Title

Predictive Models for Length of Stay and Discharge Disposition in Elective Spine Surgery:
Development, Validation, and Comparison to the ACS NSQIP Risk Calculator

Authors

Arora, Ayush
Lituiev, Dmytro
Jain, Deeptee
et al.

Predictive Models for Length of Stay and Discharge Disposition in Elective Spine Surgery: Development, Validation, and Comparison to the ACS NSQIP Risk Calculator

Ayush Arora, BSE[1], **Dmytro Lituiev, PhD**[2], **Deeptee Jain, MD**[3], **Dexter Hadley, MD, PhD**[4], **Atul J. Butte, MD, PhD**[2,5,6], **Sigurd Berven, MD**[1], **Thomas A. Peterson, PhD**[1,2]

[1]Department of Orthopaedic Surgery, University of California, San Francisco, San Francisco, CA, USA.

[2]Bakar Computational Health Sciences Institute, University of California, San Francisco, San Francisco, CA, USA.

[3]Department of Orthopaedic Surgery, Washington University in St. Louis, St. Louis, MO

[4]Department of Pathology, University of Central Florida, FL, USA.

[5]Department of Pediatrics, University of California, San Francisco, San Francisco, CA, USA.

[6]Center for Data-driven Insights and Innovation, University of California Health, Oakland, USA

Abstract

Study Design: Retrospective study at a single academic institution

Objective: The purpose of this study is to utilize machine learning to predict hospital length of stay (LOS) and discharge disposition following adult elective spine surgery, and to compare performance metrics of machine learning models to the ACS NSQIP prediction calculator.

Summary of Background Data: 3,678 adult patients undergoing elective spine surgery between 2014–2019, acquired from the Electronic Health Record (EHR).

Methods: Patients were divided into 3 stratified cohorts: cervical degenerative, lumbar degenerative, and adult spinal deformity groups (ASD). Predictive variables included demographics, BMI, surgical region, surgical invasiveness, surgical approach, and comorbidities. Regression, classification trees, and Least Absolute Shrinkage and Selection Operator (LASSO) were used to build predictive models. Validation of the models was conducted on 16% of patients (N=587), using area under the receiver operator curve (AUROC), sensitivity, specificity, and

---

Corresponding Author: Name: Ayush Arora, Ayush.Arora@ucsf.edu, Address: 1241 4th Ave, San Francisco, CA 94122, Phone: 734.277.9437.

correlation. Patient data were manually entered into the ACS NSQIP online risk calculator to compare performance. Outcome variables were discharge disposition (home vs rehabilitation) and LOS (days).

Results: Of 3,678 patients analyzed, 51.4% were male (n=1,890) and 48.6% were female (n=1,788). The average LOS was 3.66 days. 78% were discharged home and 22% discharged to rehabilitation. Compared to NSQIP (Pearson R^2=0.16), the predictions of poisson regression (R^2=0.29) and LASSO (R^2=0.29) models were significantly more correlated with observed LOS (p=0.025 and p=0.004, respectively). Of the models generated to predict discharge location, logistic regression yielded an AUROC of 0.79, which was statistically equivalent to the AUROC of 0.75 for NSQIP (p= 0.135).

Conclusion: The predictive models developed in this study can enable accurate preoperative estimation of LOS and risk of rehabilitation discharge for adult patients undergoing elective spine surgery. The demonstrated models exhibited better performance than NSQIP for prediction of LOS and equivalent performance to NSQIP for prediction of discharge location.

MINI ABSTRACT

Accurate preoperative identification of patients at risk for extended length of stay (LOS) and discharge to rehabilitation can provide substantial benefit for patients undergoing elective spine surgery. We built machine learning models that predicted both outcomes and compared performance metrics to that of the ACS NSQIP prediction calculator.

Introduction

Complications and delayed recovery following elective spine surgery can greatly impact patient quality of life and perception of improvement [1]. Given perioperative medical complication rates between 25–52% for highly invasive spine surgeries, such as long-segment fusions for adult spinal deformity, patients may require extended hospital length of stay (LOS) and rehabilitation services postoperatively [2,3]. LOS is notable as a composite measurement of the postoperative course, as patients with systemic illnesses, elderly age, and those with hospital-acquired infections stay longer in the hospital [4,5]. Discharge to rehabilitation may be an avenue for patients requiring need for extended care and aid in return to function [6,7]. From a cost perspective, extended LOS has been identified as a reliable predictor for catastrophic costs over $100,000 following spine surgery, while usage of rehabilitation services can account for 30% of the cost of care [8–10]. Even in cases where rehabilitation discharge is not due to a complication, an alternative disposition to home incurs a substantial cost in a shared risk payment model and represents an important outcome. Hence, both extended LOS and discharge to rehabilitation care may reflect a combination of worsening patient morbidity, cost, and postoperative outcome.

Accurate preoperative identification of patients at risk for extended LOS and discharge to rehabilitation can provide substantial benefit, including more transparent communication on expected benefits and risks of surgery, postoperative planning, cost savings, preemptive administrative action, and optimization of modifiable patient risk factors [11–13]. Many studies have determined significant risk factors in spine surgery, but most have been unable to create robust predictive models due to small cohort sizes and limited granularity of patient

data [14,15]. Of the reported predictive models, few capture the breadth of elective spinal cases, normally focusing on single types of procedures, diagnosis, or patient groups [16]. A notable tool used for all types of surgeries is the American College of Surgeon's National Surgical Quality Improvement Program's (ACS NSQIP) online calculator, which utilizes 21 inputted preoperative factors to predict both LOS and discharge status [17]. While met with moderate accuracy for general surgical procedures, numerous studies have shown that it does not provide accurate predictions for patients undergoing spine surgery [18–21].

The purpose of this study is to estimate LOS and likelihood of discharge to rehabilitation following adult elective spine surgery while creating a machine learning prediction tool to assess patient-specific risk, which cannot be accomplished using traditional statistical association or regression techniques. Comorbidities, demographic, and operative risk factors will be used to inform model training. Finally, we compare performance metrics of the predictive models for both LOS and discharge outcome to those of the ACS NSQIP prediction calculator.

Methods

Data Sources

Data were gathered retrospectively on patients undergoing spine surgery from the Electronic Health Record (EHR) at a single academic tertiary care institution from 2014–2019. Patient demographical information (age, gender, ethnicity), body mass index (BMI), and written procedure description were collected for all patients through automated data acquisition from the EHR. Patient diagnostic category and select medical comorbidities were determined by utilization of International Classification of Diseases, Volume 10 codes (ICD10) [22]. No identifying patient information was acquired. Information from the dataset was utilized to determine predictive factors for LOS and discharge to rehabilitation for adult patients undergoing elective spine surgery.

Study Sample and Selection Criteria

The study population consisted of adult patients undergoing elective spine fusions and/or decompressions of the cervical, thoracic, and lumbar spine. Patients with diagnosis that indicated a non-elective procedure were excluded. The criteria queued for exclusion included: age<18, malignancy, spinal infection, extradural and subdural abscess, spinal fractures/trauma, collapsed vertebra, spinal dislocation, preexisting neuromuscular disorders, and revision procedures [23]. Cases of missing BMI, demographic information, LOS, and unknown discharge location were removed. Patients were selected using the criteria provided in Supplementary Table 1 and Supplementary Table 2 and underwent further manual review of the procedure description notes.

Predictors and Outcomes

The study outcomes included LOS and discharge to rehabilitation or skilled nursing facility (SNF) following elective spine surgery. LOS was measured in days, while discharge disposition to rehab/SNF was captured as a binary variable (yes/no). Demographics,

comorbidities, and operative variables were used as predictors of LOS and discharge disposition.

Demographic variables included age (18–39, 40–49, 50–59, 60–69, 70–79, 80), gender, and race/ethnicity (Asian, Black, White, Hispanic/Latino, Other). BMI was classified as normal (BMI<25), overweight(25 BMI<30), obese(30 BMI<35), and morbidly obese (BMI 35).

