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Individual differences in postoperative recovery trajectories for adult symptomatic lumbar scoliosis

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OBJECTIVE The Adult Symptomatic Lumbar Scoliosis–1 (ASLS-1) trial demonstrated the benefit of adult symptomatic lumbar scoliosis (ASLS) surgery. However, the extent to which individuals differ in their postoperative recovery trajectories is unknown. This study's objective was to evaluate variability in and factors moderating recovery trajectories after ASLS surgery.

METHODS The authors used longitudinal, multilevel models to analyze postoperative recovery trajectories following ASLS surgery. Study outcomes included the Oswestry Disability Index (ODI) score and Scoliosis Research Society–22 (SRS-22) subscore, which were measured every 3 months until 2 years postoperatively. The authors evaluated the influence of preoperative disability level, along with other potential trajectory moderators, including radiographic, comorbidity, pain/function, demographic, and surgical factors. The impact of different parameters was measured using the R^2, which represented the amount of variability in ODI/SRS-22 explained by each model. The R^2 ranged from 0 (no variability explained) to 1 (100% of variability explained).

RESULTS Among 178 patients, there was substantial variability in recovery trajectories. Applying the average trajectory to each patient explained only 15% of the variability in ODI and 21% of the variability in SRS-22 subscore. Differences in preoperative disability (ODI/SRS-22) had the strongest influence on recovery trajectories, with patients having moderate disability experiencing the greatest and most rapid improvement after surgery. Reflecting this impact, accounting for the preoperative ODI/SRS-22 level explained an additional 56%–57% of variability in recovery trajectory, while differences in the rate of postoperative change explained another 7%–9%. Among the effect moderators tested, pain/function variables—such as visual analog scale back pain score—had the biggest impact, explaining 21%–25% of variability in trajectories. Radiographic parameters were the least influential, explaining only 3%–6% more variance than models with time alone. The authors identified several significant trajectory moderators in the final model, such as significant adverse events and the number of levels fused.

CONCLUSIONS ASLS patients have highly variable postoperative recovery trajectories, although most reach steady state at 12 months. Preoperative disability was the most important influence, although other factors, such as number of levels fused, also impacted recovery.

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KEYWORDS adult spinal deformity; longitudinal data analysis; multilevel models; spine surgery; scoliosis; lumbar

ABBREVIATIONS ASLS = adult symptomatic lumbar scoliosis; ASLS-1 = Adult Symptomatic Lumbar Scoliosis–1; MCS = Mental Component Summary; ODI = Oswestry Disability Index; PCS = Physical Component Summary; SRS-22 = Scoliosis Research Society–22; VAS = visual analog scale.

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Adult spinal deformity is a major cause of disability in the United States and worldwide,[1–3] helping explain the rapid growth in deformity surgery among older adults.[4] Nonetheless, surgery for adult spinal deformity is associated with both high costs and risk of complications,[5–10] creating substantial uncertainty regarding the relative benefits of surgical versus nonoperative treatment.[11,12] To address the need for further evidence-based guidance, the Adult Symptomatic Lumbar Scoliosis–1 (ASLS-1) trial recently demonstrated substantial benefit for operative versus nonoperative treatment after 2 and 5 years.[13,14]

While the results of that study offered important evidence regarding the benefit of surgery for adult symptomatic lumbar scoliosis (ASLS), the analysis focused on final 2-year health status rather than the trajectory of postoperative recovery. Such trajectory-based analyses offer several advantages compared with those that only evaluate change from preoperative quality of life until the 2-year follow-up. First, analyses focusing only on outcome at final follow-up are subject to increase variance (i.e., “noise”) associated with one-time measurements. By using all postoperative follow-up data, longitudinal analyses provide a more comprehensive and stable view of postoperative outcome. In addition, by leveraging longitudinal models, such analyses can define a typical recovery trajectory as well as the extent to which patients vary from that typical path. Finally, longitudinal analyses can distinguish factors that moderate preoperative disability levels from those impacting postoperative change. While both types of factors are relevant to the final outcome achieved, understanding these differences can help inform patient counseling regarding their postoperative recovery. For example, some factors may slow recovery but not impact final outcome, important information for setting appropriate patient expectations.

