ORIGINAL ARTICLE

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Artificial Intelligence Models Predict Operative Versus Nonoperative Management of Patients with Adult Spinal Deformity with 86% Accuracy

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■ OBJECTIVE: **Patients with ASD show complex and highly variable disease. The decision to manage patients operatively is largely subjective and varies based on surgeon training and experience. We sought to develop models capable of accurately discriminating between patients receiving operative versus nonoperative treatment based only on baseline radiographic and clinical data at enrollment.**

■ METHODS: **This study was a retrospective analysis of a multicenter consecutive cohort of patients with ASD. A total of 1503 patients were included, divided in a 70:30 split for training and testing. Patients receiving operative treatment were defined as those undergoing surgery up to 1 year after their baseline visit. Potential predictors included available demographics, past medical history, patient-reported outcome measures, and premeasured radiographic parameters from anteroposterior and lateral films. In total, 321 potential predictors were included. Random forest, elastic net regression, logistic regression, and support vector machines (SVMs) with radial and linear kernels were trained.**

■ RESULTS: **Of patients in the training and testing sets, 69.0% (n = 727) and 69.1% (n = 311), respectively, received operative management. On evaluation with the testing dataset, performance for SVM linear (area under the curve =0.910), elastic net (0.913), and SVM radial (0.914) models was excellent, and the logistic regression (0.896) and random forest (0.830) models performed very well for predicting operative management of patients with ASD. The SVM linear model showed 86% accuracy.**

■ CONCLUSIONS: **This study developed models showing excellent discrimination (area under the curve >0.9) between patients receiving operative versus nonoperative management, based solely on baseline study enrollment values. Future investigations may evaluate the implementation of such models for decision support in the clinical setting.**

INTRODUCTION

Adult spinal deformity (ASD) encompasses a set of spinal disorders that are complex and heterogeneous with highly individualized surgical planning. The shared decision-making model synthesizes medical and technical knowledge from surgeons with values and preferences from patients to achieve theoretically superior outcomes.[1] Decision aid tools for patients improve knowledge and may facilitate alignment of choice with a patient's values.[2,3] Within orthopedics, Fraenkel et al.[4] showed that patients with knee pain experienced superior decisional self-efficacy with use of an informational computer-based tool. The

Key words
- Adult spinal deformity
- Operative management
- Predictive modeling

Abbreviations and Acronyms
ASD: Adult spinal deformity
AUC: Area under the receiver operating characteristic curve
PROM: Patient-reported outcome measure
SVA: Sagittal vertical axis
SRS: Scoliosis Research Society
SVM: Support vector machine
TPA: T1-pelvic angle

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decision to manage patients with ASD operatively versus nonoperatively incorporates a wide array of factors, including baseline patient quality of life, comorbidities, and objective spinal alignment. Predicting which patients are more likely to be managed surgically may be clinically valuable.

Machine learning algorithms have shown promise in spine surgery. Models have been developed to predict a broad range of outcomes, including mortality and length of stay, as well as both overall and specific complications.[5-14] Despite a large number of models to predict outcomes, there are relatively few models to support clinical decision making.[10] The Nijmegen Decision Tool for Chronic Low Back Pain is under development to assist spine care specialists in deciding to refer to a surgical versus nonsurgical spine care specialist; this model was developed with an expert panel.[13] Decision support systems may be deployed in the spine surgery setting to optimize patient selection.

This investigation sought to develop models to predict whether patients with ASD were managed operatively versus nonoperatively, using only data available at baseline study enrollment. Further, we sought to understand the relative contribution of individual variables to our models, and any potential variation in predictive power between individual study centers.

METHODS

Patient Sample

This study used a multicenter prospectively defined consecutive cohort of patients with ASD. Patients were included in the database if they were ≥18 years old and met ≥1 of the following criteria: maximum Cobb angle of ≥20°, sagittal vertical axis (SVA) >5 cm, pelvic tilt >25°, or thoracic kyphosis >60°. In total, 1503 patients with baseline data were included. The sample was randomly divided into training and testing datasets at a 70:30 ratio.

Outcome Measures and Predictors

Patients receiving operative treatment were defined as those undergoing surgery up to 1 year after their baseline visit. A total of 584 potential predictors were initially considered, including available demographics, past medical history, patient-reported outcome measures (PROMs), and premeasured radiographic parameters from anteroposterior and lateral films. Variables with >10% missing data (258 variables) and those comprising text strings or dates (4 variables) were discarded. The remaining 321 variables underwent median imputation, accomplished separately for training and testing datasets. The full list of predictors is included in Supplementary Table 1.

Statistical Analysis

All statistical analysis was conducted in R 3.5.0 (R Foundation for Statistical Computing, Vienna, Austria).[15] Random forest, elastic net regression, logistic regression, and support vector machines (SVMs) with radial and linear kernels were trained. Logistic regression was selected as a benchmark against which modern algorithms could be compared. The random forest, elastic net, and SVM model approaches were chosen to include a broad but nonexhaustive range of relatively diverse and frequently used machine learning algorithms. All models were trained using the *caret* package, with cross-validation and model-specific grid-based tuning, as applicable[16] (Supplementary Figure 1). For each model, data preprocessing steps included discarding of near-zero-variance variables, as well as centering and scaling. Model performance was evaluated by area under the receiver operating characteristic curve (AUC). Partial dependence plots were generated using the *pdp* package.[17] Computations were performed on the computer facilities of the Brown University Center for Computation & Visualization.

RESULTS

Descriptive Statistics

In total, 1503 patients were included in this study, divided randomly into 1053 patients in the training set and 450 patients in the testing set. Of patients in the training and testing sets, 69.0% (n = 727) and 69.1% (n = 311) were managed operatively, respectively. The mean age in the training dataset was 57.0 years (standard deviation, 16.0), and 77.0% (n = 811) of patients were female (Table 1).

Model Evaluation

On evaluation with the testing dataset, the SVM linear (AUC = 0.910), elastic net (AUC = 0.913), SVM radial (AUC = 0.914), and logistic regression (AUC = 0.896) models performed statistically significantly better than the random forest model (AUC = 0.830) ($P < 0.05$ for the 4 comparisons) (Figure 1). The highest accuracy was achieved by the SVM linear model (85.8%), with sensitivity of 87.8% and specificity of 80.5% (Table 2). In the SVM radial model, PROMs were particularly important for making predictions; the top 5 most important variables based on receiver operating characteristic curve importance were Scoliosis Research Society (SRS) appearance score, SRS total score, Oswestry Disability Index, Short-Form 36 bodily pain, and SRS activity scores (Figure 2). Case examples of several patients are presented in Figure 3.

The performance of the radial SVM model on the testing dataset was stratified by anonymized study site (Figure 4). To reduce the likelihood of site re-identification, only sites contributing >10 patients to the cohort were depicted. The AUCs at sites contributing a large number of patients to the cohort were all >0.9. Only 1 site was markedly separate from the others: this site contributed a small to moderate number of patients and showed an AUC <0.5.

Partial dependence plots from the random forest model were generated to examine relationships between various predictors and operative management (Figure 5). Peak probability of operative management was observed for patients between approximately 50 and 75 years of age. Patients with both very low (e.g., <20) and very high (e.g., >40) body mass index (calculated as weight in kilograms divided by the square of height in meters) were less likely to be managed operatively. Although higher SVA was associated with increased likelihood of operative management, the likelihood tended to decline after approximately 100 mm. Similarly, patients with T1-pelvic angle (TPA) between approximately 25° and 40° were more likely to undergo surgery.

