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ORIGINAL ARTICLE

Development of a machine learning algorithm predicting discharge placement after surgery for spondylolisthesis

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Abstract

Purpose We aimed to develop a machine learning algorithm that can accurately predict discharge placement in patients undergoing elective surgery for degenerative spondylolisthesis.

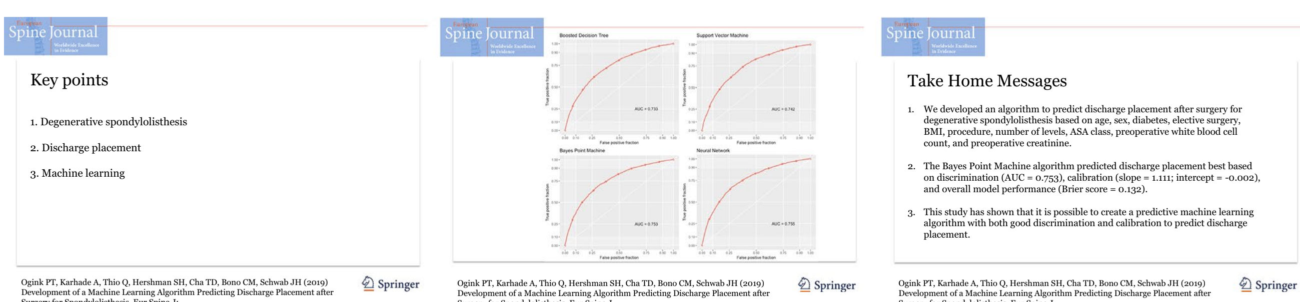
Methods The National Surgical Quality Improvement Program (NSQIP) database was used to select patients that underwent surgical treatment for degenerative spondylolisthesis between 2009 and 2016. Our primary outcome measure was non-home discharge which was defined as any discharge not to home for which we grouped together all non-home discharge destinations including rehabilitation facility, skilled nursing facility, and unskilled nursing facility. We used Akaike information criterion to select the most appropriate model based on the outcomes of the stepwise backward logistic regression. Four machine learning algorithms were developed to predict discharge placement and were assessed by discrimination, calibration, and overall performance.

Results Nine thousand three hundred and thirty-eight patients were included. Median age was 63 (interquartile range [IQR] 54–71), and 63% ($n = 5{,}887$) were female. The non-home discharge rate was 18.6%. Our models included age, sex, diabetes, elective surgery, BMI, procedure, number of levels, ASA class, preoperative white blood cell count, and preoperative creatinine. The Bayes point machine was considered the best model based on discrimination (AUC = 0.753), calibration (slope = 1.111; intercept = − 0.002), and overall model performance (Brier score = 0.132).

Conclusion This study has shown that it is possible to create a predictive machine learning algorithm with both good accuracy and calibration to predict discharge placement. Using our methodology, this type of model can be developed for many other conditions and (elective) treatments.

Graphical abstract

These slides can be retrieved under Electronic Supplementary Material.



Keywords Degenerative spondylolisthesis · Discharge · Machine learning

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Extended author information available on the last page of the article

Introduction

Decreasing the length of hospitalization can significantly reduce healthcare costs; each extra day in hospital costs roughly between $424 in Spain and $5220 in the USA depending on the type of hospital and the hospital's location [1]. Despite a recent trend toward early discharges after major orthopedic surgery, patients' outcomes have largely remained similar [2, 3]. Recent studies have demonstrated that a disproportionate part of patients' total hospitalization is related to delays while patients wait to be discharged to a rehabilitation facility (RF) or skilled nursing facility (SNF) [4, 5]. Hwabejire et al. [6] consulted their institution's case management department and found that 47% of prolonged hospitalizations were due to difficulties in RF placement. More importantly, prolonged hospitalization is a known risk factor for adverse events, such as venous thromboembolism and hospital-acquired infections [7, 8].

Some studies have looked at which variables affect discharge to RF/SNF following spine surgery [9–12], and others have developed grading scales which can help predict patient disposition [13–15]; however, to our knowledge there have been no studies utilizing machine learning algorithms to help predict discharge placement. Preoperatively determining which patients are likely to require RF/SNF placement can reduce the risk of prolonged hospitalization and can potentially allow healthcare personnel to reserve a place in a RF/SNF well in advance of a patient's discharge. This could therefore minimize many of the risks associated with extended hospital stay, allow for more efficient departmental planning, and can potentially increase surgical volume.