Longitudinal analyses are rare in the spine surgery literature because they require frequent postoperative evaluations. With scheduled follow-up visits every 3 months postoperatively, the ASLS-1 study is uniquely well suited to modeling the longitudinal change in spine-related disability after surgery. Consequently, the objective of this study was to analyze the postoperative recovery trajectory following ASLS surgery and to identify factors that moderate that course.

Methods

Patient Population

The details regarding the ASLS-1 study have been described previously.[13,15] Briefly, ASLS-1 was a prospective randomized and observational study of ASLS patients 40–80 years of age who were treated at one of 9 North American centers from 2010 to 2014. Inclusion criteria included a lumbar coronal Cobb angle ≥ 30° and Oswestry Disability Index (ODI) score ≥ 20 or Scoliosis Research Society–22 (SRS-22) score ≤ 4.0 in pain, function, and/or self-image domains. The study excluded patients with past spine fusion or multilevel decompression.[13,15] In this analysis, we included all patients who received surgery, regardless of study arm or initial treatment assignment.

TABLE 1. List of variables evaluated as potential trajectory moderators

Radiographic variables
Lumbar Cobb angle
Fractional Cobb angle
Coronal balance
Sagittal balance
Pelvic tilt
No. of stenotic levels
Pain/function variables
SF-12 PCS score
SF-12 MCS score
Back VAS score
Leg VAS score
Amount of analgesic medication use
Comorbid conditions
Comorbidity sum score
Recent/current nicotine use
BMI
Demographic variables
Age
Sex
Education level
Income
Employment status
Surgical variables
No. of levels fused
No. of significant AEs
Need for revision surgery

AE = adverse event.

Predictors and Outcome Assessment

The outcomes of interest were change in preoperative ODI and SRS-22 subscore until 24 months after surgery.[16,17] We focused on these two outcomes since they represented well-accepted lumbar-specific and deformity-specific outcome measures, which also served as primary outcomes in the ASLS-1 trial. We used the 24-month follow-up period both to mirror the ASLS-1 trial and because previous results indicated that most study patients should reach their outcome plateau during that period.[13] We evaluated potential radiographic, pain/functional, demographic, comorbidity, and surgical/complication recovery modulators. A list of potential predictor variables considered as trajectory moderators are shown in Table 1. Since most patients with major medical comorbidities were excluded from the study, we used a simple comorbidity summary score where patients were assigned 1, 2, or 3 points for each mild, moderate, or severe comorbidity, respectively, noted in the ASLS data set.

Statistical Analysis

Hierarchical, longitudinal growth analysis modeled postoperative recovery trajectories. This technique models repeated outcome measures over time to separate the variance within subjects from the variability between subjects. The impact of preoperative disability level on recov-

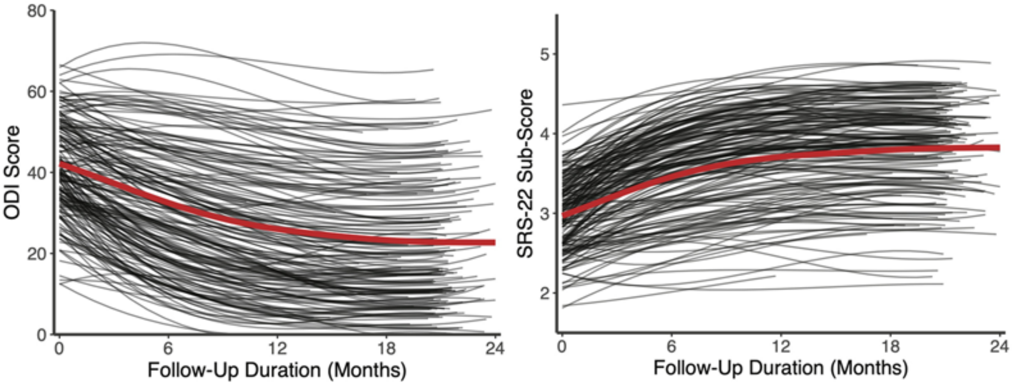

FIG. 1. Population average and individual recovery trajectories based on models with random intercepts and random slopes. Results are shown for ODI score (**left**) and SRS-22 subscore (**right**). Figure is available in color online only.

