Predictive Models to Assess Risk of Extended Length of Stay in Adults with Spinal Deformity and Lumbar Degenerative Pathology: Development and Internal Validation

Ayush Arora, BSE¹; Joshua Demb, PhD, MPH²; Daniel D. Cummins, BS¹; Matt Callahan, MBA¹; Aaron J. Clark, MD, PhD³; Alekos A. Theologis, MD*

¹ Department of Orthopedic Surgery, University of California - San Francisco (UCSF), San Francisco, CA, USA
² Department of Medicine, Division of Gastroenterology, University of California - San Diego, La Jolla, CA, USA
³ Department of Neurological Surgery, UCSF, San Francisco, CA, USA

* Corresponding Author
Alekos A. Theologis, MD
Department of Orthopedic Surgery
University of California - San Francisco
500 Parnassus Ave, MUW 3rd Floor
San Francisco, CA 94143
E-mail: alekos.theologis@ucsf.edu
Phone: 415-476-1167

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Abstract
Background Context. Post-operative recovery after adult spinal deformity (ASD) operations is arduous, fraught with complications, and often requires extended hospital stays. A need exists for a method to rapidly predict patients at risk for eLOS in the preoperative setting.

Purpose. To develop a machine learning model to preoperatively estimate the likelihood of extended length of stay (eLOS) following elective multi-level lumbar/thoracolumbar spinal instrumented fusions (≥3 segments) for adult spinal deformity (ASD).

Study Design/Setting. Retrospectively from a state-level inpatient database hosted by the Healthcare cost and Utilization Project (HCUP).

Patient Sample. 8,866 patients of age≥50 with ASD undergoing elective lumbar or thoracolumbar multi-level instrumented fusions.

Outcome Measures. The primary outcome was eLOS (>7 days).

Methods. Predictive variables consisted of demographics, comorbidities, and operative information. Significant variables from univariate and multivariate analyses were used to develop a logistic regression-based predictive model that utilized six predictors. Model accuracy was assessed through area under the curve (AUC), sensitivity, and specificity.

Results. 8,866 patients met inclusion criteria. A saturated logistic model with all significant variables from multivariate analysis was developed (AUC=0.77), followed by generation of a simplified logistic model through stepwise logistic regression (AUC=0.76). Peak AUC was reached with inclusion of six selected predictors (combined anterior and posterior approach, surgery to both lumbar and thoracic regions, ≥8 level fusion, malnutrition, congestive heart
failure, and academic institution). A cutoff of 0.18 for eLOS yielded a sensitivity of 77% and specificity of 68%.

Conclusions. This predictive model can facilitate identification of adults at risk for eLOS following elective multi-level lumbar/thoracolumbar spinal instrumented fusions for ASD. With a fair diagnostic accuracy, the predictive calculator will ideally enable clinicians to improve preoperative planning, guide patient expectations, enable optimization of modifiable risk factors, facilitate appropriate discharge planning, stratify financial risk, and accurately identify patients who may represent high-cost outliers. Future prospective studies that validate this risk assessment tool on external datasets would be valuable.

Keywords: Deformity, Predictive Models, Length of Stay, Internal Validation
Introduction

Adult spinal deformity (ASD) is a highly prevalent condition with a definitive negative impact on health-related quality of life [1,2]. Such patients have greater functional limitations and pain than patients with other chronic conditions, even when compared with age-matched controls [3,4]. When expectant management and physical therapy fails to provide relief, elective surgical intervention can be pursued [5]. While surgical intervention can provide considerable benefit, post-operative recovery after ASD operations is arduous, fraught with complications, and often requires extended hospital stays, and rehabilitation [6-8].

Measurement of eLOS can serve as a composite reflection of the postoperative course for ASD patients, with extended stay associated with increased risk of hospital-acquired infections, medical complications, and readmissions [9-11]. The resulting retention of patients in post-acute care settings can result in significant administrative challenges due to the ensuing disruption of patient flow and bed shortages, limiting access to care [12]. Furthermore, eLOS has also been identified as one of the top predictors of catastrophic costs, of over $100,000 for ASD patients [13]. Hence, there exists a significant interest in predicting which patients will have eLOS following surgery for ASD.

While numerous studies have identified independent risk factors associated with eLOS, few are specific to ASD patients, major discrepancies exist on importance of selected risk factors [14-16]. Additionally, assessment of risk through a combination of many significant variables, each with respective odds ratio or relative risk, can make preoperative evaluation difficult. Therefore, a need exists for a method to rapidly predict patients at risk for eLOS in the preoperative setting. Thus, the goal of this study is to develop a machine learning model to pre-
operatively estimate the likelihood of eLOS for patients with elective multi-level lumbar/thoracolumbar spinal instrumented fusions for spinal deformity.
Methods

Source of Data

Data were acquired retrospectively on ASD patients from state-level inpatient database hosted by the Healthcare cost and Utilization Project (HCUP) [17]. Data were derived from both public and private healthcare institutions in the states of California, Florida, Nebraska, New York, North Carolina, and Utah from the period of 2005-2013. No patient identifiers were gathered throughout data collection. Data included patient demographic variables, comorbidities, operative information, and LOS measured in days for each patient.

Participants, Sample Size, and Missing Data

Inclusion criteria were ASD patients with age ≥50 years undergoing elective multi-level spine fusions (≥ 3 levels) to the lumbar or thoracolumbar regions (Figure 1). Cases of malignancy, trauma, or infection were excluded. Patients with unknown LOS, discharge against medical advice, or missing data were also excluded. Inclusion and exclusion criteria were applied by utilization of International Classification of Diseases, Volumes 9 codes (ICD-9) [18].

