Building a Patient Experience Model

Improve patient experience and satisfaction

Data from CMS.gov

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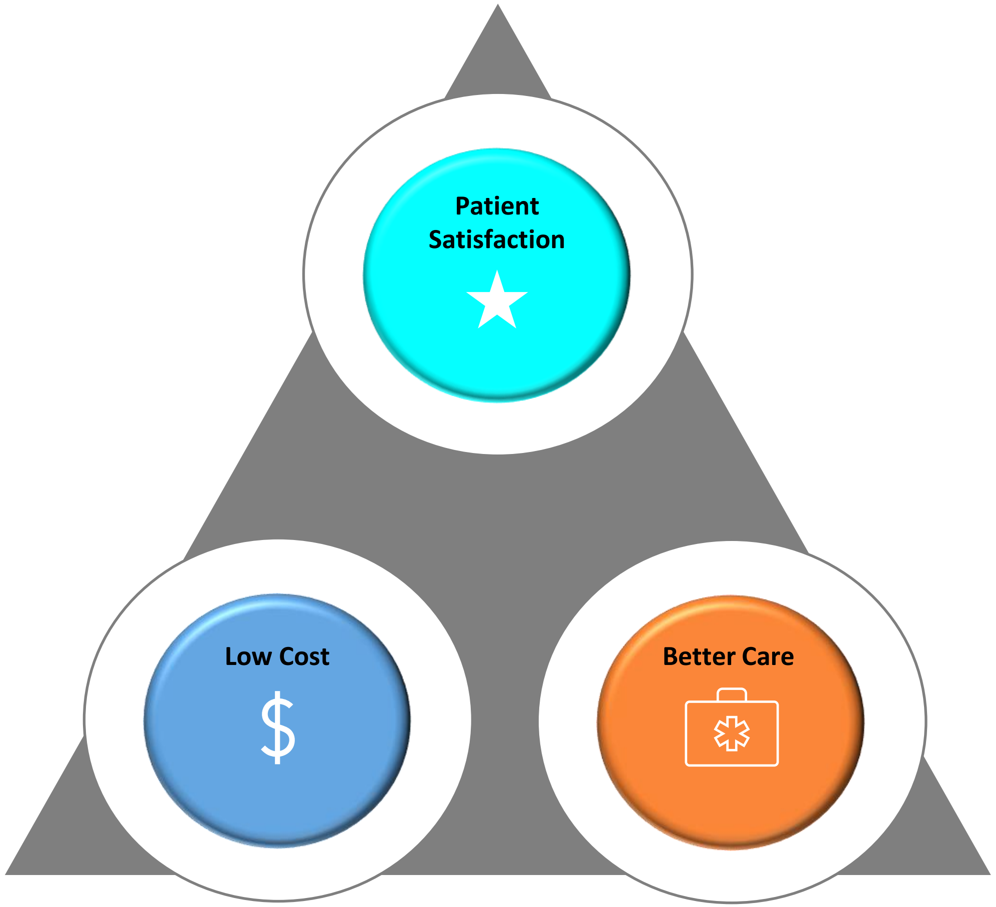
Targeting Patient Experience

The Benefits

- Increase patient engagement
- Better patient outcomes
- Continuity of care
- Increase employee moral
- Improve hospital reputation
- Reduce risks of malpractice
- Increase hospital financial success