ery was first analyzed by examining trajectories stratified into three groups, defined as mean preoperative disability level (ODI or SRS-22 subscore) ± 1 standard deviation.

Next, potential trajectory moderators were investigated. Given the large number of potential moderators, model development was performed in steps. First, missing data (0.6%–14%) for the radiographic findings, SF-12 scores, and number of levels fused underwent single imputation using the missForest package.[18] This package uses nonparametric random forests—a tree-based machine learning approach—to impute missing variables based on interactions and nonlinear relationships with other model variables. There was no imputation of study outcomes. Next, pairwise correlations of continuous variables were examined to avoid variables with high collinearity. Next, separate multivariable growth models were fit for each of the five categories noted above. Variables that were statistically significant in bivariate analyses were included in their respective categorical model. For each of the five categorical models, we tested whether each moderator influenced the model intercept (i.e., starting value) and postoperative slope (i.e., change over time). Finally, composite multivariable models were created by selecting predictors that were statistically significant in each of the five categorical models. An interaction of time and presence of eventual revision surgery in the composite models was included. The goal of this sequential approach was to limit the number of variables with high collinearity (i.e., shared variance) in the final composite model, which may give the false impression that no individual variable was independently associated with the outcome.

When analyzing longitudinal data, modeling approaches vary in the extent to which they quantify individual differences in starting values and change over time. In this study, random intercepts allowed each patient to assume their own starting value for each patient-reported outcome. Multilevel models can also include a “random slope,” which models individual differences in how patient-reported outcomes change over time at the individual level. Thus, random intercepts and slopes model differences in both baseline disability and recovery from surgery. This analytical approach makes it possible to separate different sources of variance (e.g., how much variability in recovery is due to preoperative disability vs postoperative change over time).[19] Finally, expecting that change over time would assume a nonlinear form, we tested several functional forms of the data and found that a cubic polynomial transformation provided the best fit (data not shown).

Traditional (i.e., frequentist) statistical methods are often unable to estimate all parameters noted for complex, hierarchical models. Consequently, Bayesian multivariable growth models were used to avoid problems with model convergence.[20] Unlike frequentist models that provide a single point estimate for each model parameter, Bayesian models provide a distribution (a range of possible values) for each model parameter, accounting for the inherent uncertainty in those estimates. These parameter distributions are typically generated using a process known as Markov chain Monte Carlo simulation. This method is often able to produce parameter estimates that cannot be achieved when trying to “solve” for a single parameter estimate using traditional approaches.[21–23] Another distinction from traditional models is that Bayesian models incorporate “prior values” that reflect previous knowledge about likely estimates for a model parameter, which traditional models do not.[21,24] For this analysis, minimally informative priors were specified for each parameter. This approach improves model estimation by defining impossible associations (e.g., a parameter coefficient of 100 when predicting the SRS-22 subscore) while not biasing the results based on preexisting expectations.

