Development of a preoperative predictive model for major complications following adult spinal deformity surgery

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OBJECTIVE The operative management of patients with adult spinal deformity (ASD) has a high complication rate and it remains unknown whether baseline patient characteristics and surgical variables can predict early complications (intraoperative and perioperative [within 6 weeks]). The development of an accurate preoperative predictive model can aid in patient counseling, shared decision making, and improved surgical planning. The purpose of this study was to develop a model based on baseline demographic, radiographic, and surgical factors that can predict if patients will sustain an intraoperative or perioperative major complication.

METHODS This study was a retrospective analysis of a prospective, multicenter ASD database. The inclusion criteria were age ≥ 18 years and the presence of ASD. In total, 45 variables were used in the initial training of the model including demographic data, comorbidities, modifiable surgical variables, baseline health-related quality of life, and coronal and sagittal radiographic parameters. Patients were grouped as either having at least 1 major intraoperative or perioperative complication (COMP group) or not (NOCOMP group). An ensemble of decision trees was constructed utilizing the C5.0 algorithm with 5 different bootstrapped models. Internal validation was accomplished via a 70/30 data split for training and testing each model, respectively. Overall accuracy, the area under the receiver operating characteristic (AUROC) curve, and predictor importance were calculated.

RESULTS Five hundred fifty-seven patients were included: 409 (73.4%) in the NOCOMP group, and 148 (26.6%) in the COMP group. The overall model accuracy was 87.6% correct with an AUROC curve of 0.89 indicating a very good model fit. Twenty variables were determined to be the top predictors (importance ≥ 0.90 as determined by the model) and included (in decreasing importance): age, leg pain, Oswestry Disability Index, number of decompression levels, number of interbody fusion levels, Physical Component Summary of the SF-36, Scoliosis Research Society (SRS)–Schwab coronal curve type, Charlson Comorbidity Index, SRS activity, T-1 pelvic angle, American Society of Anesthesiologists grade, presence of osteoporosis, pelvic tilt, sagittal vertical axis, primary versus revision surgery, SRS pain, SRS total, use of bone morphogenetic protein, use of iliac crest graft, and pelvic incidence–lumbar lordosis mismatch.

CONCLUSIONS A successful model (87% accuracy, 0.89 AUROC curve) was built predicting major intraoperative or

ABBREVIATIONS ANN = artificial neural network; ASA = American Society of Anesthesiologists; ASD = adult spinal deformity; AUROC = area under the receiver operating characteristic; BMI = body mass index; BMP = bone morphogenetic protein; CCI = Charlson Comorbidity Index; HRQOL = health-related quality of life; MCS = Mental Component Summary of the SF-36; NRS = numeric rating scale; ODI = Oswestry Disability Index; PCS = Physical Component Summary of the SF-36; PI-LL = pelvic incidence–lumbar lordosis mismatch; PT = pelvic tilt; SRS = Scoliosis Research Society; SRS-22r = SRS-22r questionnaire; SVA = sagittal vertical axis; TK = thoracic kyphosis; T1PA = T-1 pelvic angle.

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perioperative complications following ASD surgery. This model can provide the foundation toward improved education and point-of-care decision making for patients undergoing ASD surgery.

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KEY WORDS complications; adult spinal deformity; ASD; predictive modeling; scoliosis; sagittal malalignment; decision tree

THE surgical management of adult spinal deformity (ASD) can provide significant improvements in pain, disability, and health-related quality of life (HRQOL).^{6,7,28,34,36–38,40–45} However, these procedures are technically demanding and are associated with a high complication rate. The patient population suitable for these complicated surgeries continues to increase, including patients of advanced age.^{2,16,17,27} The reported complication rates in the literature are varied and range from 14% to 71%.^{11,13,39,47,48} It has been demonstrated that complication rates increase for patients undergoing revision surgery,¹³ 3-column osteotomies,^{8,23,30,49,50} and those of older age.^{2,16,20,39} Despite the abundant literature characterizing complication rates and the types of complications in ASD surgery,^{47,48} there is currently no model to predict which patients may develop complications following the surgical correction of ASD.