Table 1. Descriptive Statistics (Selected Variables)

	Training Dataset		Testing Dataset	
	Mean/%	SD/N	Mean/%	SD/N
Number of patients	1053	—	450	—
Operative management				
No	31.0%	326	30.9%	139
Yes	69.0%	727	69.1%	311
Demographics				
Age at baseline	57.0	16.0	57.6	15.7
Female gender	77.0%	811	80.4%	362
Past medical history				
Previous spine surgery	40.0%	421	37.8%	170
Clinical parameters				
Body mass index	27.4	6.1	26.8	5.8
Patient-reported outcome measures				
Oswestry Disability Index	39.5	19.8	37.7	19.7
SF-36 physical component score	34.0	10.9	34.7	11.0
SF-36 mental score	46.4	13.1	47.3	12.9
Scoliosis Research Society 22 total score	2.9	0.7	3.0	0.7
Lateral radiographic parameters				
Pelvic tilt	22.7	10.9	23.3	10.9
Pelvic incidence	54.2	13.7	56.0	14.9
Pelvic incidence minus lumbar lordosis	13.0	21.3	14.0	23.6
Maximal lumbar lordosis	49.6	16.9	51.3	18.1
Maximal thoracic kyphosis	−50.0	18.1	−50.0	18.5
Plumbline C7-S1 (sagittal vertical axis)	53.2	70.1	56.7	73.4
T1-pelvic angle	20.8	13.1	21.6	13.6

A comprehensive table of descriptive statistics for all predictors is provided in Supplementary Table 1.
SD, standard deviation; SF-36, Short-Form 36.

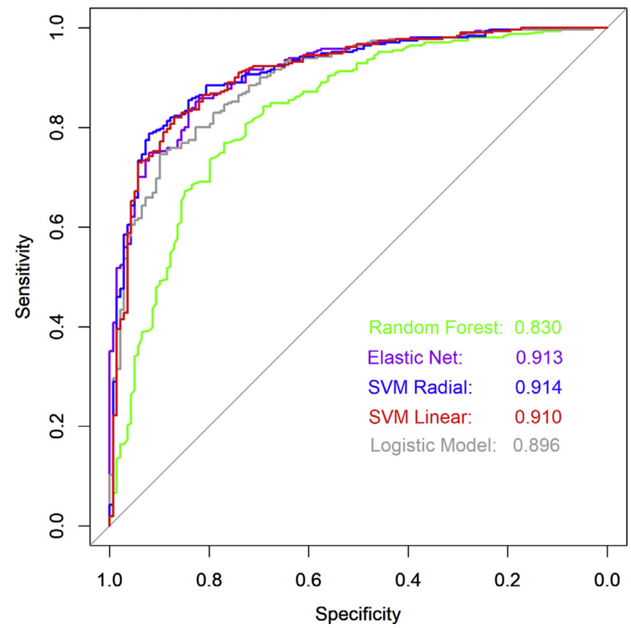


Figure 1. Area under the curve analysis by model for operative management. SVM, support vector machine.

DISCUSSION

This investigation developed models to predict operative versus nonoperative management of patients with ASD based solely on information available at baseline. The best performing models showed excellent discrimination, with AUC >0.9.[18-20] Baseline PROMs were particularly instrumental in these models. Overall, there was a moderate degree of variability in model performance between study sites.

The primary purpose of this study was to create predictive models and to evaluate their performance. The AUCs for our best models were >0.9, indicating excellent discrimination. This study showed that the shared decision-making process for operative versus nonoperative management in ASD can be emulated computationally. This finding is impressive, given the complexity of factors involved in such decisions. However, these models simply predict who was managed surgically; they do not predict who should undergo surgery. This is an important question and should also be investigated, as highlighted by recent efforts to develop criteria for appropriateness of surgery in ASD.[21,22] It is possible that select patients who were not managed operatively would have otherwise had positive outcomes with surgery, and vice versa.

However, clinical management is not solely dictated by the probability of benefit. Shared decision making is influenced by a wide range of factors unique to patients, surgeons, and

Table 2. Comparison of Model Performance

	Accuracy	Sensitivity	Specificity
Random forest	0.79	0.81	0.74
Elastic net regression	0.85	0.89	0.75
SVM linear	0.86	0.88	0.80
SVM radial	0.84	0.86	0.79
Logistic regression	0.82	0.88	0.69

SVM, support vector machine.

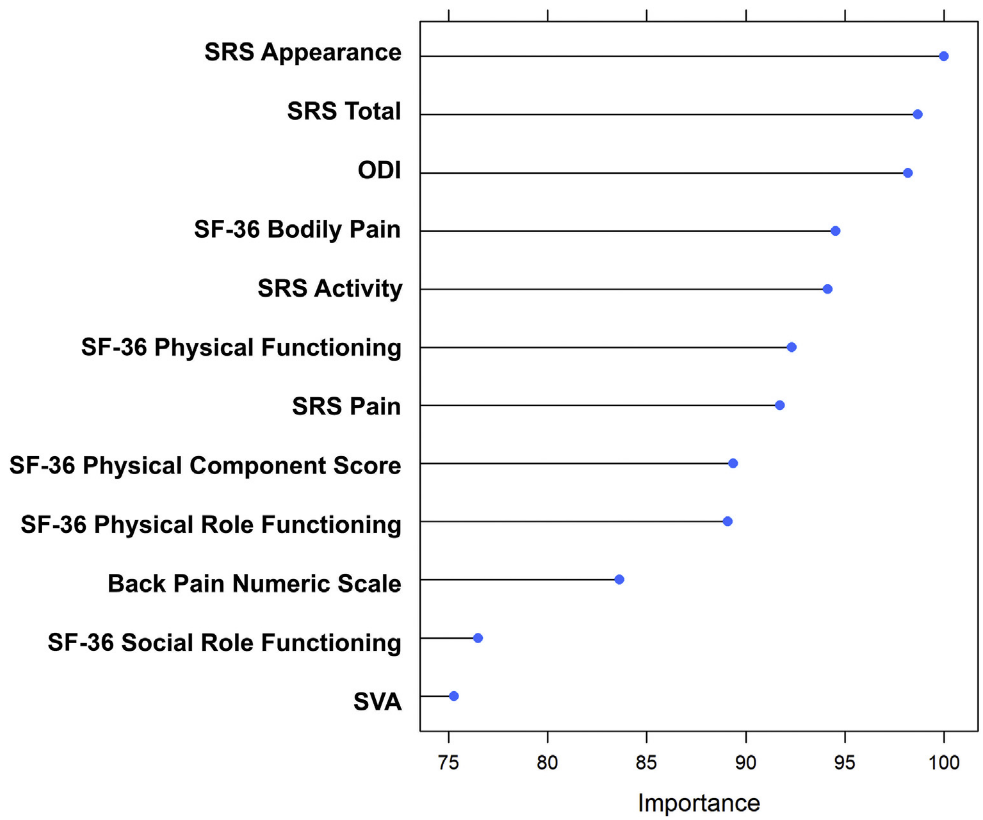
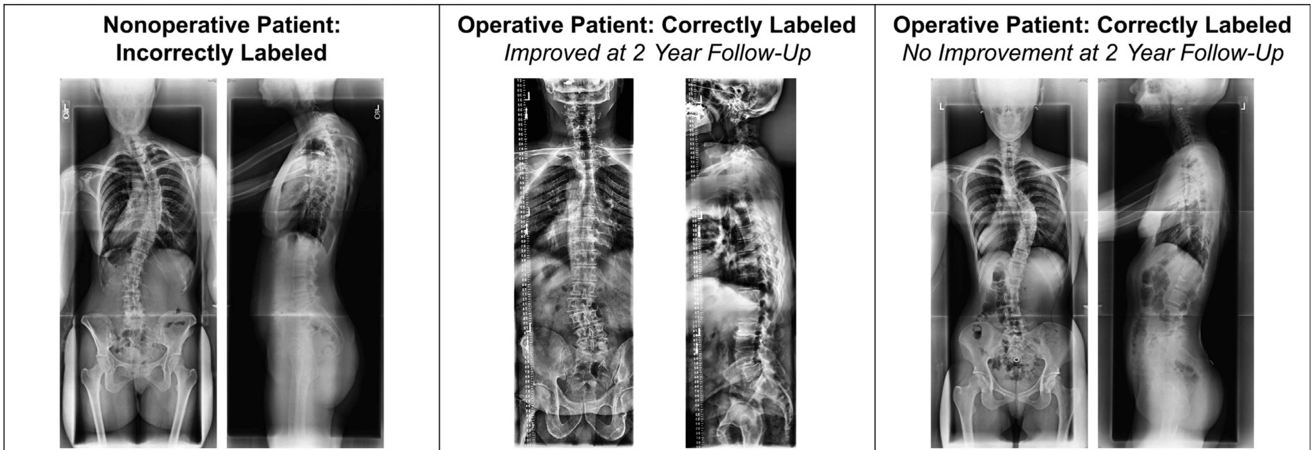


