Research Article

A Novel Scoring System to Predict Length of Stay After Anterior Cervical Discectomy and Fusion

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ABSTRACT

Introduction: The movement toward reducing healthcare expenditures has led to an increased volume of outpatient anterior cervical diskectomy and fusions (ACDFs). Appropriateness for outpatient surgery can be gauged based on the duration of recovery each patient will likely need.

Methods: Patients undergoing 1- or 2-level ACDFs were retrospectively identified at a single Level I spine surgery referral institution. Length of stay (LOS) was categorized binarily as either less than two midnights or two or more midnights. The data were split into training (80%) and test (20%) sets. Two multivariate regressions and three machine learning models were developed to predict a probability of LOS $\geq$ 2 based on preoperative patient characteristics. Using each model, coefficients were computed for each risk factor based on the training data set and used to create a calculatable ACDF Predictive Scoring System (APSS). Performance of each APSS was then evaluated on a subsample of the data set withheld from training. Decision curve analysis was done to evaluate benefit across probability thresholds for the best performing model.

Results: In the final analysis, 1,516 patients had a LOS $<$2 and 643 had a LOS $\geq$2. Patient characteristics used for predictive modeling were American Society of Anesthesiologists score, age, body mass index, sex, procedure type, history of chronic pulmonary disease, depression, diabetes, hypertension, and hypothyroidism. The best performing APSS was modeled after a lasso regression. When applied to the withheld test data set, the APSS-lasso had an area under the curve from the receiver operating characteristic curve of 0.68, with a specificity of 0.78 and a sensitivity of 0.49. The calculated APSS scores ranged between 0 and 45 and corresponded to a probability of LOS $\geq$2 between 4% and 97%.

Conclusion: Using classic statistics and machine learning, this scoring system provides a platform for stratifying patients undergoing ACDF into an inpatient or outpatient surgical setting.

The modern American healthcare system has exerted pressure on spine surgeons to increasingly do anterior cervical diskectomy and fusions (ACDF) on an outpatient basis to curtail hospital stay and expenditures.[1-3] The Centers for Medicare and Medicaid Services (CMS) has furthered this movement through a recent "site-neutral" reimbursement policy,[4] where physicians are compensated the same, regardless of the surgical setting. Although spinal fusions are still more commonly done as an inpatient, the proportion of ACDFs in an ambulatory surgical center is increasing.[1]

From a patient safety perspective, ambulatory ACDF is at least noninferior to those done in a hospital setting and may improve patient satisfaction.[3,5-7] Recovery from ACDF in most instances is one to two nights; however, length of stay (LOS) can vary widely, with some patients requiring a multiday recuperative period.[8] Although the rare chance of life-threatening postoperative airway compromise is always looming, this is not typically the primary concern when choosing a facility.[9,10] Selecting the appropriate setting for an ACDF relative to a patient's impending LOS is indispensable for reaping the healthcare utilization benefits associated with ambulatory surgeries. The alternative would lead to some patients being transferred from ambulatory to inpatient settings, causing frustration and increased cost.[11,12] The purpose of this investigation was to develop the novel ACDF Predictive Scoring System (APSS) algorithm for forecasting LOS after a one- or two- level ACDF based on patient-specific preoperative characteristics and comorbidities. The secondary aim was to compare statistical and machine learning models for developing the scoring system.

Methods

Data Collection

This was an Institutional Review Board–approved analysis of retrospectively collected data. Subject authorization to collect protected health information was waived and the minimum necessary standard for data collection was applied. Patient selection was limited to individuals older than or equal to 18 years of age. Collected information included demographics and comorbidities from patients undergoing one- or two-level ACDF for radiculopathy at a single institution between January 2011 and December 2016. Subjects were identified using Current Procedure Terminology codes 22551 and 22552, with subsequent chart review for confirmation. All surgical candidates were originally booked for inpatient services. Procedures were done by one of seven fellowship-trained spine surgeons at a large Level I regional spine surgery referral center. The primary outcome was LOS obtained from hospital records. Patient characteristic data included age (<65 or 65+), sex, body mass index (BMI; <35 kg/m^2 or 35 + kg/m^2, World Health Organization class II obesity), smoking status (current or former/nonsmoker), American Society of Anesthesiologists (ASA) physical status classification system score, and medical and psychological history.