The widely applicable information criterion and leave-one-out cross-validation selected the best fitting models, which are methods for assessing overall fit and out-of-sample accuracy of Bayesian models.[25] We considered a 95% credible interval (the Bayesian equivalent of a confidence interval) that did not include 0 as statistically significant. Model performance was examined by computing a marginal R^2, which estimates the variance in outcome explained by all model fixed effects (i.e., applying the average estimate of each model parameter to every participant). The R^2 ranges from 0 (no variance explained) to 1 (100% of variance explained). A conditional R^2, which accounts for the additional variance explained by allowing each participant to vary in their intercept and slope

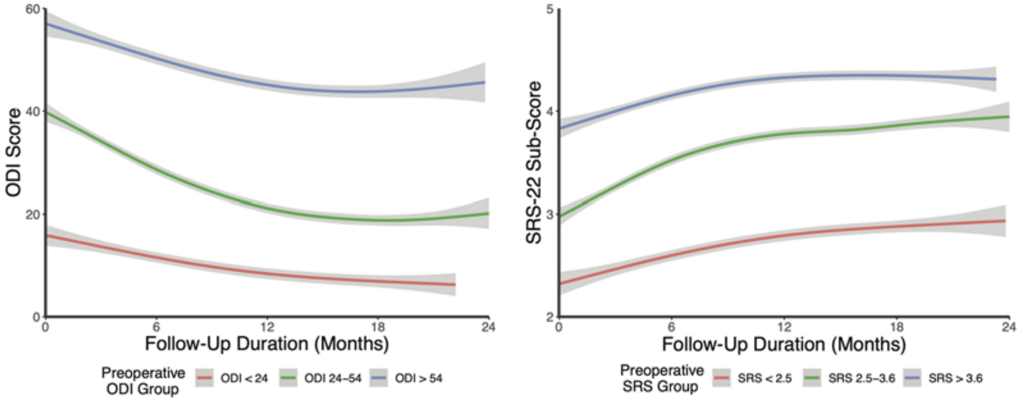

FIG. 2. Postoperative recovery trajectories stratified by preoperative disability (mean ± 1 SD). Results are shown for ODI score (**left**) and SRS-22 subscore (**right**). Figure is available in color online only.

values, was also calculated.[26] Finally, the marginal effects of select significant predictors were examined graphically, which displayed predicted change in outcome at different levels of a moderator, while holding other predictors fixed at average or reference levels.

All analyses were conducted using R version 4.0.2. The Bayesian multilevel models were fit using the brms package, and model performance was evaluated using the Performance package.[26,27] Model-predicted values for graphing were obtained using the tidybayes package.[28]

TABLE 2. Parameters included and marginal R^2 for categorical component model

	ODI	SRS-22 Subscore
Radiographic parameter		
Parameters tested†	Sagittal balance, no. of stenotic levels, lumbar Cobb angle	Fractional Cobb angle, PT, no. of stenotic levels
Marginal R^2	0.21	0.24
Pain/function parameter		
Parameters tested†	SF-12 PCS, SF-12 MCS, leg VAS, back VAS, analgesic medication	SF-12 PCS, SF-12 MCS, leg VAS, back VAS, analgesic medication
Marginal R^2	0.42	0.49
Comorbidity parameter		
Parameters tested†	BMI, nicotine use, comorbidity sum score	BMI, nicotine use, comorbidity sum score
Marginal R^2	0.24	0.28
Demographic parameter		
Parameters tested†	Education, income, employment status, age	Education, income, employment status, age
Marginal R^2	0.25	0.32
Surgical parameter		
Parameters tested†	Revision surgery, no. of significant AEs, no of levels fused	Revision surgery, no. of significant AEs
Marginal R^2	0.28	0.27
Composite model		
Parameters included‡	Time*revision surgery; no. of levels fused*time; no. of significant AEs*time; education, age*time; income; education; BMI; nicotine*time; comorbidity sum score; SF-12 PCS *time; SF-12 MCS; leg VAS; sagittal balance; lumbar Cobb; no. of stenotic levels*time	Time*revision surgery; no. of significant AEs; fractional Cobb; no. of stenotic levels*time; PT*time; income; education; employment status*time; age*time; SF-12 MCS; SF-12 PCS; back VAS*time; BMI; nicotine use; comorbidity sum score
Marginal R^2	0.50	0.57

PT = pelvic tilt.