Figure 2. Relative importance of the top 12 variables for the support vector machine radial model. These values were generated in a univariable manner, may be influenced by collinearity between variables, and may vary between models. ODI, Oswestry Disability Index; SF-36, Short-Form 36; SRS, Scoliosis Research Society; SVA, sagittal vertical axis.

institutions.[13] The models produced in this study may provide valuable insight to clinicians and patients considering ASD surgery. For example, patients engaged in shared decision making may find it helpful or comforting to know the likelihood that another patient with similar characteristics would undergo surgery. Spine surgeons may be interested to compare their rates of operative versus nonoperative management with those predicted by the model. Hospitals and insurers may use the model to allocate resources based on the predicted ASD surgery volume.

Another interesting finding in this study was that model performance varied by study site. The radial SVM model performed excellently among sites contributing a large number of patients to the cohort. This finding is to be expected, because the training of the model was disproportionately reliant on patients from these locations. However, for 1 site, the model showed an AUC <0.5, indicating worse discrimination than random guessing. This study site contributed relatively few patients (<20) to the overall testing cohort, which may have contributed to such poor performance. Nevertheless, this observation highlights the highly complex and variable nature by which surgeons and patients make clinical decisions. It is possible that other factors not included in this investigation play a strong role in decision making at these centers (e.g., patient preferences and referral patterns). Future investigations may broaden the array of predictors used in model training to improve site-level accuracy. Site-level accuracy may also be improved by including a broader array of centers in the sample. These models were developed using data from patients at primarily academic medical centers, seen by surgeons specializing in ASD correction. The generalizability of our models to other hospitals with a lower volume of patients with ASD remains to be determined.

This study used partial dependence plots from the random forest model to evaluate the change in likelihood of operative management across several continuous variables. Random forests capture nonparametric relationships between predictors and outcomes. Patient age, body mass index, SVA, and TPA all showed distinctly nonlinear relationships with likelihood of surgery. Specifically, increased SVA was associated with



Variable	Baseline
Demographics	40 year-old woman
SRS Appearance	3.4
SRS Total	3.3
ODI	22.2

Variable	Baseline	2 Years
Demographics	68 year-old man	
SRS Appearance	2.8	4
SRS Total	2.9	4.2
ODI	42	10

Variable	Baseline	2 Years
Demographics	21 year-old woman	
SRS Appearance	3.2	4.2
SRS Total	3.7	3.6
ODI	8	26

Figure 3. Case examples by model performance. ODI, Oswestry Disability Index; SRS, Scoliosis Research Society.

increased likelihood of surgery until approximately 100 mm, at which point the probability mildly decreased. TPA showed a similar phenomenon after approximately 40°. A previous study

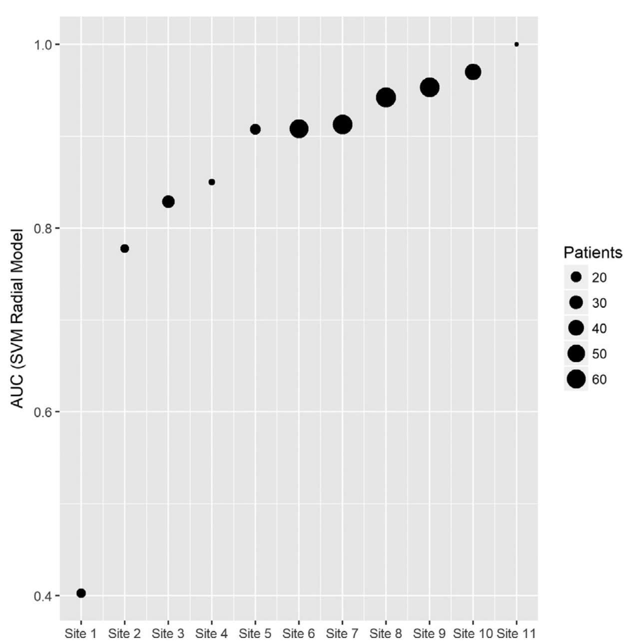


Figure 4. Support vector machine (SVM) radial model: area under the curve (AUC) by study site.

by Passias et al.[23] found no statistically significant difference in propensity-matched t tests for SVA among patients initially managed operatively versus nonoperatively. Our results suggest that this lack of significant difference may be attributable to a nonlinear relationship. Among patients with marked radiographic global deformity, surgeons may be more hesitant to operate given increased anticipated invasiveness. It is also possible that patients with very significant global deformity may show greater baseline comorbidity, which was associated with lower likelihood of surgery in our study; further studies are required to assess this hypothesis.