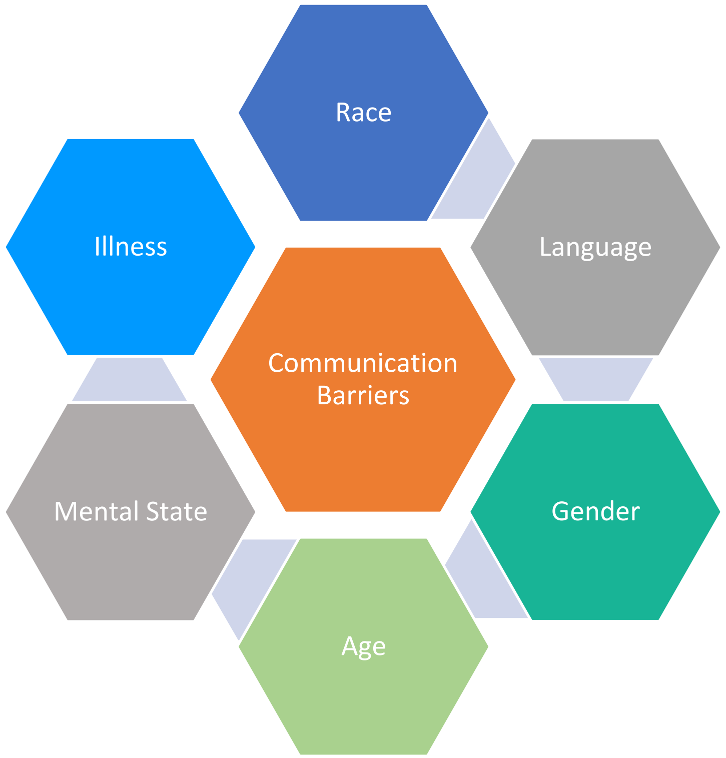


Improve Patient Experience

Ways to Improve Patient Experience

1. Communication

- Courtesy and Respect
- Listen to Concerns
- Provide Explanations



HCAHPS Survey Analysis

What is HCAHPS?

- First national, standardized, publicly-reported survey of patients' perspectives of hospital care
- Captures the patients' experience of communication with doctors and nurses, responsiveness of hospital staff, communication about medicines, cleanliness and quietness of the hospital, discharge information, transition to post-hospital care and overall rating of the hospital
- Administered between 2 and 42 days after discharge to a random sample of patients, by mail, telephone and interactive voice response, in a variety of languages

Top Box Rating

1 2 3 4 5

Rating Scale

Classification of Ratings

1	2	3	4	5
0	0	0	0	1

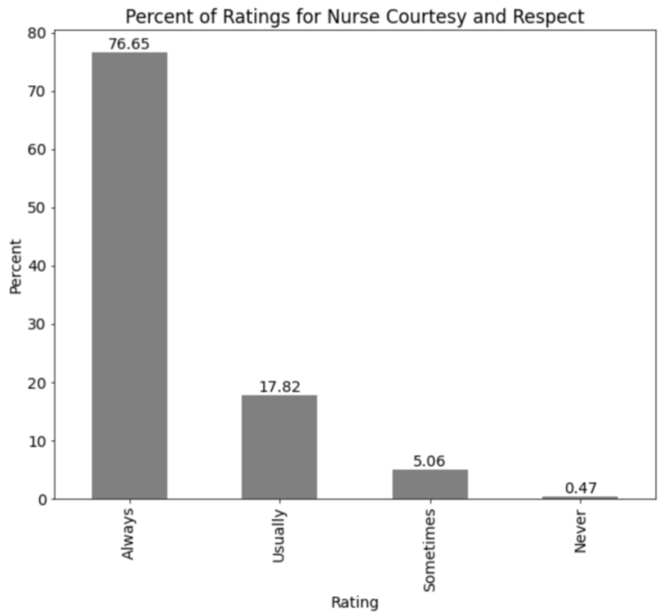
Deep Dive into Nurse Communication

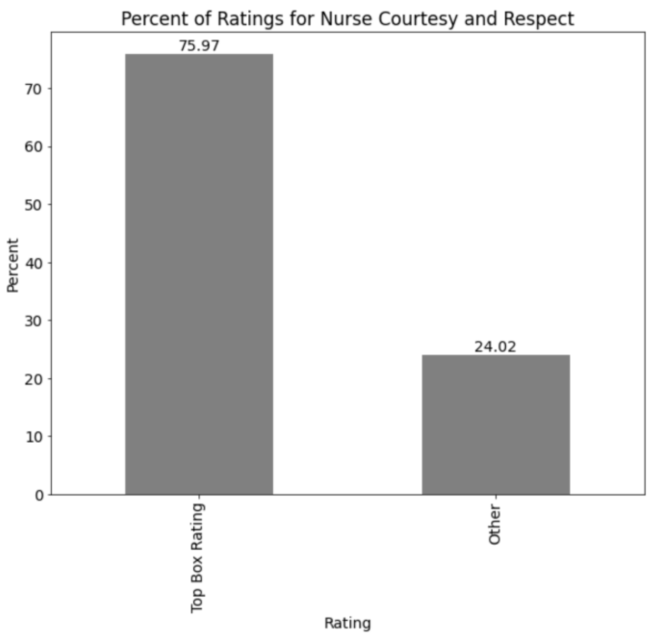
Nurses are on the front lines of health care

- A healthy nurse-patient relationship built on trust and respect goes a long way
- It’s important to understand the uniqueness of this relationship and how it contributes to the overall patient experience

