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Discharge decision-making after complex surgery: Surgeon behaviors compared to predictive modeling to reduce surgical readmissions

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ABSTRACT

Background: Little is known about how information available at discharge affects decision-making and its effect on readmission. We sought to define the association between information used for discharge and patients' subsequent risk of readmission.
Methods: 2009–2014 patients from a tertiary academic medical center's surgical services were analyzed using a time-to-event model to identify criteria that statistically explained the timing of discharges. The data were subsequently used to develop a time-varying prediction model of unplanned hospital readmissions. These models were validated and statistically compared.
Results: The predictive discharge and readmission regression models were generated from a database of 20,970 patients totaling 115,976 patient-days with 1,565 readmissions (7.5%). 22 daily clinical measures were significant in both regression models. Both models demonstrated good discrimination (C statistic = 0.8 for all models). Comparison of discharge behaviors versus the predictive readmission model suggested important discordance with certain clinical measures (e.g., demographics, laboratory values) not being accounted for to optimize discharges.
Conclusions: Decision-support tools for discharge may utilize variables that are not routinely considered by healthcare providers. How providers will then respond to these atypical findings may affect implementation.

1. Introduction

The Centers for Medicare and Medicaid Services (CMS) have placed increased scrutiny on hospital readmissions.[1–3] As mandated by the Patient Protection and Affordable Care Act, CMS has begun adjusting hospital payments through the Hospital Readmissions Reduction Program according to hospitals' rate of “excess” vs. “expected” Medicare readmissions for pneumonia, acute myocardial infarction, and heart failure with a future planned expansion into surgical patients.[2,4–7] Previous estimates suggest that even a small reduction of 5% in readmission rates could prevent over 2,000 inpatient hospitalizations with Medicare cost savings of $31 million.[8]

One of the surgeon's most challenging clinical decisions is balancing the need to promptly discharge patients versus a clinical and financially incentivized goal of reducing readmissions.[8–10]

Balancing countervailing needs has often been addressed through the use of risk-based modeling and decision-support tools. The financial implications of readmissions have also led to many scientific inquiries into risk-adjusted predictions for readmission. A recent systematic review found 26 unique models of readmission employing a variety of data sources and types of inpatient populations.[11] An ongoing limitation of these prediction tools has been the decreasing statistical discrimination of models when broadening patient populations to include surgical patients, especially those undergoing a wide variety of procedures.[11–15]

We believe that improving discharge decision-making via

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evidence-based decision-support tools will lower readmissions while maintaining or decreasing LOS. This approach requires two central elements: (a) statistical identification of variables that discriminate between likelihood of discharge and likelihood of subsequent readmission; and (b) development of decision-support software that can aid discharge decision-making by effectively operationalizing this risk-adjusted understanding of readmission into the clinical provider's daily work.

We sought to develop a data-driven predictive model for surgical readmission to identify the association between clinical information used for discharge decision-making and patients' subsequent risk of readmission. Retrospective, large-data analysis of a prospectively collected clinical data warehouse was used in a time-to-event model to identify criteria that (statistically) explain timing of inpatient postoperative discharge. Subsequent development of a prediction model of readmission with validation helps identify dissonant criteria across postoperative discharges and readmissions. Specifically, we researched possible discordance between intrinsic human behavior and optimized modeling with the assumption that such discordance could interfere with future uptake of decision-support tools. In particular, we wanted to identify differences in how surgeons behave in practice and how a predictive model of readmission might improve discharge decision-making.

2. Materials and methods

2.1. Patient population

De-identified patient data from all patients undergoing inpatient general (including gastrointestinal, endocrine, skin and soft tissue) and vascular surgical procedures between 2009 and 2014 were obtained from the academic medical center's clinical data warehouse. Both elective and emergency cases were included and controlled for in the models described below. Patients who were dead at discharge were excluded. This dataset included all electronically collected information during the patient's admission including demographic information, procedures performed, medications administered, laboratory test results, diagnostic imaging, and nursing documentation. Readmissions were captured by repeat encounters within 30 days of index admission. Outside hospital encounters that did not result in a transfer back to the index hospital could not be obtained.