This study has several potential limitations, several of which were noted earlier. In addition, the models used a large number of predictors. Our efforts to reduce the number of predictors to a level that would allow for manual data input sacrificed accuracy. A preponderance of variables may hinder efforts to implement these models in clinical practice. However, with the use of electronic medical records, collated patient-level data are readily accessible.[24-26] It is possible that collaboration with local information technology experts may facilitate automated extraction of the required information from a patient's chart. The impact of this barrier to implementation may be less than expected. In addition, the variables that we included were selected based on availability in the database. There exist other potential variables that might have been helpful in this study. This study group meets multiple times each year and has evolved in clinical practice over time based on clinical results, and therefore, the models developed in this study may not be extrapolated to all surgeons, who may have different training and experience.[27]

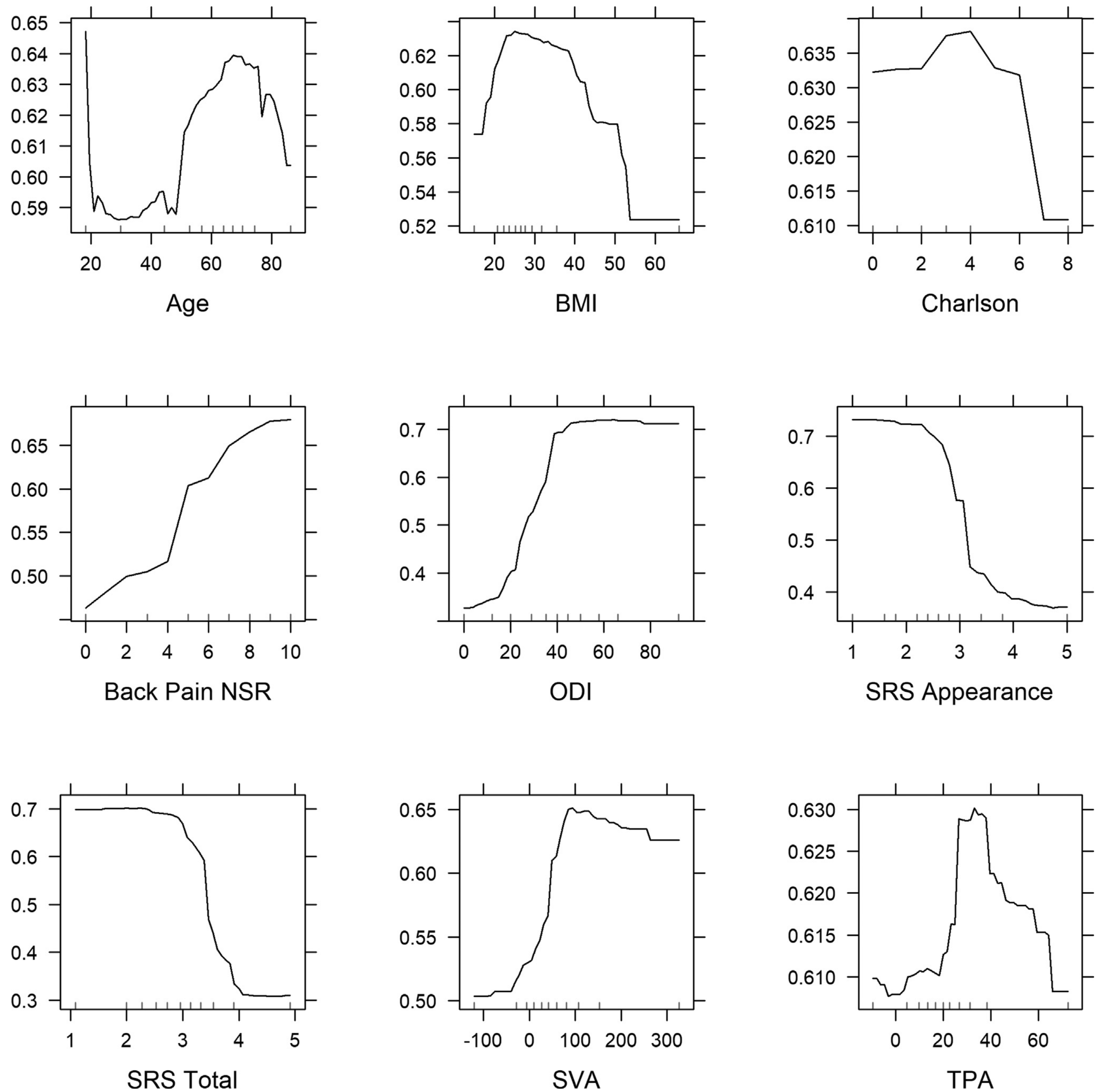


Figure 5. Random forest partial dependence plots of operative management. BMI, body mass index; ODI, Oswestry Disability Index; SRS, Scoliosis Research Society; SVA, sagittal vertical axis; TPA, T1-pelvic angle; NRS, numeric rating scale.

CONCLUSIONS

This study developed models showing excellent discrimination between patients receiving operative versus nonoperative management, based solely on baseline preoperative values. PROMs were particularly instrumental in making these predictions. These results indicate that operative versus nonoperative decision making of experienced surgeons may be emulated with appropriately trained artificial intelligence algorithms. Future investigations may evaluate the implementation of such models for decision support in the clinical setting.

CRediT AUTHORSHIP CONTRIBUTION STATEMENT

Wesley M. Durand: Conceptualization, Methodology, Writing - original draft, Formal analysis. **Alan H. Daniels:** Conceptualization, Methodology, Writing - original draft, Supervision. **David K. Hamilton:** Conceptualization, Writing - review & editing, Data curation. **Peter Passias:** Conceptualization, Writing - review & editing, Data curation. **Han Jo Kim:** Conceptualization, Writing - review & editing, Data curation. **Themistocles Protopsaltis:** Conceptualization, Writing - review & editing, Data curation. **Virginie LaFage:** Conceptualization, Writing - review & editing, Data curation. **Justin S. Smith:** Conceptualization, Writing - review & editing, Data curation. **Christopher Shaffrey:** Conceptualization, Writing - review & editing, Data curation. **Munish Gupta:** Conceptualization, Writing - review & editing, Data curation. **Eric Klineberg:** Conceptualization, Writing - review & editing, Data curation. **Frank Schwab:** Conceptualization, Writing - review & editing, Data curation. **Doug Burton:** Conceptualization, Writing - review & editing, Data curation. **Shay Bess:** Conceptualization, Writing - review & editing, Data curation. **Christopher Ames:** Conceptualization, Writing - review & editing. **Robert Hart:** Conceptualization, Writing - review & editing, Data curation.

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Medical, and K2M; and serves on the board of directors for Nemaris, Inc. D.B. receives royalties from DePuy Spine; is a consultant for DePuy Spine; serves on the board of directors for ISSG, SRS, and University of Kansas Physicians; and receives research support from DePuy Spine, Bioventus, and Pfizer. S.B. receives grants from K2, DePuy Spine, and Nuvasive; receives royalties from K2M; is a consultant for K2M; serves on the scientific advisory board for EOS and MISONIX; and receives grants from ISSGF. C.A. receives royalties from Stryker, Zimmer Biomet, DePuySynthes, Nuvasive, Next Orthosurgical, K2M, and Medicrea; is a consultant for DePuySynthes, Medtronic, Medicrea, and K2M; and receives research support from Titan Spine, DePuySynthes, and ISSG; and receives grants from SRS. R.H. receives royalties from Seaspine and DSS; is a consultant for Globus; and receives grants from ISSGF.

