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Completed Research

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Abstract

Health organizations are diligently working to achieve the zenith in service outcome and furtherance of patient satisfaction by embracing patient-centric policies. Patient recommendation is a critical indicator of patient satisfaction and hospital service quality. Evidence suggests that patient recommendation is the most valuable form of marketing. However, hospitals often encounter patients' unwillingness to recommend them. Prior studies mainly rely on patient survey data to determine factors that impact patients' willingness to recommend hospitals. Our study aims to identify factors that are not readily available in the patient surveys but have significant impact on hospital recommendation. Our proposed Machine Learning (ML) based model has incorporated multidimensional approach by identifying various affecting factors related to diverse hospital services for predicting the patient willingness to recommend the hospital. These factors will help providers to ameliorate quality of their services and implement more proactive measures that elevate hospital recommendations. Our results have shown that Random Forest (RF) to be the best technique for the prediction of hospital recommendation with a 0.08 RMSE and 0.59 adjusted R2. We have found that ED throughput, preventive care, and patient satisfaction related factors play a crucial role in influencing the patient's decision to recommend the hospital.

Keywords

Timely and effective care, preventive care, HCAHPS, patient satisfaction, hospital recommendation.

Introduction

Healthcare recorded tremendous growth in the past decade. Patient satisfaction has emerged as an essential factor in measuring the quality and success of the healthcare system. In this paper, we focus on patients' willingness to recommend a hospital. Becoming the $6.0 trillion industry by 2027, healthcare providers rely on hospital recommendations to judge patient satisfaction (Lee et al. 2020; Tabrizi et al. 2016). However, nowadays, a large number of patients in the U.S. do not respond positively to the hospital survey question whether they will recommend the hospital to other people. A recent study by Masson (2020) found that 20 % of patients of different hospitals in the USA would not recommend the hospitals where they received treatments. The COVID-19 pandemic has further exacerbated the issue. During the pandemic, 23% of patients would not recommend their hospitals because they felt rushed by their health care provider, and 15% said that they were confused about the instructions they got for their treatment (Funk and Gramlich 2020).

Hospitals have invested tremendous amount of money in identifying the factors that impact hospital recommendation by conducting various patient satisfaction surveys and hire third party consultants to evaluate hospital services (Khoie et al. 2017). Researchers have identified various factors that can contribute to a patient's unwilling to recommend a hospital. For example, overcrowding, discontinuity of care, and uncertainties during the treatment have been found to be factors that patients considered while recommending a hospital (Nichol et al. 2016). Patient-physician interactions and communications have also been found to be directly associated with the patient's hospital recommendation (Flood et al. 2016). Identifying the factors influencing the hospital recommendation provides significant contributions to various stakeholders including hospital management, clinical staff, healthcare regulators, and patients in varying degrees (Cheng et al. 2003). It helps hospital management and clinic staff to assess the quality of their services, implement more proactive measures to improve patient care, and consequently improve the probability of hospital recommendations. It also helps healthcare regulators develop benchmark guidelines for hospitals to improve their services. Nowadays, patients often rely on personal experience and recommendation from friends and family to select a hospital or a physician. Knowing the factors influencing hospital recommendation and a given hospital's performance along these factors helps patients make informed decisions for their choice of healthcare providers.

The objective of this research is to identify various factors influencing patient hospital recommendation and develop a machine learning (ML) model based on the factors for predicting hospital recommendations. Our research aims to identify the factors from a multi-dimensional approach, considering various factors related to diverse hospital services and derived from different sources. This make it different from prior research such as (Kumah 2019; Kunjir et al. 2019; Tabrizi et al. 2016) that only relied on one data source - patient survey data. Drawing upon existing research on patient satisfaction and hospital quality, we identify various factors that are not available in the patient surveys but can influence patients' decisions in hospital recommendation. For example, Joshi et al. (2020) found that annually, more than 2 million patients visit emergency departments (EDs) and leave without being seen due to delays in initiating care. We hence consider ED throughput measure such as delays and long wait times as potential factors that may result in unwillingness in hospital recommendation. Drawing upon existing research such as (Deb et al. 2019; Kahn et al. 2019; Owen et al. 2014; Rhee et al. 2019) that investigates the impact of preventive care on hospital quality, we include these preventive care measures such as "Percentage of patients who have got proper sepsis care" for predicting hospital recommendations.

