The Spine Journal 000 (2022) 1–10

Clinical Study

Predictive models to assess risk of extended length of stay in adults with spinal deformity and lumbar degenerative pathology: development and internal validation

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Received 31 May 2022; revised 13 October 2022; accepted 24 October 2022

Abstract

BACKGROUND CONTEXT: Postoperative 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 extended length of stay (eLOS) in the preoperative setting.

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

STUDY DESIGN/SETTING: Retrospectively from a state-level inpatient database hosted by the Health care cost and Utilization Project.

PATIENT SAMPLE: Of 8,866 patients of age ≥50 with ASD undergoing elective lumbar or thoracolumbar multilevel 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 use six predictors. Model accuracy was assessed through area under the curve (AUC), sensitivity, and specificity.

RESULTS: Of 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 multilevel 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

FDA device/drug status: Not applicable.

Author disclosures: ***AA*:** Nothing to disclose. ***JD***: Nothing to disclose. ***DDC*:** Nothing to disclose. ***MC:*** Nothing to disclose. ***AJC:*** Nothing to disclose. ***AAT:*** Nothing to disclose.

No funds or financial support were used in support of this study. The authors report no study-specific conflict of interest-associated biases in relation to this manuscript.

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https://doi.org/10.1016/j.spinee.2022.10.009

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: Adult Spinal Deformity; Deformity; Internal validation; Length of stay; Multi-level fusions; Predictive models

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]. Although surgical intervention can provide considerable benefit, postoperative 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 postacute 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.

Although 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 preoperatively estimate the likelihood of eLOS for patients with elective multilevel 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 Health care cost and Utilization Project [17]. Data were derived from both public and private health care 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 multilevel spine fusions (≥3 levels) to the lumbar or thoracolumbar regions (Fig. 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. Preoperative 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 health care 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. The p-values <.05 were considered statistically significant.