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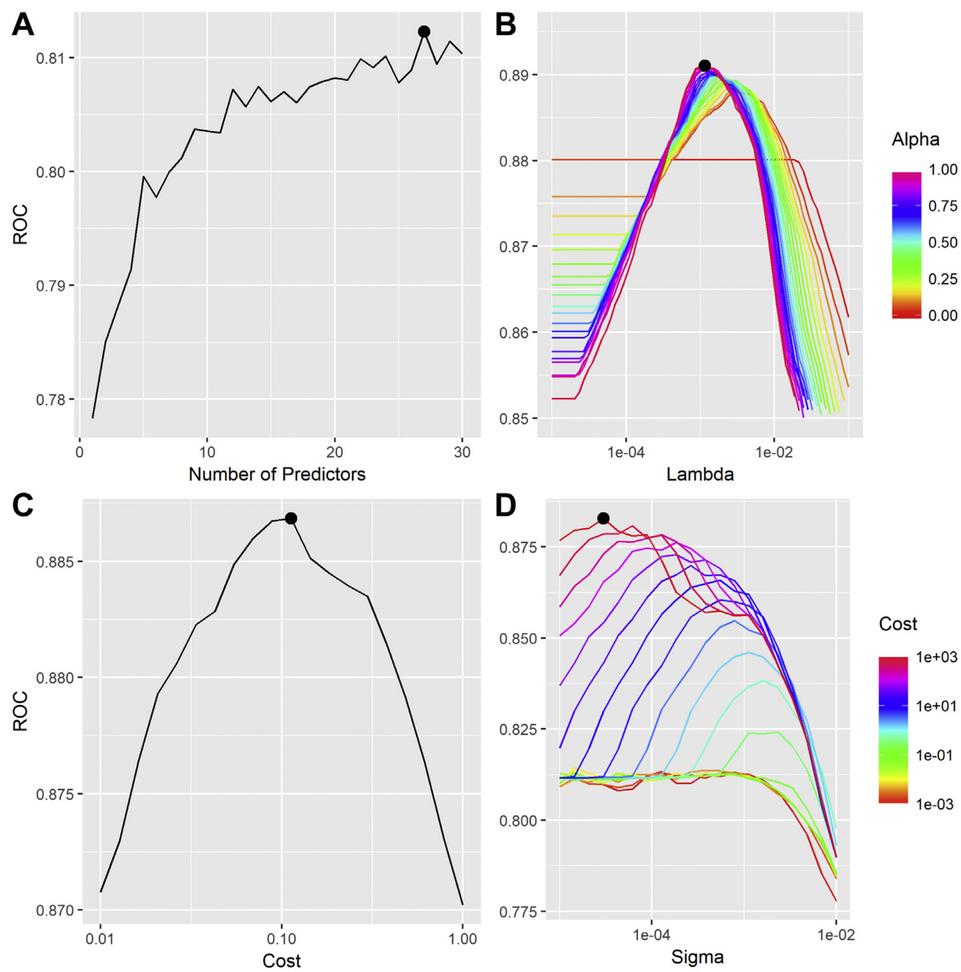
SUPPLEMENTARY DATA



Supplementary Figure 1. Model tuning curves: (**A**) random forest; (**B**) elastic net regression; (**C**) support vector machine linear model; (**D**) support vector machine radial model. ROC, receiver operating characteristic.

Supplementary Table 1. Descriptive Statistics

	Training Dataset		Testing Dataset	
	Mean/%	SD/N	Mean/%	SD/N
Number of patients	1053	—	450	—
Operative management				
No	0.31	326	0.31	139
Yes	69.0%	727	69.1%	311
Demographics				
Age at baseline	57.02	16.01	57.58	15.66
Female gender	77.0%	811	80.4%	362
Race				
Asian	1.8%	19	1.6%	7
Black	3.6%	38	2.9%	13
Hispanic	2.7%	28	2.9%	13
White	91.4%	962	92.2%	415
Other	0.6%	6	0.4%	2
Past medical history				
Years with spine problems	4.26	1.03	4.22	1.04
Previous spine surgery	40.0%	421	37.8%	170
Previous decompression	19.4%	204	17.6%	79
Previous fusion	29.4%	310	27.6%	124
Previous fusion anterior	6.2%	65	5.1%	23
Previous fusion posterior	21.5%	226	22.0%	99
Previous fusion lateral	0.9%	10	1.8%	8
Previous fusion type unknown	3.9%	41	3.6%	16
Previous fusion UIV				
L3	3.9%	41	4.4%	20
L2	3.7%	39	3.3%	15
L4	3.2%	34	3.1%	14
T10	2.2%	23	1.8%	8
T4	1.9%	20	1.6%	7
Other	12.1%	127	11.1%	50
Previous fusion LIV				
S1	9.8%	103	9.6%	43
L5	5.1%	54	4.7%	21
L4	2.9%	31	4.0%	18
Ilium	2.0%	21	2.7%	12
L3	1.8%	19	1.6%	7
Other	5.4%	57	2.9%	13
Previous fusion level unknown	3.0%	32	2.9%	13
Previous decompression upper level				

Continues

Supplementary Table 1. Continued

	Training Dataset		Testing Dataset	
	Mean/%	SD/N	Mean/%	SD/N
L3	3.0%	32	3.8%	17
L4	3.7%	39	3.6%	16
L2	3.1%	33	2.2%	10
L1	0.9%	10	1.3%	6
C3	0.8%	8	1.1%	5
Other	3.2%	34	2.2%	10
Previous decompression lower level				
L5	5.9%	62	4.7%	21
S1	4.2%	44	4.2%	19
L4	1.8%	19	1.8%	8
C7	0.9%	10	0.9%	4
L3	0.9%	9	0.9%	4
Other	1.2%	13	1.8%	8
Previous decompression level unknown	5.7%	60	3.6%	16
Previous surgery complications	12.1%	127	11.3%	51
Previous surgery pseudarthrosis	3.4%	36	3.1%	14
Previous infection-deep	1.0%	11	1.8%	8
Previous infection-superficial	0.6%	6	0.4%	2
Previous neurologic-weakness	2.5%	26	2.2%	10
Previous neurologic-numbness	2.5%	26	2.2%	10
Previous neurologic-chronic pain	4.8%	51	4.4%	20
Previous revision	6.9%	73	6.0%	27
Past history bowel incontinence	7.9%	83	7.3%	33
Past history bladder incontinence	15.7%	165	15.3%	69
Past history numbness, tingling in legs	54.6%	575	45.1%	203
Past history leg weakness	44.3%	467	42.4%	191
Past history loss balance	39.1%	412	34.9%	157
Neurologic examination normal	77.0%	811	76.9%	346
Neurologic gait steady	88.4%	931	86.7%	390
Work status				
Disabled	8.7%	92	8.7%	39
Employed	47.7%	502	38.4%	173
Retired	27.8%	293	38.0%	171
Retired due to BP	6.8%	72	5.3%	24
Unemployed	8.9%	94	9.6%	43
Smoker	8.7%	92	6.4%	29
Smoker packs	0.55	0.72	0.35	0.61