The ability to accurately identify these patients preoperatively constitutes a significant challenge, yet an accurate predictive model could be beneficial for both the patient and surgeon. The results of such a model could aid in the discussion between the patient and surgeon of whether to pursue a surgical intervention and, for those who opt for surgery, in adjusting the goals of surgery within the context of potential complication development. Additionally, the surgeon can plan accordingly for the operation and may employ additional techniques and/or preventative measures to potentially reduce the risk of the patient developing these complications. This patient-specific approach at complication avoidance could reduce the overall complication rate and thus potentially decrease patient morbidity.

With the advent of modern advanced predictive analytics techniques, one can now create accurate, patient-specific, predictive models with high accuracy, which can provide very useful information to aid in clinical decision making.¹⁵ Although traditional statistical methods can also be very clinically useful, these methods tend to be limited for use in developing patient-specific predictive models.¹ Furthermore, they are generally designed to test specific hypotheses, have many assumptions that need to be satisfied before use, and use patient group means, not accounting for individual changes.^{1,32} Modern predictive modeling algorithms are very different because they can identify patterns in the data, allowing for accurate predictions without the need for a hypothesis. Thus, patient-specific models can be developed to provide valuable, detailed information, which can then be applied when discussing the risks of surgery with a patient. The goal of this study was to develop a model based on baseline demographic, radiographic, and surgical factors that could predict the patients likely to sustain a major intraoperative or perioperative complication.

Methods

Patient Population

This study is a retrospective review of a prospective multicenter ASD database, which is composed of patients from 11 sites across the US. All patients were enrolled in an IRB-approved protocol by each site. Inclusion criteria for the databases were age ≥ 18 years and the presence of spinal deformity, as defined by any coronal Cobb angle $\geq 20^\circ$, sagittal vertical axis (SVA) ≥ 5 cm, pelvic tilt (PT) $\geq 25^\circ$, or thoracic kyphosis (TK) $\geq 60^\circ$. Exclusion criteria included spinal deformity of a neuromuscular etiology and presence of active infection or malignancy.

Data Collection, Radiographic Assessment, and HRQOL

The demographic and clinical data collected included patient age, sex, body mass index (BMI), number of comorbidities, Charlson Comorbidity Index (CCI),¹⁰ preoperative anemia, history of depression, osteoporosis, American Society of Anesthesiologists (ASA) physical status classification, as well as all intraoperative and perioperative complications. Surgical data collected included primary versus revision surgery, single versus staged procedures, posterior fusion rod diameter and material, the uppermost instrumented vertebra, the lowermost instrumented vertebra, use of direct spinal decompression, number of decompression levels, number of Smith-Petersen osteotomies, presence of a 3-column osteotomy (pedicle subtraction osteotomy or vertebral column resection), number of interbody fusions, use of an iliac graft, use of recombinant human bone morphogenetic protein (BMP), and number of posterior vertebral levels fused. The surgical variables were included under the assumption that the same factors could be derived from a preoperative surgical plan and that their inclusion would yield a more complete preoperative predictive model.

Full-length (36-inch cassette) posteroanterior and lateral spine radiographs at baseline and 6 weeks follow-up were analyzed using validated software^{9,33} (SpineView, ENSAM, Laboratory of Biomechanics). Only baseline radiographic measures were included in the model and the 6-week radiographs were used for complication determination. All radiographic measures were performed at a central location based on standard techniques³¹ and included: maximum coronal Cobb angles of thoracic and lumbar curves (grouped by $< 30^\circ$, 30° – 60° , and $> 60^\circ$); coronal C-7 plumb line; TK (T4–T12; Cobb angle between superior endplate of T-4 and inferior endplate of T-12); lumbar lordosis (Cobb angle between superior endplate of L-1 and superior endplate of S-1); SVA (offset of C-7 plumb line relative to S-1); PT; the mismatch between pelvic incidence and lumbar lordosis (PI-LL); and the T-1 pelvic angle (T1PA; the angle between the line from the

femoral head axis to the centroid of T-1 and the line from the femoral head axis to the middle of the S-1 endplate). Based on the above radiographic parameters, patients were additionally stratified by the SRS-Schwab ASD classification.³⁵