Operative variables included surgical approach (anterior alone, posterior alone, combined approach – same day, and combined staged approach), surgical invasiveness index (1–2, 3–6, 7–12, 13–18, 19–24, 25), and diagnosis group (cervical degenerative, lumbar degenerative, and adult spinal deformity). Diagnoses were derived from ICD10 codes, while surgical invasiveness index and surgical approach were manually assessed based on textual information contained in the written procedure description. Of note, combined staged approach indicated when anterior and posterior components of the surgery were conducted during the same episode of healthcare but completed sequentially on different days. Surgical invasiveness is a robust indicator developed by Mirza et al. that is obtained by adding the number of vertebral levels receiving decompression, fusion, and/or instrumentation in the anterior and posterior approaches, with a scoring range between 0–48 [24]. The index was manually calculated for each individual patient in this study and has successfully predicted estimated blood loss, operative time, and surgical site infections in the reported literature [25].

Preoperative risk factors included cardiovascular, respiratory, smoking status, renal, metabolic, and other comorbidities as indicated by ICD10 codes (Supplementary Table 3). Cardiovascular risk factors included history of hypertension (HTN), heart failure, peripheral arterial disease (PAD), heart block, past stroke, cardiomyopathy, arrythmia, and myocarditis. Respiratory risk factors consisted of chronic obstructive pulmonary disease (COPD), dyspnea at presentation, asthma, and ventilator dependence. Smoking status was classified as current smoker, former smoker, and never smoker. Renal risk factors included acute renal failure, renal dialysis, and chronic kidney disease (CKD). Metabolic risk factors were diabetes and acute liver damage. Other comorbidities were cancer history, osteoporosis, inflammatory disease, insomnia, sleep apnea, depression, anxiety, gastroesophageal reflux disease (GERD), and opioid addiction disorder.

Development of Predictive Models

Regression, Decision Learning, and Least Absolute Shrinkage and Selection Operator (LASSO) were used to build predictive models. Of note, prediction models were optimized to output a numerical estimation of LOS and a percentage probability for discharge to rehabilitation. For discharge prediction, the models utilized included decision learning, logistic regression, and LASSO given a binary outcome. For LOS prediction, generalized linear regression (GLM): Poisson distribution was chosen given that LOS is a non-parametric outcome, consists of independently associated count data, and is bounded at zero. Cohorts were split into 84% training and 16% validation cohorts. To assess diagnostic performance for numerical LOS predictions, correlation, root mean squared error (RMSE), and mean absolute error (MAE) were calculated. To assess diagnostic performance for

discharge prediction, area under the receiver operator curve (AUROC), sensitivity, and specificity were determined.

Comparison to ACS NSQIP Calculator and Statistical Tests

Patient data from the 16% validation cohort were manually entered into the online ACS NSQIP risk calculator, and NSQIP predictions for LOS and probability of discharge to rehabilitation were retrieved. Diagnostic performance, such as AUROC, sensitivity, specificity, correlation, RMSE, and MAE were calculated for the NSQIP predictions. Statistical tests were conducted to compare performance of the predictive models and NSQIP calculator. Correlation coefficients were compared via Fisher's z-transformation, and model AUROCs were compared through DeLong's test [26]. P-values less than 0.05 were considered significant. Analysis was conducted in MATLAB version 2020b [27].

Results

Exploratory data analysis

Among 7,554 patients in the spine dataset, 3,678 patients met the inclusion criteria (Supplemental Digital Content Figure 1)). Of these, 22% were discharged to rehabilitation, and 15.5% had an extended LOS beyond seven days (Table 1 and Table 2). The average LOS was 3.7 days. Mean age was 60.1 years, with a nearly even male to female ratio (51.4 % vs 48.6%). 71.1% of patients fell into BMI categories of overweight, obese, or morbidly obese. The most common surgical approach was posterior approach (61.5%), followed by anterior approach (15.3%). Surgical procedures conducted on the selected cohort are described in Table 3. The most common diagnosis group was lumbar degenerative, consisting of 50.1% of total procedures. Highly prevalent comorbidities in the cohort included hypertension (45.9%) and former smoking history (39.3%).

Predictive Models: Discharge Disposition

Three predictive models were created for prediction of discharge to rehabilitation. These included logistic regression (AUROC=0.79), LASSO (AUROC=0.79), and decision tree learning (AUROC=0.69). 84% of the cohort (N=3,091) were used to generate each model with validation on the remaining 16% (N=587). The NSQIP calculator produced an AUROC= 0.75 (Supplemental Digital Content Figure 2). Beta coefficients, odds ratios, and p-values for the logistic model, which had the highest AUROC, are displayed in Table 4. Significant variables that increased likelihood of discharge to rehabilitation included age, black race, BMI, surgical invasiveness index, arrhythmia, COPD, current smoker, diabetes, and depression. Variables that decreased likelihood of discharge to rehabilitation included male gender, Asian race, anterior approach, and combined same-day staged approach. Of the models trained to predict discharge location, the AUROC of 0.79 for both logistic and LASSO regression were statistically equivalent to the AUROC of 0.75 for NSQIP (p=0.135). At a predictive probability threshold of 0.16, the logistic regression model produced a sensitivity of 0.80 and a specificity of 0.64.

Predictive Models: Length of Stay (LOS)

Two predictive models were created for numerical prediction of LOS. These included GLM: Poisson Distribution (R^2=0.29, RMSE=5.94 days, MEA=1.66 days) and LASSO regression (R^2=0.29, RMSE=7.28 days, MEA=1.72 days). 84% of the cohort (n=3,091) were used to train each model with validation on the remaining 16% (n=587). The NSQIP calculator produced a R^2=0.16, RMSE=17.81 days, and MAE=1.84 days. Plots of predicted LOS vs observed LOS for each model and NSQIP predictions of the *n*=587 validation patients are displayed in Supplemental Digital Content Figure 3.

Model coefficients for GLM: Poisson distribution, which produced the lowest RMSE and MEA, are displayed in Table 5. Significant variables that increased LOS included age, black race, diagnosis of spine deformity, surgical invasiveness index, combined staged approach on a different day, PAD, arrythmia, former smoking history, COPD history, acute renal failure, diabetes, anxiety, GERD, and opioid addiction disorder. Significant variables that decreased LOS included male gender, diagnosis of cervical degenerative pathology, anterior approach, combined same-day staged approach, and inflammatory disease. Compared to NSQIP (R^2=0.16), the predictions of GLM: Poisson distribution (R^2=0.29) and LASSO (R^2=0.29) models were significantly more correlated with observed LOS (*p*=0.025 and *p*=0.004, respectively).

Discussion

The goal of this study was to develop a machine learning model that could predict LOS and discharge location following adult elective spine surgery with a higher accuracy than the ACS NSQIP risk calculator. With a statistically significant R^2=0.29 for predicting LOS and a statistically equivalent AUROC=0.79 for predicting discharge to rehabilitation, the predictive models are valuable tools that can be utilized preoperatively to assess patient risk. The logistic and GLM: Poisson regression models, with provided coefficients, can be easily translated for preoperative implementation.

The associations found within this study are concordant with those reported in the literature. The association between increasing age and BMI with perioperative complications and non-home discharges is well documented and demonstrates a more profound effect at higher ends of the spectrum [28,29]. Worse outcomes in women may be explained by the fact that women undergo surgery at more advanced diseased states compared to men [30]. Patients with diagnosis of adult spinal deformity represent a particularly disabled group with more functional limitations than those with other chronic medical conditions and have been associated with worse postoperative outcomes [31]. The relation between increasing surgical invasiveness index with increased LOS and likelihood of rehab discharge makes intuitive sense, as higher scores have been associated with multiple medical complications [32]. Risk factors such as arrythmias, COPD, and diabetes have been thoroughly reported to worsen perioperative morbidity [7,33]. As expected, there was overlap between risk factors that were significantly associated with discharge to rehabilitation and those associated with longer LOS.