76% of patients said nurses were always courteous and respectful

24% of patients said nurses were not always courteous and respectful





Dealing with unbalanced data

Missing Values in Survey

Handling Missing Values

- Surveys contain missing responses if questions do not apply to the respondent
- If missing values are removed, this may cause a significant amount of data loss
- Missing values were replaced with a category to capture the missing data

Q01_06	0.89
Q02_06	1.06
Q03_06	1.42
Q04_06	3.18
Q05_06	1.51
Q06_06	1.83
Q07_06	1.87
Q08_06	2.29
Q09_06	2.01
Q10_06	4.72
Q11_06	51.35
Q12_06	3.65
Q13_06	30.67
Q14_06	30.58
Q15_06	6.76
Q16_06	45.49
Q17_06	46.42
Q18_06	1.91
Q19_06	13.66
Q20_06	15.62
Q21_06	2.10
Q22_06	2.27
Q23_06	2.71
Q24_06	4.60
Q25_06	9.91
Q26A_06	8.75
Q26B_06	9.25
Q26C_06	9.59
Q26D_06	10.10
Q26E_06	10.18
Q27_06	4.15

Model Building

Target	Predictors
Nurse Courtesy and Respect	Nurses Listen, Nurses Explain, Spring, Summer, Gender, Critical Patient, Admission Source

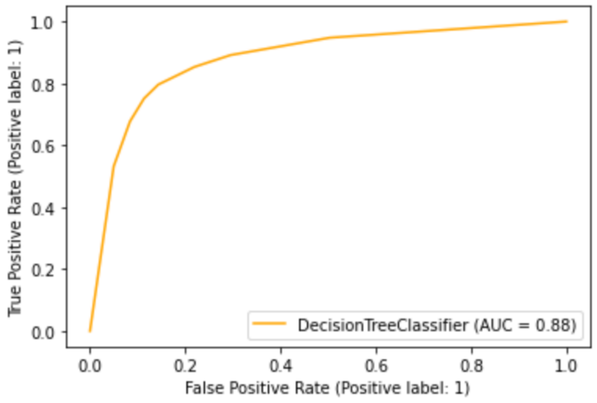
Model Type	Accuracy	ROC AUC	Misclassified
Logistic Regression w/ Train, Test, Split	84.70	79.9	False Positives: 4056 False Negatives: 4691
Logistic Regression w/ Kfolds = 10		87.36	
Logistic Regression w/ Cross Validation = 10		87.03	False Positives: 13410 False Negatives: 15254
Decision Tree – using undersampling	82.57	87.1	False Positives: 1976 False Negatives: 2814
Random Forest – using undersampling ** All variables were thrown into the model, so that a feature selection could be ran	82.62	88.8	False Positives: 1953 False Negatives: 2825
Random Forest w/ Feature Variables – using undersampling	82.62	88.2	False Positives: 1958 False Negatives: 2818
Decision Tree w/ Feature Variables – using undersampling	82.62	88.2	False Positives: 1958 False Negatives: 2818

Final Model – Decision Tree (using features of importance)