In this proof-of-concept application of machine learning for predicting disposition, we aim to develop a machine learning algorithm using the ACS-NSQIP database that can accurately predict discharge placement in patients with degenerative spondylolisthesis. Machine learning lies at the intersection of statistics and computer science and is increasingly being used in medicine to develop prediction models and decision-making tools from large datasets [16, 17]. We selected degenerative spondylolisthesis because (1) this group represents a sizeable portion of the spine surgery population, (2) patients are relatively older and thereby at risk of discharge to RF/SNF, and (3) most surgeries are elective which means there is time to arrange an RF/SNF placement if we were to develop a useful predictive algorithm.

Methods

Patient selection

We selected all patients from the American College of Surgeons (ACS) National Surgical Quality Improvement Program (NSQIP) database (ACS-NSQIP database). The ACS-NSQIP database is a multi-institutional database that has previously been used in numerous spine studies [18–21]. The database consists of prospectively collected patient demographics, comorbidities, laboratory values, and perioperative and postoperative outcomes in the 30 days following surgery. Unlike administrative databases, the data are collected by trained reviewers leading to better registration of outcomes [22, 23]. The American College of Surgeon aims to ensure data reliability by training participating hospitals, ongoing education, and systematic audits.

We included patients who met the following criteria: (1) International Classification of Disease Ninth Revision (ICD-9) code 738.4 for acquired spondylolisthesis or ICD-10 code M43.10, (2) Current Procedural Terminology (CPT) codes for decompression, fusion, or fixation, and (3) year of surgical treatment between 2009 and 2016. Ultimately, 9,338 patients were included for the development of the algorithm.

Variable selection and data analysis

The primary outcome measure was non-home discharge which was defined as any discharge not to home for which we grouped together all non-home discharge destinations including rehabilitation facility, skilled nursing facility, and unskilled nursing facility. We performed a bootstrap stepwise backward logistic regression with the following candidate variables: age [years], sex [male, female], body mass index (BMI) (kg/m^2), race [Caucasian, African–American, other], diabetes [no, oral medication, insulin dependent], anti-hypertensive medication [yes, no], specialty [neurosurgery, orthopedics], ASA class [I, II, III, IV], elective surgery [yes, no], type of procedure [decompression, fusion, decompression and fusion], approach [anterior, posterior], number of levels [1 or 2, 3 or more], preoperative white blood cell count (10^3/μL), preoperative creatinine (mg/dL), preoperative platelets (10^3/mm^3), preoperative albumin (g/dL), preoperative blood urea nitrogen(mg/dL), and preoperative sodium (mEq/L).

We subsequently used Akaike information criterion to select the most appropriate model with independently significant variables based on the outcomes of the stepwise backward logistic regression [24]. This model included age, sex, diabetes, elective surgery, BMI, procedure, number of levels, ASA class, preoperative white blood cell count, and preoperative creatinine.

Boosted decision tree, support vector machine, Bayes point machine, and neural network algorithms were trained with these variables to predict which patients were not discharged home. We did a stratified 80:20 split of the dataset into a training set and a test set. We used the training set for algorithm training and assessment of performance by cross-validation (10×). The algorithms were subsequently used in the test set to make predictions on discharge placement. The predictions were then compared with the actual outcomes of the test set to assess the performances outside the training set.

Model performance

Model performance was measured with the following three metrics: discrimination, calibration, and overall model performance.

Discrimination is the ability to distinguish patients discharged to home from patients who were not discharged to home. We assessed discrimination with receiver-operating curves (ROC) and with the c-statistic. Models with discrimination similar to chance have a c-statistic of 0.5, and models with a perfect discrimination have a c-statistic of 1.0.