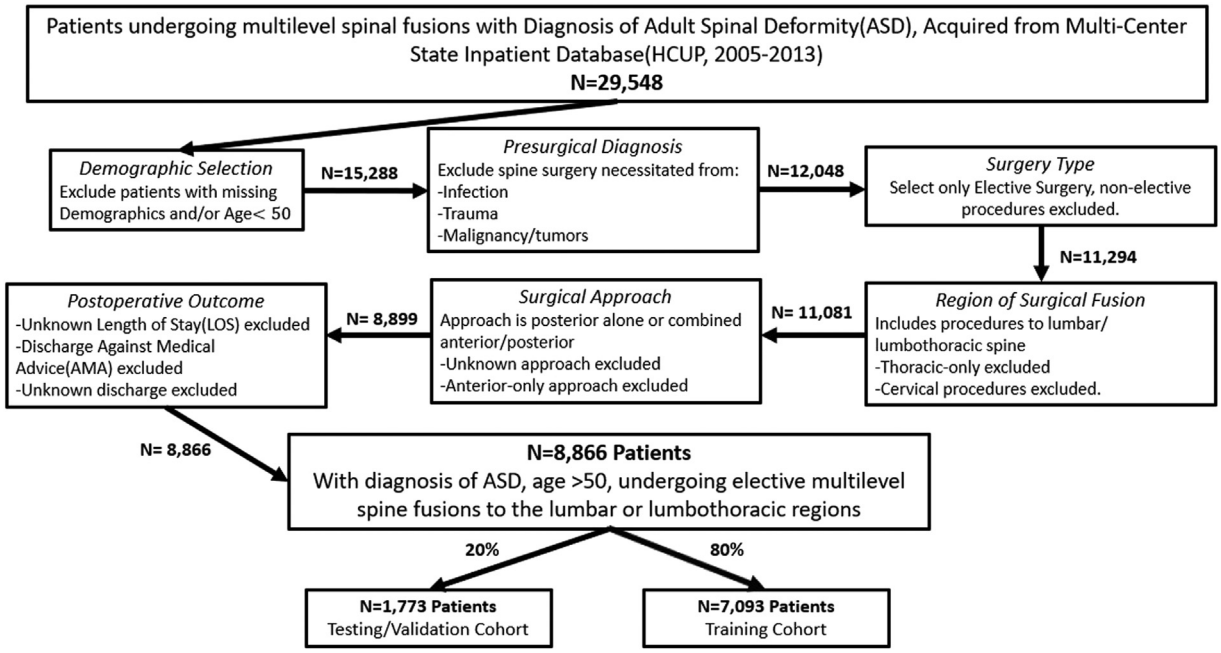

Fig. 1. Patient Selection Flowchart.

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

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 with 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 comorbidities were HTN (65.5%), COPD (23.0%), and hypothyroidism (19.0%). Of the patients with eLOS, 58.2% were discharged to a postacute care facility and 41.8% were discharged to home, whereas the patients with non-eLOS, 40.8% were discharged to a postacute care facility and 59.2% were discharged to home (discharge location p<.001).

Univariate and multivariate analyses

Results from univariate and multivariate analysis are displayed in Table 2. Preoperative 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<.001), surgery at both lumbar and thoracic regions

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 d (%)		Length of stay>7 d (%)		p
	N	%	N	%	N	%	
Population	8,866	(100.0%)	6,872	(77.5%)	1994	(22.5%)	–
Age - Median (Q1, Q3)	68	(61, 74)	68	(61, 74)	66	(60, 74)	<.001
50−59	1,847	(20.8%)	1,362	(73.7%)	485	(26.3%)	
60−69	3,259	(36.8%)	2,506	(76.9%)	753	(23.1%)	
70−79	2,909	(32.8%)	2,326	(80.0%)	583	(20.0%)	
≥80	851	(9.6%)	678	(79.7%)	173	(20.3%)	
Patient sex							<.001
Male	2,832	(31.9%)	2,262	(79.9%)	570	(20.1%)	
Female	6,034	(68.1%)	4,610	(76.4%)	1,424	(23.6%)	
Race							.008
White	7,544	(85.1%)	5,848	(77.5%)	1,696	(22.5%)	
Asian	420	(4.7%)	308	(73.3%)	112	(26.7%)	
Black	211	(2.4%)	153	(72.5%)	58	(27.5%)	
Hispanic	99	(1.1%)	83	(83.8%)	16	(16.2%)	
Native American or Multiracial	592	(6.7%)	480	(81.1%)	112	(18.9%)	
Surgical approach							
Posterior	6,970	(78.6%)	5,755	(82.6%)	1,215	(17.4%)	<.001
Anterior and posterior (Combined)	1,896	(21.4%)	1,117	(58.9%)	779	(41.1%)	
Region of surgery							<.001
Lumbar only	7,218	(81.4%)	5,921	(82.0%)	1,297	(18.0%)	
Lumbar and thoracic	1,648	(18.6%)	951	(57.7%)	697	(42.3%)	
Revision surgery	1,983	(22.4%)	1,428	(72.0%)	555	(28.0%)	<.001