Predictors and Outcomes

The primary outcome was whether a patient had eLOS, defined as >7 days. Pre-operative variables consisted of demographics, insurance status, comorbidities, and operative variables. Demographics included age allocated into ranges (50-59, 60-69, 70-79, 80+), sex (male, female), race/ethnicity (White, Hispanic, Black, Asian, Native American/Other), and healthcare
institution type (Academic vs. Non-Academic). Insurance type was designated as either public (Medicare/Medicaid), private (Commercial), or other (Self-Pay/No Insurance). Comorbidities included Charlson’s Comorbidity Index (CCI: 1, 2, 3, 4), as well as the individual comorbid conditions used to calculate the CCI [19]. Substance abuse variables were captured in terms of smoking history, alcohol abuse, and drug abuse. Mental health variables consisting of anxiety and depression were also acquired. Operative variables included whether the procedure was a revision (yes/no), surgical approach (posterior alone vs anterior and posterior), surgical region (lumbar vs lumbar and thoracic), and number of levels instrumented/fused (3-7 levels vs. ≥8 levels).

Statistical Analysis

Chi-Square and Fisher’s exact tests were used for univariate analysis to determine the association between predictor variables and an eLOS, with generation of odds ratios and corresponding 95% confidence intervals (CI), and p-values. P-values <0.05 were considered statistically significant. Multivariate analyses were then conducted on all significant variables through binary logistic regression.

Development and Validation of Predictive Models

In development of machine learning models, the cohorts were separated into 80% derivation and 20% validation groups. For the derivation group, all significant variables from multivariate analysis were used to develop a saturated logistic regression model. The model was then tested on the validation group to predict the probability of eLOS, with generation of Area
Under the Receiver Operating Curve (AUC) and corresponding 95% CIs to assess model performance.

Following development of the saturated logistic model, a simplified model with retention of diagnostic accuracy was the aim. Least absolute and selection operator (LASSO) was used to identify the most important variables in the saturated predictive model. Variables with the highest LASSO coefficients were then sequentially entered into a stepwise logistic model, in order of highest magnitude LASSO coefficient. The corresponding model AUC was calculated for each additional variable added, and inclusion of additional variables was stopped when AUC failed to increase by more than 0.5%.

To create a clinically applicable tool with estimation of predictive probability of eLOS, beta coefficients for the simplified logistic model were determined. In addition to AUC, model characteristics such as sensitivity, specificity, positive predictive value, and negative predictive value were calculated at varying thresholds.

Software/Tools Used

MATLAB version 2020b was used to conduct all statistical analyses and predictive model development [20].
Results

Participants (Table 1)

Inclusion criteria was met for 8,866 patients, 22.5% (n=1,994) of whom had an eLOS. (Table 1). The median age for eLOS patients was 66 years (Q1-Q3: 60-74), compared to a median of 68 years (Q1-Q3: 61-74) for patients with non-eLOS. Male patients consisted of 31.9% of the cohort. Most operations involved only the lumbar spine (81.4%) with utilization of a posterior approach (78.6%). A substantial number of patients had a CCI≥4 (36.9%) with all individuals in the study having a CCI score ≥1. Common co-morbidities were HTN (65.5%), COPD (23.0%), and hypothyroidism (19.0%). Of the patients with eLOS, 58.2% were discharged to a post-acute care facility and 41.8% were discharged to home, while of the patients with non-eLOS, 40.8% were discharged to a post-acute care facility and 59.2% were discharged to home (discharge location p<0.001).

Univariate and Multivariate Analyses (Table 2)

Results from univariate and multivariate analysis are displayed in Table 2. Pre-operative variables significantly associated with increased likelihood of eLOS in the multivariate analysis included: combined anterior and posterior surgical approach (OR=3.59, 95% CI: 3.19-4.04, p<0.001), surgery at both lumbar and thoracic regions (OR=2.49, 95% CI: 2.15-2.89, p<0.001), ≥8 level fusion (OR=1.83, 95% CI: 1.54-2.17, p<0.001), academic institution (OR=1.56, 95% CI: 1.36-1.79, p<0.001), self-pay/no insurance status (OR=1.62, 95% CI: 1.30-2.03, p<0.001), congestive heart failure (OR=2.09, 95% CI: 1.69-2.58, p<0.001), hemiplegia/paraplegia (OR=1.43, 95% CI: 1.03-1.99, p=0.034), malnutrition (OR=2.39, 95% CI: 1.70-3.37, p<0.001),
alcohol abuse (OR=1.75, 95% CI: 1.27-2.42, p=0.001), and drug abuse (OR=1.41, 95% CI: 1.05-1.88, p=0.021). Only one variable, male sex (OR=0.88, 95% CI: 0.78-1.00, p=0.045), was significantly associated with a decreased likelihood of eLOS.

Saturated Model Development

Data from 80% of patients the cohort (n=7,093) were used to train the machine learning models with validation on 20% (n=1,773). All significant variables from multivariate analysis were used in the development of the saturated logistic regression predictive model (AUC=0.77, 95% CI: 0.74-0.80). The ROC is displayed in Figure 2.

