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Original Contribution

Predicting 72-hour emergency department revisits☆

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ABSTRACT

Objectives: To develop a predictive model that hospitals or healthcare systems can use to identify patients at high risk of revisiting the ED within 72 h so that appropriate interventions can be delivered.
Methods: This study employed multivariate logistic regression in developing the predictive model. The study data were from four Veterans medical centers in Upstate New York; 21,141 patients in total with ED visits were included in the analysis. Fiscal Year (FY) 2013 data were used to predict revisits in FY 2014. The predictive variables were patient demographics, prior year healthcare utilizations, and comorbidities. To avoid overfitting, we validated the model by the split-sample method. The predictive power of the model is measured by c-statistic.
Results: In the first model using only patient demographics, the c-statistics were 0.55 (CI: 0.52–0.57) and 0.54 (95% CI: 0.51–0.56) for the development and validation samples, respectively. In the second model with prior year utilization added, the c-statistics were 0.70 (95% CI: 0.68–0.72) for both samples. In the final model where comorbidities were added, the c-statistics were 0.74 (CI: 0.72–0.76) and 0.73 (95% CI: 0.71–0.75) for the development and validation samples, respectively.
Conclusions: Reducing ED revisits not only lowers healthcare cost but also shortens wait time for those who critically need ED care. However, broad intervention for every ED visitor is not feasible given limited resources. In this study, we developed a predictive model that hospitals and healthcare systems can use to identify "frequent flyers" for early interventions to reduce ED revisits.

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1. Introduction

The cost of providing care in the Emergency Department (ED) is relatively high. The average cost of ED visits is $1038 compared to $176 for primary care visits in the United States [1]. Moreover, ED use is on the rise; according to the National Health Statistics Reports from CDC, the number of ED visits increased from 119.2 million (40.5 visits per 100 persons) in 2006 to 136.3 million (44.5 visits per 100 persons) in 2011 [2,3]. Further, a systematic review revealed that frequent-flyer patients constitute a key factor of ED crowding, resulting in treatment delays and excessive mortality [4,5]. Thus, reducing unnecessary ED use, especially repeated visits, should be a key part of the solution to the problem.

However, compared to hospital readmissions, which have been used by the Centers for Medicare & Medicaid Services (CMS) since October 1, 2012 to reduce payments to the hospitals with excessive readmissions [6], ED revisits have received less attention [7]. To develop interventions to reduce ED revisits, accurate predictive modeling that can identify high risk patients is needed. Although there is some published literature analyzing factors influencing ED revisits, research on predictive modeling of ED revisits is limited [8-17]. There are a few studies intended to predict 30-day or 6-month ED revisits [18-20]; however, we have not been able to find any published studies designed to predict 72-hour ED revisits [1,21-23].

In this study, we developed a statistical model that predicts patient risk of revisiting the ED within 72 h of discharge, which can be used to identify high risk frequent-flyers for appropriate intervention. With rapid adaptation of Meaningful Use of Health Information Technology, administrative data have been becoming increasingly closer to real time and offering greater potentials for improving patient care. Our model, based on administrative data and publically available case-mix schemes, could offer a valuable tool for the field.

2. Method

2.1. Data source and study variables

In the present study, we analyzed fiscal years (FY) 2013 and 2014 ED visit data from Veterans Healthcare Network Upstate New York (VISN 2 Upstate), which is one of the 21 Networks through which the US Department of Veterans Affairs (VA) delivers care to its 5.8 million patients

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annually. VISN 2 Upstate, with five medical centers and 31 outpatient clinics across upstate New York, serves approximately 140,000 patients with an annual budget of one billion dollars (starting from FY16, VISN 2 was restructured to include NY downstate VA hospitals). In FY 2014 for VISN 2 Upstate, 21,141 patients had ED visits in four of the medical centers which provide ED services.

VA National Patient Care Database (NPCD) hosted at the VA Information and Computing Infrastructure (VINCI) was the primary data source for this study. We used Outpatient Care File (OPC) and clinical stop code 130 to identify index ED visits and revisits. In addition to encounter information such as visit dates and ICD-9 CM codes, OPC also contains patient demographic and socioeconomic variables such as age, gender, race and income. NPCD, including OPC, is the gold standard for VA operational analysis and research. Most of the data fields such as visit dates and clinical information like ICD-9 CM codes are routinely and rigorously validated with strict business rules. Its income information is means tested. One exception is that its race information is often incomplete because the VA does not mandate veterans to report race status. However, for the last several years, VA has systematically gathered race information from other data sources such as Medicare and Department of Defense (DOD); as a result, the updated race data is deemed accurate and reliable [24,25].

We also used Decision Support System (DSS) files that contain actual patient care costs rather than claims or paid as in private health plans. DSS costs are the primary financial data for internal operations and congressional inquiries. For case-mix or patient risk, we used a publically available and widely used algorithm, Clinical Classifications Software (CCS), developed by Agency for Healthcare Research and Quality (AHRQ) [26], which classifies patients into 285 homogeneous groups based on ICD-9 codes.