Vertebral levels							<.001
3−7 levels	7,841	(88.4%)	6,303	(80.4%)	1,538	(19.6%)	
≥8 levels	1,025	(11.6%)	569	(55.5%)	456	(44.5%)	
Institutional type							<.001
Nonacademic	6,864	(82.9%)	5,385	(78.5%)	1,479	(21.5%)	
Academic	1,418	(17.1%)	980	(69.1%)	438	(30.9%)	
Insurance type							<.001
Public	5,727	(64.6%)	4,512	(78.8%)	1,215	(21.2%)	
Private	2,596	(29.3%)	1,993	(76.8%)	603	(23.2%)	
Other	543	(6.1%)	367	(67.6%)	176	(32.4%)	
Charlson's Comorbidity Index (CCI)							.009
CCI (1)	1,066	(12.0%)	800	(75.0%)	266	(25.0%)	
CCI (2)	2,073	(23.4%)	1,616	(78.0%)	457	(22.0%)	
CCI (3)	2,458	(27.7%)	1,955	(79.5%)	503	(20.5%)	
CCI (≥4)	3,269	(36.9%)	2,501	(76.5%)	768	(23.5%)	
Comorbidities							
COPD	2,037	(23.0%)	1,521	(74.7%)	516	(25.3%)	<.001
CHF	491	(5.5%)	309	(62.9%)	182	(37.1%)	<.001
Hemiplagia/Paraplegia	201	(2.3%)	135	(67.2%)	66	(32.8%)	<.001
Past myocardial infarction	566	(6.4%)	420	(74.2%)	146	(25.8%)	.052
Renal disease	439	(5.0%)	302	(68.8%)	137	(31.2%)	<.001
Rheumatic disease	636	(7.2%)	480	(75.5%)	156	(24.5%)	.201
Hypertension	5,809	(65.5%)	4,546	(78.3%)	1,263	(21.7%)	.020
Malnutrition	162	(1.8%)	85	(52.5%)	77	(47.5%)	<.001
Coronary artery disease	1,532	(17.3%)	1,184	(77.3%)	348	(22.7%)	.817
Hypothyroidism	1,686	(19.0%)	1,300	(77.1%)	386	(22.9%)	.195
Osteoporosis	1,344	(15.2%)	980	(72.9%)	364	(27.1%)	<.001
Diabetes (DMII)							
No DMII	7,282	(82.1%)	5,623	(77.2%)	1,659	(22.8%)	<.001
Controlled DMII	1,470	(16.6%)	1,161	(79.0%)	309	(21.0%)	
Uncontrolled DMII	114	(1.3%)	88	(77.2%)	26	(22.8%)	
Substance abuse							
Smoking history	2,778	(31.3%)	2,164	(77.9%)	614	(22.1%)	.350
Alcohol abuse	207	(2.3%)	139	(67.1%)	68	(32.9%)	.003
Drug abuse	264	(3.0%)	172	(65.2%)	92	(34.8%)	<.001
Mental health							
Anxiety	1,062	(12.0%)	796	(75.0%)	266	(25.0%)	.033
Depression	2,056	(23.2%)	1,538	(74.8%)	518	(25.2%)	.008
Discharge disposition							
Home	4,904	(55.3%)	4,070	(83.0%)	834	(17.0%)	
Postacute care facility	3,962	(44.7%)	2,802	(70.7%)	1,160	(29.3%)	<.001