Data Analysis

The distribution of LOS after ACDF from the literature is right skewed, with most patients staying in the hospital for 1 or 2 days.[8] Therefore, we built a binary model predicting the likelihood of a patient having a LOS of less than two midnights (LOS <2 group) or two or more midnights (LOS ≥2 group), a definition under CMS' Two-Midnight Rule.[13] Categorical data were summarized by frequency tables. Continuous variables with a normal distribution were summarized by mean and SD. The association between LOS and each clinical factor was evaluated by Chi-squared or Fisher exact tests. Multiple imputation using random forests (RFs) predicted missing values with less than 30% missing data using the missForest package in R (R Core Team; Vienna, Austria).[14]

The data were split into a training set (80%) and a test set (20%). Synthetic Minority Oversampling Technique was used to create balanced LOS groups in the training set. Because the primary goal was to develop an easily scorable algorithm to predict LOS, a logistic regression model was developed. A second logistic regression using lasso regularization was also developed. The purpose of this second logistic model was to limit overfitting and provide a simpler algorithm by only including the strongest predictors. To compare the performance of the two logistic regressions to popular machine learning models, three additional models were developed using RF, linear support vector machine, and k-nearest neighbors (KNN). All five models were tuned using the caret package in R and trained using 10-fold cross validation, repeated five times with area under the curve (AUC) of the receiver operator curve as the optimization metric. Models were summarized by reporting the AUC, accuracy, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), calibration intercept and slope, and the Brier score.

The model coefficients from the two logistic models were used to create two separate algorithms—APSS-logistic and APSS-lasso for the logistic and lasso regressions, respectively. Specifically, the model coefficients were multiplied by 10 and rounded to the nearest integer. APSS scores were then computed for each patient in the training and test data sets. As before, the training data set was used to predict LOS from each APSS score, separately, using logistic regression with 10-fold cross-validation, repeated five times. Finally, performance of the two APSS models and three machine learning models was evaluated on the withheld (test) data set. Receiver operator curves were plotted for all five models on the training and test sets.

For selecting one of the APSS models, a decision curve analysis was done to evaluate the net benefit and the number of hospital settings avoided per 100 patients of the model across probability thresholds.[15,16] The APSS algorithm is designed to predict which patients would necessitate inpatient versus outpatient postoperative care. Therefore, the benefit of the APSS model was compared with the strategy of treating all patients as inpatient. Statistical significance was set at $P < 0.05$. All statistical analyses were done in RStudio version 1.2.5033 (RStudio) and R version 3.6.3 (R Core Team).

Results

Cohort Characteristics

The final analysis included 2,159 patients—1,516 in the LOS <2 midnights group and 643 in the LOS ≥2 midnights group. Summary of the cohort characteristics is shown in Table 1. Smoking was removed from the subsequent analysis, given its low prevalence. Only three variables had missing data—type of procedure (n = 9, 0.42%), ASA score (n = 67, 3.1%), and BMI (n = 15, 0.69%). On univariate analysis, the LOS <2 cohort had a notably smaller proportion of patients with preoperative risk factors and seemed healthier in general. The distribution of ASA scores was significantly different ($P < 0.001$), especially for ASA = 2 (70.5% versus 49.2%) and ASA = 3 (21.9% versus 48.0%). Although most patients underwent a two-level procedure, the LOS <2 cohort (64.9%) had a smaller proportion when compared with LOS ≥2 (73.6%).

Multivariate Analysis—Training Set

The training and test data sets contained 1,728 and 431 patients, respectively. No notable differences existed between the two data sets. After Synthetic Minority Oversampling Technique, the training data set included 2,060 samples (1,030 patients in each of the two LOS groups). These 2,060 samples were used to train each model, the results of which are summarized in Table 2. AUC ranged from a low of 0.76 for the lasso regression to a high of 0.83 for the RF. Both the regression models

Table 1. **Summary of Patient Cohort, Comparing Patients With Length of Stay (LOS) of Less Than Two Midnights With Those With LOS of Two or More Midnights**