Model Specification: Simplified Predictive Model

LASSO regression identified seven variables as relevant to the predictive model (most to least important): combined anterior and posterior approach, surgery to both lumbar and thoracic regions, ≥8 level fusion, malnutrition, CHF, academic institution, and renal disease. Stepwise logistic regression, with generation of corresponding AUC for each added variables, is shown in Figure 3. Peak AUC of 0.76 (95% CI: 0.73-0.79) was reached with six of the seven variables. The addition of renal disease increased AUC by only 0.2% and was hence excluded from the model. For use as a predictive calculator to predict eLOS likelihood, beta coefficients for the simplified logistic model were determined (Supplementary Table 1). For each component of the simplified model, ORs and 95% CIs for each model component were also derived (Table 3).
**Model Performance (Table 4)**

Performance characteristics such as sensitivity, specificity, positive predictive value, and negative predictive value are shown in Table 4 for each corresponding predictive probability threshold. At a threshold of 0.18, the simplified model produced a sensitivity of 0.77 and a specificity of 0.68. The cutoff threshold can be adjusted based on the acceptable risk tolerance of the healthcare team.
Discussion

Model Interpretation

The aim of this study was to develop a machine learning model to pre-operatively predict eLOS in patients undergoing elective multi-level lumbar or thoracolumbar instrumented fusion for a diagnosis of ASD. The model created utilized six essential pre-operative patient variables (combined anterior and posterior approaches, thoracic+lumbar regions, >8 instrumented/fused levels, malnutrition, congestive heart failure, academic institution) and produced a diagnostic AUC of 0.76, with a sensitivity of 77% and specificity of 68% at a selected threshold of 0.18. Given that the saturated logistic model utilizing all significant variables had an AUC of 0.77, the goal was met in creation of a simplified pre-operative model that kept diagnostic accuracy. With the provided beta coefficients, clinicians can easily utilize the model pre-operatively within the clinical setting to facilitate rapid risk assessment.

Overall, the associations determined between significant predictive variables and eLOS agree with the literature. For example, male sex has been widely associated with reduced LOS and lower readmission rates in patients undergoing surgery for lumbar degenerative pathology [21,22]. Combined anterior and posterior approaches, surgery to both lumbar and thoracic regions, and a greater number of fused interspaces (≥8) have been proven to increase chances postoperative infection risk, medical complications, and LOS in ASD patients [23-26]. Certain comorbidities, such as CHF, renal disease, malnutrition, and osteoporosis, have been well documented as significant mortality risks following elective spine surgery [27-30]. While the association between alcohol use disorder and poor perioperative outcome is mixed for ASD patients, our current findings confirm that alcohol abuse disorder could be a significant risk factor [29,30].
While prior literature is sparse, a limited number of studies have derived predictive models for eLOS in ASD patients from large patient databases, such as the National Surgical Improvement Program Database and NSQIP databases. Such studies have produced fairly accurate AUCs, typically between 0.65-0.80 [31,32]. Current predictive calculators, including the ACS NSQIP Surgical Risk Calculator, have provided an applicable tool that can estimate LOS based on over twenty patient variables [33]. However, no study has conducted stratification or exclusion patients with trauma, malignancy, or infection – cases which represent vastly different patient and complication profiles when compared to elective surgery [34]. Moreover, tools such as the ACS NSQIP calculator provide no option for users to specify patient diagnosis and are not specific to spine patients. Additionally, studies which have captured more comprehensive and granular information on patient comorbidities are often based on a single institution and lack broader applicability [2,35,36].

**Implications**

A critical implication of the pre-operative predictive model is the potential to predict financial risk. The relation between eLOS and costs of care is significant and represents a driving factor behind the need for accurate pre-operative assessment. For example, for spine deformity patients, a single additional day in the hospital can incur over $10,000 in insurance charges and over $5,000 in hospital costs, accompanied with significant associated financial risks of returning to the operating room within 90 days [37]. Moreover, the direct cost per day in the hospital is significantly greater than that of a post-acute care rehabilitation facility [38,39]. Of note, while a portion of patients require an eLOS due need for management of perioperative complications, a substantial amount of eLOS patients reside longer in the hospital due to delays
in the discharge transfer process to a rehabilitation or skilled nursing facility [40]. Thus, such patients represent cost outliers as they incur high costs associated with both eLOS and rehabilitation.

Under reimbursement models such as Bundled Payments for Care Improvement Initiative (BPCI), where reimbursement is fixed for the duration of care, eLOS can cause catastrophic financial loss and inability for the hospital to sustain surgical spine care [41-43]. Ensuring financial viability of elective surgeries is important to ensure that hospital systems can continue to operate. Therefore, a key utility of the predictive calculator derived in this study is to stratify financial risk and accurately identify patients who may represent high-cost outliers.

Usage of the predictive calculator to predict patients at risk of eLOS may also aid in alleviating hospital bed shortages and therefore improve patient access to care [12]. Administrative teams may establish an acceptable predictive model risk tolerance depending on the hospital’s typical space availability. The predictive calculator threshold can be changed depending on the most recent occupancy of the post-acute care unit and the acceptable risk tolerance as determined by the healthcare team. With the predictive calculator in hand, clinicians can ensure greater transparency with patients, better manage post-operative expectations, and have additional tools in the shared-decision making process on the risks and benefits of surgery [44].

**Strengths and Limitations**

A key strength of this study is that it utilizes a large cohort size with patients from multiple healthcare institutions in different states within the United States while retaining a
sufficient granularity of patient information. The usage of large sample size in training the models is critical for robust machine learning and predictive model development [36]. Moreover, application of inclusion criteria to focus only on elective procedures for ASD provides a reasonable control against confounding conditions, which few prior studies have done. The predictive model only utilized six variables, with retention of diagnostic accuracy when compared to the fully saturated model, and is preferable to other models that require every single feature of the patient’s risk profile. The resulting predictive calculator, with corresponding beta coefficients, can be easily applied in the clinical setting to rapidly facilitate pre-operative identification of adult patients at risk for eLOS following spinal deformity surgery. Future prospective studies that validate the risk assessment tool on an external dataset would be valuable. As additional data become available, the relative contribution of each variable to the prediction of eLOS can be modified for improved accuracy.