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	.012	0.98	0.84–1.14	.814
70–79	0.70	0.61–0.81	<.001	0.94	0.78–1.14	.541
≥80	0.72	0.59–0.87	.001	1.08	0.85–1.38	.518
Patient sex						
Female	Ref	–	–	–	–	–
Male	0.82	0.73–0.91	<.001	0.88	0.78–1.00	.045
Race						
White	Ref	–	–	–	–	–
Hispanic	1.25	1.00–1.57	.048	1.27	1.00–1.61	.054
Black	1.31	0.96–1.78	.095	–	–	–
Asian	0.66	0.39–1.14	.146	–	–	–
Native American/Other	1.13	0.82–1.56	.447	–	–	–
Surgical approach						
Posterior	Ref	–	–	–	–	–
Anterior and posterior (Combined)	3.30	2.95 - 3.68	<.001	3.59	3.19– 4.04	<.001
Region of surgery						
Lumbar only	Ref	–	–	–	–	–
Lumbar and thoracic	3.35	2.98 - 3.75	<.001	2.49	2.15–2.89	<.001
Revision surgery	1.47	1.31 - 1.65	<.001	1.039	0.91–1.18	.559
Vertebral levels						
3–7 Levels	Ref	–	–	–	–	–
≥8 Levels	3.28	2.87–3.76	<.001	1.83	1.54–2.17	<.001
Institutional type						
Nonacademic	Ref	–	–	–	–	–
Academic	1.63	1.43–1.85	<.001	1.56	1.36–1.79	<.001
Insurance type						
Public	Ref	–	–	–	–	–
Private	1.78	1.47–2.15	<.001	1.00	0.86–1.15	.956
Other	1.12	1.01–1.26	.042	1.62	1.30– 2.03	<.001
Charlson's Comorbidity Index (CCI)						
CCI (1)	Ref	–	–	–	–	–
CCI (2)	0.85	0.72–1.01	.073	–	–	–
CCI (3)	0.77	0.65–0.92	.003	0.96	0.84–1.09	.507
CCI (≥4)	0.92	0.79–1.08	.341	–	–	–
Comorbidities						
COPD	1.23	1.09–1.38	.001	1.07	0.94–1.21	.318
CHF	2.13	1.76–2.58	<.001	2.09	1.69–2.58	<0.001
Hemiplegia/Paraplegia	1.71	1.27–2.30	.001	1.43	1.03–1.99	.034
Past MI	1.21	1.00–1.48	.054	–	–	–
Renal disease	1.60	1.30–1.98	.000	1.61	1.28–2.04	<.001
Rheumatic disease	1.13	0.94–1.36	.200	–	–	–
Hypertension	0.88	0.80–0.98	.021	0.93	0.83–1.04	.212
Malnutrition	3.21	2.35–4.38	<.001	2.39	1.70–3.37	<.001
Coronary artery disease	1.02	0.89–1.16	.814	–	–	–
Hypothyroidism	1.03	0.91–1.17	.674	–	–	–
Osteoporosis	1.34	1.18–1.53	<.001	1.19	1.03–1.39	.021
Diabetes (DMII)						
No DMII	Ref	–	–	–	–	–
Controlled DMII	0.90	0.79–1.04	.151	–	–	–
Uncontrolled DMII	1.00	0.65–1.56	1.000	–	–	–
Substance abuse						
Smoking history	0.97	0.87–1.08	.565	–	–	–
Alcohol abuse	1.71	1.27–2.30	.001	1.75	1.27–2.42	.001
Drug abuse	1.88	1.46–2.44	<.001	1.41	1.05–1.88	.021
Mental health						
Anxiety	1.18	1.01–1.36	.034	0.86	0.72–1.01	.073
Depression	1.22	1.08–1.37	.001	1.03	0.90–1.17	.705