A unique feature of this study is the implementation of a large cohort (n=3,678) with granular patient data. Ability to stratify patients by diagnosis category and include novel variables pertaining to type of surgical intervention (surgical invasiveness index and staged surgery) may be credited for our ability to achieve higher predictive performance. The study alternate hypothesis was that diagnostic category would be an important independent predictor of LOS and discharge, and hence diagnostic category was modelled as a predictor variable. The results demonstrated that patients with adult spinal deformity were indeed significantly associated with extended LOS. Additionally, no studies have developed predictive models utilizing knowledge about type of surgical intervention, even though staged anterior and posterior procedures are routinely conducted and represent an increased chance for hospital acquired complications [34].

Existing predictive models have shown mixed ability to predict outcomes following elective spine surgery. Models such as NSQIP and the Risk Assessment Tool (RAT) use a combination of demographics, procedure codes, operative variables, and comorbidities to determine postoperative outcome following surgery [17,35]. Previous studies have validated NSQIP and RAT tools as having moderate utility in predicting complications and discharge location, with comparable AUROCs between 0.64 and 0.70 [36,37]. NSQIP predictions for LOS have shown to be highly inaccurate, and no studies have conducted validation within spine patients [38]. In this study, the predictive models outperformed NSQIP in predicting LOS and were equivalent to NSQIP in predicting discharge location. Compared to other studies that have developed predictive models for outcomes in spine surgery, this is the first to conduct a high level of stratification among patients, utilize a substantial sample size greater than N=300, and compare performance to a gold-standard [16].

The importance of this study is to develop more accuracy in our ability to predict LOS and discharge disposition to enable medical centers in calculating expected costs of care. Ideally, the predictive models can be used to generate predictions in the preoperative encounter. Especially for health systems utilizing bundled payment models, accurate predictive analytics on LOS and discharge outcomes can facilitate critical financial savings. Currently under bundled payment plans, patients requiring utilization of more-than-expected hospital services incur financial losses that are placed directly on the healthcare team and hospital system [39]. Resulting catastrophic costs and the inability for hospitals to afford high volumes of patients with poor outcomes necessitate usage of predictive analytics to maintain financial viability [10]. Preemptive identification of patients at risk for complications through the predictive models provided could ensure better cost management and treatment planning to reduce unnecessary suffering. Finally, accurate preoperative analytics can empower patient informed choice by increasing transparency on the expected benefits and risks of surgery.

A key limitation of this study is utilization of data from a singular institution. Although the predictive models developed may be less generalizable to other settings, the tradeoff is that single-institution data provides better granularity than that of multi-center datasets. Our goal was to build a predictive model that could incorporate granular variables such as surgical invasiveness index, diagnosis group, staged surgery, and numerous medical comorbidities – information used by few other predictive models. We intend our study to

be foundational for development of granular models derived from multiple data sources. Moreover, variables such as socioeconomic status, education, and income level have shown potential in improving predictive accuracy [40]. Measuring social support through the Risk Assessment and Prediction Tool (RAPT) presents a valuable future avenue [41]. Lastly, while this retrospective study utilized ICD10 codes to acquire components of patient data, some uncertainty on accuracy of ICD10 codes has been reported that could have resulted in an underestimation of risk factors [42].

Conclusion

This study utilizing n=3,678 patients facilitated development of predictive models that can preoperatively assess likelihood of discharge to rehabilitation and LOS following adult elective spine surgery. The models utilized highly granular data consisting of patient demographics, BMI, diagnostic category, surgical invasiveness index, surgical region, surgical staging, and patient comorbidities. Performance metrics from the predictive models were tested in comparison to the ACS NSQIP calculator. For prediction of LOS, the GLM: Poisson and LASSO models had a better accuracy than the ACS NSQIP calculator. For prediction of discharge location, the logistic regression model had a statistically equivalent accuracy when compared to the ACS NSQIP calculator.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgements

References

1. Hart RA, Cabalo A, Bess S, et al. Comparison of patient and surgeon perceptions of adverse events after adult spinal deformity surgery. Spine (Phila Pa 1976). Apr 20 2013;38(9):732–6. doi:10.1097/BRS.0b013e31827ae242 [PubMed: 24477053]

2. Campbell PG, Yadla S, Nasser R, Malone J, Maltenfort MG, Ratliff JK. Patient comorbidity score predicting the incidence of perioperative complications: assessing the impact of comorbidities on complications in spine surgery. J Neurosurg Spine. Jan 2012;16(1):37–43. doi:10.3171/2011.9.SPINE11283 [PubMed: 22035101]

3. Reis RC, de Oliveira MF, Rotta JM, Botelho RV. Risk of complications in spine surgery: a prospective study. Open Orthop J. 2015;9:20–5. doi:10.2174/1874325001509010020 [PubMed: 25674185]

4. Gruskay JA, Fu M, Bohl DD, Webb ML, Grauer JN. Factors affecting length of stay after elective posterior lumbar spine surgery: a multivariate analysis. Spine J Jun 1 2015;15(6):1188–95. doi:10.1016/j.spinee.2013.10.022 [PubMed: 24184639]

5. Klineberg EO, Passias PG, Jalai CM, et al. Predicting Extended Length of Hospital Stay in an Adult Spinal Deformity Surgical Population. Spine (Phila Pa 1976). Jul 1 2016;41(13):E798–E805. doi:10.1097/BRS.0000000000001391 [PubMed: 26679876]

6. Ames CP, Scheer JK, Lafage V, et al. Adult Spinal Deformity: Epidemiology, Health Impact, Evaluation, and Management. Spine Deform. Jul 2016;4(4):310–322. doi:10.1016/j.jspd.2015.12.009 [PubMed: 27927522]

7. Soroceanu A, Burton DC, Oren JH, et al. Medical Complications After Adult Spinal Deformity Surgery: Incidence, Risk Factors, and Clinical Impact. Spine (Phila Pa 1976). Nov 15 2016;41(22):1718–1723. doi:10.1097/BRS.0000000000001636 [PubMed: 27105460]

8. Ames CP, Smith JS, Gum JL, et al. Utilization of Predictive Modeling to Determine Episode of Care Costs and to Accurately Identify Catastrophic Cost Nonwarranty Outlier Patients in Adult Spinal Deformity Surgery: A Step Toward Bundled Payments and Risk Sharing. Spine (Phila Pa 1976). Mar 1 2020;45(5):E252–E265. doi:10.1097/BRS.0000000000003242 [PubMed: 31513120]

9. Stephens BF 2nd, Khan I, Chotai S, Sivaganesan A, Devin CJ. Drivers of Cost in Adult Thoracolumbar Spine Deformity Surgery. World Neurosurg. Oct 2018;118:e206–e211. doi:10.1016/j.wneu.2018.06.155 [PubMed: 29966783]

10. Theologis AA, Lau D, Dalle-Ore C, Tsu A, Deviren V, Ames CP. Costs and utility of post-discharge acute inpatient rehabilitation following adult spinal deformity surgery. Spine Deform May 2021;9(3):817–822. doi:10.1007/s43390-020-00251-w [PubMed: 33400227]

11. Maitra S, Mikhail C, Cho SK, Daubs MD. Preoperative Maximization to Reduce Complications in Spinal Surgery. Global Spine J Jan 2020;10(1 Suppl):45S–52S. doi:10.1177/2192568219882349 [PubMed: 31934520]

12. Menendez JY, Omar NB, Chagoya G, et al. Patient Satisfaction in Spine Surgery: A Systematic Review of the Literature. Asian Spine J Dec 2019;13(6):1047–1057. doi:10.31616/asj.2019.0032 [PubMed: 31352720]

