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Clinical Study

Hospitalization cost after spine surgery in the United States of America

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ABSTRACT

The objective of this study was to develop and validate a predictive model of hospitalization costs after spine surgery. Several initiatives have been put in place to minimize healthcare expenditures but there are limited data on the magnitude of the contribution of procedure-specific drivers of cost. We performed a retrospective cohort study involving 672,591 patients who underwent spine surgery and were registered in the National Inpatient Sample from 2005–2010. The cohort underwent 1:1 randomization to create derivation and validation subsamples. Regression techniques were used for the creation of a parsimonious predictive model of total hospitalization cost after spine surgery. Included were 356,783 patients (53.1%) who underwent fusions, and 315,808 (46.9%) non-fusion surgeries. The median hospitalization cost was $14,202 (interquartile range $4772–23,632). Common drivers of cost identified in the multivariate analysis included the length of stay, number of admission diagnoses and procedures, hospital size and region, patient income, fusion surgery, acute renal failure, sex, and coagulopathy. The model was validated in an independent cohort and demonstrated a final coefficient of determination that was very similar to the initial model. The predicted and observed values in the validation cohort demonstrated good correlations. This national study quantified the magnitude of significant drivers of hospitalization cost after spine surgery. We developed a predictive model that can be utilized as an adjunct in the cost containment debate and the creation of data driven policies.

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1. Introduction

The Centers for Medicare and Medicaid Services is using a series of measures to monitor and prevent overutilization of health care resources [5,14]. The inability to meet these benchmarks will result in financial penalties for the involved institutions, and common procedures with rising costs, such as spine surgery, will be targeted. Over the last 30 years, there is evidence that the rates and cost of spine surgery have increased significantly in the USA [4]. A variety of factors may have contributed to this phenomenon, including improved biomechanical understanding of the human spine, advances in diagnostic imaging and device technology, as well as the increased life expectancy of the population [4]. Estimation of the hospitalization cost for each patient undergoing spine surgery, and the identification of modifiable drivers of cost could allow physicians to understand the economic aspects of spine surgery, and modify their practice accordingly. Future attempts at cost containment could take into account these procedure-specific factors and avoid penalizing the care of particular subgroups of patients.

Several studies have compared the difference in the cost or charges of various spine procedures [8,10–13,15,16,19]. Some of them were retrospective analyses of single institutions, producing results with limited generalizability given the inherent selection bias. Large database studies have focused on the comparison of the cost of specific procedures [15]. There had been no analyses of modifiable drivers of cost after spine surgery, and no model exists for cost approximation.

The National Inpatient Sample (NIS; Healthcare Cost and Utilization Project, Agency for Healthcare Research and Quality, Rockville, MD, USA) [17] is an all payer, hospital discharge database that represents approximately 20% of all inpatient admissions to non-federal hospitals in the USA. It allows the unrestricted study of the patient population in question. Using this database, several socioeconomic variables, as well as patient and hospital level factors associated with increased cost after spine surgery, were identified. Based on these data, a predictive model of cost after spine surgery was developed and validated in an independent cohort.

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2. Methods

2.1. NIS database

All patients undergoing spine surgery who were registered in the NIS [17] database between 2005 and 2010 were included in the analysis.

2.2. Cohort definition

In order to establish the cohort of patients, we used the international classification of disease-9th edition-current modification (ICD-9-CM) codes to identify patients in the registry who underwent spine surgery (ICD-9-CM code 03.2–03.29, 03.0, 03.01, 03.02, 03.09, 03.1, 03.4, 03.51, 03.53, 03.59, 03.6, 80.5, 80.50, 80.51, 80.52, 80.59, 81.00, 81.01, 81.02, 81.03, 81.04, 81.05, 81.06, 81.07, 81.08, 81.09, 81.3, 81.30, 81.31, 81.32, 81.33, 81.34, 81.35, 81.36, 81.37, 81.38, 81.39, 81.62, 81.63, 81.64, 84.51) between 2005 and 2010 (Fig. 1).

2.3. Outcome variable

The primary outcome variable was the total hospitalization cost after spine surgery. Cost data were obtained by conversion of the hospital charges using the group average cost to charge ratio for each hospital in the database, following similar methods to prior literature [9]. Group average cost to charge ratios and hospital charges are available in the NIS database. All costs were adjusted to their 2010 dollar value using the National Consumer Price Index.