Key limitations of this study include the lack of additional variables that could influence the likelihood of eLOS. For example, social variables such as education level, income, and at-home support have been widely associated with postoperative outcomes in spine surgery [45,46]. Further, patients on high-dose narcotics pre-operatively often require longer recovery times and were not able to be identified and assessed within this study [47]. Furthermore, while no studies have reported the effect of postoperative pain on eLOS in patients with ASD, the patient’s subjective readiness to be discharged from the hospital could possibly influence the length of hospital stay. Future studies could utilize pain scores and document narcotic use to determine any association with eLOS.

Delays in the referral process to a post-operative care facility due to administrative barriers can also result in eLOS [35]. Unfortunately, identification of patients with a prolonged
discharge referral process was not feasible in this study, as the dataset does not allow one to assess and/or differentiate between reasons for an eLOS (i.e. secondary to additional postoperative management needed vs. complication vs. waiting for transfer to rehabilitation/SNF). Of note, eLOS and discharge disposition were interdependent outcomes, as discharge location was significant for eLOS on univariate analysis. However, discharge disposition was not factored into the predictive model development because the primary goal of this study was to utilize only variables available pre-operatively.

We also acknowledge that since the composition of our cohort is dependent on the accuracy of the ICD codes queried, it is possible that patients with purely degenerative pathology were treated in this cohort. Also unavailable were information on the prevalence of individual diagnoses and granular information on etiologies of the ASD patients that comprised our cohort. Furthermore, we realize that information on the patient’s condition prior to surgery, such as ambulatory status, neurological function, pre-operative narcotic usage, and pre-operative living situation, can influence eLOS, and were not utilized in this study. While more granular data with additional risk factors may be attained from a single institution, building a predictive model from one institution with a more limited patient cohort size would likely be overly specific to that singular location and lack broader generalizability. The predictive model we have presented is the first to utilize high-volume patient data from multiple healthcare institutions for ASD patients specifically, and hence represents a foundational tool that can be improved in the future as more granular patient data become available.
Conclusion

In this study of 8,866 ASD patients, a predictive calculator was created that can facilitate pre-operative identification of adults at risk for eLOS following elective multi-level lumbar/thoracolumbar spinal instrumented fusions for ASD. The predictive calculator built utilized six essential pre-operative predictors (surgical approach, surgical region, levels fused, malnutrition, congestive heart failure, and institution type). With a diagnostic AUC of 0.76, this predictive calculator will ideally enable clinicians to improve pre-operative planning, guide patient expectations, enable optimization of modifiable risk factors, facilitate appropriate discharge planning, stratify financial risk, and accurately identify patients who may represent high-cost outliers. Future prospective studies that validate this risk assessment tool on external datasets would be valuable.
References

1. 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/jjspd.2015.12.009
2. Safaee MM, Scheer JK, Ailon T, et al. Predictive Modeling of Length of Hospital Stay Following Adult Spinal Deformity Correction: Analysis of 653 Patients with an Accuracy of 75% within 2 Days. World Neurosurg. Jul 2018;115:e422-e427. doi:10.1016/j.wneu.2018.04.064
3. 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
4. Theis J, Gerdhem P, Abbott A. Quality of life outcomes in surgically treated adult scoliosis patients: a systematic review. Eur Spine J. Jul 2015;24(7):1343-55. doi:10.1007/s00586-014-3593-3
5. Terran J, McHugh BJ, Fischer CR, et al. Surgical treatment for adult spinal deformity: projected cost effectiveness at 5-year follow-up. Ochsner J. Spring 2014;14(1):14-22.
6. Campbell PG, Yadla S, Nasser R, Malone J, Malenfort 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
7. 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:10.2174/18743250150109010020
8. Uribe JS, Deukmedjian AR, Mummaneni PV, et al. Complications in adult spinal deformity surgery: an analysis of minimally invasive, hybrid, and open surgical techniques. Neurosurg Focus. May 2014;36(5):E15. doi:10.3171/2014.3.FOCUS13534
9. Barnett AG, Page K, Campbell M, et al. The increased risks of death and extra lengths of hospital and ICU stay from hospital-acquired bloodstream infections: a case-control study. BMJ Open. Oct 31 2013;3(10):e003587. doi:10.1136/bmjopen-2013-003587
10. Hauck K, Zhao X. How dangerous is a day in hospital? A model of adverse events and length of stay for medical inpatients. Med Care. Dec 2011;49(12):1068-75. doi:10.1097/MLR.0b013e31822efb09
11. Kim RB, Wilkerson C, Karsy M, et al. Prolonged Length of Stay and Risk of Unplanned 30-Day Readmission After Elective Spine Surgery: Propensity Score-Matched Analysis of 33,840 Patients. Spine (Phila Pa 1976). Sep 15 2020;45(18):1260-1268. doi:10.1097/BRS.0000000000003520
12. Toh HJ, Lim ZY, Yap P, Tang T. Factors associated with prolonged length of stay in older patients. Singapore Med J. Mar 2017;58(3):134-138. doi:10.11622/smedj.2016158
13. 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
14. Horn SR, Passias PG, Bortz CA, et al. Predicting extended operative time and length of inpatient stay in cervical deformity corrective surgery. *J Clin Neurosci.* Nov 2019;69:206-213. doi:10.1016/j.jocn.2019.07.064

15. Joshi RS, Lau D, Haddad AF, Deviren V, Ames CP. Risk factors for determining length of intensive care unit and hospital stays following correction of cervical deformity: evaluation of early severe adverse events. *J Neurosurg Spine.* Oct 23 2020;1-12. doi:10.3171/2020.6.SPINE20826

16. 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

17. HCUP State Inpatient Databases (SID). Healthcare Cost and Utilization Project (HCUP). 2005-2013. Agency for Healthcare Research and Quality R, MD. www.hcup-us.ahrq.gov/sidoverview.jsp.