Continues

Supplementary Table 1. Continued

	Training Dataset		Testing Dataset	
	Mean/%	**SD/N**	**Mean/%**	**SD/N**
No comorbidities	18.7%	197	15.3%	69
Alcohol or drug abuse	2.1%	22	2.7%	12
Anemia	8.0%	84	11.6%	52
Arthritis	33.8%	356	37.6%	169
Blood clots	4.2%	44	3.3%	15
Cancer	11.1%	117	9.8%	44
Depression	22.5%	237	22.7%	102
Diabetes	8.5%	89	6.4%	29
Heart disease	9.9%	104	10.7%	48
Hypertension	31.4%	331	31.1%	140
Kidney disease	3.4%	36	2.7%	12
Liver disease	1.5%	16	1.3%	6
Lung disease	4.7%	50	5.6%	25
Nervous system disorders	3.5%	37	2.2%	10
Osteoporosis	13.7%	144	15.1%	68
Peripheral vascular disease	2.6%	27	1.1%	5
Psychiatric disorders	4.4%	46	5.3%	24
Ulcer and/or stomach disease	11.1%	117	11.3%	51
Clinical parameters				
Height	164.49	9.95	163.76	9.64
Weight	74.27	19.23	71.94	17.47
Body mass index	27.37	6.14	26.78	5.77
Back pain NRS	6.60	2.56	6.36	2.63
Leg pain NRS	4.21	3.23	3.93	3.24
None	18.7%	197	15.3%	69
Total number	1.76	1.70	1.81	1.64
Charlson Score	1.51	1.65	1.50	1.51
Cancer treatment type specified	0.7%	7	0.4%	2
Patient-reported outcome measures				
Oswestry Disability Index	39.51	19.84	37.67	19.67
SF-36 physical component score	34.02	10.88	34.69	11.00
SF-36 mental score	46.43	13.07	47.31	12.88
SRS-22 activity domain score	3.07	0.96	3.15	0.96
SRS-22 pain domain score	2.59	0.94	2.67	0.96
SRS-22 appearance domain score	2.64	0.83	2.66	0.85
SRS-22 mental domain score	3.48	0.89	3.56	0.88
SRS-22 satisfaction domain score	2.87	1.05	2.91	1.07
SRS-22 total score	2.94	0.73	3.01	0.73

Continues

Supplementary Table 1. Continued

	Training Dataset		Testing Dataset	
	Mean/%	**SD/N**	**Mean/%**	**SD/N**
SF36—physical functioning	33.31	12.36	33.91	12.78
SF36—role-physical	33.89	12.32	34.17	12.59
SF36—body pain	34.68	10.03	35.69	10.03
SF36—general health	45.99	10.29	47.02	9.96
SF36—vitality	42.20	10.99	43.34	11.68
SF36—social functioning	38.51	13.64	39.37	13.46
SF36—role-emotional	41.44	14.63	41.69	14.79
SF36—mental health	45.03	12.30	46.49	11.79
Anteroposterior radiographic parameters				
Sacral obliquity	1.96	5.23	0.95	12.84
Pelvic obliquity	0.32	3.02	0.21	2.86
Coronal balance	−3.38	42.47	−0.24	43.28
Coronal inclination	−0.34	4.56	−0.02	4.73
Leg length discrepancy	7.59	6.49	7.54	6.63
T1 coronal inclination	−1.65	6.61	−1.29	6.67
Sacral obliquity (absolute value)	4.43	3.46	5.48	11.67
Pelvic obliquity (absolute value)	2.36	1.92	2.18	1.86
Coronal balance (absolute value)	31.45	28.92	31.54	29.70
Coronal inclination (absolute value)	3.33	3.13	3.39	3.30
Leg length discrepancy (absolute value)	7.59	6.49	7.54	6.63
T1 coronal inclination (absolute value)	4.89	4.74	4.92	4.69
Slope of superior S1	2.02	6.23	1.81	6.36
Slope of inferior L5	3.00	8.58	2.84	8.85
Slope of superior L5	3.83	11.12	3.53	11.30
Slope of inferior L4	4.29	15.81	4.01	15.22
Slope of superior L4	3.76	17.53	3.61	16.96
Slope of inferior L3	1.87	19.05	1.77	18.25
Slope of superior L3	0.56	18.12	0.39	17.48
Slope of inferior L2	−2.50	15.76	−2.70	15.89
Slope of superior L2	−3.87	14.50	−4.23	15.03
Slope of inferior L1	−5.92	14.42	−6.26	14.96
Slope of superior L1	−6.74	15.06	−6.89	15.51
Slope of inferior T12	−7.68	16.63	−7.99	16.89
Slope of superior T12	−7.91	17.05	−8.16	17.24
Slope of inferior T11	−7.79	17.18	−8.31	17.40

SD, standard deviation; SF-36, Short-Form 36; SRS-22, Scoliosis Research Society 22; UIV, upper instrumented vertebra; LIV, lower instrumented vertebra; BP, back pain; NRS, numeric rating scale; FH, femoral head.

Continues

Supplementary Table 1. Continued

	Training Dataset		Testing Dataset	
	Mean/%	SD/N	Mean/%	SD/N
Slope of superior T11	−7.18	16.44	−7.88	16.88
Slope of inferior T10	−6.13	15.45	−6.92	15.94
Slope of superior T10	−4.78	14.12	−5.74	14.98
Slope of inferior T9	−3.33	12.89	−4.20	13.89
Slope of superior T9	−1.56	11.79	−2.48	12.96
Slope of inferior T8	0.13	11.27	−0.83	12.30
Slope of superior T8	1.83	11.07	0.94	12.07
Slope of inferior T7	3.28	11.39	2.70	11.82
Slope of superior T7	5.01	11.81	4.45	11.96
Slope of inferior T6	6.11	12.28	5.76	12.27
Slope of superior T6	7.10	12.40	6.63	12.26
Slope of inferior T5	7.26	12.35	6.99	12.25
Slope of superior T5	6.84	11.77	6.87	11.83
Slope of inferior T4	5.98	11.04	6.18	11.23
Slope of superior T4	4.56	10.02	4.75	10.25
Slope of inferior T3	3.23	9.02	3.46	9.36
Slope of superior T3	1.59	8.13	1.98	8.50
Slope of inferior T2	0.52	7.72	0.99	7.99
Slope of superior T2	−0.68	7.17	−0.24	7.42
Slope of inferior T1	−1.13	6.94	−0.77	7.15
Slope of superior T1	−1.65	6.61	−1.29	6.67
Slope of inferior C7	−1.74	6.39	−1.27	6.33
Slope of superior C7	−1.82	6.13	−1.43	5.90
Obliquity of superior S1	1.92	5.27	1.74	5.64
Obliquity of inferior L5	2.93	7.59	2.80	8.08
Obliquity of superior L5	3.79	10.10	3.52	10.51
Obliquity of inferior L4	4.28	14.81	4.08	14.43
Obliquity of superior L4	3.77	16.51	3.75	16.17
Obliquity of inferior L3	1.87	18.15	1.93	17.60
Obliquity of superior L3	0.54	17.38	0.52	16.94
Obliquity of inferior L2	−2.51	15.36	−2.62	15.66
Obliquity of superior L2	−3.90	14.41	−4.20	15.04
Obliquity of inferior L1	−5.98	14.73	−6.25	15.19
Obliquity of superior L1	−6.86	15.53	−6.93	15.79
Obliquity of inferior T12	−7.81	17.16	−7.97	17.21
Obliquity of superior T12	−8.03	17.61	−8.14	17.54
Obliquity of inferior T11	−7.90	17.71	−8.31	17.74
Obliquity of superior T11	−7.25	16.97	−7.82	17.24