Standardized HRQOL measures were recorded at baseline and included the Oswestry Disability Index (ODI), SF-36, and Scoliosis Research Society-22r questionnaire (SRS-22r). Two standard summary scores were calculated based on the SF-36, the Physical Component Summary (PCS) and the Mental Component Summary (MCS). The SRS-22r provides a total score and multiple subdomains, including activity, pain, appearance, mental, and satisfaction. A numeric rating scale (NRS) score ranging from 0 (no pain) to 10 (most unbearable pain) was collected for back and leg pain separately.

Patients were grouped as either having at least 1 major intraoperative or perioperative complication (COMP group) or not (NOCOMP group). Perioperative complications were defined as those occurring within 6 weeks of surgery. Major and minor complications were classified according to the study of Glassman et al.¹⁸ All of the patients included had a minimum of 6 weeks of follow-up to capture any perioperative complications. The complication categories included cardiopulmonary, electrolyte, gastrointestinal, implant, infection, musculoskeletal, neurological, operative, radiographic, renal, vascular, wound, and other.

Statistical Analysis and Predictive Model Construction

Continuous variables were described with means and standard deviations. Baseline variables were compared between the groups. Normality of data was determined using the Shapiro-Wilk test. Comparison of baseline means between the groups included the Student t-test or Wilcoxon rank-sum tests where appropriate. Frequency analyses for categorical variables were conducted via Pearson's χ^2 analysis. All statistical analyses were conducted using commercially available software (SPSS version 22, IBM Inc.) and the level of significance was set at $p < 0.05$ for all tests.

For the predictive model, missing values within the database were imputed using standard techniques such as mean and median imputation.¹ Once a complete data set was constructed, an ensemble of decision trees was constructed with a binary target variable that included patients who sustained at least 1 major intraoperative or perioperative complication, as defined above (code = 1), or not having any major intraoperative or perioperative complications (code = 0). The decision-tree algorithm was C5.0 and 5 different bootstrapped models were built.¹ Internal validation was accomplished via a 70/30 data split for training and testing the model, respectively.¹ Final overall predictions from the models were combined and chosen by voting with random selection for tied votes. Overall accuracy and the area under the receiver operating characteristic (AUROC) curve were calculated as well as predictor importance as determined by the model. The model was built using commercially available software (SPSS Modeler version 16, IBM Inc.).

Results

Patient Population

A total of 557 operative patients were available and included in the study. Of those, 409 did not sustain a major complication (NOCOMP group, 73.4%), and 148 had at least 1 intraoperative or perioperative major complication (COMP group, 26.6%). From the total, 390 patients (70%) were used for model training and 167 (30%) for testing the model. The percentage split was determined randomly but was within the acceptable splitting percentage options for predictive modeling.¹ There were 439 women (78.8%) and 118 men (21.2%) and the mean age was 57.5 ± 15.3 years with a mean BMI of 27.6 ± 8.6 kg/m² (Table 1). The COMP group was significantly older, had a greater mean BMI, higher mean CCI, higher mean ASA score, and a higher proportion of patients with osteoporosis ($p < 0.05$ for all, Table 1). The COMP group had a significantly higher proportion of patients with baseline SRS-Schwab coronal curve type of L (47.6% vs 30.8%, $p < 0.05$, Table 1).

Surgical Data

The COMP group had a larger proportion of patients who underwent a revision (41.9%) versus primary surgery (31.5%; $p = 0.023$) and who had a direct decompression (25.7% vs 20.3%, $p = 0.0034$; Table 2). In addition, the COMP group had a significantly higher proportion of patients who underwent an interbody fusion, iliac crest graft, and BMP use ($p < 0.05$ for all, Table 2). The mean number of posterior levels fused was statistically similar between groups ($p > 0.05$, Table 2). Both groups also had