13. Zambouri A Preoperative evaluation and preparation for anesthesia and surgery. Hippokratia. Jan 2007;11(1):13–21. [PubMed: 19582171]

14. Amin RM, Raad M, Jain A, et al. Risk factors for nonroutine discharge in adult spinal deformity surgery. Spine J Feb 2019;19(2):357–363. doi:10.1016/j.spinee.2018.06.366 [PubMed: 30661516]

15. Lovecchio F, Steinhaus M, Elysee JC, et al. Factors Associated With Short Length of Stay After Long Fusions for Adult Spinal Deformity: Initial Steps Toward Developing an Enhanced Recovery Pathway. Global Spine J. Jul 2021;11(6):866–873. doi:10.1177/2192568220941448 [PubMed: 32787569]

16. Lubelski D, Ehresman J, Feghali J, et al. Prediction calculator for nonroutine discharge and length of stay after spine surgery. Spine J Jul 2020;20(7):1154–1158. doi:10.1016/j.spinee.2020.02.022 [PubMed: 32179154]

17. Bilimoria KY, Liu Y, Paruch JL, et al. Development and evaluation of the universal ACS NSQIP surgical risk calculator: a decision aid and informed consent tool for patients and surgeons. J Am Coll Surg Nov 2013;217(5):833–42 e1–3. doi:10.1016/j.jamcollsurg.2013.07.385 [PubMed: 24055383]

18. Alzahrani SM, Ko CS, Yoo MW. Validation of the ACS NSQIP Surgical Risk Calculator for Patients with Early Gastric Cancer Treated with Laparoscopic Gastrectomy. J Gastric Cancer. Sep 2020;20(3):267–276. doi:10.5230/jgc.2020.20.e27 [PubMed: 33024583]

19. Johnson C, Campwala I, Gupta S. Examining the validity of the ACS-NSQIP Risk Calculator in plastic surgery: lack of input specificity, outcome variability and imprecise risk calculations. J Investig Med. Mar 2017;65(3):722–725. doi:10.1136/jim-2016-000224

20. McCarthy MH, Singh P, Nayak R, et al. Can the American College of Surgeons Risk Calculator Predict 30-day Complications After Spine Surgery? Spine (Phila Pa 1976). May 1 2020;45(9):621–628. doi:10.1097/BRS.0000000000003340 [PubMed: 31770319]

21. Narain AS, Kitto AZ, Braun B, et al. Does the ACS NSQIP Surgical Risk Calculator Accurately Predict Complications Rates After Anterior Lumbar Interbody Fusion Procedures? Spine (Phila Pa 1976). Jun 15 2021;46(12):E655–E662. doi:10.1097/BRS.0000000000003893 [PubMed: 33337678]

22. World Health Organization. (2004). ICD-10: international statistical classification of diseases and related health problems : tenth revision neWHO.

23. Diebo BG, Passias PG, Marascalchi BJ, et al. Primary Versus Revision Surgery in the Setting of Adult Spinal Deformity: A Nationwide Study on 10,912 Patients. Spine (Phila Pa 1976). Nov 2015;40(21):1674–80. doi:10.1097/BRS.0000000000001114 [PubMed: 26267823]

24. Mirza SK, Deyo RA, Heagerty PJ, Turner JA, Lee LA, Goodkin R. Towards standardized measurement of adverse events in spine surgery: conceptual model and pilot evaluation. BMC Musculoskelet Disord Jun 20 2006;7:53. doi:10.1186/1471-2474-7-53 [PubMed: 16787537]

25. Cizik AM, Lee MJ, Martin BI, et al. Using the spine surgical invasiveness index to identify risk of surgical site infection: a multivariate analysis. J Bone Joint Surg Am Feb 15 2012;94(4):335–42. doi:10.2106/JBJS.J.01084 [PubMed: 22336972]

26. DeLong ER, DeLong DM, Clarke-Pearson DL. Comparing the areas under two or more correlated receiver operating characteristic curves: a nonparametric approach. Biometrics. Sep 1988;44(3):837–45. [PubMed: 3203132]

27. Matlab [Computer Software]. Version 2020b. Natick MM.

28. Bono OJ, Poorman GW, Foster N, et al. Body mass index predicts risk of complications in lumbar spine surgery based on surgical invasiveness. Spine J Jul 2018;18(7):1204–1210. doi:10.1016/j.spinee.2017.11.015 [PubMed: 29155339]

29. Passias PG, Poorman GW, Bortz CA, et al. Predictors of adverse discharge disposition in adult spinal deformity and associated costs. Spine J. Oct 2018;18(10):1845–1852. doi:10.1016/j.spinee.2018.03.022 [PubMed: 29649611]

30. Siccoli A, Staartjes VE, de Wispelaere MP, Schroder ML. Gender differences in degenerative spine surgery: Do female patients really fare worse? Eur Spine J. Oct 2018;27(10):2427–2435. doi:10.1007/s00586-018-5737-3 [PubMed: 30132176]

31. Pellise F, Vila-Casademunt A, Ferrer M, et al. Impact on health related quality of life of adult spinal deformity (ASD) compared with other chronic conditions. Eur Spine J. Jan 2015;24(1):3–11. doi:10.1007/s00586-014-3542-1 [PubMed: 25218732]

32. Lee MJ, Konodi MA, Cizik AM, Bransford RJ, Bellabarba C, Chapman JR. Risk factors for medical complication after spine surgery: a multivariate analysis of 1,591 patients. Spine J. Mar 2012;12(3):197–206. doi:10.1016/j.spinee.2011.11.008 [PubMed: 22245448]

33. DeWald CJ, Stanley T. Instrumentation-related complications of multilevel fusions for adult spinal deformity patients over age 65: surgical considerations and treatment options in patients with poor bone quality. Spine (Phila Pa 1976). Sep 1 2006;31(19 Suppl):S144–51. doi:10.1097/01.brs.0000236893.65878.39 [PubMed: 16946632]

34. Warner JL, Zhang P, Liu J, Alterovitz G. Classification of hospital acquired complications using temporal clinical information from a large electronic health record. J Biomed Inform. Feb 2016;59:209–17. doi:10.1016/j.jbi.2015.12.008 [PubMed: 26707449]

35. Ratliff JK, Balise R, Veeravagu A, et al. Predicting Occurrence of Spine Surgery Complications Using "Big Data" Modeling of an Administrative Claims Database. J Bone Joint Surg Am. May 18 2016;98(10):824–34. doi:10.2106/JBJS.15.00301 [PubMed: 27194492]

36. Merrill RK, Ibrahim JM, Machi AS, Raphael JS. Analysis and Review of Automated Risk Calculators Used to Predict Postoperative Complications After Orthopedic Surgery. Curr Rev Musculoskelet Med Jun 2020;13(3):298–308. doi:10.1007/s12178-020-09632-0 [PubMed: 32418072]

37. Veeravagu A, Li A, Swinney C, et al. Predicting complication risk in spine surgery: a prospective analysis of a novel risk assessment tool. J Neurosurg Spine. Jul 2017;27(1):81–91. doi:10.3171/2016.12.SPINE16969 [PubMed: 28430052]

38. Riley CA, Barton BM, Lawlor CM, et al. NSQIP as a Predictor of Length of Stay in Patients Undergoing Free Flap Reconstruction. OTO Open. Jan-Mar 2017;1(1):2473974X16685692. doi:10.1177/2473974X16685692

39. Dietz N, Sharma M, Alhourani A, et al. Bundled Payment Models in Spine Surgery: Current Challenges and Opportunities, a Systematic Review. World Neurosurg. Mar 2019;123:177–183. doi:10.1016/j.wneu.2018.12.001 [PubMed: 30553071]

40. Barrie U, Montgomery EY, Ogwumike E, et al. Household Income as a Predictor for Surgical Outcomes and Opioid Use After Spine Surgery in the United States. Global Spine J Jan 10 2022:21925682211070823. doi:10.1177/21925682211070823 [PubMed: 35007170]

41. Sconza C, Respizzi S, Grappiolo G, Monticone M. The Risk Assessment and Prediction Tool (RAPT) after Hip and Knee Replacement: A Systematic Review. Joints. Jun 2019;7(2):41–45. doi:10.1055/s-0039-1693459 [PubMed: 31879730]

42. Roof MA, Lygrisse K, Keitel L, et al. How Accurate Is ICD-10 Coding for Revision Total Knee Arthroplasty? J Arthroplasty. Dec 2021;36(12):3950–3958. doi:10.1016/j.arth.2021.08.021 [PubMed: 34538547]

Key Points

- We utilized machine learning to develop predictive models that generated an estimation of LOS and likelihood of discharge to rehabilitation following adult elective spine surgery.