	Overall		LOS < 2		LOS ≥ 2		*P*
	N = 2,159	%	N = 1,516	%	N = 643	%	
2-Level ACDF	1,450	67.4	982	64.9	468	73.6	<0.001
ASA score							<0.001
1	121	5.8	109	7.3	12	2.0	—
2	1,348	64.4	1,055	70.5	293	49.2	—
3	614	29.3	328	21.9	286	48.0	—
4	9	0.4	4	0.3	5	0.8	—
BMI: 35+	366	17.1	235	15.6	131	20.4	0.01
Smoker	28	1.3	22	1.5	6	0.9	0.44
Age: 65+	333	15.4	162	10.7	171	26.6	<0.001
Sex: Female	1,024	47.4	679	44.8	34	53.7	<0.001
COPD	299	13.8	176	11.6	123	19.1	<0.001
HTN	658	30.5	410	27.0	248	38.6	<0.001
Diabetes	218	10.1	139	9.2	79	12.3	0.03
Hypothyroidism	244	11.3	150	9.9	94	14.6	0.002
Depression	384	17.8	239	15.8	145	22.6	<0.001

ACDF, anterior cervical diskectomy and fusion; ASA, American Society of Anesthesiologists; BMI, body mass index; COPD = chronic obstructive pulmonary disease, HTN = hypertension, LOS, length of stay

Table 2. Summary Statistics Describing the Performance of the Logistic Regression, Lasso Regression, RF, SVM, and KNN Models Using the Training Data

	Logistic	Lasso	RF	SVM	KNN
AUC	0.76	0.76	0.83	0.76	0.81
Accuracy	0.71	0.70	0.77	0.70	0.74
Sensitivity	0.69	0.67	0.72	0.73	0.81
Specificity	0.72	0.73	0.82	0.68	0.68
Positive predictive value	0.72	0.71	0.80	0.70	0.72
Negative predictive value	0.70	0.69	0.74	0.71	0.78
Calibration intercept	2.94	−2.72	10.91	2.24	−1.59
Calibration slope	0.94	1.26	0.68	0.92	0.95
Brier score	0.20	0.21	0.18	0.20	0.18

AUC, area under the curve; KNN, k-nearest neighbors; RF, random forest; SVM, support vector machine

Table 3. APSS Scoring Coefficients From the Logistic Regression Model and the Lasso Logistic Regression Model

	APSS-Logistic	APSS-Lasso
ASA score	8	7a
Age 65+	10	7
COPD	7	4
DM	4	1
BMI	3	—
Hypothyroidism	7	4
Female	3	—
HTN	5	3
Depression	5	3
2-Level ACDF	2	—

ACDF, anterior cervical diskectomy and fusion; APSS, ACDF Predictive Scoring System; ASA, American Society of Anesthesiologists; BMI, body mass index COPD = chronic obstructive pulmonary disease, DM = diabetes mellitus, HTN = hypertension,
[a]ASA Score is Multiplied by the Given coefficient.
The remaining coefficients are summed.

and the RF models had higher specificity than sensitivity, whereas the support vector machine and KNN models had higher sensitivity than specificity. Sensitivity and NPV were highest for the KNN model, whereas specificity and PPV were highest for the RF model. Calibration for the RF model was particularly poor, with a calibration intercept of 10.9 and a slope of 0.68.

Given the performance on the training data set, coefficients for the APSS algorithm were calculated based on the two regression models (APSS-logistic versus APSS-lasso) and are summarized in Table 3. The APSS-lasso model did not include BMI, sex, or type of procedure. Reapplying the regression models based on these coefficients instead generated APSS-logistic scores ranging from 8 to 66 with a median and interquartile range of 29 (21 and 39), and APSS-lasso scores ranging from 7 to 43 with a median and interquartile range of 21 (14 and 27). An APSS-logistic score of 31 or higher was predicted to have LOS ≥2. An APSS-lasso score of 22 or higher was predicted to have LOS ≥2. Although APSS-lasso only included seven of the 10 predictors, it did similarly to APSS-logistic in the training data set (Table 4). AUC was slightly higher for the APSS-logistic model, which also had a higher sensitivity and NPV. However, specificity and PPV were higher for the APSS-lasso regression. Calibration was slightly better for the APSS-lasso algorithm with an intercept of 1.27 and slope of 0.96.