Calibration shows how well the model's predicted probabilities are in line with the actual observed occurrences in the test set. The calibration intercept measures whether the model is over- or underestimating the probabilities, and the calibration slope measures whether the predictor effects in the training and test set are the same. A perfect model has an intercept value of 0 and a slope value of 1. The Brier score was used to assess overall model performance. It combines discrimination and calibration and is calculated by obtaining the mean-squared error between the probabilities given by the model and the actual observed values. Smaller Brier scores (closer to zero) indicate better overall performance. However, the Brier score must always take into account the prevalence of the outcome in the patient sample. Therefore, the null Brier score was determined by assigning probabilities to every patient similar to the prevalence of the outcome.

Application

The model was subsequently developed into a web-based application making it accessible on smartphones, computers, and tablets. The application is designed to let the user input the necessary variables, calculate the scores using the selected algorithm, and output the results. Microsoft Azure, STATA 13 (StataCorp LP, College Station, TX, USA), RStudio version 1.0.153, and Python version 3.6 (Python Software Foundation) (Anaconda distribution) were used for data analysis, model creation, and application development.

Results

The non-home discharge rate was 18.6% for the 9338 included patients. Median age was 63 (interquartile range [IQR] 54–71), and 63% ($n = 5887$) were female. Baseline characteristics are shown in Table 1. The c-statistics of the four models ranged from 0.733 for the boosted decision tree to 0.755 for the neural network (Table 2; Fig. 1). Calibration slope values ranged from 0.459 for the boosted decision tree to 1.111 for the Bayes point machine, while calibration intercept values ranged from −0.015 for the boosted decision tree to 0.123 for the neural network (Table 2; Fig. 2).

Overall model performance, based on the Brier score, ranged from 0.132 for the Bayes point machine and neural network to 0.146 for the boosted decision tree. The null Brier model performance was 0.152. Considering the performance in calibration and overall assessment, the Bayes

Table 1 Baseline characteristics of patients, $n = 9338$

Variable	All patients ($n = 9338$)
	Median (IQR)
Age (years)	63 (54–71)
BMI (kg^2/m^2)	30 (26–34)
Creatinine levels (mg/dL)	0.86 (0.72–1.00)
White blood cell count ($10^3/\mu L$)	6.9 (5.7–8.3)
	Number (%)
Female	5887 (63)
Race	
Caucasian	8369 (90)
African–American	695 (7.4)
Other	274 (2.9)
Procedure	
Decompression and fusion	5897 (63)
Fusion	2857 (31)
Decompression	584 (6.3)
ASA Class	
I	238 (2.6)
II	4632 (50)
III	4288 (46)
IV	180 (1.9)
Diabetes	
Oral diabetics	1123 (12)
Insulin dependent	494 (5.3)
Elective surgery	9114 (98)
Anti-hypertensive medication	5580 (60)

BMI = body mass index; ASA = American Society of Anesthesiologists

Table 2 Machine learning model performance for discharge disposition prediction in patients undergoing surgery for degenerative spondylolisthesis

Method	Metric	Machine learning algorithm			
		Boosted decision tree	Support vector machine	Bayes point machine	Neural network
Discrimination	c-statistic	0.733	0.742	0.753	0.755
	AUC-PR	0.388	0.399	0.417	0.420
Calibration	Calibration slope	0.459	0.994	1.111	0.970
	Calibration intercept	−0.015	−0.003	−0.002	0.123
Overall	Brier score	0.146	0.134	0.132	0.132
	Null model brier score	0.152			