18. World Health Organization. (2004). ICD-9 : international statistical classification of diseases and related health problems : ninth revision neWHO.

19. Charlson ME, Pompei P, Ales KL, MacKenzie CR. A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. *J Chronic Dis.* 1987;40(5):373-383. doi:10.1016/0021-9681(87)90171-8

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

21. Ilyas H, Golubovsky JL, Chen J, Winkelman RD, Mroz TE, Steinmetz MP. Risk factors for 90-day reoperation and readmission after lumbar surgery for lumbar spinal stenosis. *J Neurosurg Spine.* Apr 5 2019;31(1):20-26. doi:10.3171/2019.1.SPINE18878

22. Zeidan M, Goz V, Lakomkin N, Spina N, Brodke DS, Spiker WR. Predictors of Readmission and Prolonged Length of Stay After Cervical Disc Arthroplasty. *Spine (Phila Pa 1976).* Apr 15 2021;46(8):487-491. doi:10.1097/BRS.0000000000003839

23. Blumberg TJ, Woelber E, Bellabarba C, Bransford R, Spina N. Predictors of increased cost and length of stay in the treatment of postoperative spine surgical site infection. *Spine J.* Feb 2018;18(2):300-306. doi:10.1016/j.spinee.2017.07.173

24. 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

25. Le HV, Wick JB, Lafage R, et al. Surgical Factors and Treatment Severity for Perioperative Complications Predict Hospital Length of Stay in Adult Spinal Deformity Surgery. *Spine (Phila Pa 1976).* Jan 15 2022;47(2):136-143. doi:10.1097/BRS.0000000000004122

26. Schwartz DA, Hui X, Schneider EB, et al. Worse outcomes among uninsured general surgery patients: does the need for an emergency operation explain these disparities? *Surgery.* Aug 2014;156(2):345-51. doi:10.1016/j.surg.2014.04.039

27. 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

28. 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

29. Elsamadicy AA, Adogwa O, Vuong VD, et al. Impact of alcohol use on 30-day complication and readmission rates after elective spinal fusion (>=/=2 levels) for adult spine
deformity: a single institutional study of 1,010 patients. *J Spine Surg.* Sep 2017;3(3):403-410. doi:10.21037/jss.2017.08.12

30. Han H, Liu H, et al. Alcohol Abuse and Alcohol Withdrawal Are Associated with Adverse Perioperative Outcomes Following Elective Spine Fusion Surgery. *Spine (Phila Pa 1976).* May 1 2021;46(9):588-595. doi:10.1097/BRS.0000000000003868

31. Etzel CM, Veeramani A, Zhang AS, et al. Supervised Machine Learning for Predicting Length of Stay After Lumbar Arthrodesis: A Comprehensive Artificial Intelligence Approach. *J Am Acad Orthop Surg.* Dec 17 2021;doi:10.5435/JAAOS-D-21-00241

32. Zhang AS, Veeramani A, Quinn MS, Alsoof D, Kuris EO, Daniels AH. Machine Learning Prediction of Length of Stay in Adult Spinal Deformity Patients Undergoing Posterior Spine Fusion Surgery. *J Clin Med.* Sep 9 2021;10(18)doi:10.3390/jcm10184074

33. Basques BA, Fu MC, Buerba RA, Bohl DD, Golinvaux NS, Grauer JN. Using the ACS-NSQIP to identify factors affecting hospital length of stay after elective posterior lumbar fusion. *Spine (Phila Pa 1976).* Mar 15 2014;39(6):497-502. doi:10.1097/BRS.0000000000001848

34. Watanabe M, Sakai D, Matsuyama D, Yamamoto Y, Sato M, Mochida J. Risk factors for surgical site infection following spine surgery: efficacy of intraoperative saline irrigation. *J Neurosurg Spine.* May 2010;12(5):540-6. doi:10.1011/j spine.2020.02.022

35. 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 spineec.2020.02.022

36. Figueroa RL, Zeng-Traitler Q, Kandula S, Ngo LH. Predicting sample size required for classification performance. *BMC Med Inform Decis Mak.* Feb 15 2012;12:8. doi:10.1186/1472-6947-12-8

37. Boylan MR, Riesgo AM, Chu A, Paulino CB, Feldman DS. Costs and complications of increased length of stay following adolescent idiopathic scoliosis surgery. *J Pediatr Orthop B.* Jan 2019;28(1):27-31. doi:10.1097/PPBP.0000000000000543

38. Elsamadicy AA, Koo AR, Kundishora AJ, et al. Impact of patient and hospital-level risk factors on extended length of stay following spinal fusion for adolescent idiopathic scoliosis. *J Neurosurg Pediatr.* Aug 2 2019;1-7. doi:10.1011/j Peds19161

39. 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

40. New PW, Andrianopoulos N, Cameron PA, Olver JH, Stoelwinder JU. Reducing the length of stay for acute hospital patients needing admission into inpatient rehabilitation: a multicentre study of process barriers. *Intern Med J.* Sep 2013;43(9):1005-11. doi:10.1111/imj.12227

41. Dietz N, Sharma M, Alhouri 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

42. Miller HD. From volume to value: better ways to pay for health care. *Health Aff (Millwood).* Sep-Oct 2009;28(5):1418-28. doi:10.1377/hlthaff.28.5.1418

43. Siddiqi A, White PB, Murphy W, Terry D, Murphy SB, Talmo CT. Cost Savings in a Surgeon-Directed BPCI Program for Total Joint Arthroplasty. *Surg Technol Int.* Nov 11 2018;33:319-325.