Healthcare settings often comprises plan, analysis and evaluation process to support an improvement. Hence, by complimenting existing conceptual frameworks provided by (Abo-Hamad and Arisha 2013) and (Asplin et al. 2003), our study represents an amalgamation and extension of these two frameworks. We have adopted the ED throughput concept from these two studies and included the preventive care concept. Therefore our, proposed approach is a combination of ED throughput and preventive care measures.

Literature Review

With the digital up-gradation of hospital systems, the compiled survey data of patients plays a vital role in the hospitals recommendation (Kunjir et al. 2019). Most of existing research such as (Kumah 2019; Kunjir et al. 2019; Tabrizi et al. 2016) has used the Hospital Consumer Assessment of Healthcare Providers and Systems Patient Survey (HCAHPS) to identify factors that impact patient recommendations. The HCAHPS survey aims to capture distinct aspects of patient's viewpoints toward patient care and include different patient satisfaction-related measures such as "whether nurses communicated well or not" and "whether staff explains about medicine or not".

Shirley and Sanders (2016) suggest that accurate assessment of hospital recommendation requires a multidimensional approach, and satisfaction surveys alone are not sufficient. We hence explored the studies that do not directly investigate hospital recommendations but highlight various factors associated with patient satisfaction and hospital quality. These factors may also impact patients' hospital recommendations. Patient satisfaction is considered the reference point by many healthcare authorities to judge the hospital care and recommendation (Tabrizi et al. 2016). Researchers have found some essential factors affecting patient satisfaction based on emergency department (ED) inpatient data. Researchers such as (Beck et al. 2016; Haq et al. 2018; Sun et al. 2020) have focused on ED throughput (i.e., time management during ED operations) as an essential factor for understanding the barriers faced by healthcare providers while managing the patient flow. The length of stay and wait time in EDs have emerged as critical factors that affect patient satisfaction and need to be reduced (Haq et al. 2018). Mentzoni et al. (2019) have emphasized that patient satisfaction level and overall impact of hospital workflow enormously lean on crowding and length of stay based on six years of ED inpatient data in their study. Nichole et al. (2016) have used ED data and studied the relationships between patient overall experience and the wait time to be seen by a provider. We hence include the ED measure such as average ED stay time and average ED wait time in our model for predicting patient hospital recommendation.

Another type of measures that are potentially related to hospital recommendations are preventive care measures. Several studies such as (Deb et al. 2019; Kahn et al. 2019; Rhee et al. 2019) have used preventive care measures, especially sepsis prevention, to assess the hospitals qualities. Rhee et al. (Rhee et al. 2019) asserted that sepsis dissemination in hospitals aggravates the death count, and roughly 1.7 million adults get affected by this. Kahn et al. (2019) and Deb et al. (2019) have considered timely and effective care to improve sepsis prevention an important factors affecting hospital quality.

Existing studies such as (Graham et al. 2018; Hong et al. 2018; Raita et al. n.d.) have proven the significance of applying the machine learning (ML) techniques like logistic regression (LR), gradient boosting (XGBoost), and deep neural networks (DNN) to address the prediction-based problems such as ED patient flow and admission rate. With this we have adopted the idea of applying ML techniques to predict the patient's willingness to recommend the hospitals.

In this paper, we intend to carry out in-depth research for identifying factors that predict hospital recommendations. We have adopted a multidimensional approach that targets several factors coming from different sources, which make our research different from existing research that primarily relies on only patient survey data. We draw upon existing research and incorporate measures that have previously been found to be related to patient satisfaction and hospital quality, including ED throughput and preventive care measures in addition to patient satisfaction survey measures. We believe these measures can also impact patients' hospital recommendation.