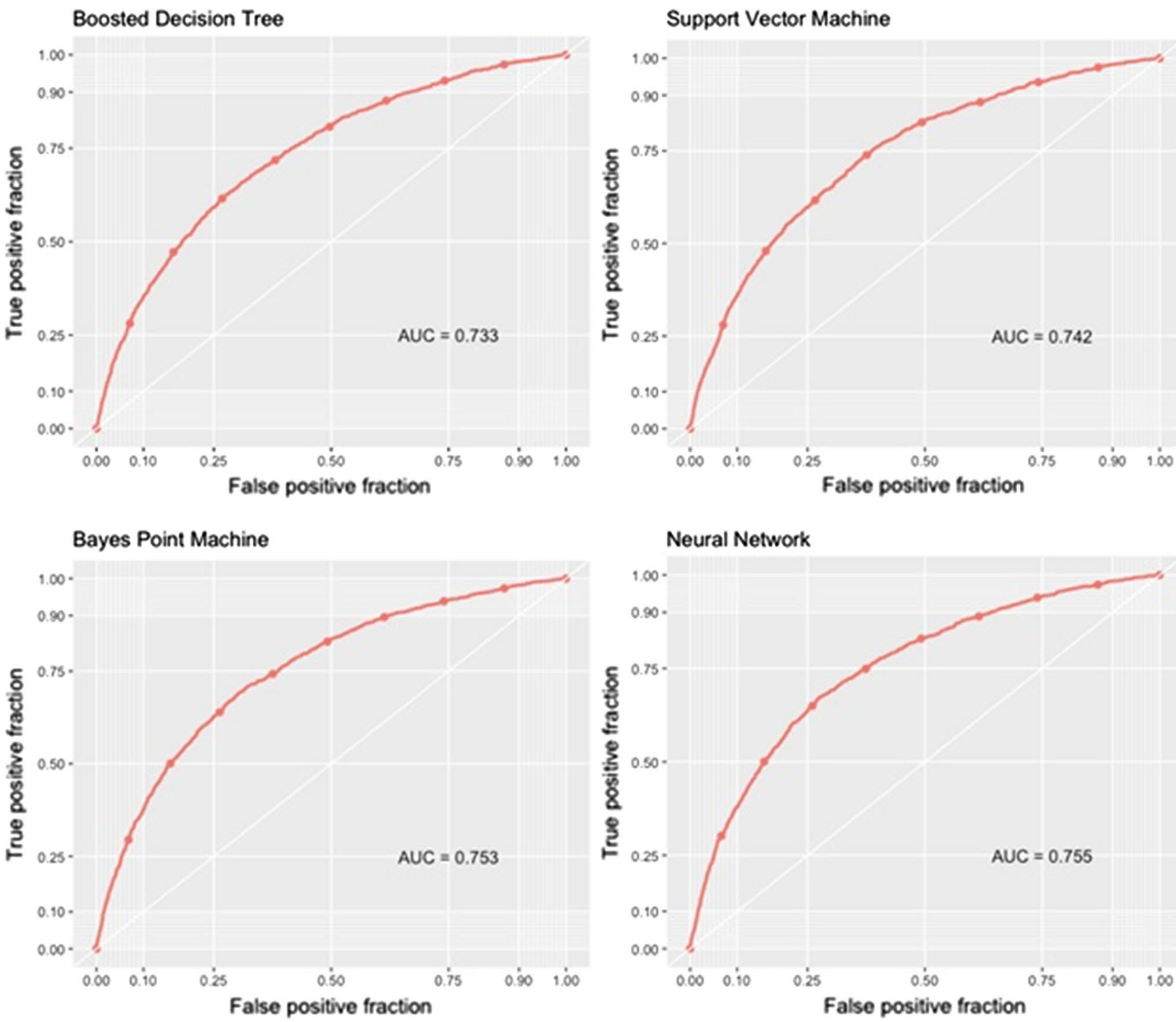

Fig. 1 Receiver operating curve by model for prediction of discharge disposition

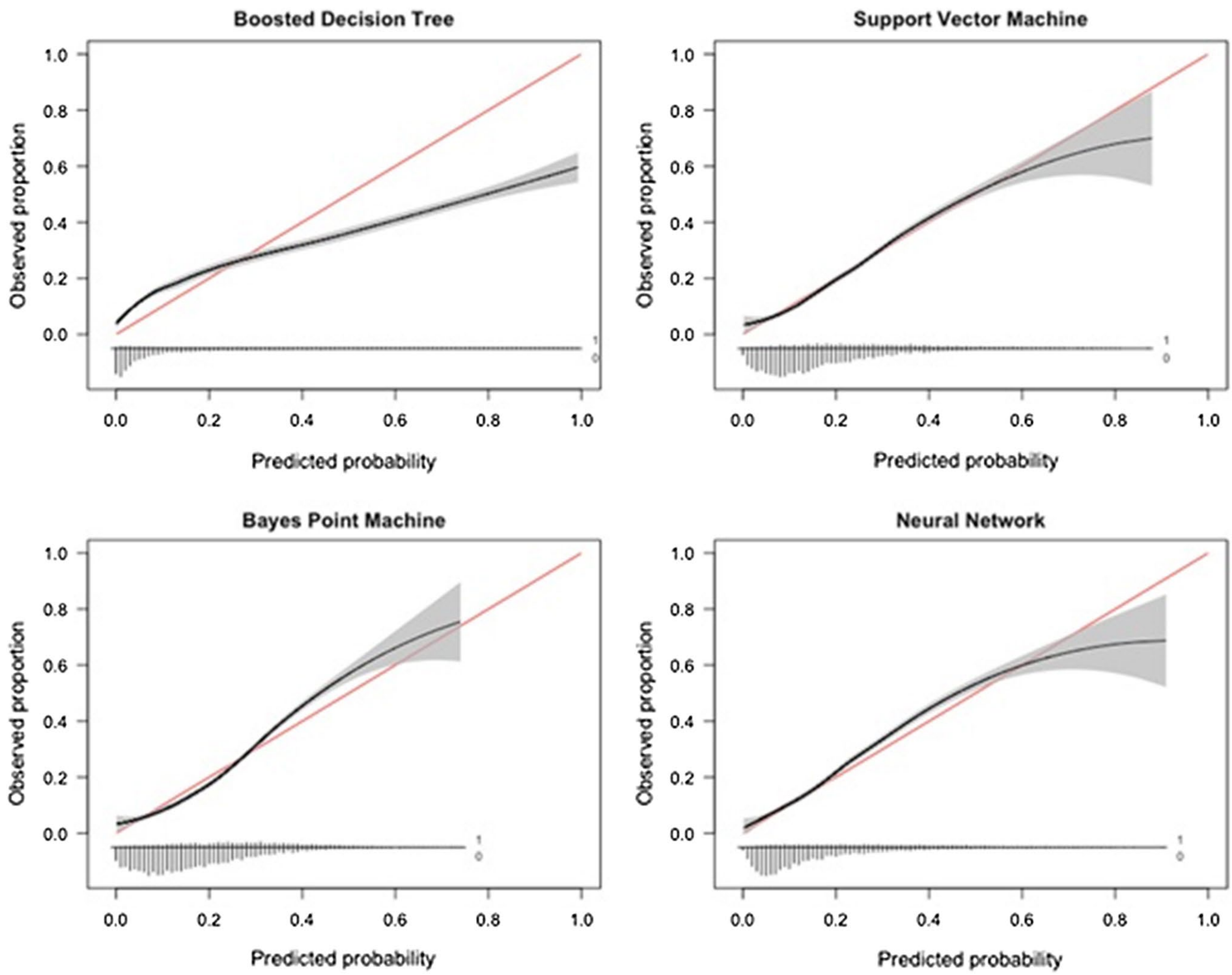

Fig. 2 Calibration curve by model for prediction of 30-day mortality in the test set

point machine was chosen as the final model. The web application based on the Bayes point machine model can be accessed at https://sorg-apps.shinyapps.io/spondydisposition/.

Discussion

Unexpected non-home discharge is a potential cause for extended length of stay and subsequent adverse events for patients. We aimed to develop a machine learning algorithm to predict which patients are likely to have a non-home discharge.

Our model included age, sex, diabetes, elective surgery, BMI, procedure, number of levels, ASA class, preoperative white blood cell count, and preoperative creatinine. Of the four tested machine learning algorithms, the Bayes point machine was considered the best model based on discrimination (AUC = 0.753), calibration (slope = 1.111; intercept = − 0.002), and overall model performance (Brier score = 0.132).

This study has limitations. First, despite ACS-NSQIP database being frequently used and the rigorous oversight, it comes with the inherent limitations of potential miscoding and missing values. A study by Rolston et al. [25] found varying degrees of miscoding in neurosurgical outcomes. These inaccuracies may bias our outcomes and thus our algorithm. Furthermore, the database does not contain all the variables of interest that other studies identified as risk factors for non-home discharge. For instance, insurance status, employment status, and preoperative patient-reported outcomes scores, which have all been established as important predictors for discharge placement, were not available. Despite the lack of these variables and potential miscoding, the ACS-NSQIP database provides a large patient set, which is required for predictive algorithms, with a sizable number of important variables. External validation of the algorithm is crucial to check its applicability. Second, although the database is constructed with data from 690 hospitals, the patient population may not be reflective of all the patients for which it's intended, especially if this model were to be used outside the USA.