TABLE 1. Demographic data of all the patients as well as each group

Variable	All Patients	COMP	NOCOMP	p Value
No. of patients	557	148	409	
Mean age $\pm$ SD (yrs)	57.5 $\pm$ 15.3	61.5 $\pm$ 12.3	56 $\pm$ 16.1	0.0004
Females/males	439/118	119/29	320/89	0.5806
Mean BMI $\pm$ SD	27.6 $\pm$ 8.6	28.6 $\pm$ 6	27.3 $\pm$ 9.3	0.0013
Mean CCI $\pm$ SD	1.5 $\pm$ 1.7	1.9 $\pm$ 1.7	1.4 $\pm$ 1.6	0.0009
Mean ASA score $\pm$ SD	2.3 $\pm$ 0.7	2.4 $\pm$ 0.6	2.3 $\pm$ 0.7	0.0061
Preop anemia (%)	52 (9.3)	12 (8.1)	40 (9.8)	0.5491
Osteoporosis (%)	70 (12.6)	28 (18.9)	42 (10.3)	0.0065
Depression (%)	131 (23.5)	35 (23.6)	96 (23.5)	0.9653
SRS-Schwab coronal curve type (%)				0.0047
N	33.6	30.3	34.8	
T	5.9	4.8	6.3	
L	35.3	47.6	30.8	
D	25.1	17.2	28.0	

SRS-Schwab coronal curve types: N = patients with no coronal curve $> 30^\circ$ (i.e., no major coronal deformity); T = patients with a thoracic major curve $> 30^\circ$ (apical level of T-9 or higher); L = patients with a lumbar or thoracolumbar major curve $> 30^\circ$ (apical level of T-10 or lower); and D = patients with a double major curve, with each curve $> 30^\circ$.

Boldface type indicates statistically significant differences between the COMP and NOCOMP groups.

TABLE 2. Surgical data of all the patients as well as each group

Surgical Data	All Patients (%)	COMP (%)	NOCOMP (%)	p Value
No. of patients	557	148	409	
Primary/revision	366/191	86/62	280/129	0.0230
Mean no. of posterior levels fused $\pm$ SD	11.2 $\pm$ 4.2	11.6 $\pm$ 3.8	11 $\pm$ 4.4	0.5383
Decompression	343 (61.6)	106 (71.6)	237 (57.9)	0.0034
3-column osteotomy	121 (21.7)	38 (25.7)	83 (20.3)	0.1736
Smith-Petersen osteotomy	291 (52.2)	81 (54.7)	210 (51.3)	0.4799
Interbody fusion	332 (59.6)	105 (70.9)	227 (55.5)	0.0010
Iliac crest graft	163 (29.3)	53 (35.8)	110 (26.9)	0.0411
BMP use	356 (63.9)	105 (70.9)	251 (61.4)	0.0376
Posterior rod diameter in mm				0.626
4.5	2 (0.4)	0 (0)	2 (0.5)	
5.5	360 (64.6)	91 (61.5)	269 (65.8)	
6.0	66 (11.8)	19 (12.8)	47 (11.5)	
6.35	129 (23.1)	38 (25.7)	91 (22.2)	
Posterior rod material				0.7519
Cobalt chromium	340 (61.0)	92 (62.2)	248 (60.6)	
Stainless steel	115 (20.6)	27 (18.2)	88 (21.5)	
Titanium	101 (18.1)	29 (19.6)	72 (17.6)	
Other	1 (0.2)	0 (0)	1 (0.2)	

Boldface type indicates statistically significant differences between the COMP and NOCOMP groups.

statistically similar proportions of patients with different rod diameters and materials ($p > 0.05$ for both, Table 2). The proportion of patients who suffered major complications and specific complication subtypes are presented in Table 3.

Radiographic Data

Baseline radiographic parameters of the COMP and NOCOMP groups are shown in Table 4. The COMP group had significantly greater mean baseline SVA (77.7 mm vs 61.2 mm, $p = 0.015$) and T1PA (25.0° vs 21.4°, $p = 0.014$) than the NOCOMP group ($p < 0.05$ for both). Both groups had similar baseline mean PT, PI-LL, TK, C-7 coronal plumb line, and proportion of patients in each of the maximum coronal Cobb angle groups ($p > 0.05$ for all).

