Predicting non-routine discharge after elective spine surgery: external validation of machine learning algorithms using institutional data

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Predicting nonroutine discharge after elective spine surgery: external validation of machine learning algorithms

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OBJECTIVE Nonroutine discharge after elective spine surgery increases healthcare costs, negatively impacts patient satisfaction, and exposes patients to additional hospital-acquired complications. Therefore, prediction of nonroutine discharge in this population may improve clinical management. The authors previously developed a machine learning algorithm from national data that predicts risk of nonhome discharge for patients undergoing surgery for lumbar disc disorders. In this paper the authors externally validate their algorithm in an independent institutional population of neurosurgical spine patients.

METHODS Medical records from elective inpatient surgery for lumbar disc herniation or degeneration in the Transitional Care Program at Brigham and Women's Hospital (2013–2015) were retrospectively reviewed. Variables included age, sex, BMI, American Society of Anesthesiologists (ASA) class, preoperative functional status, number of fusion levels, comorbidities, preoperative laboratory values, and discharge disposition. Nonroutine discharge was defined as postoperative discharge to any setting other than home. The discrimination (c-statistic), calibration, and positive and negative predictive values (PPVs and NPVs) of the algorithm were assessed in the institutional sample.

RESULTS Overall, 144 patients underwent elective inpatient surgery for lumbar disc disorders with a nonroutine discharge rate of 6.9% (n = 10). The median patient age was 50 years and 45.1% of patients were female. Most patients were ASA class II (66.0%), had 1 or 2 levels fused (80.6%), and had no diabetes (91.7%). The median hematocrit level was 41.2%. The neural network algorithm generalized well to the institutional data, with a c-statistic (area under the receiver operating characteristic curve) of 0.89, calibration slope of 1.09, and calibration intercept of –0.08. At a threshold of 0.25, the PPV was 0.50 and the NPV was 0.97.

CONCLUSIONS This institutional external validation of a previously developed machine learning algorithm suggests a reliable method for identifying patients with lumbar disc disorder at risk for nonroutine discharge. Performance in the institutional cohort was comparable to performance in the derivation cohort and represents an improved predictive value over clinician intuition. This finding substantiates initial use of this algorithm in clinical practice. This tool may be used by multidisciplinary teams of case managers and spine surgeons to strategically invest additional time and resources into postoperative plans for this population.

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KEYWORDS machine learning; artificial intelligence; prediction model; nonroutine discharge; positive predictive value; negative predictive value

ABBREVIATIONS ACS = American College of Surgeons; ASA = American Society of Anesthesiologists; AUC = area under the ROC curve; CCI = Charlson Comorbidity Index; IQR = interquartile range; NPV = negative predictive value; NSQIP = National Surgical Quality Improvement Program; PPV = positive predictive value; RAT = Risk Assessment Tool; ROC = receiver operating characteristic; TCP = Transitional Care Program.

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A great deal of attention has been given to the management of medical populations,[2,11,12] particularly those patients with chronic disease, but relatively little has been done in this regard with surgical populations.[13] Given the introduction of bundled payments for health insurance reimbursement and the increasing focus on patient outcomes and satisfaction as metrics for healthcare quality,[6] there is a growing need for attention to this population group, with a major focus on discharge planning.[22,23] Well-executed discharge planning can reduce healthcare costs and improve outcomes and patient satisfaction by reducing length of stay, complications, and readmission rates. While the evidence to support the use of individualized discharge planning has had mixed success,[10] it is clearly possible to improve patient education and patient selection, and to streamline the entire discharge planning process in a standardized manner for certain elective surgical procedures that have a predictable postoperative recovery. Our group, for example, successfully implemented a Transitional Care Program (TCP) for neurosurgical patients with a goal of managing this surgical population, which focused on patient education and postoperative planning. This program resulted in significantly shorter length of stay, lower readmission rates, and reduced costs.[18,24]