Methodology

Data Collection

We conducted our research using different data sources collected by (Cms 2020) , including Hospital Consumer Assessment of Healthcare Providers and Systems patient Survey (HCAHPS), Hospital General Information (HGI), and Timely and Effective Care Data. HCAHPS is a collection of consumer-oriented patient satisfaction information for hospitals. It contains responses regarding a patient's willingness to recommend the hospital or not. The dataset consists of a total of 454212 observations. The HGI dataset has fields such as provider ID, type, state, and so on for the US hospitals(Cms 2020). The dataset consists of 5320 observations. The Timely and Effective Care dataset possesses the effective measures that include the percentage of hospital patients who receive the treatments known to get the best results for certain common, severe medical conditions or surgical procedures. The dataset consists of 90193 observations.

Data Pre-Processing

```
BEGIN
        SELECT C_i of T_i
            FROM T_i
            JOIN T_i ON T_i+1 for C_i
            WHERE Cv_i of T_i LIKE Dv_i
            AND Cv_i of T_i IN {Iv_i}

        CREATE V
            SELECT C_i
            CASE if Cv_i == "Iv_i" then S AS NC_i
            FROM T_i
END
```

Figure 1. Pseudocode: Data Extraction

Publicly available secondary data often possesses irregularities and anomalies and may not directly fulfill the study purpose. Therefore, extensive data preprocessing is required for the proposed work. We first manually reviewed variables in the datasets because the datasets include various dimensions that could make it difficult to identify relevant variables (Tabrizi et al. 2016). For instance, we removed the standard demographic and geographic information from all three datasets. Figure 1 shows the pseudocode for utilizing customized structure query (SQL) operations for joining different datasets (i.e., tables) and extracting the variables, whereby, C_i represents the column name of Table T_i , Cv_i represents the values in the column, Dv_i Represents the value of the dependent variable, Iv_i is for values of the independent variable, S is for score values of the independent variables, NC_i represents the column alias name and V represents the view name. As a part of feature engineering, we have extracted the variables related to ED Throughput, preventive care, and patient satisfaction survey that may influence patient hospital recommendations. After data preprocessing, we obtained a dataset that includes 24 variables and a total of 1836 observations, each representing one hospital in the U.S.

Variable Selection

Dimension	Variable Name	Description
ED Throughput	OP-31	Percentage of patients who had improvement after cataract surgery.
	OP-29	percentage of patients who have got recommendation for colonoscopy
	OP-2	percentage of patients who got drug for heath attack after arrival.
	EDV	ED volume
	ED-2b	Average ED wait time of patient to get inpatient admission
	OP-18b	Average ED stay time
	OP-18c	Average Mental health patients ED stay time
	OP-22	Percentage of patients LWS
	OP-23	Percentage of patients received brain scan in shorter time after arrival
	OP-33	Percentage of patients received care for cancer spread to bone
	OP-8	Percentage of patients received MRI before therapy
	OP-10	Percentage of patients received abdomen CT scan
	OP-13	Percentage of patients received cardiac stress test
Preventive Care	SEP-1	Percentage of patients who have got proper sepsis care
	OP-3b	Percentage of patients received abdomen CT scan (OP-10), percentage of patients received cardiac stress test.
	IMM_3	Healthcare workers given influenza vaccination to patients.
Patient Satisfaction	Nurse_Communications	Patient responded whether nurse communicated well or not.
	Doctor_ Communications	Patient responded whether doctor communicated well or not
	Staff_Communication	Patient responded whether staff communicated well or not
	Medicine_Comm	Patient responded whether staff explains about medicine or not
	H_CLEAN	Patient responded whether hospital is clean or not
	Quietness	Patient responded whether hospital ambience is quiet/ or not
	Discharge_Info	Patient responded whether they get instruction for home recovery or not
	Care	Patient responded whether they understand the selfcare after discharge or not

Table 1. Various dimensions and their variable name and description

After aggregating all three datasets, we have various ED throughput, preventive care, and patient satisfaction survey-associated variables as shown in Table 1. The dependent variable used in our research is "percentage of patients that will recommend a given hospital", derived from the HCAHPS survey dataset. To identify the independent variables that have significant impact on the dependent variable, we used the stepwise regression analysis for variable selection. Therefore, the final set of ED throughput variables are ED-2b, Op-22, Op-8, Op-2, and Op-18b. The final set of variables for preventive care are SEP-1, IMM_3, and OP-3b. The final set of variables for patient satisfaction are H_CLEAN, Nurse_Communications, Staff_Communication, and Doctor Communications.