- The models utilized highly granular data consisting of patient demographics, BMI, surgical invasiveness index, surgical region, surgical staging, and patient comorbidities.

- While accuracy in prediction of discharge was same to that of the ACS NSQIP calculator, the models built outperformed NSQIP in predicting LOS.

- Compared to other studies that have developed predictive models for outcomes in spine surgery, this is the first to conduct a high level of stratification among patients, utilize a substantial sample size greater than N=300, and compare performance to a gold-standard.

Figure 1:
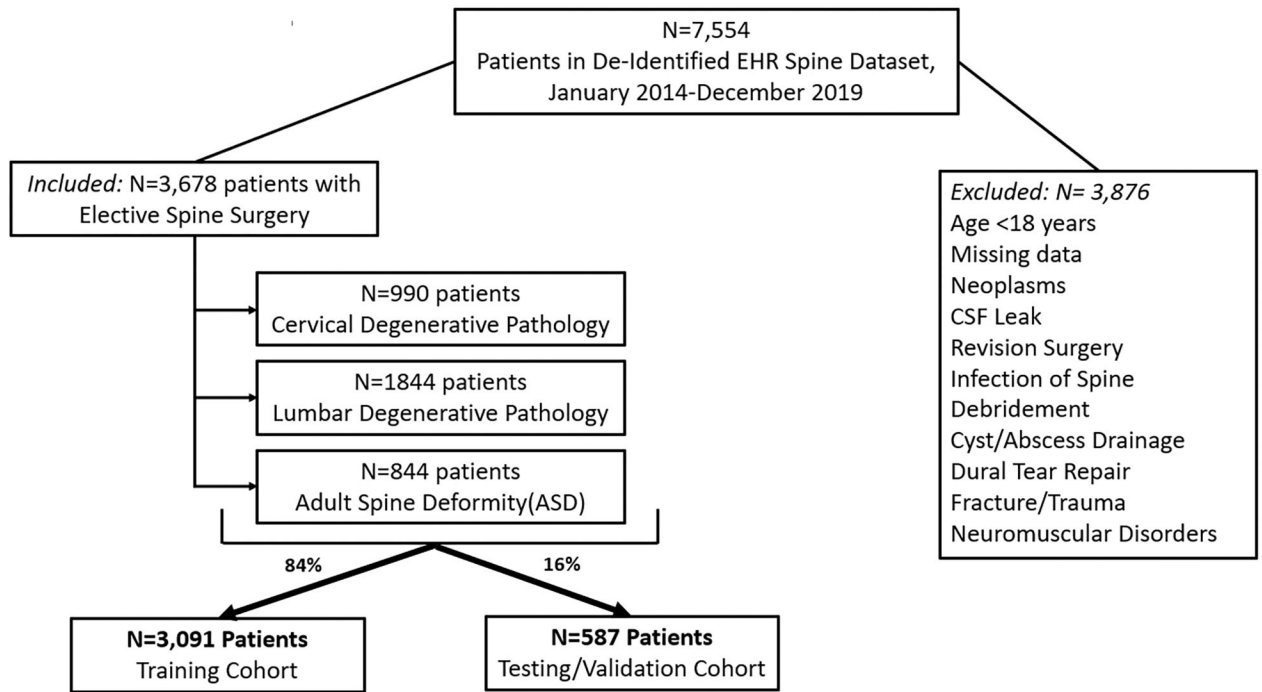Patient Selection Map
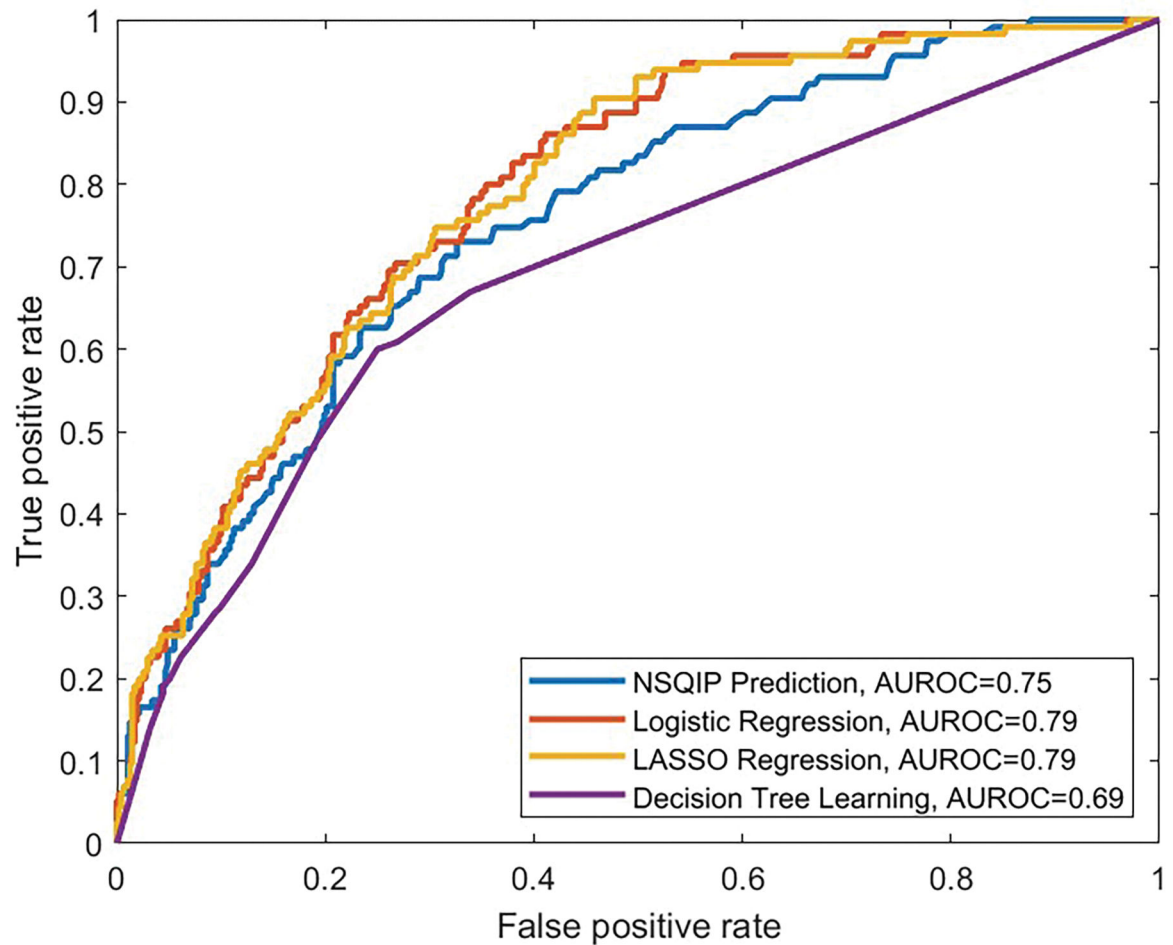
Figure 2:
Receiver Operating Curve (ROC) for ACS NSQIP calculator and trained predictive models, which included: logistic regression, LASSO, and decision tree learning for discharge to rehabilitation. The AUROCs were 0.75, 0.79, 0.79, and 0.69, respectively.
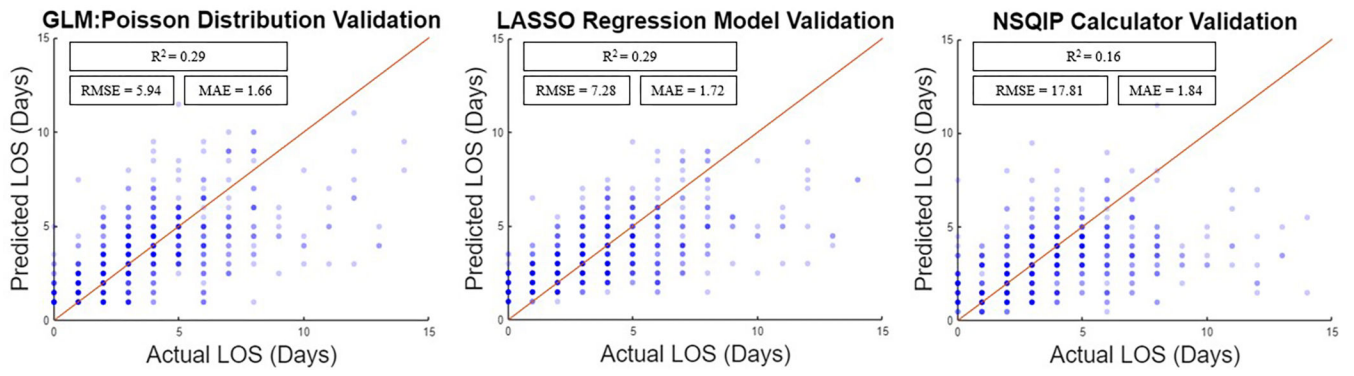
Figure 3:
Predicted vs observed Length of Stay (LOS) for ACS NSQIP Calculator and Predictive models.