Table 4. Summary Statistics Describing the Performance of the APSS Scoring Algorithm Developed From the Logistic Model Coefficients and the Logistic Lasso Model Coefficients

	APSS-Logistic	APSS-Lasso
AUC	0.77	0.75
Accuracy	0.71	0.70
Sensitivity	0.70	0.64
Specificity	0.72	0.76
PPV	0.71	0.73
NPV	0.70	0.68
Intercept	3.70	1.27
Slope	0.92	0.96
Brier	0.20	0.20

APSS, ACDF Predictive Scoring System; AUC, area under the curve; NPV, negative predictive value; PPV, positive predictive value

Table 5. Summary Statistics Describing the Performance of the APSS-Logistic Score, APSS-Lasso Score, RF, SVM, and KNN Models Using the Test Data

	APSS-Logistic	APSS-Lasso	RF	SVM	KNN
AUC	0.68	0.68	0.67	0.68	0.63
Accuracy	0.66	0.69	0.65	0.66	0.64
Sensitivity	0.52	0.49	0.48	0.58	0.45
Specificity	0.72	0.78	0.73	0.67	0.73
PPV	0.44	0.48	0.43	0.45	0.41
NPV	0.78	0.78	0.77	0.80	0.76

APSS, ACDF Predictive Scoring System; AUC, area under the curve; KNN, k-nearest neighbors; NPV, negative predictive value; PPV, positive predictive value; RF, random forest; SVM, support vector machine

Multivariate Analysis—Test Set

On the test data set, the five models did far more similarly to each other than on the training data set (Table 5 and Figure 1). Sensitivity was generally poorer in the test set, whereas specificity in the test set was similar to specificity in the training data set. The confusion matrices based on the test set using either the APSS-logistic and APSS-lasso model coefficients are shown in Table 6. Because the APSS-lasso model did similarly to the others although being the simplest, this was chosen for the final algorithm and evaluated by the decision curve analysis (Figure 2). Compared with the "treat all patients as inpatient" strategy, the model had a higher net benefit at probability thresholds above 18%; however, this benefit is marginal until probability thresholds above 23%. Below a threshold of 43%, the model avoids more unnecessary inpatient admissions than a strategy of treating all patients as inpatient. The APSS-lasso scores associated with 23% and 43% probability thresholds are 13 and 19 points, respectively.

To compute the risk (or probability) of a patient having LOS ≥2 based on their APSS score, the following formula was applied using coefficients from the intercept (3.101) and slope (0.146) of the lasso regression:

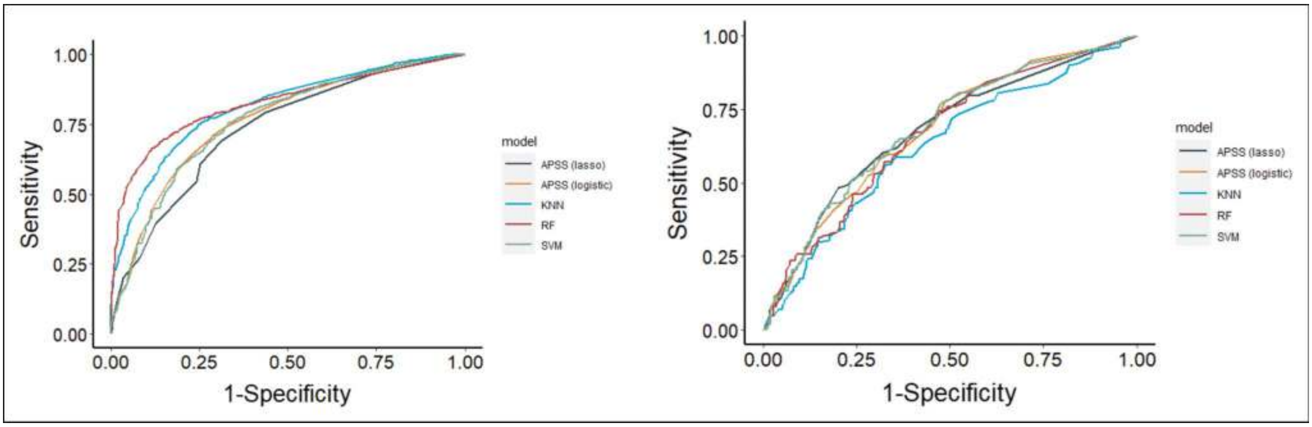
$$\frac{1}{1 + e^{(3.101 - 0.146 * score)}}$$

A summary of how to calculate patients' APSS score for predicting the likelihood of LOS ≥2 is shown in Figure 3 along with each score's associated probabilities.