Lumbar disc disorders are the most common indication for elective spine surgery, and account for a significant portion of Medicare spending.[9,30] The rate of nonroutine discharge (i.e., postoperative discharge to any setting other than home) after surgery for lumbar disc disorders has been reported to be between 9.28% and 19.1%.[7,14,16,19,20,31] Several risk factors for nonroutine discharge in this population have been identified, such as age > 65 years; female sex; African American race; single living status; BMI > 40 kg/m^2; congestive heart failure; atrial fibrillation; diabetes mellitus; smoking; osteoporosis; hypertension; hematocrit < 35%; international normalized ratio > 1.3; dependent functional status; American Society of Anesthesiologists (ASA) physical classification status of 4; number of levels of decompression; operative time > 3 hours; in-hospital complications; less mobility during postoperative inpatient stay; lower sitting and standing balance score; longer length of stay; and surgical complications.[3,14,20,25]

Our team recently developed a machine learning algorithm from national surgical data that predicts nonhome discharge of patients undergoing elective spine surgery.[16] The algorithm was derived from more than 26,000 patients in the American College of Surgeons (ACS) National Surgical Quality Improvement Program (NSQIP) who underwent surgery for lumbar degenerative disc disorders, and was able to predict nonroutine discharge with a c-statistic (area under the receiver operating characteristic [ROC] curve, or AUC) of 0.823. Given the surprising recent findings that clinicians tend to underestimate the rate of nonroutine discharge for their patients,[1,28] a discharge prediction algorithm could enable preoperative risk stratification of patients and risk-mitigating planning for postoperative care. Importantly, before it can be used as a clinical decision-making tool, an algorithm must be calibrated and validated on independent data sets. In the present study, we sought to externally validate our algorithm in an independent institutional population of neurosurgical spine patients.

Methods

The Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD) guidelines were followed in this study.[7]

Validation

Compared to the development cohort for the algorithm, which included patients from the NSQIP database of more than 600 surgical centers in North America, the patients for this study came from an institutional population at an urban, academic, tertiary care center. The patients in the NSQIP database are enrolled by trained surgical reviewers on a 6-day cycle at participating institutions and the development study included patients undergoing inpatient elective surgery for lumbar disc disorders.[14]

Source of Data

Patients enrolled in a TCP at the Brigham and Women's Hospital Department of Neurosurgery from 2013 to 2015 were retrospectively reviewed.[18,24] Details of this TCP have been previous described.[24] The objective of the TCP was to improve patient education and surveillance surrounding discharge after elective neurosurgery.

For the purposes of this study, all patients considered eligible for the TCP were assessed for inclusion in this validation analysis. Additional inclusion criteria were 1) age greater than 18 years; 2) inpatient surgery; 3) lumbar decompression or fusion; and 4) operative diagnosis of lumbar disc herniation or disc degeneration, hereafter referred to as disc disorders, on the basis of ICD-9/10 coding and operative notes. Patients were excluded if they underwent nonelective procedures or underwent surgery for a diagnosis other than disc disorders.

Outcome

The primary outcome of interest was postoperative discharge destination. This was dichotomized as discharge to home or discharge to any setting other than home (such as a skilled nursing facility or inpatient rehabilitation).

Predictors

The input variables retrospectively collected for the TCP patients correspond to the predictive factors in the original derivation cohort study by Karhade et al.,[16] which were predictive factors selected by random forest algorithms. These variables included 1) age (years); 2) sex (male, female); 3) BMI (kg/m^2); 4) ASA physical classification status (I, II, III, or IV); 5) functional status (independent, dependent); 6) extent of surgery (1 or 2 levels, ≥ 3); 7) fusion; 8) diabetes (none, oral medication, insulin dependent); and 9) preoperative hematocrit value.[16] The definition of functional status was based on the definition from the derivation cohort for the algorithm and was based on the patient's level of self-care and ability to conduct activities of daily living at the time the patient was being considered a candidate for surgery.[4]

Missing Data

Patients were only included in this study if they had complete data for the variables required for the previously developed algorithm, because the algorithm requires complete data for estimates of nonhome discharge. One hundred forty-four of the TCP patients met the inclusion criteria. The most common missing variable was ASA class.