Table 1:

Cohort demographics, interventions, comorbidities, stratified by discharge disposition

VARIABLE	N (% of Cohort)	Discharge to Home (%)	Discharge to Rehab/SNF (%)
Population	3,678 (100.0%)	2,869 (78.0%)	809 (22.0%)
Age (Mean, SD)	60.1 ± 13.8	57.9 ± 13.9	67.7 ± 10.3
18–39	349 (9.5%)	338 (96.8%)	11 (3.2%)
40–49	424 (11.5%)	393 (92.7%)	31 (7.3%)
50–59	804 (21.9%)	688 (85.6%)	116 (14.4%)
60–69	1123 (30.5%)	849 (75.6%)	274 (24.4%)
70–79	807 (21.9%)	513 (63.6%)	294 (36.4%)
80	171 (4.6%)	88 (51.5%)	83 (48.5%)
Gender			
Male	1890 (51.4%)	1576 (83.4%)	314 (16.6%)
Female	1788 (48.6%)	1293 (72.3%)	495 (27.7%)
Ethnicity			
Asian	231 (6.3%)	178 (77.1%)	53 (22.9%)
Black	171 (4.6%)	115 (67.3%)	56 (32.7%)
White	2842 (77.3%)	2240 (78.8%)	602 (21.2%)
Hispanic/Latino	310 (8.4%)	246 (79.4%)	64 (20.6%)
Other	124 (3.4%)	90 (72.6%)	34 (27.4%)
BMI			
Normal BMI(BMI<25)	1062 (28.9%)	840 (79.1%)	222 (20.9%)
Overweight(25 BMI<30)	1397 (38.0%)	1116 (79.9%)	281 (20.1%)
Obese(30 BMI<35)	787 (21.4%)	617 (78.4%)	170 (21.6%)
Morbidly Obese (BMI 35)	432 (11.7%)	296 (68.5%)	136 (31.5%)
Diagnosis			
Cervical Degenerative	990 (26.9%)	855 (86.4%)	135 (13.6%)
Lumbar Degenerative	1844 (50.1%)	1592 (86.3%)	252 (13.7%)
Spine Deformity	844 (22.9%)	422 (50.0%)	422 (50.0%)
Surgical Invasiveness			
1–2	978 (26.6%)	934 (95.5%)	44 (4.5%)
3–6	622 (16.9%)	516 (83.0%)	106 (17.0%)
7–12	922 (25.1%)	760 (82.4%)	162 (17.6%)
13–18	616 (16.7%)	427 (69.3%)	189 (30.7%)
19–24	247 (6.7%)	140 (56.7%)	107 (43.3%)
25	293 (8.0%)	92 (31.4%)	201 (68.6%)
Surgical Approach			
Anterior	561 (15.3%)	512 (91.3%)	49 (8.7%)

VARIABLE	N (% of Cohort)	Discharge to Home (%)	Discharge to Rehab/SNF (%)
Posterior	2261 (61.5%)	1838 (81.3%)	423 (18.7%)
Combined- Same Day	498 (13.5%)	374 (75.1%)	124 (24.9%)
Combined - Staged Different Day	358 (9.7%)	145 (40.5%)	213 (59.5%)
Cardiovascular Risk Factors			
Hypertension	1690 (45.9%)	1201 (71.1%)	489 (28.9%)
Heart Failure	110 (3.0%)	68 (61.8%)	42 (38.2%)
Peripheral Arterial Disease	92 (2.5%)	60 (65.2%)	32 (34.8%)
Past Myocardial Infarction	46 (1.3%)	34 (73.9%)	12 (26.1%)
Heart Block	40 (1.1%)	24 (60.0%)	16 (40.0%)
Past Stroke	51 (1.4%)	27 (52.9%)	24 (47.1%)
Cardiomyopathy	39 (1.1%)	29 (74.4%)	10 (25.6%)
Arrhythmia	526 (14.3%)	335 (63.7%)	191 (36.3%)
Myocarditis	65 (1.8%)	45 (69.2%)	20 (30.8%)
Respiratory Risk Factors			
COPD	203 (5.5%)	109 (53.7%)	94 (46.3%)
Dyspnea	32 (0.9%)	22 (68.8%)	10 (31.3%)
Asthma History	453 (12.3%)	329 (72.6%)	124 (27.4%)
Ventilator Dependent	20 (0.5%)	7 (35.0%)	13 (65.0%)
Smoking Status			
Current Smoker	242 (6.6%)	197 (81.4%)	45 (18.6%)
Former Smoker	1445 (39.3%)	1066 (73.8%)	379 (26.2%)
Never Smoker	1991 (54.1%)	1606 (80.7%)	385 (19.3%)
Renal Risk Factors			
Acute Renal Failure	94 (2.6%)	44 (46.8%)	50 (53.2%)
Renal Dialysis	12 (0.3%)	5 (41.7%)	7 (58.3%)
Chronic Kidney Disease	329 (8.9%)	192 (58.4%)	137 (41.6%)
Metabolic Risk Factors			
Diabetes	564 (15.3%)	381 (67.6%)	183 (32.4%)
Acute Liver Damage	53 (1.4%)	37 (69.8%)	16 (30.2%)
Other Risk Factors			
Cancer History	581 (15.8%)	444 (76.4%)	137 (23.6%)
Osteoporosis	297 (8.1%)	162 (54.5%)	135 (45.5%)
Inflammatory Disease	114 (3.1%)	78 (68.4%)	36 (31.6%)
Insomnia	60 (1.6%)	34 (56.7%)	26 (43.3%)
Sleep Apnea	516 (14.0%)	356 (69.0%)	160 (31.0%)
Depression	511 (13.9%)	342 (66.9%)	169 (33.1%)
Anxiety	397 (10.8%)	280 (70.5%)	117 (29.5%)
GERD	841 (22.9%)	575 (68.4%)	266 (31.6%)
Opioid Addiction Disorder	40 (1.1%)	20 (50.0%)	20 (50.0%)