Discussion

Recent shifts in reimbursement models toward cost reduction have resulted in a greater proportion of spine surgeries occurring as an outpatient.[1] The cost of surgery in the outpatient setting is approximately 30% less

Figure 1



Graphs demonstrating receive operator curves (ROCs) for the ACDF Predictive Scoring System (APSS)-logistic, APSS-lasso, k nearest neighbors (KNN), support vector machine (SVM), and random forest (RF) models on the training (left) and test (right) data sets). Although RF and KNN seemed to have superior performance on the training data set, KNN seemed to have the worst performance on the test set. The performance of the remaining four models were comparable with each other.

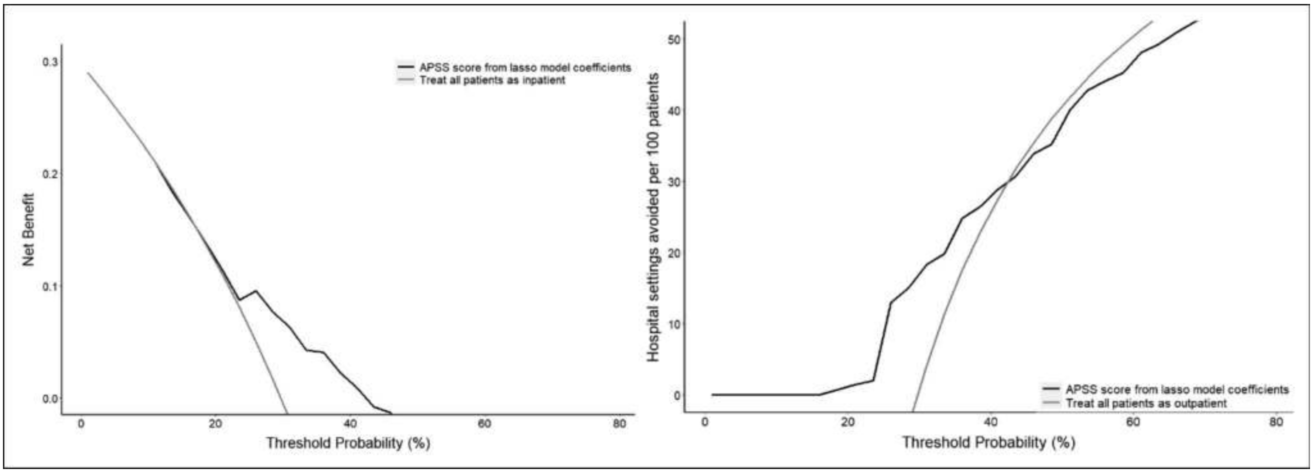
Table 6. Confusion Matrices Based on the Test Data Using the (A) APSS-Logistic Coefficient Model and (B) APSS-Lasso Coefficient Model

(A) APSS-Logistic	Actual	
Predicted	**LOS $<$ 2**	**LOS $\geq$ 2**
LOS $<$ 2	218	61
LOS $\geq$ 2	85	67
(B) APSS-Lasso	**Actual**	
Predicted	**LOS $<$ 2**	**LOS $\geq$ 2**
LOS $<$2	235	65
LOS $\geq$2	68	63

compared with inpatient.[17] More specifically, Purger and colleagues reported that 90-day cumulative charges for an ambulatory ACDF saved over $30,000 per patient.[3] The APSS is a novel method, based on classic statistics and machine learning, for predicting LOS and assessing suitability for outpatient surgery. A notable strength of this investigation is that the cohort encompassed only inpatient cases, reducing the potential selection bias of discriminatory discharge relative to admission status. This is in contrast to previous reports where notable baseline differences existed between patients undergoing ACDF as an outpatient versus inpatient, indicating a selection for healthier patients for outpatient procedures.[1,3,18] Although each APSS score has an associated probability for prolonged LOS, no guidelines can be suggested as of yet without external validation. However, the algorithm is a platform for exploring how a clinical decision support algorithm might assist in shared decision-making and management of patients' expectations.