Continues

Supplementary Table 1. Continued

	Training Dataset		Testing Dataset	
	Mean/%	SD/N	Mean/%	SD/N
Obliquity of inferior T10	−6.20	15.97	−6.90	16.34
Obliquity of superior T10	−4.89	14.62	−5.69	15.37
Obliquity of inferior T9	−3.51	13.32	−4.18	14.32
Obliquity of superior T9	−1.80	12.17	−2.48	13.34
Obliquity of inferior T8	−0.16	11.53	−0.88	12.61
Obliquity of superior T8	1.49	11.20	0.86	12.20
Obliquity of inferior T7	2.88	11.38	2.60	11.84
Obliquity of superior T7	4.55	11.68	4.35	11.89
Obliquity of inferior T6	5.59	12.04	5.62	12.12
Obliquity of superior T6	6.60	12.14	6.50	12.09
Obliquity of inferior T5	6.77	12.08	6.86	12.12
Obliquity of superior T5	6.41	11.55	6.74	11.68
Obliquity of inferior T4	5.61	10.87	6.03	11.08
Obliquity of superior T4	4.26	9.91	4.61	10.08
Obliquity of inferior T3	2.99	8.99	3.31	9.26
Obliquity of superior T3	1.42	8.19	1.85	8.45
Obliquity of inferior T2	0.40	7.84	0.87	8.00
Obliquity of superior T2	−0.81	7.33	−0.36	7.47
Obliquity of inferior T1	−1.24	7.11	−0.89	7.26
Obliquity of superior T1	−1.75	6.79	−1.41	6.85
Obliquity of inferior C7	−1.87	6.61	−1.39	6.55
Obliquity of superior C7	−1.95	6.39	−1.53	6.16
Lateral radiographic parameters				
Sacral slope	31.46	13.03	32.63	14.22
Pelvic tilt	22.72	10.86	23.31	10.92
Pelvic incidence	54.21	13.69	55.95	14.92
Pelvic incidence minus lumbar lordosis	13.01	21.30	13.97	23.59
Lumbar lordosis L1-S1	41.15	20.83	41.97	22.43
Lumbar lordosis T12-S1	38.07	21.74	38.86	23.56
Maximal lumbar lordosis	49.65	16.92	51.26	18.06
Maximal lumbar lordosis levels				
L3-S1	22.8%	240	22.7%	102
L2-S1	21.8%	230	18.7%	84
L1-S1	12.3%	130	15.1%	68
T12-S1	10.4%	110	11.1%	50
L4-S1	10.1%	106	9.3%	42
Other	22.5%	237	23.1%	104

Continues

Supplementary Table 1. Continued

	Training Dataset		Testing Dataset	
	Mean/%	SD/N	Mean/%	SD/N
Number of levels in maximal lumbar lordosis	4.69	2.22	4.50	2.17
Thoracolumbar alignment T10-L2	−11.71	17.89	−12.31	18.72
Thoracic kyphosis T4-T12	−33.84	18.41	−33.74	19.27
Thoracic kyphosis T2-T12	−37.94	18.99	−37.42	19.89
Maximal thoracic kyphosis	−49.98	18.09	−49.98	18.54
Maximal thoracic kyphosis levels				
T1-L2	11.3%	119	9.3%	42
T1-L1	7.7%	81	8.4%	38
T1-L3	5.7%	60	4.9%	22
T2-L2	4.9%	52	4.9%	22
T2-L1	4.7%	49	4.2%	19
Other	65.7%	692	68.2%	307
Number of levels in maximal thoracic kyphosis	10.49	2.52	10.48	2.61
Sacral slope from T1	28.43	13.77	28.16	13.49
Plumbline C7 to S1 (sagittal vertical axis)	53.24	70.14	56.70	73.38
T9 spinopelvic inclination (angle between vertical and FH to T9)	−10.51	6.32	−10.09	6.79
T1 spinopelvic inclination (angle between vertical and FH to T1)	−1.84	5.85	−1.59	6.03
Angle L4-FH-S1	10.62	5.62	11.14	5.77
Angle L1-FH-S1	10.30	10.29	11.14	10.79
Angle T9-FH-S1	12.21	12.09	13.22	13.07
Angle T4-FH-S1	17.25	12.84	18.21	13.86
Angle T1-FH-S1	20.83	13.09	21.58	13.63
Angle T1-FH-L1 (T1PA-L1PA)	10.67	8.24	10.60	8.33
Apex lumbar lordosis (between S1 and L1)	22.65	0.64	22.61	0.65
Apex thoracic kyphosis (between T12 and T4)	14.82	1.10	14.87	1.16
Lumbar lordosis unfused baseline instrumentation	38.69	22.27	39.94	23.59
Lumbar lordosis number level unfused baseline instrumentation	5.06	1.85	5.01	1.93
Thoracic kyphosis unfused baseline instrumentation	−32.14	17.99	−31.97	18.71
Thoracic kyphosis number level unfused baseline instrumentation	8.36	2.06	8.24	2.28
Angle between FH-S1 and S1-L5	−41.97	19.37	−44.14	20.61

Continues

Supplementary Table 1. Continued

	Training Dataset		Testing Dataset	
	Mean/%	SD/N	Mean/%	SD/N
Angle between S1-L5 and L5-L4	14.23	10.60	14.17	11.83
Angle between L5-L4 and L4-L3	13.80	9.00	14.31	9.00
Angle between L4-L3 and L3-L2	7.09	8.90	7.53	9.39
Angle between L3-L2 and L2-L1	−1.03	8.84	−0.50	9.57
Angle between L2-L1 and L1-T12	−3.77	7.79	−4.17	8.22
Angle between L1-T12 and T12-T11	−3.78	6.54	−3.86	6.63
Angle between T12-T11 and T11-T10	−3.59	5.91	−3.71	5.89
Angle between T11-T10 and T10-T9	−2.76	5.15	−2.57	5.39
Angle between T10-T9 and T9-T8	−2.63	4.52	−2.64	4.62
Angle between T9-T8 and T8-T7	−4.05	4.16	−3.85	4.35
Angle between T8-T7 and T7-T6	−5.48	4.01	−5.34	4.12
Angle between T7-T6 and T6-T5	−5.88	3.99	−5.90	4.03
Angle between T6-T5 and T5-T4	−5.00	3.91	−4.99	3.81
Angle between T5-T4 and T4-T3	−3.88	4.20	−3.91	3.92
Angle between T4-T3 and T3-T2	−2.37	3.97	−2.07	4.01
Angle between T3-T2 and T2-T1	−0.10	3.92	−0.17	4.38
Angle between T2-T1 and T1-C7	2.37	4.39	2.59	4.14
Angle between T1-C7 and C7-C6	6.01	5.44	6.10	5.33
Angle between C7-C6 and C6-C5	4.48	6.26	4.25	6.33
Angle between C6-C5 and C5-C4	−0.11	7.15	−0.22	7.56
L5-pelvic angle	6.20	2.41	6.35	2.36
L4-pelvic angle	10.62	5.62	11.14	5.77
L3-pelvic angle	11.25	7.92	11.99	8.26
L2-pelvic angle	10.66	9.35	11.49	9.80
L1-pelvic angle	10.30	10.29	11.14	10.79
T12-pelvic angle	10.43	10.95	11.31	11.54
T11-pelvic angle	10.86	11.44	11.79	12.15
T10-pelvic angle	11.50	11.81	12.48	12.66
T9-pelvic angle	12.21	12.09	13.22	13.07
T8-pelvic angle	12.98	12.33	13.89	13.17
T7-pelvic-angle	13.86	12.53	14.77	13.40
T6-pelvic angle	14.87	12.65	15.82	13.60
T5-pelvic angle	16.07	12.82	17.03	13.81
T4-pelvic angle	17.25	12.84	18.21	13.86
T3-pelvic angle	18.52	12.96	19.41	13.85
T2-pelvic angle	19.69	12.99	20.45	13.56

SD, standard deviation; SF-36, Short-Form 36; SRS-22, Scoliosis Research Society 22; UIV, upper instrumented vertebra; LIV, lower instrumented vertebra; BP, back pain; NRS, numeric rating scale; FH, femoral head.