2.2. Designing discharge and readmission models with validation

Time-varying and fixed data for all patients were analyzed using a time-to-event regression model to identify significant time-point predictors of discharge on a given hospital day and a logit regression model to identify significant predictors of readmission. With the exception of the dummy variables, standardized values of all independent variables were used in both models. Both models included 23 procedural grouping variables (e.g., colectomy, hepatectomy, ventral hernia repair) to control for the type of procedure performed. In addition, we created a dummy variable ("Pre-Optimize") to control for patients who were admitted for a surgical procedure with the procedure delayed beyond the initial day of admission.

A Cox survival model was used for time-point (i.e., daily) discharge predictions allowing for different baseline hazards across procedures. Time-varying variables were grouped for analysis by hospital day. Variables reported more than once daily (up to 3) were averaged. Patients with a missing variable on the hospital day examined had the last known observed value of that variable carried over (i.e., step imputation). If a variable was never recorded for the entire hospital stay, the normalized value (i.e., mean of the upper and lower limit) of that variable within the population was used for all hospital days. Using other methods of imputation did not meaningfully change the predictive factors of the model. A logit model with procedure-fixed effects was used to model readmissions using data from the day prior to discharge; a time-to-event specification for readmissions was not possible without time-point data following discharge. All explanatory variables were selected for using stepwise Akaike information criterion thresholds, which also accounted for Type I multiple testing error.[16]

Both models were validated via a series of in-sample and out-of-sample tests using bootstrapped, partitioned patient data and C statistic test for discrimination. Iterations were conducted with a 90% in-sample and 10% out-of-sample partition, 70% in-sample and 30% out-of-sample partition, and a 50% in-sample and 50% out-of-sample partition. The normalized regression estimated coefficients of the empirical discharge model and the readmission predictive model were directly compared. All statistical analyses and modeling were performed using Stata® version 14.0 (StataCorp, College Station, TX).

Both methodologies were reviewed and approved by the Emory University and Georgia State University Institutional Review Boards.

3. Results

A total of 20,970 patients were identified from the institution's clinical data warehouse representing a wide range of surgical procedures. The median age of the patient population was 54 (range 13–96); 38.8% were male; 57.7% were white and 33.0% were black. Patients had a median length of stay after surgery of 2 days, and the distribution was skewed toward patients with prolonged lengths of stay (mean = 5.5 days, IQR = 1–6 days). Common comorbidities such as cancer (11.2%), hypertension (39.5%), and diabetes (16.1%) were frequently observed. The majority of operations (69.5%; 14,570) were gastrointestinal in nature. The 30-day

Table 1
Study population summary statistics. 20,970 patients' daily clinical observations were extracted from an institutional data warehouse for all inpatient general and vascular surgery procedures from 2009 to 2014.

Age, median	54
Age, range	13–96
LOS, median (days)	2
LOS, mean (days)	5.53
	n (%)
Sex	
Male	8,143 (38.8%)
Female	12,827 (61.2%)
Race	
White	12,101 (57.7%)
Black	6,913 (33.0%)
Other	1,956 (9.3%)
Comorbidities	
Diabetes	3,376 (16.1%)
Cancer	2,354 (11.2%)
Heart disease	1,203 (5.74%)
Hypertension	8,270 (39.5%)
Procedure category	
Gastrointestinal	14,570 (69.5%)
Endocrine	3,097 (16.8%)
Skin and soft tissue	2,668 (12.7%)
Orthopedic	426 (2.03%)
Thoracic	87 (0.4%)
Vascular	122 (0.6%)
30-day readmission	1,565 (7.47%)
Total patients	**20,970**
Total patient-days of observations	**115,976**