HRQOL Data

The COMP group had significantly worse baseline mean scores for ODI, PCS, SRS activity, SRS pain, SRS total, and leg pain NRS ($p < 0.05$ for all, Table 5). All other HRQOL variables were statistically similar between the groups ($p > 0.05$ for all).

Model Results

The overall model accuracy was 87.6% correct with an AUROC of 0.89 indicating a very good model fit. In total, 20 variables were determined to be the top predic-

TABLE 3. Distribution of complication number and types for the COMP group

Variable	Value (%)
Total no. of patients	148
No. of major complications	
1	117 (79.1)
2	18 (12.2)
3	7 (4.7)
4	3 (2)
5 or more	3 (2)
Complication type	
Cardiopulmonary	34 (23)
Electrolyte	0 (0)
Gastrointestinal	1 (0.7)
Implant	10 (6.8)
Infection	23 (15.5)
Musculoskeletal	0 (0)
Neurological	34 (23)
Operative	57 (38.5)
Other	1 (0.7)
Radiographic	11 (7.4)
Renal	4 (2.7)
Vascular	0 (0)
Wound	7 (4.7)

tors (importance ≥ 0.90 out of 0–1 as determined by the model) and included (in decreasing importance): age, leg pain NRS, ODI, number of levels decompressed, number of levels with an interbody fusion, PCS, SRS-Schwab coronal curve type, CCI, SRS activity, T1PA, ASA grade, presence of osteoporosis, PT, SVA, primary version revi-

TABLE 4. Preoperative radiographic data parameters included in the model for all patients and the COMP and NOCOMP groups

Preop Radiographic Parameter	All Patients	COMP	NOCOMP	p Value
Mean PT $\pm$ SD (°)	23.3 $\pm$ 10.7	25.1 $\pm$ 10.4	22.7 $\pm$ 10.7	0.086
Mean PI-LL $\pm$ SD (°)	15.7 $\pm$ 21	18.5 $\pm$ 20.9	14.6 $\pm$ 21	0.0523
Mean TK $\pm$ SD (°)	35.2 $\pm$ 19.1	36.7 $\pm$ 19.1	34.7 $\pm$ 19.1	0.3538
Mean SVA $\pm$ SD (mm)	65.6 $\pm$ 74.2	77.7 $\pm$ 73.6	61.2 $\pm$ 74	0.0148
Mean T1PA $\pm$ SD (°)	22.3 $\pm$ 13.2	25 $\pm$ 13.3	21.4 $\pm$ 13.1	0.0138
Mean C-7 coronal plumb line $\pm$ SD (mm)	35 $\pm$ 33.1	38 $\pm$ 36.5	33.9 $\pm$ 31.8	0.2349
Max coronal Cobb angle groups (%)				0.1158
<30°	211 (37.9)	51 (34.5)	160 (39.1)	
30°–60°	247 (44.3)	76 (51.4)	171 (41.8)	
>60°	99 (17.8)	21 (14.2)	78 (19.1)	

Boldface type indicates statistically significant differences between the COMP and NOCOMP groups.

TABLE 5. HRQOL measures for all patients and the COMP and NOCOMP groups

Preop HRQOL	All Patients*	COMP*	NOCOMP*	p Value
ODI	44.5 ± 18.6	49 ± 17.8	42.9 ± 18.6	0.0007
PCS	31.4 ± 9.4	29.3 ± 8.5	32.1 ± 9.7	0.0021
MCS	45.2 ± 13.2	44.7 ± 12.6	45.4 ± 13.4	0.3787
SRS				
Activity	2.9 ± 0.9	2.7 ± 0.8	2.9 ± 0.9	0.0068
Pain	2.4 ± 0.8	2.3 ± 0.9	2.4 ± 0.8	0.0239
Appearance	2.4 ± 0.8	2.3 ± 0.7	2.4 ± 0.8	0.183
Mental	3.4 ± 0.9	3.4 ± 0.9	3.4 ± 0.9	0.9881
Satisfaction	2.7 ± 1.1	2.6 ± 1	2.8 ± 1.1	0.1857
Total	2.8 ± 0.7	2.7 ± 0.6	2.8 ± 0.7	0.0276
Back pain NRS	7.2 ± 2.2	7.4 ± 2.2	7.2 ± 2.2	0.1086
Leg pain NRS	4.5 ± 3.2	5.4 ± 3.2	4.2 ± 3.2	0.0002

Boldface type indicates statistically significant differences between the COMP and NOCOMP groups.