44. O’Donnell FT. Preoperative Evaluation of the Surgical Patient. *Mo Med.* May-Jun 2016;113(3):196-201.
45. Adogwa O, Elsamadicy AA, Vuong VD, et al. Effect of Social Support and Marital Status on Perceived Surgical Effectiveness and 30-Day Hospital Readmission. *Global Spine J.* Dec 2017;7(8):774-779. doi:10.1177/21925682177696696

46. Yap ZL, Summers SJ, Grant AR, Moseley GL, Karran EL. The role of the social determinants of health in outcomes of surgery for low back pain. A systematic review and narrative synthesis. *Spine J.* Nov 27 2021;doi:10.1016/j.spinee.2021.11.013

47. Hardy N, Zeba F, Ovalle A, Yanac A, Nzugang-Noutonsi C, Abadier M, Ovalle A, Chahin A. Association of prescription opioid use on mortality and hospital length of stay in the intensive care unit. *PLoS One.* 2021 Apr 22;16(4):e0250320. doi: 10.1371/journal.pone.0250320. PMID: 33886667; PMCID: PMC8061930.

**Figure Legends**

**Figure 1.** Patient Selection Flowchart.
Figure 2. Receiver Operating Curve (ROC) for logistic regression predictive model for extended length of stay. The AUC was 0.76 (95% CI: 0.73-0.79).

Figure 3. Stepwise Logistic Regression. Each curve represents a logistic predictive model using one additional variable. For example, the black curve represents a predictive model only using surgical approach (combined anterior and posterior), while the light-blue curve represents model
using surgical approach (combined anterior and posterior), surgical region (lumbar and thoracic), and number of interspaces instrumented/fused (8+).

**Table 1.** Baseline data of patients with respect to length of stay following operations for multi-level lumbar instrumented fusions

| VARIABLE                        | Entire Cohort | Length of Stay ≤7 Days (%) | Length of Stay>7 Days (%) | p    |
|---------------------------------|---------------|---------------------------|---------------------------|------|
|                                 | N %           | N %                       | N %                       |      |

![Graph showing ROC curves with AUC values](image)
|                     | Population | Age - Median (Q1, Q3) | Patient Sex | Race | Surgical Approach | Region of Surgery | Revision Surgery | Vertebral Levels |
|---------------------|------------|-----------------------|-------------|------|-------------------|-------------------|-----------------|------------------|
|                     | 8866       | 68 (61, 74)           | 2832        | 7544 | 6970 (78.6%)      | 7218 (81.4%)     | 1983 (22.4%)    | 7841             |
| Age - Median (Q1, Q3) | 6872       | 68 (61, 74)           | 2262        | 5948 | 5755 (82.6%)      | 5921 (82.0%)     | 1428 (72.0%)    | 6303             |
| 50-59               | 1994       | 66 (60, 74)           | 570         | 1696 | 1215 (17.4%)      | 1297 (18.0%)     | 555 (28.0%)     | 1538             |
| 60-69               | <0.001     | 485 (26.3%)           | 20.1%       | <0.001 | 41.1%            | <0.001           | <0.001          |
| 70-79               | 1994       | 2326 (80.0%)          | 4610        | 3259 | 1117 (58.9%)      | 951 (57.7%)      | 456 (19.6%)     | 569 (80.4%)      |
| ≥80                 | 1994       | 173 (20.3%)           | 1424        | 311  | 678 (79.7%)       | 1117 (58.9%)     | 456 (19.6%)     | 569 (80.4%)      |
| **Population**      | 8866       | 6872                  | 1994        | 7544 | 6970              | 7218              | 1983            | 7841             |
| **Age - Median (Q1, Q3)** | 8866       | 6872                  | 1994        | 7544 | 6970              | 7218              | 1983            | 7841             |
| **Patient Sex**     | 8866       | 6872                  | 1994        | 7544 | 6970              | 7218              | 1983            | 7841             |
| **Race**            | 8866       | 6872                  | 1994        | 7544 | 6970              | 7218              | 1983            | 7841             |
| **Surgical Approach** | 8866       | 6872                  | 1994        | 7544 | 6970              | 7218              | 1983            | 7841             |
| **Region of Surgery** | 8866       | 6872                  | 1994        | 7544 | 6970              | 7218              | 1983            | 7841             |
| **Revision Surgery** | 8866       | 6872                  | 1994        | 7544 | 6970              | 7218              | 1983            | 7841             |
| **Vertebral Levels** | 8866       | 6872                  | 1994        | 7544 | 6970              | 7218              | 1983            | 7841             |
| ≥8 Levels       | (11.6%) | (55.5%) | (44.5%) |
|-----------------|---------|---------|---------|
| Institutional Type | | | |
| Non-Academic | 6864 (82.9%) | 5385 (78.5%) | 1479 (21.5%) |
| Academic | 1418 (17.1%) | 980 (69.1%) | 438 (30.9%) |
| Insurance Type | | | |
| Public | 5727 (64.6%) | 4512 (78.8%) | 1215 (21.2%) |
| Private | 2596 (29.3%) | 1993 (76.8%) | 603 (23.2%) |
| Other | 543 (6.1%) | 367 (67.6%) | 176 (32.4%) |
| Charlson's Comorbidity Index (CCI) | | | |
| CCI (1) | 1066 (12.0%) | 800 (75.0%) | 266 (25.0%) |
| CCI (2) | 2073 (23.4%) | 1616 (78.0%) | 457 (22.0%) |
| CCI (3) | 2458 (27.7%) | 1955 (79.5%) | 503 (20.5%) |
| CCI (≥4) | 3269 (36.9%) | 2501 (76.5%) | 768 (23.5%) |
| Co-Morbidities | | | |
| COPD | 2037 (23.0%) | 1521 (74.7%) | 516 (25.3%) |
| CHF | 491 (5.5%) | 309 (62.9%) | 182 (37.1%) |
| Hemiplegia/Paraplegia | 201 (2.3%) | 135 (67.2%) | 66 (32.8%) |
| Past Myocardial Infarction | 566 (6.4%) | 420 (74.2%) | 146 (25.8%) |
| Renal Disease | 439 (5.0%) | 302 (68.8%) | 137 (31.2%) |
| Rheumatic Disease | 636 (7.2%) | 480 (75.5%) | 156 (24.5%) |
| Hypertension | 5809 (65.5%) | 4546 (78.3%) | 1263 (21.7%) |
| Malnutrition | 162 (1.8%) | 85 (52.5%) | 77 (47.5%) |
| Coronary Artery Disease | 1532 (17.3%) | 1184 (77.3%) | 348 (22.7%) |
| Hypothyroidism | 1686 (19.0%) | 1300 (77.1%) | 386 (22.9%) |
| Osteoporosis | 1344 (15.2%) | 980 (72.9%) | 364 (27.1%) |
| Diabetes (DMII)                      | 7282 (82.1%) | 5623 (77.2%) | 1659 (22.8%) | <0.001 |
|--------------------------------------|--------------|--------------|--------------|--------|
| No DMII                              | 1470 (16.6%) | 1161 (79.0%) | 309 (21.0%)  |        |
| Controlled DMII                      | 114 (1.3%)   | 88 (77.2%)   | 26 (22.8%)   |        |
| Uncontrolled DMII                    |              |              |              |        |