The variables included in our model have been identified through other studies examining risk factors for non-home discharges in degenerative spine surgery. Murphy et al. [26] found age, BMI, number of levels, ASA class, diabetes, and female gender to be predictors of not being discharged home after decompression without fusion. Abt et al. [27] similarly found age, BMI, ASA class, and diabetes to be predictors, but they found male gender rather than female gender was more likely to suggest a non-home discharge. Best et al. [11] concluded that age > 65 years was by far the greatest predictor for non-routine discharge after fusion for intervertebral disk disorders. The only variables in our model not featured in these studies are preoperative white blood cell count and creatinine although preoperative creatinine has been identified as predictor of discharge status in other specialties [28, 29]. While adding intraoperative and immediate postoperative outcomes, e.g., operation time or complications, would likely have increased the model's performance, we opted to include only preoperatively known variables. Otherwise, the prediction would lose much of its value considering the window of opportunity for all of the potential benefits—preoperative arrangements and education—would be gone. We envision the model being used after the visit to the surgeon and anesthesiologist, when all variables are known, in a preoperative visit with a nurse practitioner or case management. This would allow for education and potentially initiate arrangements to be made.

Two previous studies tested predictive grading scales in all degenerative spine patients. McGirt et al. [13] constructed a grading system for extended length of stay, discharge to rehab, and hospital readmission after elective spine surgery. Their grading system included the variables age > 70 years, ASA class > III, Oswestry disability index, diabetes, non-independent ambulation, and non-private insurance. While age, ASA class, and diabetes are included in our model, and ambulation and insurance status were not available in the NSQIP database. Furthermore, they reported a c-statistic of 0.731 compared to our 0.755. Slover et al. [14] tested the Risk Assessment and Prediction Tool—which stratifies patients into high and low-risk groups for non-home discharge after total joint replacement—on spinal fusion patients. This tool is based on points for age and sex—also present in our study—combined with walking distance, use of gait aid, community support, and a caregiver at home. They did not report any c-statistic. Importantly, both these studies fail to report calibration metrics, which are essential to determine whether the predictive models/scoring systems are useful. While most studies being published on predictive models report c-statistics, many of them lack assessment of calibration. A predictive model may be able to discriminate well between those who will be discharged home and those who will not, but give inaccurate risk estimates for individual patients due to poor calibration. Clinically useful prediction tools need to discriminate well and be well calibrated in order to make an accurate risk assessment. [30]

In our study, the model with the best discrimination, the neural network, was inferior to the Bayes point machine with respect to calibration over the full range of prediction (Fig. 2). Future studies on predictive models should assess calibration graphically and numerically to determine model performance.

Waiting on RF/SNF placement has been determined to be a major factor in delayed discharges [4, 6, 31]; unfortunately, simply increasing capacity is not the answer. Gaughan et al. [32] studied whether increasing the supply of nursing home beds would reduce the number of delayed discharges. They determined that this would only reduce delayed discharges by 6–9% and that this small effect would make this intervention more costly instead of reducing cost. Implementation of our predictive model could potentially prevent some delayed discharges without incurring additional costs. However, implementation of predictive models in clinical practice is difficult and has not been done on a large scale yet, despite the multitude of models currently available [33, 34]. First and foremost, rigorous testing of a model's predictive ability and external validation should be performed to prevent unintended consequences. Nonetheless, with the pressure of reducing costs, the obvious role that waiting time plays in delaying discharges, and the increasing use of predictive analytics by caregivers, implementing a model which can predict discharge placement may be worth pursuing.

Conclusion

This study has shown that it is possible to create a predictive machine learning algorithm with both good discrimination and calibration to predict discharge placement. Using our methodology, this type of model can be developed for many other conditions and (elective) treatments. Integrating these models into practice could potentially make hospitals more efficient, save unnecessary healthcare costs, and minimize adverse events for patients due to delayed discharges.