Statistical Analysis

The neural network algorithm previously developed in the derivation study was applied to the institutional cohort and the algorithm's discrimination and calibration were calculated. Discrimination was assessed by the c-statistic (also known as the area under the curve for binary classification); perfect models have a c-statistic = 1 and models with predictions no better than random chance have a c-statistic = 0.5.[27] Calibration was assessed with calibration plots that compare the algorithm's predictions to the observed outcome in the population. In addition, calibration intercept and calibration slope were calculated for the algorithm in this population; perfect models have calibration intercept = 0 and calibration slope = 1.[27] The algorithm is also assessed using the Brier score, a proper score function that measures the accuracy of probabilistic predictions. The Brier score is the squared error of a probabilistic forecast; the best possible score is 0 and the worst possible score is 2.[5] Furthermore, algorithm performance was assessed with positive and negative predictive values (PPVs and NPVs) at a threshold of 0.25 (25% probability of nonroutine discharge). Data analysis was performed using Python (version 3.6) and the R programming language (version 3.5.1).

Results

A total of 144 patients who underwent elective inpatient surgery for lumbar disc disorders were included in the validation cohort. The rate of nonhome discharge was 6.9% (n = 10), the median age was 50 years (interquartile range [IQR] 39–63 years), and 45.1% of patients were female. The majority of patients had an ASA class of II (n = 95, 66.0%), were functionally independent (n = 116, 80.6%), had 1 or 2 fusion levels (n = 116, 80.6%), and did not have diabetes (n = 132, 91.7%). For a comprehensive listing of the baseline characteristics of the study population, see Table 1.

Validation of the algorithm yielded a c-statistic (AUC) of 0.89, a calibration slope of 1.09, and a calibration intercept of −0.08. The Brier score was 0.049. Figure 1 illustrates the ROC curve of the algorithm validation. Figure 2 shows the calibration plot of the algorithm validation, which plots predicted probability against observed proportion. The algorithm's calibration intercept (−0.08) showed that the predictions of the algorithm were well calibrated with the observed outcomes in the validation cohort. The calibration plot further shows that the algorithm's predicted probabilities concurred with the observed outcomes over the range of predicted probabilities.

As discussed in the development study for this algorithm (Karhade et al., 2018[16]), the performance of the algorithm depends on the threshold set by the clinician.

TABLE 1. Baseline characteristics of study population

Variable	Value
Median age (IQR), yrs	50.0 (39.0–63.0)
Female sex, n (%)	65 (45.1)
Median BMI (IQR), kg/m^2	28.0 (25.0–32.0)
ASA class, n (%)	
I	12 (8.3)
II	95 (66.0)
III	37 (25.7)
Functional status, n (%)	
Independent	116 (80.6)
Dependent	28 (19.4)
Fusion, n (%)	30 (20.8)
Levels, n (%)	
1 or 2 levels	116 (80.6)
≥3 levels	28 (19.4)
Diabetes, n (%)	
None	132 (91.7)
Medication	12 (8.3)
Insulin	0 (0.0)
Median hematocrit (IQR)	41.2% (38.7%–43.5%)
Nonhome discharge, n (%)	10 (6.9)

The threshold relates to the clinician's tolerance of risk; for example, at a threshold of 0.25, the algorithm predicts a probability of nonroutine discharge of 25% or greater. This threshold dependence is illustrated in the decision curve, which reveals that the algorithm shows greater net benefit when management changes are based on the

