CKME 136 Data Analytics: Capstone Course

Final Report

Chang School of Continuing Education, Ryerson University

Title: The Effects of Perceived Quality and Satisfaction on Hospital Rating

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**Introduction**

There is complexity in evaluating the efficacy of a health care system due to a combination of scientific, technological, economic, and epidemiological imperatives [1]. As such, the common proxy for quality of hospital care is the patients’ ratings of their hospital [2]. The perceived quality and satisfaction of patients is of particular importance as it can be a salient indicator used to draw detailed contextual descriptions of hospital’s different components to identify patterns that may have an impact on other outcomes of a health care system. In addition, the findings of these comparative analyses can recommend policies that are aimed at system-level improvements. I will evaluate the official hospital compare datasets provided by Center for Medicare and Medicaid (CMS) for hospital quality comparison [3]. Classification methods will be used to predict the overall hospital rating and identify the characteristics of hospitals. For predictive modelling, three classification algorithms will be explored: (1) decision tree, (2) Naïve Bayes, and (3) logistic regression. These methods will be implemented using a combination of Weka and R.

**Literature Review**

The quality of health care is hard to quantify as it is contingent on several factors. Based on the literature review, there is a lack of exploration on the hospital performance on measurements of patients’ ratings and performance with respect to one characteristic of hospitals (e.g., mortality national comparison) related to performance with respect to another characteristic (e.g., readmission national comparison). In addition, the quality metrics for characterizing a hospital of high quality has yet to be discussed. For example, do patients who receive care in hospitals with key characteristics (not-for-profit hospital, below national average timeliness, etc.) report better experiences than patients in hospitals without these characteristics? DeLancey et al. in 2017 published their results on the associations between hospital characteristics, measure reporting, and the CMS Overall Hospital Quality Star Ratings [4]. Based on this article, hospitals with star ratings between 4 and 5 were considered to have high quality while hospitals with 1 to 3 stars were considered to have low quality. The principal investigators have concluded that smaller hospitals more frequently achieved a high star rating compared with larger hospitals.

National policies to improve health care quality have largely focused on clinical provider outcomes and payment reform; however, the study conducted by Tsai et al. in 2015 revealed the association between hospital leadership and quality [5]. Also, the paper outlines the increase in quality of care with hospitals practicing more effective management. In particular, the hospital ownership type determined the management style which validates the relevance and inclusion of the Hospital Ownership attribute in the analysis. In addition, Bloom and his team explored whether different management style affected hospital performance [6]. They published that higher competition results in higher management quality and improved hospital performance.

With regards to the meaningful use of electronic health records (EHRs), it is a challenge to validate the relevance as the external rules, regulations and pressures have influenced the credibility of such a metric. The recent passage of the American Recovery and Reinvestment Act (ARRA) of 2009, which includes the Health Information Technology for Economic and Clinical Health (HITECH) Act, made available over $20 billion dollars for health care practitioners who become “meaningful users” of health IT. Thus, ARRA introduces the single largest financial incentive ever to facilitate electronic health record (EHR) implementation. Recent studies reveal strong evidence that supports the superficial validation and implementation of the meaningful use of EHRs criteria, as such, the attribute regarding meaningful use of EHRs will be eliminated [7].

**Dataset**

The dataset used in this analysis is sourced from the Hospital ratings dataset from Kaggle [8]. This is derived from the official dataset used on Medicare.gov (<https://www.medicare.gov/>) for hospital quality comparison.

The dataset consisted of 4812 observations and 28 attributes. The nominal variables include Hospital Name, Address, City, State, County Name, Hospital Type, Hospital Ownership, Emergency Services, Meets criteria for meaningful use of EHRs, and the following variables had themselves and the respective footnotes: Hospital Overall Rating, Mortality National Comparison, Safety of Care National Comparison, Readmission National Comparison, Patient Experience National Comparison, Effectiveness of Care National Comparison, Timeliness of Care National Comparison, and Efficient Use of Medical Imaging National Comparison. The criteria to include and/or exclude certain attributes will be further discussed in the Approach section, in particular with reference to Multiple Factor Analysis (MFA) and redundant information.

**Approach**

**Step 1: Data Preparation**

The detailed approach accompanied by the respective programming can be found on the GitHub page (<https://github.com/fleejy/ckme136-capstone/>).