Marginal R^2 refers to the variance explained by the fixed-effects parameters in each model (i.e., applying the population average effect to each patient). The conditional R^2, which accounted for the variance explained by allowing each patient to have their own intercept and slope, was 0.79 for ODI and 0.86 for SRS-22 subscore.

† All parameters in component models were tested with an interaction of follow-up time as a cubic polynomial.

‡ "Time" refers to months from surgery treated as a cubic polynomial. Asterisks indicate interaction of follow-up time and the variables included in the composite model.

Institutional review board approval and patient informed consent were obtained at each participating study site.

Results

Of 286 patients enrolled in the ASLS-1 study, 179 received surgery during the study period. One patient who received surgery at an outside facility and lacked surgical details was excluded from this analysis, leaving 178 eligible patients. Included patients had a mean of 20.4 ± 3.2 months of follow-up in the first 2 years after surgery, and 98% of patients had at least 12 months of postoperative follow-up. Population demographic and clinical characteristics have been reported previously but are summarized in Supplemental Table 1.

ODI Outcomes

Population average and individual patient recovery trajectories for ODI are shown in Fig. 1 left. There was substantial variability across patients in both starting disability and postoperative change, although most improvement was achieved in the first 12 months after surgery. Corresponding to the substantial individual differences, the model R^2 considering only the average starting value and average effect of time was 0.15. Allowing subjects to assume different starting values for ODI increased the R^2 to 0.72, and allowing subjects to also assume different slopes for time further increased the R^2 to 0.79.

The impact of preoperative disability was also examined graphically in Fig. 2 left. As shown in the figure, patients with moderate preoperative ODI scores (24–54) experienced the greatest and most rapid improvement. Patients with more mild (ODI < 24) or severe (ODI > 54) disability generally had slower (i.e., smaller slope) and/or less overall change in ODI.

The components included in the five models separating categories of trajectory moderators, along with the variance explained by each model, is shown in Table 2. The model for pain/function—which included SF-12 Physical Component Summary (PCS) and Mental Component Summary (MCS) scores, leg/back visual analog scale (VAS) score, and analgesic medication use—explained the most variance, with an R^2 of 0.42. By comparison, the model with radiographic parameters—sagittal balance, lumbar Cobb angle, and number of stenotic levels—explained the least variance ($R^2 = 0.21$), adding 6% compared with the model with only time.

The composite model for the variables predicting both the intercept (preoperative disability) and slope (change over time) is shown in Table 3. There were five variables that were significantly associated with preoperative ODI, including SF-12 PCS and MCS scores, ongoing or recent nicotine use, number of significant adverse events, and number of stenotic levels. Age was marginally associated with initial ODI level. Five variables were significantly associated with the recovery trajectory after surgery, including the number of adverse events, nicotine use, age, leg VAS score, and the number of levels fused. Graphical representations of select trajectory moderators are shown in Fig. 3. For example, patients with one or more significant adverse events had worse recovery, and substantial ODI differences persisted at 24 months. By comparison, patients with more levels fused had a slower initial recovery, although such difference dissipated by about 1 year postoperatively. The marginal R^2 considering the impact of these effect moderators was 0.50, meaning that these variables collectively explained 50% of variability in recovery trajectories.

TABLE 3. Parameter estimates and 95% credible intervals for factors predicting ODI

Variable	Estimate	95% CI Lower	95% CI Upper
SF-12 PCS*†	−0.724	−0.917	−0.529
SF-12 MCS*	−0.381	−0.502	−0.256
Present or recent nicotine use*†	9.594	2.987	16.544
No. of significant AEs*†	4.032	2.044	5.947
No. of levels w/ stenosis*	−1.201	−2.396	−0.066
Age†	−0.156	−0.342	0.021
Leg VAS†	−0.161	−0.710	0.387
No. of levels fused†	0.146	−0.316	0.620
BMI	0.080	−0.207	0.364
Comorbidity sum score	0.135	−0.448	0.718
Education level	−0.526	−1.609	0.569
Income $40,000–$75,000 (vs <$20,000)	2.380	−1.977	6.396
Income >$75,000 (vs <$20,000)	−0.005	−3.874	3.601
Lumbar Cobb	−0.008	−0.119	0.106
Sagittal balance	0.004	−0.030	0.037
Revision surgery	0.450	−3.180	4.208

CI = credible interval.