2.4. Exposure variables

The association of the outcome with the pertinent exposure variables was examined in a multivariate analysis. Age was a continuous variable. The categorical variables were sex, race (African American, Hispanic, Asian or other, with Caucasian being the reference value), insurance (private insurance, self-pay, Medicaid, with Medicare being the reference value), and income (defined as the median income based on zip code; income was divided into quartiles, with the lowest quartile being the reference value).

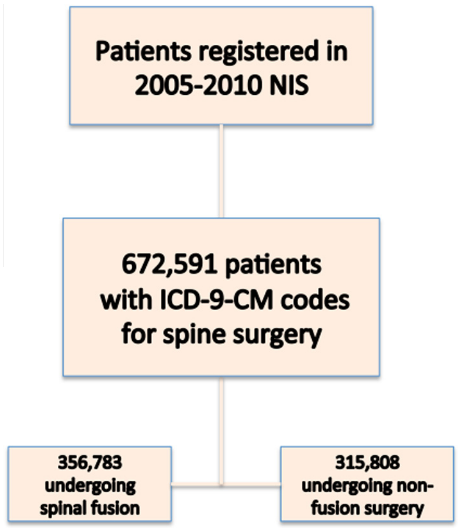

Fig. 1. Cohort selection for the study. ICD-9-CM = International Classification of Disease-9th edition-Current Modification, NIS = National Inpatient Sample.

The patient level comorbidities (categorical variables) were diabetes mellitus, tobacco exposure, hypertension, hyperlipidemia, peripheral vascular disease, congestive heart failure, coronary artery disease, history of prior ischemic stroke, obesity, chronic renal failure, neurologic deficit, and coagulopathy (Supp. Table 1). The patient level operative/postoperative variables (categorical variables) were fusion surgery, postoperative complications (cardiac, neurologic, infectious, hemorrhagic, and wound), deep vein thrombosis, pulmonary embolism, and acute renal failure (Supp. Table 1). Lastly, hospitalization-specific factors (continuous variables) were length of stay (LOS), number of procedures performed (NPx) during the hospitalization, and number of admission diagnoses (NDx).

The hospital characteristics used in the analyses as categorical variables included hospital region (West, South, Midwest, with Northeast being the reference value), hospital location (urban teaching, urban non-teaching, with rural being the reference value), and hospital bed size (medium, large, with small being the reference value). More information of the definitions of the various categories of hospital characteristics can be found at http://www.hcup-us.ahrq.gov/db/vars/nis_stratum/nisnote.jsp.

2.5. Statistical analyses

Continuous variables were compared using the Student's t-test or Mann–Whitney test, as appropriate, and categorical variables were compared using the chi-squared test. Continuous variables are presented with the mean and standard deviation or the median and interquartile range (IQR), as appropriate. Categorical values are presented as percentages.

The initial analyses of cost data revealed significant positive skewness and kurtosis, and linear regression analyses using cost as the dependent variable resulted in a heteroskedastic variance of errors. In order to achieve normality, the data were transformed using the natural logarithm (ln) transformation. The other transformations that were attempted included square root, cube root, and inverse transformation. These were not used because the ln transformation provided the best fit for the data. The ln transformation significantly improved the skewness and kurtosis of the cost distribution (skewness = 0.302, kurtosis = 0.051). Normality was also assessed using histograms and quantile–quantile plots. The distributions of LOS, NDx, and NPx demonstrated significant positive skewness and kurtosis as well, and were also ln transformed before the analysis to achieve normality. Age data were normally distributed and, therefore, no transformation was applied.

Our cohort was then randomized (1:1 randomization to create two 50% subsamples) to a derivation and a validation cohort. Subsequently, patients with missing values were removed from each cohort using listwise deletion. A parsimonious model was then developed in the derivation cohort by performing a stepwise linear regression including all the variables discussed previously. Dummy variables were created for non-binary categorical variables. The level of significance used for retention in the model was 0.05. No colinearity was observed by assessing the tolerance and variance inflation factor. The regression diagnostics performed were the coefficient of determination (R^2) and analysis of the residuals. Normality among the distribution of residuals was verified with histograms (Supp. Fig. 1 and 2), and probability–probability plots (Supp. Fig. 3 and 4). Further diagnostics included scatter plots of the standardized predicted values *versus* the standardized residuals, which revealed a random, symmetric distribution of values around zero, suggesting a linear fit of data (Supp. Fig. 5).

The model created in the derivation cohort was applied on the validation cohort and the R^2 was calculated, and residual analysis was performed. The predicted values for the validation cohort were

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