Machine Learning Techniques

We have utilized state-of-the-art ML regressors such as Decision tree (Tree), Random Forest (RF), Multiple Linear Regression (MLR), Support Vector Regression (SVR), and K-nearest Neighbors (KNN) and Multilayer Perceptron (MLP) to predict patient's responses on hospital recommendation. The overarching goal of ML regressors is to reduce the root-mean-square error (RMSE). RMSE is used for measuring error in the prediction. A tree-based representation of attributes as a node for the prediction of target variable values is known as decision tree. We have used DT as a regressor that learns simple decision rules extracted from the data (Dumont et al. 2009). MLR uses several explanatory variables to predict the outcome. The goal of MLR is to draw the linear relationship between the independent variables and dependent variable (Kenton 2021). SVR works upon the principle of support vector machines whereby a margin is drawn to fit the data within decision boundary (or hyper plan). SVR aims to reduce the coefficient (Platt 1999). KNN is a non-parametric and lazy learning technique where K is the number of neighbors. KNN works upon the concept of distance calculation between data points and predict the outcome according to nearness and further draw a regression line to fit the data (Singh et al. 2016). To fulfill the goal of improving generalizability/robustness, a combination of several ML techniques as an estimator is used for the prediction is known as the ensemble method. Random forest is a widely known ensemble method that produces the output predicted by several decision tree techniques. Ensemble techniques were developed to reduce the chances of overfitting and noise (Singh et al. 2016). We further utilized the MLP, a class of artificial neural networks (ANN) developed on the human brain's neuron activation and learning anatomy. MLP is a feedforward neural network consisting of input, output, and multiple hidden layers whereby the weights of neurons (i.e., nodes on layers) adjusted by comparing output with desired result (Dey 2016).

Since the dataset consists of a limited set of observations therefore to train and tune the parameters of the regressors for optimum performance, we have performed the K fold cross-validation (Ex., 5-fold, 10-fold) on the training dataset.

Results and Discussion

Asplin et al. (2003) defined the ED throughput as an input-throughput-output (ITO) system in healthcare facilities, and Abo-Hamad and Arisha (2013) connected the ED throughput along with patient's satisfaction. However, we did not find an immediately aligned study or framework to our work that encompasses the ED throughput, preventive care and patient's willingness to recommend the hospital. Our approach interlinked the ED throughput, preventive care and patient willingness. Furthermore, this would contribute in the decision making process to prioritize the indicators (see Table 1) associated to efficient patient care and their willingness to recommend the hospital.

We have utilized scikit-learn, a python-based library, for the implementation of ML techniques. After the above-cited data preprocessing, we have used MinMaxScaler() method to standardize the data by scaling the features to lie between the minimum and maximum value. This helps improve model performance.

To assess the strong tie between our selected independent and dependent variables, we have performed Ordinary least Square (OLS) regression analysis. As shown below, Equation 1, 2, and 3 represents the Model 1 ,2 and 3 in Table 2 respectively. Model 1 is used to check the significance of patient survey response measures on predicting hospital recommendation. Model 2 is used to check the significance of ED Throughput measures and patient survey response measures on hospital recommendation. Model 3 is used to check the significance between the independent variables including ED Throughput measures, preventive care measures and patient survey response measures and the dependent variable percentage of patients that recommend a hospital.