Parameter estimates refer to the expected change in baseline ODI for each 1-unit change in the predictor (e.g., 1-year increase in age). Parameter estimates are not reported for predictors of time, because time was modeled as a cubic polynomial, which divided the effect into three terms.

* Variables that significantly impacted the intercept (i.e., baseline ODI).

† Variables that significantly impacted the slope of time.

SRS-22 Subscore Outcomes

The average change in SRS-22 subscore along with individual variability in that trajectory is shown in Fig. 1 right. As with ODI, most improvement was achieved by 12 months postoperatively. Considering the average preoperative SRS-22 subscore and the average recovery trajectory explained 21% of the variability in overall SRS-22 subscore values ($R^2 = 0.21$). Allowing each study participant to have their own intercept (preoperative SRS-22 subscore) increased the R^2 to 0.77. Allowing subjects to have their own recovery slope further increased the R^2 to 0.86, indicating that an additional 9% of model variance was explained.

The impact of preoperative SRS-22 subscore is displayed graphically in Fig. 2 right. As with ODI, patients with moderate SRS-22 subscores (2.5–3.6) experienced the greatest and most rapid improvement compared with those with milder (SRS-22 > 3.6) or severe (SRS-22 < 2.5) disability.

The variance explained by the five models separating categories of trajectory moderators is shown in Table 2.