Table 2:

Cohort demographics, interventions, comorbidities, stratified by Length of Stay (LOS)

VARIABLE	N (% of Cohort)	LOS<7 Days	LOS 7 Days
Population	3,678 (100.0%)	3,107 (84.5%)	571 (15.5%)
Age (Mean, SD)	60.1 ± 13.8	59.1 ± 14.2	65.2 ± 10.2
18–39	349 (9.5%)	340 (97.4%)	9 (2.6%)
40–49	424 (11.5%)	390 (92.0%)	34 (8.0%)
50–59	804 (21.9%)	701 (87.2%)	103 (12.8%)
60–69	1123 (30.5%)	905 (80.6%)	218 (19.4%)
70–79	807 (21.9%)	632 (78.3%)	175 (21.7%)
80	171 (4.6%)	139 (81.3%)	32 (18.7%)
Gender			
Male	1890 (51.4%)	1667 (88.2%)	223 (11.8%)
Female	1788 (48.6%)	1440 (80.5%)	348 (19.5%)
Ethnicity			
Asian	231 (6.3%)	204 (88.3%)	27 (11.7%)
Black	171 (4.6%)	142 (83.0%)	29 (17.0%)
White	2842 (77.3%)	2393 (84.2%)	449 (15.8%)
Hispanic/Latino	310 (8.4%)	260 (83.9%)	50 (16.1%)
Other	124 (3.4%)	108 (87.1%)	16 (12.9%)
BMI			
Normal BMI(BMI<25)	1062 (28.9%)	901 (84.8%)	161 (15.2%)
Overweight(25 BMI<30)	1397 (38.0%)	1204 (86.2%)	193 (13.8%)
Obese(30 BMI<35)	787 (21.4%)	652 (82.8%)	135 (17.2%)
Morbidly Obese (BMI 35)	432 (11.7%)	350 (81.0%)	82 (19.0%)
Diagnosis			
Cervical Degenerative	990 (26.9%)	935 (94.4%)	55 (5.6%)
Lumbar Degenerative	1844 (50.1%)	1722 (93.4%)	122 (6.6%)
Spine Deformity	844 (22.9%)	450 (53.3%)	394 (46.7%)
Surgical Invasiveness			
1–2	978 (26.6%)	966 (98.8%)	12 (1.2%)
3–6	622 (16.9%)	589 (94.7%)	33 (5.3%)
7–12	922 (25.1%)	834 (90.5%)	88 (9.5%)
13–18	616 (16.7%)	504 (81.8%)	112 (18.2%)
19–24	247 (6.7%)	138 (55.9%)	109 (44.1%)
25	293 (8.0%)	76 (25.9%)	217 (74.1%)
Surgical Approach			
Anterior	561 (15.3%)	534 (95.2%)	27 (4.8%)

VARIABLE	N (% of Cohort)	LOS<7 Days	LOS 7 Days
Posterior	2261 (61.5%)	2046 (90.5%)	215 (9.5%)
Combined- Same Day	498 (13.5%)	428 (85.9%)	70 (14.1%)
Combined - Staged Different Day	358 (9.7%)	99 (27.7%)	259 (72.3%)
Cardiovascular Risk Factors			
Hypertension	1690 (45.9%)	1354 (80.1%)	336 (19.9%)
Heart Failure	110 (3.0%)	82 (74.5%)	28 (25.5%)
Peripheral Arterial Disease	92 (2.5%)	65 (70.7%)	27 (29.3%)
Past Myocardial Infarction	46 (1.3%)	37 (80.4%)	9 (19.6%)
Heart Block	40 (1.1%)	32 (80.0%)	8 (20.0%)
Past Stroke	51 (1.4%)	40 (78.4%)	11 (21.6%)
Cardiomyopathy	39 (1.1%)	34 (87.2%)	5 (12.8%)
Arrhythmia	526 (14.3%)	394 (74.9%)	132 (25.1%)
Myocarditis	65 (1.8%)	55 (84.6%)	10 (15.4%)
Respiratory Risk Factors			
COPD	203 (5.5%)	143 (70.4%)	60 (29.6%)
Dyspnea	32 (0.9%)	25 (78.1%)	7 (21.9%)
Asthma History	453 (12.3%)	368 (81.2%)	85 (18.8%)
Ventilator Dependent	20 (0.5%)	9 (45.0%)	11 (55.0%)
Smoking Status			
Current Smoker	242 (6.6%)	216 (89.3%)	26 (10.7%)
Former Smoker	1445 (39.3%)	1163 (80.5%)	282 (19.5%)
Never Smoker	1991 (54.1%)	1728 (86.8%)	263 (13.2%)
Renal Risk Factors			
Acute Renal Failure	94 (2.6%)	51 (54.3%)	43 (45.7%)
Renal Dialysis	12 (0.3%)	6 (50.0%)	6 (50.0%)
Chronic Kidney Disease	329 (8.9%)	237 (72.0%)	92 (28.0%)
Metabolic Risk Factors			
Diabetes	564 (15.3%)	439 (77.8%)	125 (22.2%)
Acute Liver Damage	53 (1.4%)	38 (71.7%)	15 (28.3%)
Other Risk Factors			
Cancer History	581 (15.8%)	503 (86.6%)	78 (13.4%)
Osteoporosis	297 (8.1%)	198 (66.7%)	99 (33.3%)
Inflammatory Disease	114 (3.1%)	95 (83.3%)	19 (16.7%)
Insomnia	60 (1.6%)	40 (66.7%)	20 (33.3%)
Sleep Apnea	516 (14.0%)	404 (78.3%)	112 (21.7%)
Depression	511 (13.9%)	398 (77.9%)	113 (22.1%)
Anxiety	397 (10.8%)	312 (78.6%)	85 (21.4%)
GERD	841 (22.9%)	642 (76.3%)	199 (23.7%)
Opioid Addiction Disorder	40 (1.1%)	12 (30.0%)	28 (70.0%)

Table 3:

Operative Procedures Conducted on Selected Cohort, Stratified by Spinal Region

VARIABLE	N (% of Cohort)
Population	3,768 (100.0%)
Cervical	
ACDF, 1 level	85 (3.2%)
ACDF, 2–3 level	441 (11.7%)
ACDF, 4 level	35 (0.9%)
Laminoforaminotomy	102 (2.7%)
Laminectomy/Laminoplasty	257 (6.8%)
Cervical fusion (posterior or anterior/posterior), 1–3 Level	237 (6.3%)
Cervical fusion (posterior or anterior/posterior), 4–6 Level	206 (5.5%)
Lumbar	
Decompression, 1–2 level	885 (23.5%)
Decompression, 3–4 level	73 (1.9%)
Fusion (posterior or anterior/posterior), 1–4 level	883 (23.4%)
Thoracolumbar	
Fusion (posterior or anterior/posterior), 4–6 level	133 (3.5%)
Fusion (posterior or anterior/posterior), 7–12 level	220 (5.8%)
Fusion (posterior or anterior/posterior), >12 level	121 (3.2%)

[*] ACDF = Anterior Cervical Discectomy and Fusion

Table 4:

Logistic regression coefficients for prediction of discharge to rehabilitation

Variable	Beta Coefficient	Odds Ratio	95% CI		P-Value
Intercept	−5.25	--	--	--	<0.001
Age(categorical) [*]	0.67	1.96	1.75 - 2.19		<0.001
Gender					
Female	*Ref*	--	--	--	--
Male	−0.62	0.54	0.43 - 0.68		<0.001
Race					
White	*Ref*	--	--	--	--
Asian	0.47	1.60	1.03 - 2.47		0.035
Black	1.04	2.83	1.77 - 4.54		<0.001
Hispanic/Latino	0.19	1.21	0.80 - 1.82		0.371
BMI [**]	0.23	1.25	1.11 - 1.41		<0.001
Diagnosis					
Lumbar Degenerative	*Ref*	--	--	--	--
Cervical Degenerative	0.30	1.35	0.95 - 1.90		0.091
Spine Deformity	0.00	1.00	0.67 - 1.50		0.981
Surgical Invasiveness Index [***]	0.69	2.00	1.72 - 2.32		<0.001
Surgical Approach					
Posterior	*Ref*	--	--	--	--
Anterior	−1.31	0.27	0.17 - 0.42		<0.001
Combined - Staged Same Day	−0.54	0.59	0.40 - 0.86		0.007
Combined - Staged Different Day	0.07	1.07	0.73 - 1.57		0.741
Cardiovascular Risk Factors					
Hypertension	−0.02	0.98	0.78 - 1.23		0.867
Heart Failure	−0.18	0.83	0.45 - 1.54		0.562
Peripheral Arterial Disease	0.27	1.31	0.68 - 2.53		0.422
Past Myocardial Infarction	−0.40	0.67	0.23 - 1.91		0.452
Heart Block	0.29	1.34	0.55 - 3.29		0.521
Past Stroke	0.69	1.99	0.90 - 4.40		0.091
Cardiomyopathy	−0.15	0.86	0.31 - 2.39		0.779
Arrhythmia	0.53	1.71	1.27 - 2.30		<0.001
Myocarditis	−0.02	0.98	0.40 - 2.40		0.962
Respiratory Risk Factors					
COPD	0.67	1.96	1.31 - 2.94		0.001
Dyspnea	−0.59	0.55	0.16 - 1.87		0.341

Variable	Beta Coefficient	Odds Ratio	95% CI			P-Value
Asthma History	0.08	1.09	0.78	-	1.51	0.621
Ventilator Dependent	0.84	2.31	0.69	-	7.79	0.177
Smoking Status						
Never Smoker	Ref	--	--		--	--
Current Smoker	0.54	1.72	1.07	-	2.76	0.024
Former Smoker	0.16	1.17	0.94	-	1.47	0.165
Renal Risk Factors						
Acute Renal Failure	0.65	1.91	0.96	-	3.81	0.065
Renal Dialysis	0.43	1.54	0.30	-	7.83	0.605
Chronic Kidney Disease(CKD)	0.10	1.10	0.72	-	1.68	0.661
Metabolic Risk Factors						
Diabetes	0.35	1.42	1.06	-	1.90	0.019
Acute Liver Damage	0.16	1.17	0.55	-	2.48	0.682
Other Risk Factors						
Cancer History	0.19	1.21	0.89	-	1.63	0.224
Osteoporosis	0.31	1.36	0.97	-	1.92	0.074
Inflammatory Disease	−0.25	0.78	0.47	-	1.30	0.341
Insomnia	0.82	2.27	1.00	-	5.15	0.050
Sleep Apnea	0.05	1.05	0.78	-	1.43	0.733
Depression	0.58	1.79	1.29	-	2.48	<0.001
Anxiety	0.19	1.21	0.84	-	1.74	0.316
GERD	0.12	1.13	0.89	-	1.45	0.317
Opioid Addiction Disorder	0.24	1.27	0.54	-	3.01	0.582

[*] Per 1 point category increase. 18–39=0, 40–49=1, 50–59=2, 60–69=3, 70–79=4, 80=5

[**] Per 1 point category increase. BMI<25 = 0, 25 BMI<30 =1, 30 BMI<35 =2, BMI 35=3

[***] Per 1 point category increase. Index 1–2 = 0, 3–6=1, 7–12=2, 13–18=3, 19–24=4, 25=5

Table 5:

Generalized Linear Model: Poisson Distribution coefficients for numerical prediction of Length of Stay(LOS)

Variable	Coefficient	Standard Error (SE)	t-statistic	P-Value
Intercept	−0.15	0.05	−2.69	0.007
Age				
18–39	*Ref*	--	--	--
40–49	0.05	0.06	0.95	0.343
50–59	0.17	0.05	3.37	0.001
60–69	0.24	0.05	4.82	<0.001
70–79	0.27	0.05	5.34	<0.001
80	0.42	0.06	6.80	<0.001
Gender				
Female	*Ref*	--	--	--
Male	−0.08	0.02	−3.74	<0.001
Race				
White	*Ref*	--	--	--
Asian	0.02	0.04	0.38	0.705
Black	0.23	0.04	5.19	<0.001
Hispanic/Latino	0.07	0.03	1.95	0.051
BMI				
Normal BMI(BMI<25)	*Ref*	--	--	--
Overweight(25 BMI<30)	0.01	0.02	0.46	0.646
Obese(30 BMI<35)	0.04	0.03	1.38	0.167
Morbidly Obese (BMI 35)	0.05	0.03	1.44	0.149
Diagnosis				
Lumbar Degenerative	*Ref*	--	--	--
Cervical Degenerative	−0.17	0.04	−4.66	<0.001
Deformity	0.14	0.04	3.43	0.001
Surgical Invasiveness Index				
1–2	*Ref*	--	--	--
3–6	1.06	0.04	24.88	<0.001
7–12	1.25	0.05	27.64	<0.001
13–18	1.25	0.05	24.57	<0.001
19–24	1.43	0.06	22.05	<0.001
25	1.50	0.07	21.63	<0.001
Surgical Approach				
Posterior	*Ref*	--	--	--
Anterior	−0.38	0.04	−8.48	<0.001

Variable	Coefficient	Standard Error (SE)	t-statistic	P-Value
Combined - Staged Same Day	−0.06	0.04	−1.72	0.085
Combined - Staged Different Day	0.31	0.03	9.27	<0.001
Cardiovascular Risk Factors				
Hypertension	0.02	0.02	0.88	0.379
Heart Failure	−0.06	0.06	−1.07	0.284
Peripheral Arterial Disease	0.18	0.06	3.21	0.001
Past Myocardial Infarction	0.01	0.10	0.10	0.918
Heart Block	0.00	0.08	−0.03	0.980
Past Stroke	−0.02	0.08	−0.27	0.786
Cardiomyopathy	−0.13	0.11	−1.20	0.230
Arrhythmia	0.20	0.03	7.09	<0.001
Myocarditis	0.05	0.08	0.64	0.521
Respiratory Risk Factors				
COPD	0.07	0.04	1.96	0.050
Dyspnea	−0.19	0.11	−1.78	0.075
Asthma History	0.02	0.03	0.74	0.459
Ventilator Dependent	0.14	0.09	1.49	0.135
Smoking Status				
Never Smoker	*Ref*	--	--	--
Current Smoker	0.08	0.04	1.94	0.053
Former Smoker	0.06	0.02	2.98	0.003
Renal Risk Factors				
Acute Renal Failure	0.30	0.06	5.38	<0.001
Renal Dialysis	0.23	0.14	1.65	0.099
Chronic Kidney Disease (CKD)	0.02	0.04	0.50	0.618
Metabolic Risk Factors				
Diabetes	0.13	0.03	4.85	<0.001
Acute Liver Damage	0.03	0.07	0.36	0.722
Other Risk Factors				
Cancer History	−0.01	0.03	−0.21	0.832
Osteoporosis	0.04	0.03	1.32	0.186
Inflammatory Disease	−0.10	0.05	−2.07	0.038
Insomnia	−0.02	0.07	−0.27	0.790
Sleep Apnea	0.03	0.03	1.24	0.214
Depression	0.04	0.03	1.28	0.200
Anxiety	0.10	0.03	3.15	0.002
GERD	0.07	0.02	3.34	0.001
Opioid Addiction Disorder	0.19	0.06	3.07	0.002