COPD, chronic obstructive pulmonary disease; CHF, congestive heart failure; MI, myocardial infarction.

(OR=2.49, 95% CI: 2.15–2.89, p<.001), ≥8 level fusion (OR=1.83, 95% CI: 1.54–2.17, p<.001), academic institution (OR=1.56, 95% CI: 1.36-1.79, p<.001), self-pay/no insurance status (OR=1.62, 95% CI: 1.30-2.03, p<.001), congestive heart failure (OR=2.09, 95% CI: 1.69–2.58, p<.001), hemiplegia/paraplegia (OR=1.43, 95% CI: 1.03-1.99, p=.034), malnutrition (OR=2.39, 95% CI: 1.70–3.37, p<.001), alcohol abuse (OR=1.75, 95% CI: 1.27–2.42, p=.001), and drug abuse (OR=1.41, 95% CI: 1.05–1.88, p=.021). Only one variable, male sex (OR=0.88, 95% CI: 0.78–1.00, p=.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 Fig. 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 Fig. 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).

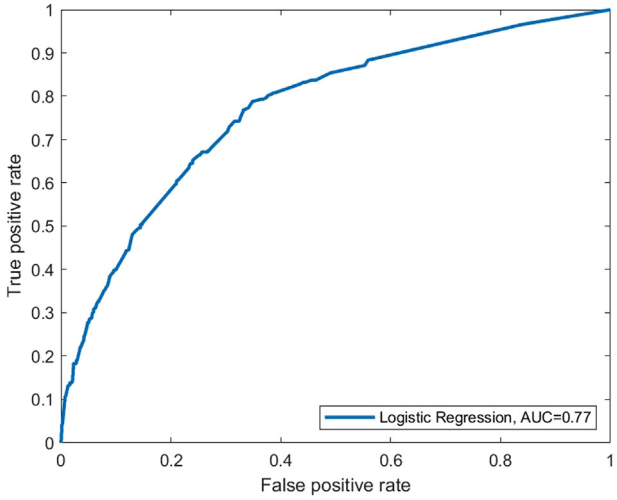

Fig. 2. Receiver Operating Curve (ROC) for logistic regression predictive model for extended length of stay. The AUC was 0.76 (95% CI: 0.73-0.79).

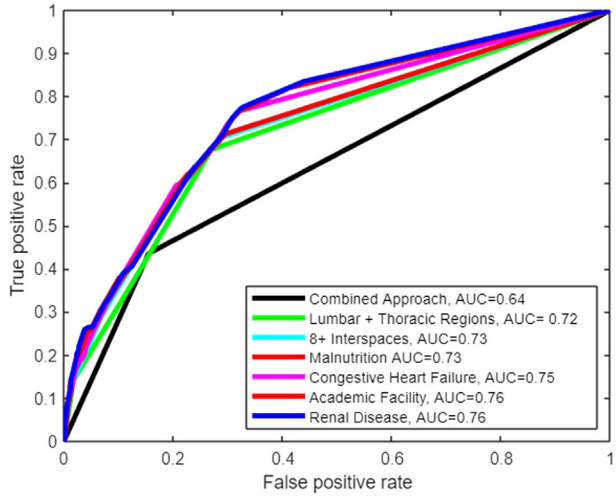

Fig. 3. Stepwise Logistic Regression. Each curve represents a logistic predictive model using one additional variable. For example, the black curve represents a predictive model only using surgical approach (combined anterior and posterior), whereas the light-blue curve represents model using surgical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

Model performance

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 health care team.

Discussion

Model interpretation

The aim of this study was to develop a machine learning model to preoperatively predict eLOS in patients undergoing elective multilevel lumbar or thoracolumbar

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	<.001
Surgical region (Lumbar+Thoracic)	2.42	2.06–2.84	<.001
# Interspaces (8+)	1.78	1.47–2.16	<.001
Malnutrition	2.72	1.87–3.95	<.001
Congestive heart failure	2.00	1.59–2.52	<.001
Academic facility	1.56	1.34–1.81	<.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

instrumented fusion for a diagnosis of ASD. The model created used six essential preoperative 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 preoperative model that kept diagnostic accuracy. With the provided beta coefficients, clinicians can easily used the model preoperatively 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]. Although 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].

Although 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 and 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 20 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 with 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 preoperative 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 preoperative 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 postacute care rehabilitation facility [38,39]. Of note, whereas 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 postacute care unit and the acceptable risk tolerance as determined by the health care team. With the predictive calculator in hand, clinicians can ensure greater transparency with patients, better manage postoperative 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 uses a large cohort size with patients from multiple health care institutions in different states within the United States whereas 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 used six variables, with retention of diagnostic accuracy when compared with 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 preoperative 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 preoperatively often require longer recovery times and were not able to be identified and assessed within this study [47]. Furthermore, whereas 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 use pain scores and document narcotic use to determine any association with eLOS.

Delays in the referral process to a postoperative 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 (ie, secondary to additional postoperative management needed versus complication versus 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 use only variables available preoperatively.

We also acknowledge that because 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 before surgery, such as ambulatory status, neurological function, preoperative narcotic usage, and preoperative living situation, can influence eLOS, and were not used in this study. Although 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 use high-volume patient data from multiple health care 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 preoperative identification of adults at risk for eLOS following elective multilevel lumbar/thoracolumbar spinal instrumented fusions for ASD. The predictive calculator built used six essential preoperative 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 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.

Supplementary materials

Supplementary material associated with this article can be found in the online version at https://doi.org/10.1016/j.spinee.2022.10.009.

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