* Data presented as mean ± standard deviation.

sion surgery, SRS pain, SRS total, use of BMP, use of iliac crest graft, and PI-LL (Table 6).

Discussion

In this investigation, a large cohort of patients with ASD who underwent surgical correction was used to construct an accurate, internally validated, patient-specific, preoperative predictive model for developing a major intra- or perioperative complication. The model is designed for preoperative use and thus the surgical variables were added retrospectively with the assumption that these could have been part of a preoperative surgical plan. This model sets the framework to create a website or ideally a mobile (i.e., tablet) application for calculating the risk of developing short-term major complications in real time as a point-of-care device. In this context, when formulating the surgical plan, and in discussion with the patient, alterations could be made to optimize the risk-benefit equation. For example, a particular maneuver that may be appropriate in one patient with an otherwise low risk profile may, in a different patient with a high predicted baseline risk, be judged to be too dangerous. Quantifying surgical risk in a given patient represents a significant challenge given the multitude of factors that interact in a complex manner to contribute to the overall risk. The model presented herein could be readily applied to this task and yield objective and accurate information to aid surgeons and inform patients.

It is important to understand the rationale behind the predictive modeling technique used in the present study. Decision trees were chosen based on many desirable properties for the given binary outcome of having a complication or not that included: 1) ability to handle hundreds of variables, both categorical and continuous; 2) feasibility with missing data; and 3) ease of construction.¹ The combination of 5 decision-tree models is termed an “ensemble” in which the final predictions are based on all 5 models. This allows for increased accuracy at the cost of decrease

TABLE 6. Variables used in the predictive model

Sex	Interbody fusion (yes/no)
(7) SRS-Schwab coronal curve type	(5) No. of interbody fusion levels
(1) Age	(19) Iliac crest graft (yes/no)
BMI	(18) BMP (yes/no)
(15) Revision surgery (yes/no)	Max Cobb angle (<30°, 30°–60°, >60°)
At least 1 comorbidity (yes/no)	Coronal C-7 plumb line distance
No. of comorbidities	(13) PT
(8) CCI	(20) PI-LL
Anemia (yes/no)	TK (T2–12)
Depression (yes/no)	(14) C-7 SVA
(12) Osteoporosis (yes/no)	(10) T1PA
Staged surgery (yes/no)	(3) ODI
(11) ASA grade	(6) SF-36 PCS
Rod diameter	SF-36 MCS
Rod material	(9) SRS activity
Uppermost instrumented vertebra	(16) SRS pain
Lowermost instrumented vertebra	SRS appearance
No. of posterior levels fused	SRS mental
Decompression (yes/no)	SRS satisfaction
(4) No. of decompression levels	(17) SRS total
Smith-Petersen osteotomy (yes/no)	Back pain NRS
No. of Smith-Petersen osteotomies	(2) Leg pain NRS
3-column osteotomy PSO/VCR (yes/no)	

PSO = pedicle subtraction osteotomy; VCR = vertebral column resection.

The top 20 variables in terms of predictive value are numbered in parentheses.

in interpretability (transparency).¹ The exact rules governing how the predictions are made are unavailable because the computer calculates all of the predictions, in contrast to logistic regression, in which one obtains odds/hazard ratios to apply. Internal validation of the model was accomplished by splitting the data in a 70/30 ratio for training and testing, respectively, to increase the generalizability of the model. Both data sets were randomly chosen with the training set used for model construction and the testing data set used to determine the accuracy (and AUROC) as those patients were not involved in the model building. And the final modeling principle involved bootstrapping the data sets (as well as each of the 5 decision trees), which results in no model receiving the same set of patient data. This greatly increases the generalizability of the final model.