The dependent variable in this study is dichotomous and indicates whether a patient had any ED revisits within 72 h in FY14. The independent or predictive variables used in this study were from FY13 and were grouped into four categories: (1) demographics: age, sex, marital status, race, period of military service, and disability rating; (2) socioeconomic variables: patient income, homeless (equals 1, otherwise 0), and patient insurance status, i.e. not covered by any insurance (equals 1, otherwise 0), enrolled in Medicare (equals 1, otherwise 0), enrolled in Medicaid (equals 1, otherwise 0), and covered by private insurance (equals 1, otherwise 0); and (3) prior year utilization and cost: ED revisit within 72 h (yes/no), ED revisit within 30 days (yes/no), the number of ED revisits within 30 days, total number of ED visits, the number of primary care visits, the number of tele-health encounters, the total outpatient visits, the number of hospitalizations, and the total cost; and (4) patient risk or comorbidities: 285 clinically homogeneous groups produced by Clinical Classifications Software (CCS) developed by Agency for Healthcare Research and Quality (AHRQ) [26].

The present study did not require or use any identifiable patient private information and therefore had expedited IRB review.

2.2. Modeling and analysis

We adopted logistic regression to predict the probability or risk of 72-hour ED revisit. Logistic regression has been the most extensively used model in predicting outcomes where the dependent variable is binary, i.e., equals 1 if the event happened, otherwise equals 0. The model's predictive or discriminative ability is measured by the c-statistic, which is defined as the proportion of times the model correctly discriminates a random pair of individuals with or without the event. It is also equivalent to the area under the receiver operating characteristic curve. A c-statistic of 0.5 indicates that the model is no better than flipping a coin; a c-statistic of 0.7–0.8 suggests that the model has good discriminative ability; and a c-statistic of 0.8 or greater suggests great discriminative ability [27].

To prevent model over-fit, we only included variables with p-values <0.05 (by stepwise) in the final regression analysis, and we also calculated shrinkage coefficient, an indicator of over-fit [28]. We further validated the model by the split-sample method [28,29]. With this method, the full sample (after merging the dependent variable from 2014 and the independent variables from 2013) was randomly split into a derivation sample (2/3) and a validation sample (1/3) [30]. The model was fitted on the derivation sample and then the estimated coefficients were applied to the validation sample to produce the risk score (probability) and the model fit statistics. The split-sample method is widely used to prevent predictive models from fitting random noises rather than a true trend or pattern. The analyses were conducted by using PROC LOGISTIC of SAS 9.3.

To demonstrate the predictive power of different independent variables, we configured and fitted three models from basic to comprehensive. Model 1: only demographic, socioeconomic variables are included in the regression as the explanatory variables, i.e., age, sex, marital status, race, income, enrolled in Medicare, enrolled in Medicaid or covered by other private insurance (no insurance status was omitted in the regression as reference). We also used three dummy variables (one is omitted as reference) as the fixed effect to take into account the potentially different practice patterns among the four medical centers. Model 2: variables in model 1, and prior year utilizations, i.e., ED revisit within 72 h (yes/no), ED revisit within 30 days (yes/no), the number of ED revisits within 30 days, total number of ED visits, the number of primary care visits, the number of tele-health encounters, the total outpatient visits, the number of hospitalizations, and the total cost. Model 3: variables in model 2, and patient comorbidities by CCS. The inclusion or exclusion of the variables in the final regression depends on the p-values in the stepwise procedure.

3. Results

All 21,141 patients who had ED visits in FY 2014 were included in this study. Among the 21,141 patients, 2346 returned to the EDs within 72 h; the overall 72-hour revisit rate was 11%. The independent variables and their descriptive statistics are reported in Table 1. The CCSs (285 indicator variables) are not reported in Table 1; instead, those 20 CCS indictor variables (representing 591 distinct ICD-9-CM codes) that were statistically significant in the final model are reported along with other variables in Table 3 showing the parameter estimates, odds ratios, and confidence intervals. Table 2 shows the top 20 most frequent diagnoses of patients with 72-hour ED revisits.

In predicting ED 72-hour revisits, the first model only included demographics, socioeconomic characteristics and the fixed effect of the medical centers, in which nine variables were statistically significant (p-values < 0.05) and kept in the model. The c-statistics were 0.55 (CI: 0.52–0.57) and 0.54 (95% CI: 0.51–0.56) for the development and validation samples, respectively. In the second model, 12 variables were statistically significant and kept in the model. The c-statistics were 0.70 (95% CI: 0.68–0.72) for both samples. In the final model, 32 variables that were statistically significant were kept in the model, and the c-statistics were 0.74 (CI: 0.72–0.76) and 0.73 (95% CI: 0.71–0.75) for the development and validation samples, respectively. The receiver operating characteristic curves of all three models based on the validation sample are reported in Fig. 1.

The parameter estimates of the full model are reported in Table 3. Note that for the age groups, we omitted aged 75 or older as the baseline in the regression and kept the three age groups that were statistically insignificant in the model as a convention.

To further examine the prediction accuracy, we graphed the observed 72-hour revisit rate against the five estimated risk categories (quintiles) in Fig. 2; as shown, the revisit rate was 1.7% among the patients in the lowest risk quintile and 26.2% in the highest risk quintile. In addition, we also estimated the shrinkage coefficient which yielded a value of 0.89, indicating no over-fit [28].