$$Equation\ 1)\ H_{Recommend} \sim H_{CLEAN} + Staff_{Communication} + Nurse_{Communication} + Doctor_{Communication}$$

$$Equation\ 2)\ H_{Recommend} \sim H_{CLEAN} + Staff_{Communication} + Nurse_{Communication} + Doctor_{Communication} + ED_{2b} + OP_{22} + OP_{8} + OP_{18b} + OP_{2}$$

$$Equation\ 3)\ H_{Recommend} \sim H_{CLEAN} + Staff_{Communication} + Nurse_{Communication} + Doctor_{Communication} + ED_{2b} + OP_{22} + OP_{8} + OP_{18b} + OP_{2} + SEP_{1} + IMM_{3} + OP_{3b}$$

Table 2 shows the statistical summary of Model 1, 2, and 3. As shown in Table 2, the combination of all the measures in model 3 showed a significant role in predicting the dependent variable at 99% CI. Model 1 from table 2 indicates that Patient survey response measures yielded an adjusted R squared value of 0.41 which gradually increased to 0.48 when ED throughput measures are included in model 1 (model 2), similarly we ended with a 0.57 adjusted R squared value when patient survey response, ED throughput, and preventive care measures are considered (model 3). Overall, results indicate the combined set of predictors (Model 3) taken into consideration has significantly improved the evaluation metrics adjusted R square and RMSE, when compared with Model 1 and 2. This makes the final variable set of Model 3 to play a crucial role in designing a hospital recommendation system in extending the research for future studies.

	Model 1	**Model 2**	**Model 3**				
Dimensions	**Variables**	**Coef.**	**P value**	**Coef.**	**P value**	**Coef.**	**P value**
Patient Survey Response	H_CLEAN	0.44	< 0.01	0.49	<0.01	0.47	<0.01
	Staff_Communication	0.59	<0.05	0.52	0.243	0.54	0.643
	Nurse_Communications	0.49	< 0.01	0.38	<0.01	0.41	<0.01
	Doctor_ Communications	0.44	< 0.01	0.39	<0.01	0.36	<0.01
ED Throughput	ED-2b			0.0019	< 0.01	0.0016	< 0.01
	OP-22			0.0037	< 0.01	0.0033	< 0.01
	OP-8			0.0016	< 0.05	0.0021	0.407
	OP-18b			0.0025	< 0.01	0.0019	< 0.01
	OP-2			0.0043	<0.05	0.0041	0.109
Preventive Care	SEP-1					0.0015	< 0.01
	IMM_3					0.0039	0.116
	OP-3b					0.0002	< 0.01
Adj. R squared	0.41	0.48	0.57				
RMSE	0.16	0.11	0.09				

Table 2. Statistical Analysis

As shown in Table 2, most of the independent variables have shown significant ties with the dependent variable at 95% confidence interval. Among our independent variables, two variables "staff communication with patients" with p-value = 0.643 in Model 3 and "percentage of patients receiving MRI before surgery" with p-value = 0.407 are not significant. Two variables including "percentage of patients who got drug for heart attack after arrival" (p-value = 0.109) and "Healthcare workers given influenza vaccination to patients" (p-value = 0.116) are moderately significant. The variables such as ED average wait time (ED-2b), average ED stay time (OP-18b), and left without seen (OP-22), proves that if the patients receive the appropriate care as soon as they intended, the hospital is more likely to receive a good recommendation. Therefore, ED throughput measures are critical for predicting the hospital recommendation. ED wait time and length of stay are the main factors that affect the ED performance and patient satisfaction which in turn affect the hospital recommendation. Few studies have tried to prove that longer the patient wait for a service and higher the quality of service tends to decrease hospital recommendation (Horwitz et al. 2010). This suggests that the hospitals need to implement innovative systems in place for reducing patient wait times and stay times especially in the ED.

Percentage of sepsis care (SEP-1), and heart attack care (OP-3b) variables represent the preventive care measures that have P values less than 0.01 indicating they are statistically significant with a 99% confidence in predicting the hospital recommendation. As sepsis and heart attack are critical disease conditions which are the most common life-threatening cases observed by a physician on a daily basis, patients tend to highly value the accuracy of the diagnosis in determining the hospital recommendations. Therefore, it is crucial for the hospital staff to educate the patient as well as their family members regarding the diagnosis in laymen terms to make the patient feel total control of the situation and clearly understand the efficiency of their clinical team in diagnosing the disease condition.