Continues

Supplementary Table 1. Continued

	Training Dataset		Testing Dataset	
	Mean/%	SD/N	Mean/%	SD/N
T1-pelvic angle	20.83	13.09	21.58	13.63
C7-pelvic angle	21.66	12.98	22.40	13.58
C6-pelvic angle	22.14	12.79	22.87	13.35
C5-pelvic angle	22.49	12.59	23.22	13.21
Slope of superior S1	31.63	12.01	33.03	11.92
Slope of inferior L5	19.15	13.78	20.70	13.81
Slope of superior L5	11.28	13.62	12.63	14.16
Slope of inferior L4	2.22	14.35	3.55	14.97
Slope of superior L4	−2.89	14.52	−1.67	14.66
Slope of inferior L3	−8.31	14.62	−7.41	15.09
Slope of superior L3	−10.34	14.29	−9.83	14.94
Slope of inferior L2	−12.77	14.12	−12.45	14.90
Slope of superior L2	−11.75	13.98	−11.46	14.97
Slope of inferior L1	−11.94	13.83	−11.55	15.08
Slope of superior L1	−9.52	13.91	−8.94	15.23
Slope of inferior T12	−9.05	13.89	−8.60	15.63
Slope of superior T12	−6.44	13.94	−5.82	15.90
Slope of inferior T11	−5.85	13.85	−5.13	16.07
Slope of superior T11	−3.25	13.73	−2.24	16.05
Slope of inferior T10	−2.80	13.61	−1.91	15.85
Slope of superior T10	−1.06	13.71	−0.14	15.64
Slope of inferior T9	−0.74	13.56	−0.04	15.35
Slope of superior T9	1.15	13.62	1.70	15.16
Slope of inferior T8	1.90	13.64	2.33	14.51
Slope of superior T8	4.72	13.71	5.09	14.26
Slope of inferior T7	6.17	13.56	6.42	14.02
Slope of superior T7	9.72	13.71	10.04	14.08
Slope of inferior T6	11.58	13.62	11.79	13.94
Slope of superior T6	15.27	13.84	15.51	13.98
Slope of inferior T5	17.20	13.88	17.47	14.09
Slope of superior T5	20.44	14.01	20.68	14.22
Slope of inferior T4	22.01	13.89	22.05	14.12
Slope of superior T4	24.66	13.87	24.86	14.29
Slope of inferior T3	25.77	13.84	25.82	14.12
Slope of superior T3	27.54	14.00	27.32	13.98
Slope of inferior T2	27.85	13.79	27.57	13.71
Slope of superior T2	28.66	13.86	28.24	13.81
Slope of inferior T1	28.39	13.83	27.95	13.62

Continues

Supplementary Table 1. Continued

	Training Dataset		Testing Dataset	
	Mean/%	SD/N	Mean/%	SD/N
Slope of superior T1	28.44	13.77	28.16	13.49
Slope of inferior C7	27.01	13.57	26.57	13.36
Slope of superior C7	26.47	13.25	26.21	13.18
Slope of inferior C6	23.76	12.57	23.71	12.69
Slope of superior C6	24.62	12.48	24.41	12.44
Slope of inferior C5	22.59	11.60	22.50	11.93
Slope of superior C5	25.07	11.65	24.92	11.78
Slope of inferior C4	22.70	10.88	22.14	11.12
Slope of superior C4	24.54	10.93	24.01	10.82
Jackson angle of superior S1	35.62	12.80	33.65	13.23
Jackson angle of inferior L5	48.11	16.16	46.00	17.13
Jackson angle of superior L5	55.97	16.40	54.02	18.01
Jackson angle of inferior L4	65.07	18.30	63.10	19.59
Jackson angle of superior L4	70.19	18.79	68.33	19.63
Jackson angle of inferior L3	75.60	19.56	74.09	20.53
Jackson angle of superior L3	77.63	19.58	76.52	20.65
Jackson angle of inferior L2	80.06	20.05	79.14	21.01
Jackson angle of superior L2	79.05	20.28	78.15	21.43
Jackson angle of inferior L1	79.24	20.46	78.25	21.82
Jackson angle of superior L1	76.82	20.78	75.63	22.21
Jackson angle of inferior T12	76.36	20.83	75.30	22.66
Jackson angle of superior T12	73.75	20.99	72.53	22.92
Jackson angle of inferior T11	73.17	20.88	71.82	23.09
Jackson angle of superior T11	70.56	20.77	68.93	23.21
Jackson angle of inferior T10	70.13	20.57	68.60	23.04
Jackson angle of superior T10	68.39	20.59	66.81	22.85
Jackson angle of inferior T9	68.07	20.41	66.70	22.52
Jackson angle of superior T9	66.17	20.24	64.94	22.18
Jackson angle of inferior T8	65.42	20.10	64.34	21.48
Jackson angle of superior T8	62.58	19.88	61.57	21.06
Jackson angle of inferior T7	61.13	19.59	60.25	20.78
Jackson angle of superior T7	57.58	19.57	56.61	20.68
Jackson angle of inferior T6	55.71	19.36	54.86	20.45
Jackson angle of superior T6	52.04	19.40	51.14	20.35
Jackson angle of inferior T5	50.11	19.39	49.17	20.41
Jackson angle of superior T5	46.85	19.35	45.95	20.44
Jackson angle of inferior T4	45.31	19.21	44.60	20.26
Jackson angle of superior T4	42.63	19.12	41.80	20.16

Continues

Supplementary Table 1. Continued

	Training Dataset		Testing Dataset	
	Mean/%	SD/N	Mean/%	SD/N
Jackson angle of inferior T3	41.52	19.06	40.82	19.90
Jackson angle of superior T3	39.76	19.08	39.33	19.60
Jackson angle of inferior T2	39.44	18.83	39.15	19.13
Jackson angle of superior T2	38.64	18.86	38.48	19.07
Jackson angle of inferior T1	38.88	18.84	38.79	18.89
Jackson angle of superior T1	38.82	18.78	38.57	18.68
Jackson angle of inferior C7	40.33	18.47	40.21	18.49
Jackson angle of superior C7	40.84	18.16	40.55	18.17
Jackson angle of inferior C6	43.53	17.41	43.18	17.43
Jackson angle of superior C6	42.71	17.12	42.44	17.17
Jackson angle of inferior C5	44.80	16.31	44.34	16.51
Jackson angle of superior C5	42.28	16.18	41.92	16.26

SD, standard deviation; SF-36, Short-Form 36; SRS-22, Scoliosis Research Society 22; UIV, upper instrumented vertebra; LIV, lower instrumented vertebra; BP, back pain; NRS, numeric rating scale; FH, femoral head.