| Substance Abuse                      |              |              |              |        |
| Smoking History                      | 2778 (31.3%) | 2164 (77.9%) | 614 (22.1%)  | 0.350  |
| Alcohol Abuse                        | 207 (2.3%)   | 139 (67.1%)  | 68 (32.9%)   | 0.003  |
| Drug Abuse                           | 264 (3.0%)   | 172 (65.2%)  | 92 (34.8%)   | <0.001 |

| Mental Health                        |              |              |              |        |
| Anxiety                              | 1062 (12.0%) | 796 (75.0%)  | 266 (25.0%)  | 0.033  |
| Depression                           | 2056 (23.2%) | 1538 (74.8%) | 518 (25.2%)  | 0.008  |

| Discharge Disposition                |              |              |              |        |
| Home                                 | 4904 (55.3%) | 4070 (83.0%) | 834 (17.0%)  | <0.001 |
| Post-acute care facility             | 3962 (44.7%) | 2802 (70.7%) | 1160 (29.3%) |        |

* COPD = chronic obstructive pulmonary disease; CHF = congestive heart failure; MI = myocardial infarction.
Table 2. Univariate and Multivariate Analyses

| VARIABLE                        | Univariate Tests | Multivariate Tests |
|---------------------------------|------------------|--------------------|
|                                 | OR  | 95% CI  | p  | OR  | 95% CI  | p  |
| Age (Continuous)                |     |         |    |     |         |    |
| 50-59                           | Ref | --      | -- | --  | --      | -- |
| 60-69                           | 0.84| 0.74 - 0.96 | 0.012| 0.98| 0.84 - 1.14 | 0.814|
| 70-79                           | 0.70| 0.61 - 0.81 | <0.001| 0.94| 0.78 - 1.14 | 0.541|
| ≥80                             | 0.72| 0.59 - 0.87 | 0.001| 1.08| 0.85 - 1.38 | 0.518|
| Patient Sex                     |     |         |    |     |         |    |
| Female                          | Ref | --      | -- | --  | --      | -- |
| Male                            | 0.82| 0.73 - 0.91 | <0.001| 0.88| 0.78 - 1.00 | 0.045|
| Race                            |     |         |    |     |         |    |
| White                           | Ref | --      | -- | --  | --      | -- |
| Hispanic                        | 1.25| 1.00 - 1.57 | 0.048| 1.27| 1.00 - 1.61 | 0.054|
| Black                           | 1.31| 0.96 - 1.78 | 0.095| --  | --      | -- |
| Asian                           | 0.66| 0.39 - 1.14 | 0.146| --  | --      | -- |
| Native American/Other           | 1.13| 0.82 - 1.56 | 0.447| --  | --      | -- |
| Surgical Approach               |     |         |    |     |         |    |
| Posterior                       | Ref | --      | -- | --  | --      | -- |
| Anterior and Posterior (Combined)| 3.30| 2.95 - 3.68 | <0.001| 3.59| 3.19 - 4.04 | <0.001|
| Region of Surgery               |     |         |    |     |         |    |
| Lumbar Only                     | Ref | --      | -- | --  | --      | -- |
| Lumbar and Thoracic             | 3.35| 2.98 - 3.75 | <0.001| 2.49| 2.15 - 2.89 | <0.001|
| Revision Surgery                | 1.47| 1.31 - 1.65 | <0.001| 1.039| 0.91 - 1.18 | .559|
| Vertebral Levels                |     |         |    |     |         |    |
| 3-7 Levels                      | Ref | --      | -- | --  | --      | -- |
| ≥8 Levels                       | 3.28| 2.87 - 3.76 | <0.001| 1.83| 1.54 - 2.17 | <0.001|
| Institutional Type              |     |         |    |     |         |    |
| Non-Academic                    | Ref | --      | -- | --  | --      | -- |
| Academic                        | 1.63| 1.43 - 1.85 | <0.001| 1.56| 1.36 - 1.79 | <0.001|
| Insurance Type | Public | Ref | -- | -- | -- | -- |
|----------------|--------|-----|-----|-----|-----|-----|
| Private        | 1.78   | 1.47 - 2.15 | <0.001 | 1.00 | 0.86 - 1.15 | 0.956 |
| Other          | 1.12   | 1.01 - 1.26 | 0.042 | 1.62 | 1.30 - 2.03 | <0.001 |