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Compliance with ethical standards

Conflict of interest All authors declare that they have no conflict of interest.

References

1. International Federation of Health Plans (2015) Variation in Medical and Hospital Prices by Country. Comp Price Rep
2. Regenbogen SE, Cain-Nielsen AH, Norton EC et al (2017) Costs and consequences of early hospital discharge after major inpatient surgery in older adults. JAMA Surg 152:e170123. https://doi.org/10.1001/jamasurg.2017.0123
3. Basques BA, Tetreault MW, Della Valle CJ (2017) Same-day discharge compared with inpatient hospitalization following hip and knee arthroplasty. J Bone Joint Surg Am 99:1969–1977. https://doi.org/10.2106/JBJS.16.00739
4. Costa AP, Poss JW, Peirce T, Hirdes JP (2012) Acute care inpatients with long-term delayed discharge: evidence from a Canadian health region. BMC Health Serv Res 12:6–11. https://doi.org/10.1186/1472-6963-12-172
5. Watkins JR, Soto JR, Bankhead-Kendall B et al (2014) What's the hold up? Factors contributing to delays in discharge of trauma patients after medical clearance. Am J Surg 208:969–973. https://doi.org/10.1016/j.amjsurg.2014.07.002
6. Hwabejire JO, Kaafarani HMA, Imam AM et al (2013) Excessively long hospital stays after trauma are not related to the severity of illness: let's aim to the right target! JAMA Surg 148:956–961. https://doi.org/10.1001/jamasurg.2013.2148
7. Andrews LB, Stocking C, Krizek T et al (1997) An alternative strategy for studying adverse events in medical care. Lancet 349:309–313. https://doi.org/10.1016/S0140-6736(96)08268-2
8. Hauck K, Zhao X (2011) How dangerous is a day in hospital? Med Care 49:1068–1075. https://doi.org/10.1097/MLR.0b013e31822efb09
9. Gruskay JA, Fu M, Bohl DD et al (2015) Factors affecting length of stay after elective posterior lumbar spine surgery: a multivariate analysis. Spine J 15:1188–1195. https://doi.org/10.1016/j.spinee.2013.10.022
10. Sharma M, Sonig A, Ambekar S, Nanda A (2014) Discharge dispositions, complications, and costs of hospitalization in spinal cord tumor surgery: analysis of data from the United States Nationwide Inpatient Sample, 2003–2010. J Neurosurg Spine 20:125–141. https://doi.org/10.3171/2013.9.SPINE13274
11. Best MJ, Buller LT, Falakassa J, Vecchione D (2015) Risk factors for nonroutine discharge in patients undergoing spinal fusion for intervertebral disc disorders. Iowa Orthop J 35:147–155
12. Niedermeier S, Przybylowicz R, Virk SS et al (2017) Predictors of discharge to an inpatient rehabilitation facility after a single-level posterior spinal fusion procedure. Eur Spine J 26:771–776. https://doi.org/10.1007/s00586-016-4605-2
13. McGirt MJ, Parker SL, Chotai S et al (2017) Predictors of extended length of stay, discharge to inpatient rehab, and hospital readmission following elective lumbar spine surgery: introduction of the Carolina–Semmes Grading Scale. J Neurosurg Spine 27:382–390. https://doi.org/10.3171/2016.12.SPINE16928
14. Slover J, Mullaly K, Karia R et al (2017) The use of the Risk Assessment And Prediction Tool in surgical patients in a bundled payment program. Int J Surg 38:119–122. https://doi.org/10.1016/j.ijsu.2016.12.038
15. Kanaan SF, Yeh H-W, Waitman RL et al (2014) Predicting discharge placement and health care needs after lumbar spine laminectomy. J Allied Health 43:88–97
16. Jordan M, Mitchell T (2015) Machine learning: trends, perspectives, and prospects. Science 80(349):255–260
17. Senders JT, Staples PC, Karhade AV et al (2018) Machine learning and neurosurgical outcome prediction: a systematic review. World Neurosurg 109:476–486.e1. https://doi.org/10.1016/j.wneu.2017.09.149