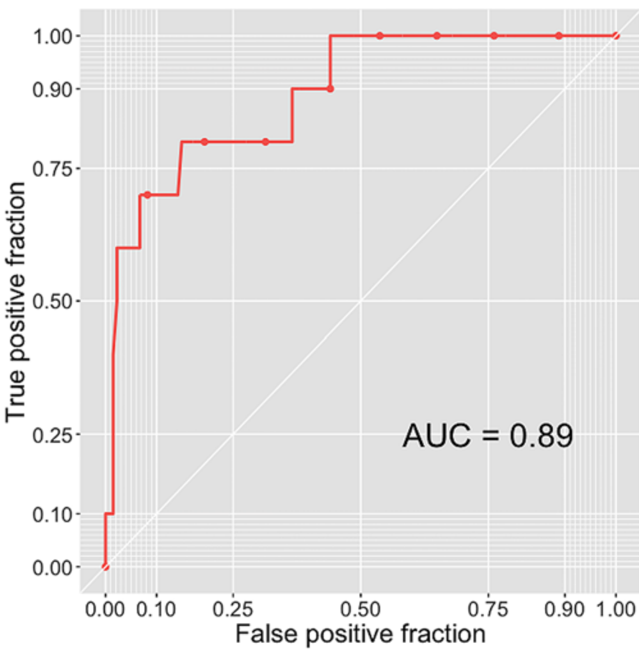

FIG. 1. ROC curve of the neural network algorithm in the validation set. Figure is available in color online only.

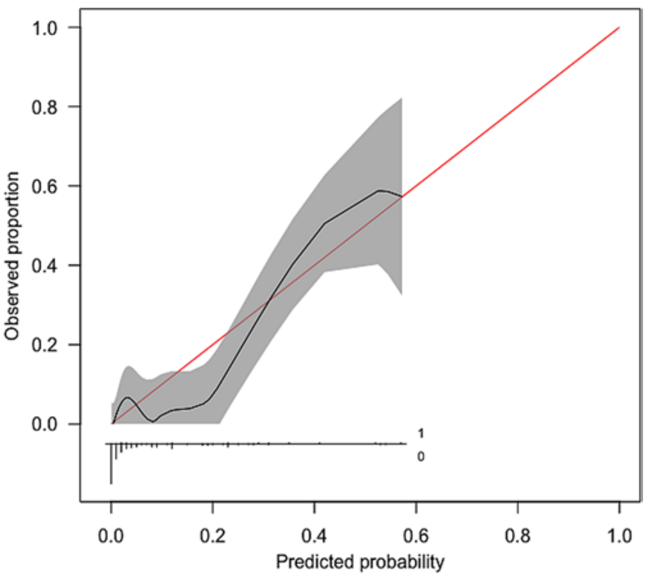

FIG. 2. Calibration plot of the neural network algorithm in the validation set, with 95% CIs. The *red line* is perfect calibration with slope 1 and intercept 0, the *black line* is our calibration plot, and the *gray area* is the 95% CI. Figure is available in color online only.

model, as opposed to the default strategies of changing management for all patients or for no patients (Fig. 3).

For example, at a threshold of 0.25, the algorithm resulted in a contingency table as displayed in Table 2, with a PPV of 0.50 (IQR 0.21–0.79) and an NPV of 0.97 (IQR 0.92–0.99). The NPV of 0.97 denotes that 4 patients (3%) are mistakenly predicted to go home but actually experience nonroutine discharge. Among these 4 "false negatives," the median age was 67.5 years, 4 (100%) were