| Charlson's Comorbidity Index (CCI) | CCI (1) | CCI (2) | CCI (3) | CCI (≥4) |
|-----------------------------------|---------|---------|---------|---------|
| Ref                               | --      | --      | --      | --      |
|                                  | 0.85    | 0.72 - 1.01 | 0.073 | 1.01 - 1.36 |
|                                  | 0.77    | 0.65 - 0.92 | 0.003 | 0.96 - 1.09 |
|                                  | 0.92    | 0.79 - 1.08 | 0.341 | 1.01 - 1.36 |

| Co-Morbidities                  | COPD    | CHF     | Hemiplegia/Paraplegia | Past MI | Renal Disease | Rheumatic Disease | Hypertension | Malnutrition | Coronary Artery Disease | Hypothyroidism | Osteoporosis | Diabetes (DMII) | No DMII | Controlled DMII | Uncontrolled DMII |
|---------------------------------|---------|---------|-----------------------|---------|---------------|-------------------|--------------|--------------|-----------------------|----------------|--------------|----------------|---------|----------------|-----------------|
|                                 | 1.23    | 2.13    | 1.71                  | 1.21    | 1.60          | 1.13              | 0.88         | 3.21         | 1.02                  | 1.03           | 1.34         | 1.34           | Ref     | --             | --              |
|                                 | 1.09 - 1.38 | 1.76 - 2.58 | 1.27 - 2.30          | 1.00    | 1.30 - 1.96  | 0.94 - 1.36      | 0.80         | 3.35         | 0.89                  | 0.91           | 1.18         | 1.18           | --      | --             | --              |
|                                 | 0.001   | <0.001  | <0.001                | 0.054   | 0.000         | 0.200             | 0.021        | <0.001       | 0.80                  | 0.91           | <0.001       | 0.001          | --      | --             | --              |
|                                 | 1.07    | 2.09    | 1.43                  | 0.054   | 1.61          | 0.200             | 0.93         | 2.39         | 1.27                  | 0.674          | 1.19         | 1.19           | --      | --             | --              |
|                                 | 0.94 - 1.21 | 1.69 - 2.58 | 1.03 - 1.99          | --      | 1.28 - 2.04  | 0.200             | 0.83         | 1.70         | 1.70                  | --             | 1.03         | 1.03           | --      | --             | --              |
|                                 | 0.318   | <0.001  | <0.001                | --      | <0.001        | 0.034             | 0.212        | 0.034        | 0.705                 | 0.021          | 1.03         | 1.03           | 0.073   | 0.021          | --              |

| Substance Abuse                 | Smoking History | Alcohol Abuse | Drug Abuse |
|---------------------------------|-----------------|--------------|-----------|
|                                 | 0.97            | 1.71         | 1.88      |
|                                 | 0.87 - 1.08     | 1.27 - 2.30  | 1.46 - 2.44 |
|                                 | 0.565           | <0.001       | <0.001    |

| Mental Health                   | Anxiety | Depression |
|---------------------------------|---------|------------|
|                                 | 1.18    | 1.22       |
|                                 | 1.01 - 1.36 | 1.08 - 1.37 |
|                                 | 0.034   | 0.001      |
|                                 | 0.86    | 1.03       |
|                                 | 0.72 - 1.01 | 0.90 - 1.17 |
|                                 | 0.073   | 0.705      |
* COPD = chronic obstructive pulmonary disease; CHF = congestive heart failure; MI = myocardial infarction.
Table 3. Characteristics of Final Logistic Regression Model for Extended Length of Stay

| Logistic Model Component                          | OR   | 95% CI      | p       |
|--------------------------------------------------|------|-------------|---------|
| Surgical Approach (Combined Anterior and Posterior) | 3.37 | 2.96 - 3.84 | <0.001  |
| Surgical Region (Lumbar+Thoracic)               | 2.42 | 2.06 - 2.84 | <0.001  |
| # Interspaces (8+)                               | 1.78 | 1.47 - 2.16 | <0.001  |
| Malnutrition                                    | 2.72 | 1.87 - 3.95 | <0.001  |
| Congestive Heart Failure                         | 2.00 | 1.59 - 2.52 | <0.001  |
| Academic Facility                               | 1.56 | 1.34 - 1.81 | <0.001  |
Table 4. Predictive Model Characteristics Depending on Threshold Level

| Threshold | Sensitivity | Specificity | Positive Predictive Value | Negative Predictive Value |
|-----------|-------------|-------------|---------------------------|---------------------------|
| 0.14      | 0.82        | 0.59        | 0.37                      | 0.92                      |
| 0.16      | 0.82        | 0.59        | 0.37                      | 0.92                      |
| 0.18      | 0.77        | 0.68        | 0.42                      | 0.91                      |
| 0.20      | 0.74        | 0.69        | 0.42                      | 0.90                      |
| 0.22      | 0.70        | 0.72        | 0.43                      | 0.89                      |
| 0.24      | 0.70        | 0.72        | 0.43                      | 0.89                      |
| 0.26      | 0.62        | 0.77        | 0.45                      | 0.87                      |
| 0.28      | 0.61        | 0.78        | 0.45                      | 0.87                      |
| 0.30      | 0.61        | 0.78        | 0.46                      | 0.87                      |
| 0.32      | 0.39        | 0.89        | 0.51                      | 0.83                      |
| 0.34      | 0.38        | 0.90        | 0.53                      | 0.83                      |