The dataset used in this analysis consisted of 4812 observations and 28 attributes. Based on literature review, the *Hospital overall rating* variable which act as the key prediction variable was converted to a nominal variable. Other nominal variables include: Hospital Name, Address, City, State, County Name, Hospital Type, Hospital Ownership, Emergency Services, Meets criteria for meaningful use of EHRs, Hospital overall rating footnote, Mortality national comparison, Mortality national comparison footnote, Safety of care national comparison, Safety of care national comparison footnote, Readmission national comparison, Readmission national comparison footnote, Patient experience national comparison, Patient experience national comparison footnote, Effectiveness of care national comparison, Effectiveness of care national comparison footnote, Timeliness of care national comparison, Timeliness of care national comparison footnote, Efficient use of medical imaging national comparison, and Efficient use of medical imaging national comparison footnote.

The numeric variables consist of Provider ID, ZIP Code, and Phone Number. They were of no significance to the purpose of this analysis; therefore, the overall dataset is qualitative such that summary statistics was not appropriate. Consequently, Principal Component Analysis (PCA) could not be conducted for dimensionality reduction; however, Multiple Factor Analysis (MFA), which is dedicated to datasets where variables are structured into groups, was conducted instead to reduce the dimensionality of the dataset [9].

From the MFA, the primary objective is to characterize hospital overall quality rating and to find a typology of the hospital overall quality rating.

In addition, outlier detection was not suitable for a categorical dataset; therefore, chi-squared test was conducted for all attributes. Chi-squared test was chosen because it is able to determine if the attributes are dependent or not, given that both response and predictors are categorical variables (i.e., hospital overall rating and all other attributes) [Figure 1.2]. For all attributes except Emergency Services (i.e., h\_es), the null hypotheses were rejected because the p-values of the observed H statistics were smaller than 0.05. This indicates that the attributes differ in their overall hospital rating, suggesting a significant effect in the overall rating. On the other hand, Emergency Services’ null hypothesis was retained because the p-value of the observed H statistic was larger than 0.05 which suggest that the attribute was not significant in its effect in relation to the overall hospital rating. As such, the Emergency Services attribute was further eliminated.

The following codes were used for attribute names:

|  |  |
| --- | --- |
| **Original Attribute Name** | **Abbreviated Attribute Name** |
| Hospital Ownership | h\_ownership |
| Hospital Overall Rating | h\_rating |
| Mortality National Comparison | h\_mortality |
| Safety of Care National Comparison | h\_soc |
| Readmission National Comparison | h\_ra |
| Patient Experience National Comparison | h\_pex |
| Effectiveness of Care National Comparison | h\_eoc |
| Timeliness of Care National Comparison | h\_toc |
| Efficient Use of Medical Imaging National Comparison | h\_imaging |

After missing data from all attributes were removed, there was a total of \_\_\_\_ observations and \_\_\_\_ attributes.

It is worth noting that all except one instance of the Critical Access Hospitals. Critical Access Hospital (CAH) is a designation given to eligible rural hospitals by the Centers for Medicare and Medicaid Services (CMS); therefore, any hospital types of CAH was removed.

* Once “Not available” instances were removed only 1 instance of Critical Access Hospital remained from h\_type. This can be explained by that fact that any rural hospitals that are CAH designated receive certain benefits, such as cost-based reimbursement for Medicare services which help to reduce their financial vulnerability while improving access to healthcare by keeping essential services in rural communities. As such, it is expected any tracking of information was not available.
* Given this characteristic and by definition, CAH being outliers for the purpose of this analysis, the attribute h\_type was additionally removed.

Children’s Hospital and CAH are both instance specific such that they are deemed unsuitable for the purpose of this analysis. Furthermore, the uniqueness of both Children’s hospitals and CAH require ---------------.

We eliminated attributes that do not contribute to the modelling purpose (i.e., Provider ID, Hospital Name, Address, City, State, ZIP Code, County Name, Phone Number, and all attributes’ footnotes). In addition, the MFA of the rest of the attributes indicated high correlation between international charge and international minutes. Therefore, we further eliminated charge attributes for day, evening, night and international [Figure 1.3].

The dataset showed significant imbalanced distribution with 2850 False for not churn and 483 True for churn. We used downsampling in Weka filter to bring down the number of False to make the ratio of the two classes equal. Therefore, the final number of sample was 922 (i.e., 461 True for churn and 461 False for churn). Most of the attributes were normal, and with no missing values in the dataset, we considered the dataset clean [Figure 1.3].