It is important to note that the predictive modeling techniques used in the present study, as well as in general, are a distinct form of analysis compared with traditional regression in several ways.¹ It involves complex algorithms that identify patterns in large data sets, which then allow for prediction of a given outcome of interest. There was no hypothesis, no control being compared, and the model relied entirely on the available data.¹ Conversely, traditional statistics are mathematical analyses used to test a hypothesis about a relationship between independent and dependent variables, and thus appropriate controls are necessary. Furthermore, the appropriate statistical test must be

selected for a given clinical question/hypothesis and type of data. Using the wrong statistical test can result in erroneous results. Predictive modeling is more flexible due to the fact that it relies on the available data. Decision trees were used in this setting because of the advantages stated above, not because of the type of data and not because of a certain hypothesis. Additionally, multiple types of models can be constructed to assess which one has the greatest utility for the aims of the model, hence the ensemble of decision trees that was used.¹ One can combine models that are similar (or different) to further enhance the goals of the model.¹ When creating a model one must balance accuracy, generalizability, and transparency.¹ We have created a model that is accurate and theoretically generalizable, yet not transparent. The type of model being built, and the balance of the 3 primary characteristics, depends on how it will be used when deployed in clinical practice.

There are few predictive models reported in the spine literature that Osorio et al. has identified,³² and for the ones that do exist, logistic regression is a popular technique that produces sets of odds ratios for developing the outcome of interest.^{12,21,24,29,46} Logistic regression is commonly used in prediction analysis because it is simple, easy to interpret and apply, and transparent.¹ Chapman and colleagues consolidated a number of logistic regression models for complications following “spine surgery” from 6 different peer-reviewed papers into a web-based predictive model.^{5,14,19,22,25,26} This was an impressive feat, but in contrast to the decision trees used in the present study, there are specific limitations to logistic regression. There are a number of assumptions that must be satisfied to apply logistic regression as mentioned above and they generally identify variables that are “predictors” without a patient-specific interpretation. Our predictive model was constructed in 1 setting as opposed to 6 different studies with all the variables in 1 database. It is more efficient, updated with current predictive algorithms, is patient specific, and applies directly to patients with ASD.

Similar to our methodology, Daubs and colleagues performed a decision-tree analysis and used an ensemble of 50 decision trees to predict psychological distress in spine patients.¹⁵ Their model was very successful using 6 variables and 188 patients, as it was 92% accurate, 92% sensitive, and 95% specific.¹⁵ And lastly, one of the more advanced predictive modeling techniques was deployed by Azimi and colleagues in which they created an artificial neural network (ANN) to predict 2-year surgical satisfaction in surgical patients for lumbar spinal canal stenosis undergoing surgery.³ They compared the ANN to logistic regression and found that the use of ANN was more accurate than the logistic regression model. These types of studies, in addition to ours, represent the beginning of the use of predictive analytics in spine surgery outcomes.⁴ As data sets get larger with time and the quality of the data increases, advanced predictive analytics will likely play a larger role in clinical decision making.

The strengths of the current study include the multicenter design and a large number of patients with ASD (n = 557). The multicenter design (11 different sites across the US) allows for better generalizability of the results. Another strength of this study is the complete preoperative

and 6-week follow-up of the patients as well as the use of 45 variables. And lastly, modern predictive analytics algorithms were used to create the model, providing a patient-specific decision-tree ensemble.

However, there are a few limitations to this study, one of which includes the retrospective design that may have introduced selection or information biases. Another limitation includes combining both intra- and perioperative complications as the target variable of interest. Ideally, with greater numbers of patients, these intraoperative and perioperative complications would be separated out. This model is one of the first of its kind and sets the groundwork for advanced predictive analytics in spinal outcomes research.

Conclusions

A successful model (87% accuracy, 0.89 AUROC) was built predicting major intra- or perioperative complications. This model can provide the foundation toward improved education and point-of-care decision making for patients undergoing ASD surgery.

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