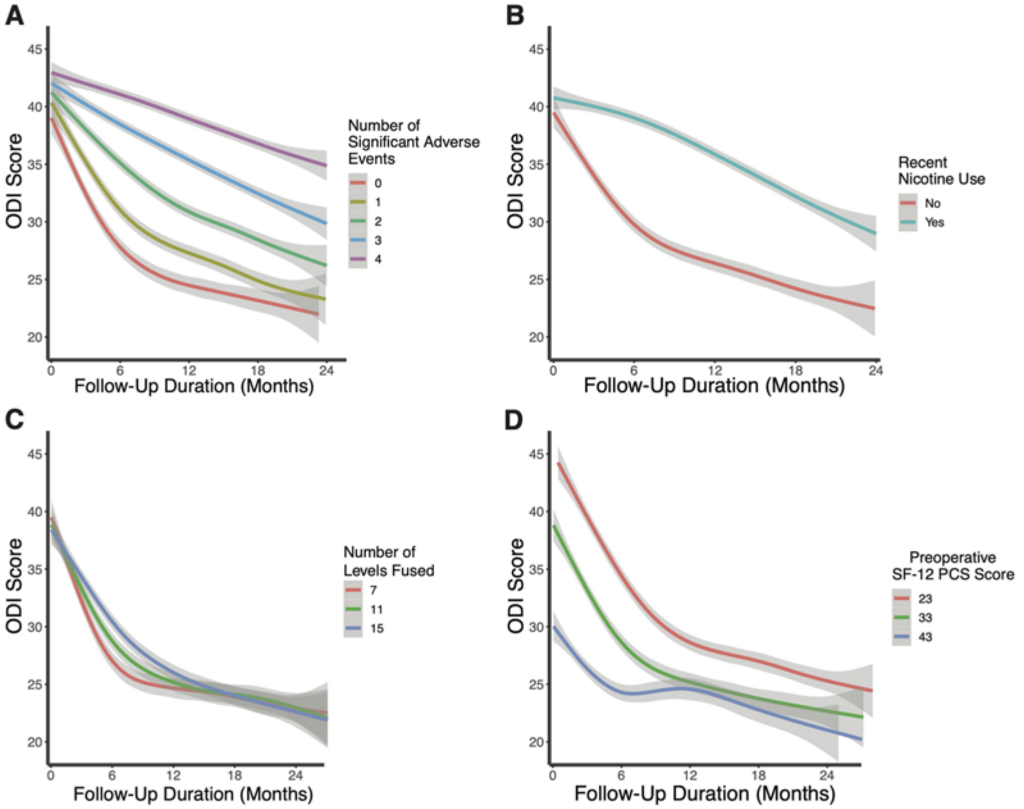

FIG. 3. Marginal effects of select ODI predictors, including significant adverse events (**A**), recent nicotine use (**B**), number of levels fused (**C**), and preoperative SF-12 PCS score (**D**). Mean values and 95% confidence intervals are shown. Figure is available in color online only.

As with ODI, radiographic parameters explained the least amount of variability in SRS-22 subscore, adding 3% compared with the model with only time ($R^2 = 0.24$). The model with pain/function parameters explained the most amount of variance ($R^2 = 0.49$). The composite model that added the radiographic, surgical, demographic, and comorbidity variables achieved an R^2 of 0.57, indicating those factors explained another 8% of variability in SRS-22 subscore. The final multivariable model for SRS-22 subscore is shown in Table 4. Several factors, including age, level of education, number of adverse events, and SF-12 MCS and PCS scores, were significantly associated with preoperative SRS-22 subscores. By comparison, age, significant adverse events, number of stenotic levels, and back VAS score were significantly associated with the rate of postoperative recovery. The impact of variables that significantly affected the recovery trajectory is displayed graphically in Fig. 4. For example, patients with worse VAS back pain had more severe preoperative disability but ultimately achieved higher function at 24 months than those with lower VAS back pain scores. By comparison, patients with more stenotic levels experienced more rapid early improvement but had similar function to those without stenosis at 24 months. A comparison of items significantly associated with intercept and slope values for ODI and SRS-22 subscore is shown in Supplemental Fig. 1.

Discussion

Leveraging the high-frequency follow-up from a large, multicenter study, we evaluated the trajectory of postoperative recovery following surgery for ASLS. We found that, on average, ASLS patients experienced a marked and sustained improvement in the ODI score and SRS-22 subscore, with most improvement seen by 12 months postoperatively. However, patients had substantial variability in their recovery trajectories, with most differences explained by patients' levels of preoperative disability. Patients with moderate preoperative disability experienced the greatest and most rapid improvement, and we identified other factors, such as the number of levels fused and significant adverse events, that also impacted recovery paths.

While the ASLS-1 study's primary results demonstrated the overall benefit of surgery for ASLS after 2 years,[13,29] the growing focus on personalized care emphasizes the need to advise patients on factors likely to impact their individual experience.[30] Most spine outcomes studies have focused on net symptom change at final follow-up.[15,31–33] While limited attempts have been made to model recovery trajectories, those studies had important limitations, including an inability to separate factors that impacted preoperative disability from those that affected change after surgery.[34–36] Using a hierarchical modeling approach, we were able to address those shortcomings and distinguish

TABLE 4. Parameter estimates and 95% credible intervals for factors predicting SRS subscore

Variable	Estimate	95% CI Lower	95% CI Upper
Age*†	0.009	0.001	0.016
SF-12 PCS*	0.023	0.017	0.028
SF-12 MCS*	0.024	0.020	0.028
No. of significant AEs*†	−0.098	−0.170	−0.030
Education level*	0.043	0.008	0.075
No. of levels w/ stenosis†	0.037	−0.004	0.078
Back VAS†	0.010	−0.019	0.039
PT	0.005	−0.002	0.012
BMI	−0.003	−0.012	0.006
Comorbidity sum score	−0.003	−0.021	0.016
Fractional Cobb	0.002	−0.002	0.006
Not working full time	0.026	−0.101	0.150
Income $40,000–$75,000 (vs <$20,000)	−0.088	−0.216	0.035
Income >$75,000 (vs <$20,000)	−0.003	−0.129	0.125
Present or recent nicotine use	−0.019	−0.209	0.171
Revision surgery	0.030	−0.105	0.168

Parameter estimates refer to the expected change in baseline SRS subscore for each 1-unit change in the predictor (e.g., 1-year increase in age). Parameter estimates are not reported for time because time was modeled as a cubic polynomial, which divided the effect into three terms.
* Variables that significantly impacted the intercept (i.e., baseline ODI).
† Variables that significantly impacted the slope of time.

factors that impacted both preoperative disability level and recovery rate.