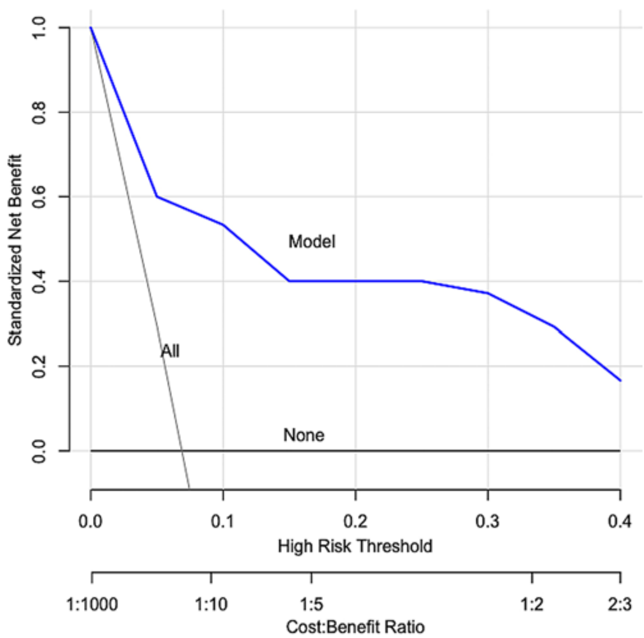

FIG. 3. Decision curve analysis for algorithm in validation set. Figure is available in color online only.

TABLE 2. Contingency table at a threshold of 0.25

Variable	Outcome: Nonhome	Outcome: Home
Prediction nonhome discharge	6	6
Prediction home discharge	4	128
PPV (IQR)		0.50 (0.21–0.79)
NPV (IQR)		0.97 (0.92–0.99)

male, the median BMI was 31.5 kg/m^2, 4 (100%) had independent functional status, 2 (50%) underwent fusion, 1 (25%) underwent ≥ 3-level surgery, 1 (25%) had diabetes requiring oral medication, and the median hematocrit was 41.2%. The NPV of 0.97 further denotes that 97% of patients predicted to go home do, in fact, go home after their stay. The PPV of 0.50 denotes that half (6/12) of patients predicted to have nonroutine discharge do, in fact, experience nonroutine discharge. The threshold of 0.25 was selected to minimize false negatives, given the significant risk of hospital-acquired complications in patients who experience extended stays.

Discussion

Adequate management of patient populations increases the value of healthcare interventions by improving outcomes and reducing cost. This concept has gained a great deal of strength in recent years.[23,26,29] In the area of surgical populations, much has been discussed in terms of patient education and streamlining of the surgical process, but little has been done to select patients likely to fail interventions. This machine learning algorithm is a tool that can augment clinicians' prediction of and planning for postoperative care, which is an important area for improvement given the recent findings that clinicians tend to underestimate nonroutine discharge risk.[1,29]

This tendency to misjudge discharge disposition was evident within our own TCP at Brigham and Women's Hospital, where 17.4% of 563 patients undergoing elective spine surgery who were predicted to go home experienced nonroutine discharge (Robertson et al., unpublished data, 2018). As demonstrated by the NPV of 0.97 reported here (Table 2), this algorithm represents an improvement from 17% to 3% of patients who are predicted to go home but actually have nonroutine discharge. Given that patients with extended hospital stays are at significantly increased risk of hospital-acquired complications, this improvement is not only statistically important but also clinically significant.

The benefits of utilizing an algorithm to augment the expertise and intuition of clinicians are multifold. For example, where our algorithm predicts that a patient is at high risk of nonroutine discharge, the clinician and their patient care team may choose to preemptively secure a bed at a rehabilitation facility. That patient would then benefit from a shorter hospital stay and faster time to initiating rehabilitation, and the hospital would benefit from alleviating resources that would have been spent on that extended length of stay.

The successful validation of this algorithm in an institutional cohort substantiates further exploration of the algorithm in clinical practice. We therefore encourage clinicians to try using the open-access web application (https://sorg-apps.shinyapps.io/discdisposition/) to explore and understand the potential use of this algorithm.

Given the success of this validation study, this algorithm has the potential to be integrated into the clinical care model in various institutions. Although an alternative approach is to derive novel algorithms for each institution and each population of patients, the success of this external validation suggests that this algorithm could be applied to many different institutions. This would prove more expedient and cost-effective than deriving institution-specific algorithms.