Hospital cleanliness (H_CLEAN), nurse communication to patients (Nurse Communications), and doctor communication to patients (Doctor_Communications) variables represent the patient survey response measures that have p values less than 0.01 indicating they are statistically significant with a 99% confidence in predicting the hospital recommendation. A good hygiene and clean ambience in hospital prevents the risk of other unprecedented infections during the treatment and regular interaction between patients and medical practitioners such as nurses and doctors help patients to understand about their health. Hence, patients consider the hospital cleanliness, communication with nurses and doctors to recommend the hospital. Therefore, health providers should take care of efficient doctor – patient communication and hospital cleanliness to make the patients feel safe and confident about their care.

$$Equation\ 4)\ Final\ H_{Recommend} \sim H_{CLEAN} + Nurse_{Communication} + Doctor_{Communication} + ED_{2b} + OP_{22} + OP_{18b} + SEP_1 + OP_{3b}$$

We removed the four variables (i.e., Staff_communication, OP-8,OP-2, and IMM_3) that have p-value >0.05 and finalized the final set of variables from Model 3, that is illustrated in Equation 4, these variables are further utilized to build various ML techniques as shown in Table 3. We split our dataset into 75% and 25% for the training and testing set, respectively. We fit the different ML models using the training set and then applied the fitted model to the test set. We used the GridSearchCV() method in the Python scikit-learn package and conducted 5-fold cross-validation to select the optimal hyperparameters for each ML model. The optimal RF hyperparameters obtained via the grid search are (criterion= gini, max_depth = None, min_samples_split = 2, n_estimators= 600), DT hyperparameter values are (criterion = gini, max_depth= 6, min_samples_split= 2}, KNN hyperparameter values are (n_neighbors= 11, p= 2), MLR hyperparameter values are (normalize= l2-norm),SVR hyperparameter values are (C= 0.1, kernel=rbf) and MLP hyperparameters are (hidden_layer_sizes=[256,128,64,32],activation=relu).

Table 3 shows the values of the model's evaluation measures including Root Mean Squared Error (RMSE) and adjusted R^2 when we applied the model to the test set. Where by RMSE represents how condensed the data around the best fit line and adjusted R^2 tells the explanatory power of model that how well independent variables affect the dependent variable.We observed that all ML techniques performed well and were able to predict the patient's willingness to recommend the hospital. RF outperformed the other models with RMSE of 0.08 and Adj R-Squared of 0.59.

Models	**RMSE**	**Adj. R^2**
KNN	0.09	0.55
Decision Tree	0.10	0.55
Multiple Linear Regression	0.09	0.57
Random Forest	**0.08**	**0.59**
SVR	0.10	0.57
MLP	0.09	0.56

Table 3. Model Evaluation measures

Conclusion

In this paper, we propose a multi-dimensional approach to identifying factors that impact patient hospital recommendation. We consider various factors related to diverse hospital services and derived from different sources and develop a ML model for hospital recommendations, based on these various factors. This work expected to be theoretically contributed to the evolving research that fosters the knowledge base regarding timely and effective care, preventive care and hospital recommendation. By aligning with prior research, this work expands the scope of ongoing research on hospital recommendation by highlighting the impact of ED average wait time, average ED stay time, left without seen, percentage of sepsis care, heart attack care, nurse communication, doctor communication, and hospital cleanliness on patient's willingness to recommend the hospital. The obtained final predictors could be utilized by healthcare providers to improve the ED care, preventive care, and patient satisfaction that will further enhance the positive rate of hospital recommendation. Presented work comprises limitations such as the availability of patient centric data that consists the direct responses from the patients. The collected data from CMS possesses the USA based hospital records, hence limit the scope of study and did not explore the observations from other continents.

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