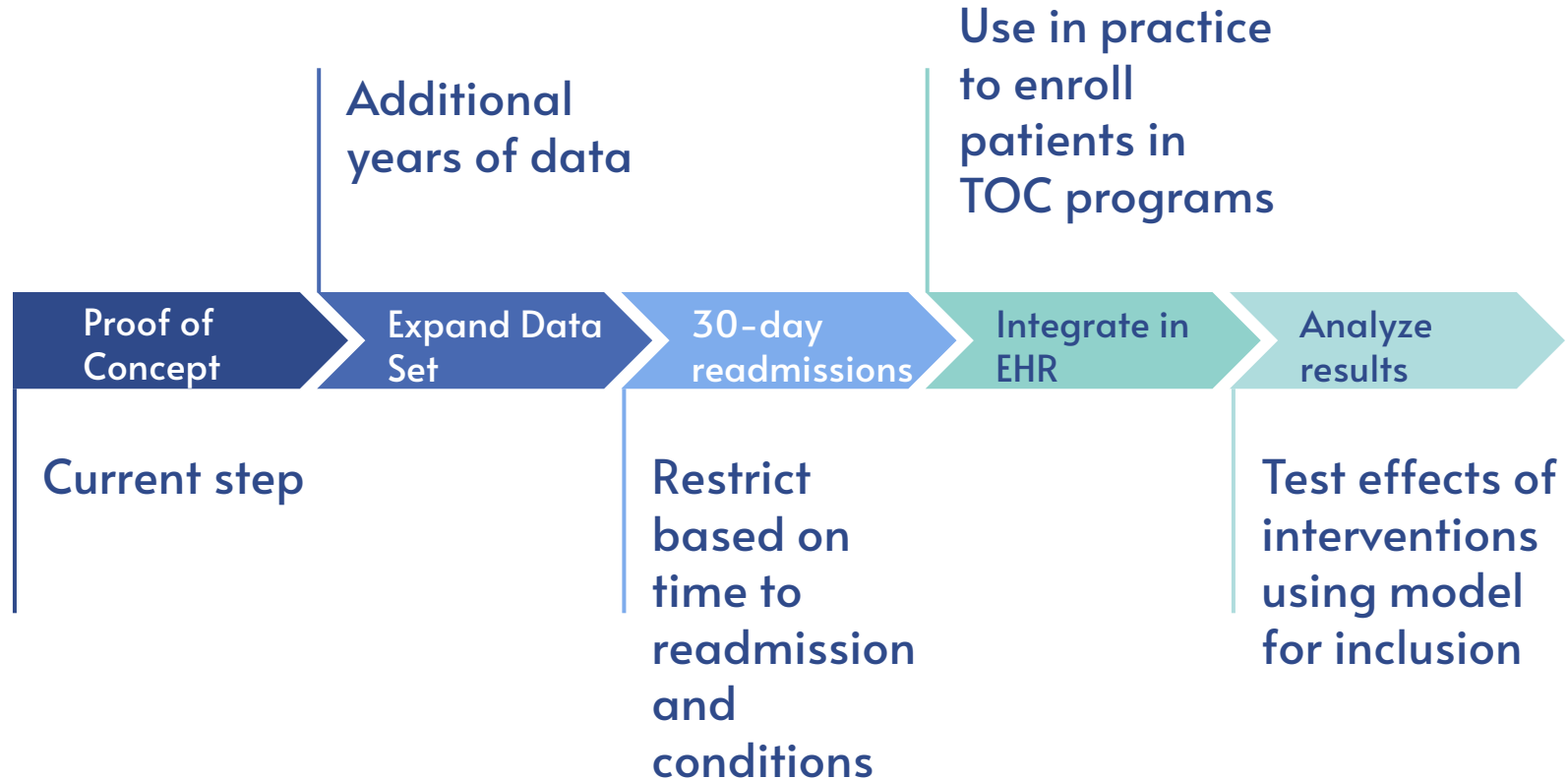
Strengths

- # of models tested adds to sensitivity analysis of methods
- Generalizability of results due to use of national survey data set
- Strong predictive results indicate potential for cost savings

Limitations

- Unable to perform exhaustive analysis due to sheer # of variables in data
- Analysis does not stratify readmissions by timeframe: 30, 60, and 90 days
- Data frame does not contain variables for all CMS designated medical conditions

Current and Future Plans



THANKS!

What questions do
you have?

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References

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