Overview of Model Accuracy

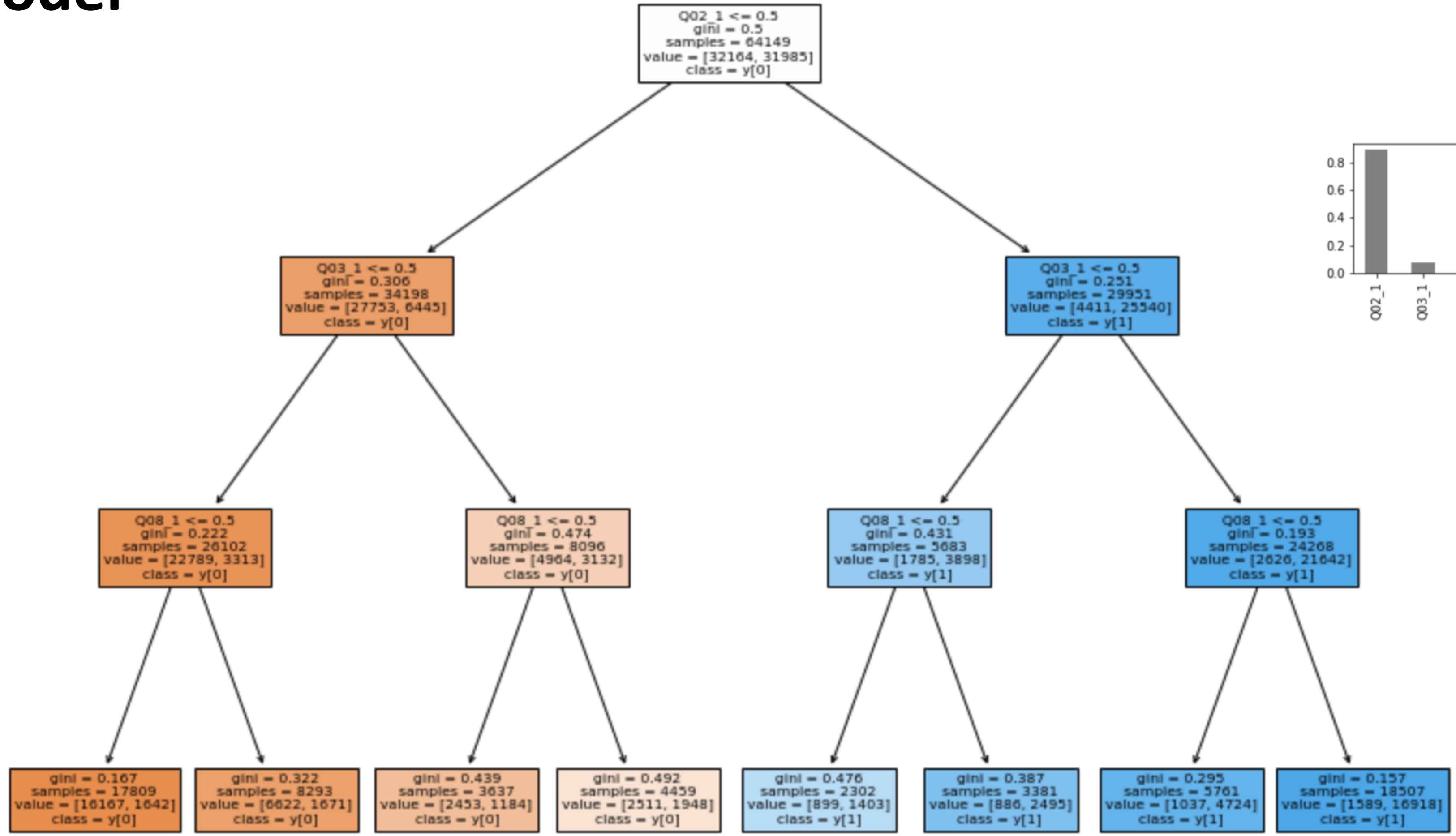
Model Type	Accuracy	ROC AUC	False Positives	Sensitivity	Specificity	
How often is the classification correct?	88.62	88.2				(True Positives + True Negatives)/Total True Positives & Predicted probabilities
How often is the model incorrect?						(False Positives + False Negatives)/Total
When the actual is yes, how often does it predict yes?				79.6		True Positives/Actual Yes
When the actual is no, how often does it predict yes?			14.3			False Positives/Actual No
When the actual is no, how often does it predict no?					85.6	True Negatives/Actual No

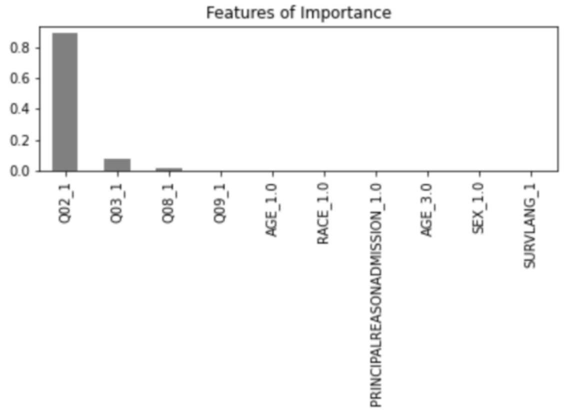
n = 27,493	Predicted: NO	Predicted: YES	Total
Actual: NO	TN = 11,699	FP = 1958	**13,657**
Actual: YES	FN = 2,818	TP = 11,018	**13,836**
Total	**14,517**	**12,976**	



Final Model – Decision Tree (using features of importance)

Results of Model





Conclusion

Nurses Courtesy & Respect

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Nurses Listen

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Nurses Explain

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Hospital Cleanliness

Recommendations

Add in new features to the dataset

- Complaints from patients
- Length of waiting times
- Patient diagnoses
- Hospital names
- Readmissions

1

2

Check data quality

Are there any issues with the dataset? Noticeable issues were discrepancies between the data dictionary and the actual dataset.

3

Cluster the data

Detect if there are similarities in different features, using the new inputs.

Q&A