18. Schoenfeld AJ, Le HV, Marjoua Y et al (2015) Assessing the utility of a clinical prediction score regarding 30-day morbidity and mortality following metastatic spinal surgery: the New England spinal metastasis score (NESMS). Spine J 16:482–490. https://doi.org/10.1016/j.spinee.2015.09.043
19. Bekelis K, Desai A, Bakhoum SF, Missios S (2014) A predictive model of complications after spine surgery: the national surgical quality improvement program (NSQIP) 2005–2010. Spine J 14:1247–1255. https://doi.org/10.1016/j.spinee.2013.08.009
20. Veeravagu A, Li A, Swinney C et al (2017) Predicting complication risk in spine surgery: a prospective analysis of a novel risk assessment tool. J Neurosurg Spine 27:81–91. https://doi.org/10.3171/2016.12.SPINE16969
21. Sebastian A, Huddleston P, Kakar S et al (2016) Risk factors for surgical site infection after posterior cervical spine surgery: an analysis of 5,441 patients from the ACS NSQIP 2005–2012. Spine J 16:504–509. https://doi.org/10.1016/j.spinee.2015.12.009
22. Steinberg SM, Popa MR, Michalek JA et al (2008) Comparison of risk adjustment methodologies in surgical quality improvement. Surgery 144:662–667. https://doi.org/10.1016/j.surg.2008.06.010 (**discussion 662–667**)
23. Davenport DL, Holsapple CW, Conigliaro J (2009) Assessing surgical quality using administrative and clinical data sets: a direct comparison of the university healthsystem consortium clinical database and the national surgical quality improvement program data set. Am J Med Qual 24:395–402. https://doi.org/10.1177/1062860609339936
24. Posada D, Buckley TR (2004) Model selection and model averaging in phylogenetics: advantages of akaike information criterion and bayesian approaches over likelihood ratio tests. Syst Biol 53:793–808. https://doi.org/10.1080/10635150490522304
25. Rolston JD, Han SJ, Chang EF (2017) Systemic inaccuracies in the national surgical quality improvement program database: implications for accuracy and validity for neurosurgery outcomes research. J Clin Neurosci 37:44–47. https://doi.org/10.1016/j.jocn.2016.10.045
26. Murphy ME, Maloney PR, McCutcheon BA et al (2017) Predictors of discharge to a nonhome facility in patients undergoing lumbar decompression without fusion for degenerative spine disease. Neurosurgery 81:638–649. https://doi.org/10.1093/neuros/nyx057
27. Abt NB, McCutcheon BA, Kerezoudis P et al (2017) Discharge to a rehabilitation facility is associated with decreased 30-day readmission in elective spinal surgery. J Clin Neurosci 36:37–42. https://doi.org/10.1016/j.jocn.2016.10.029
28. Kelly DM, Bennett R, Brown N et al (2012) Predicting the discharge status after liver transplantation at a single center: a new approach for a new era. Liver Transplant 18:796–802. https://doi.org/10.1002/lt.23434
29. Tong MZ, Pattakos G, He J et al (2015) Sequentially updated discharge model for optimizing hospital resource use and surgical patients' satisfaction. Ann Thorac Surg 100:2174–2181. https://doi.org/10.1016/j.athoracsur.2015.05.090
30. Cook NR (2007) Use and misuse of the receiver operating characteristic curve in risk prediction. Circulation 115:928–935. https://doi.org/10.1161/CIRCULATIONAHA.106.672402

31. Benson RT, Drew JC, Galland RB (2006) A waiting list to go home: an analysis of delayed discharges from surgical beds. Ann R Coll Surg Engl 88:650–652. https://doi.org/10.1308/003588406X149246
32. Gaughan J, Gravelle H, Siciliani L (2015) Testing the bed-blocking hypothesis: does nursing and care home supply reduce delayed hospital discharges? Health Econ 24:32–44. https://doi.org/10.1002/hec.3150
33. Harris AHS (2017) Path from predictive analytics to improved patient outcomes. Ann Surg 265:461–463. https://doi.org/10.1097/SLA.0000000000002023
34. Parikh RB, Kakad M, Bates DW (2016) Integrating predictive analytics into high-value care. JAMA 315:651. https://doi.org/10.1001/jama.2015.19417

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