Notwithstanding the encouraging progress of this external validation of our algorithm, it is important to consider the other predictive algorithms published for use in this population. The ACS NSQIP Surgical Risk Calculator estimates the risk of adverse postoperative outcomes; however, validation among neurosurgical patients has demonstrated less than ideal performance.[32–34] The Risk Assessment and Prediction Tool is a 6-point questionnaire that was developed for an orthopedic surgery population to predict the need for inpatient post–acute care, and when validated in a population of neurosurgical patients, the AUC was found to be 0.79.[21] The spinal Risk Assessment Tool (RAT) was developed from an administrative claims database to predict risk for patients undergoing spine surgery. When tested in comparison to the NSQIP calculator and Charlson Comorbidity Index (CCI), it was found that the RAT had an AUC of 0.67, the NSQIP calculator had an AUC of 0.669, and the CCI had an AUC of 0.55.[33] SpineSage is an online calculator that predicts medical complications in spine surgery, and when validated in a cohort of spinal surgery patients, it was found that the AUC was 0.71.[17] McGirt et al. developed a prediction model for low-back surgery, based on a prospective cohort of patients with degenerative lumbar disorder, to predict complications, hospital readmissions, return to work, and 12-month improvement in functional disability. They found an AUC for their derivation cohort of 0.72–0.84 and an AUC for their validation cohort of 0.79–0.84.[19] Our algorithm performed similarly to these existing prediction tools, with an AUC of 0.89 in the present validation study. Further research is needed in prospective samples to allow direct comparisons of this algorithm to previous ones. In comparison to previous algorithms that focused on discrimination alone (c-statistic), this derivation and validation study for this algorithm showed promising results on both discrimination and calibration. For clinical prediction models, calibration must be an integral part of model development and validation.

Future research with our algorithm will include additional external validations. The strength of this algorithm will rest in its ability to be well calibrated in many institutions. We also plan to prospectively integrate the algorithm into the clinical care model in a clinical trial setting. By prospectively checking patients with the algorithm, the team of surgical, clinical, and case management specialists will have the opportunity to act upon the potential risk that is indicated. If that trial proves successful in improving patient outcomes, patient satisfaction, and healthcare costs, then it may be feasible and useful to implement into the clinical care model.

Conclusions

This institutional external validation of a previously developed machine learning algorithm suggests a reliable method for identifying patients with lumbar disc disorder at risk for nonroutine discharge. Performance in the institutional cohort was comparable to performance in the derivation cohort and represents an improved predictive value over clinician intuition. This substantiates the initial use of this algorithm in clinical practice. This tool may be used by multidisciplinary teams of case managers and spine surgeons to strategically invest additional time and resources into postoperative plans for this population.

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Disclosures

The authors report no conflict of interest concerning the materials or methods used in this study or the findings specified in this paper.

Author Contributions

Conception and design: Gormley, Smith. Acquisition of data: Stopa, Robertson, Chua. Analysis and interpretation of data: Stopa, Karhade, Schwab. Drafting the article: Stopa. Critically revising the article: Gormley, Robertson, Karhade, Broekman, Smith. Reviewed submitted version of manuscript: Gormley. Approved the final version of the manuscript on behalf of all authors: Gormley. Statistical analysis: Karhade. Study supervision: Gormley, Broekman, Schwab, Smith.

Supplemental Information

Previous Presentations

Portions of this work were presented in abstract form and as proceedings at the Kings College London International Neurosurgical Conference, London, United Kingdom, in November 2018; the Annual Meeting of the AANS/CNS Joint Section on Disorders of the Spine and Peripheral Nerves, Spine Summit 2019, Miami, Florida, in March 2019; the Women in Data Science Conference, Cambridge, Massachusetts, in March 2019; and the 2019 AANS Annual Scientific Meeting, San Diego, California, in April 2019.

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