Admission status was defined according to the Two-Midnight Rule in this study because CMS' standards are part of the public domain and can approximate private insurance reimbursement policies.[13,19] Notably, Adogwa et al[20] found that the 75th percentile for LOS after ACDF based on the ACS National Surgical Quality Improvement Program (NSQIP) database was also 2 days. However, the definition of admission status can be inconsistent in the broader ambulatory surgery literature because outpatient can either imply surgery requiring single overnight stays or same-day surgeries without overnight stay.[21] A recent database study by Bovonratwet et al[18] showed that more than 75% of patients categorized as outpatient with a LOS equal to zero, in fact stayed overnight. Another layer of complexity arises when discussing the distinction between

Figure 2



Graphs demonstrating decision analysis curves for the net benefit (left) and hospital settings avoided per 100 patients (right) using the ACDF Predictive Scoring System (APSS)-lasso scoring algorithm. The threshold probability represents the cutoff value at which the predicted risk from the lasso regression would be used to treat patients as inpatient. At higher threshold probabilities, harm of a false-negative is less than the harm of a false positive. At threshold probability greater than 18%, the model improves on the strategy of treating all patients as inpatient (left). At threshold probabilities less than 43%, the model avoids more unnecessary inpatient admissions than the strategy of treating all patients as inpatient.

hospital outpatient departments (HOPD) and ambulatory surgery centers (ASC). HOPD are fully owned by hospital entities with specific geographic requirements in relation to inpatient services,[21] whereas ASC are completely independent from hospitals.[21] A notable proportion of ASC offer overnight services; however, states including Florida, Maine, Maryland, Nebraska, Rhode Island, and South Carolina mandate same-day discharge.[1] From a reimbursement perspective, the average cost of doing surgery in each setting ranked from most to least expensive is (1) inpatient, (2) HOPD, and (3) ASC.[3] It is likely that with the introduction of site-neutral payments in the near future, there will be a greater need to properly assess patients' recovery time. For this reason, the findings of this investigation are primarily applicable within the American healthcare system.

Figure 3

Figure demonstrating the summary of how to calculate a patient's ACDF Predictive Scoring System (APSS) score based on preoperative risk factors. Weighted coefficients were sourced from multivariate analysis. Weights from each variable are summed to generate a score between 0 and 45. For each score, an associated probability of length of stay of two or more midnights exists after anterior cervical diskectomy and fusion (ACDF). American Society of Anesthesiologists (ASA) score is multiplied by seven, whereas the remaining coefficients are summed. COPD = chronic obstructive pulmonary disease

Disagreement exists as to which comorbidities matter when discussing LOS after ACDF.[20,22-24] The analysis of elective ACDF of Gruskay et al.[22] from the 2005 to 2010 ACS-NSQIP database reported an association between age, anemia, diabetes, and prolonged LOS. However, Adogwa et al found no such associations after analyzing a larger ACS-NSQIP cohort between 2008 and 2014.[20] A recent multidisciplinary panel suggested that certain cardiovascular risk factors, presurgical anxiety, and socioeconomic factors precluded patients from an outpatient ACDF.[25] However, this consensus study was limited to 10 practitioners and had limited statistical analysis. The APSS algorithm presented in this study was formulated to begin tackling the heterogenous results related to this topic. From a data science perspective, preoperative risk factors constitute *high dimensional data*, meaning that many more independent variables exist than dependent variables.[26] Weighing the importance of each variable can be arduous, unless a means of condensing the information into a practical format exists. The APSS represents one of the few tools using statistical and machine learning models for exploring clinical decision support tools for spine surgery.

Several limitations exist to this study. The retrospective nature limited the identification of specific causality of LOS, and some comorbidities were not directly included because of low incidence. In addition, many socioeconomic factors associated with recovery were unavailable and unaccounted for.[27] The algorithm is also predicated on LOS data and not complication rates; thus, the decision curve analysis pertains to healthcare utilization, not patient safety concerns. Although inpatient status was defined by CMS standards, the results may have been confounded by the distinction between outpatient surgery versus same-day discharge.[1,21] The ideal approach would have been to collect LOS data based on a discrete number of admission hours; however, this was not possible within our current electronic medical record system. Such discrepancies could also be resolved if the two-midnight rule was amended by the CMS, a debate that is still on-going.[18,28-30] Opportunity also exists for debate related to the selection of comorbidities for building the APSS. We opted to include variables that were readily available and based on P values from bivariate analysis, instead of relying exclusively on background knowledge. This was done because of the variation of results reported in previous publications.[20,22-24] Finally, although the sample size of this cohort was large relative to the spine surgery literature, we concede that additional power is desirable when developing clinical decision support tools. Some of the loss of performance on the test set and the disappointing results of the machine learning models can be attributed to the sample size.

Conclusion

The APSS is a novel means for predicting the probability of a LOS of two or more midnights for patients undergoing one- or two-level ACDF. This algorithm may help when deciding to undergo surgery in either an outpatient or inpatient setting and serve as a basis for external validation studies.

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