By leveraging the high-frequency follow-up in the ASLS-1 study, we found that most variability in recovery trajectories (72%–77%) was explained by differences in preoperative ODI scores and SRS-22 subscores. This is a novel finding and, to our knowledge, provides the first quantification of the degree to which preoperative disability level shapes postoperative recovery from ASLS surgery. In particular, patients with moderate preoperative ODI scores and SRS-22 subscores experienced the greatest and most rapid improvement after surgery, a finding relevant to counseling patients considering surgery. We also examined the impact of pain intensity and SF-12 PCS and MCS scores to capture the influence of other health conditions on physical and mental health, which may be particularly important in complex deformity patients. Consistent with the strong influence of preoperative ODI scores and SRS-22 subscores, preoperative measures of physical and mental health and pain explained the greatest variability among the recovery moderators tested. Notably, while patients with worse mental health (lower SF-12 MCS scores) had worse preoperative disability, they did not differ in their recovery trajectories. This result offers insight into a long-standing question regarding the role of mental health in deformity surgery[15,37,38] and suggests that worse mental health does not affect response to surgery, after accounting for patients' preoperative levels of disability.

Although the pain/function parameters explained substantial variability in recovery trajectories, other domains with a weaker association with preoperative ODI scores and SRS-22 subscores had a much lower influence. For example, the radiographic variables only added 3%–6% more variance than models with only time. This weak association may partly reflect the relative homogeneity of radiographic deformity, as well as the consistent surgical correction performed across study sites. Nonetheless, this finding also suggests that while worse radiographic deformity may be associated with more severe disability, after accounting for clinical disease severity, radiographic parameters alone have only a small impact on patient outcomes. This finding is consistent with previous studies showing that many patients remain asymptomatic or minimally symptomatic from radiographic lumbar scoliosis.[2] Similarly, the modest impact of comorbid conditions—explaining 6%–9% more variability than models with only time—also likely reflected the intentional exclusion of patients with severe comorbid disease.

While not explaining a large amount of overall model variance, several significant recovery moderators provided important insights that are relevant to individual patients. For example, recent nicotine users had notably worse recovery trajectories than nonusers, consistent with previous findings.[39,40] This finding provides surgeons with concrete data to inform current/recent nicotine users that they are likely to both experience a more prolonged recovery than nonusers and still achieve worse functional outcome, a novel conclusion from this analysis. In addition, we found that patients with more levels fused can expect greater disability initially after surgery, but these differences are largely gone by 12 months postoperatively. Lastly, patients with significant adverse events typically had slightly more severe preoperative disability but substantially worse recovery trajectories. Collectively, these results offer surgeons an expanded ability to counsel patients in the preoperative setting and continue to guide their expectations through their postoperative recovery. The heterogeneity of outcomes and recovery trajectories, as seen in Fig. 1, emphasize the difficulty of using the means to counsel patients and encourage further development of personalized care pathways.

This study has several limitations. First, because all operative patients were deemed to be appropriate candidates for complex deformity surgery, caution should be used when extrapolating these findings to broader populations of adult spine deformity patients. Second, recovery trajectories are affected by the follow-up window evaluated. We limited follow-up to 24 months to both mirror the primary ASLS-1 analysis and avoid added heterogeneity from diverse effects farther from surgery. Consequently, these results should be interpreted within that context. Finally, this study was a secondary analysis of a data set powered for a comparative effectiveness clinical trial. Therefore, these results should be considered exploratory until verified in future studies.

Conclusions

On average, ASLS patients experienced a sizable and

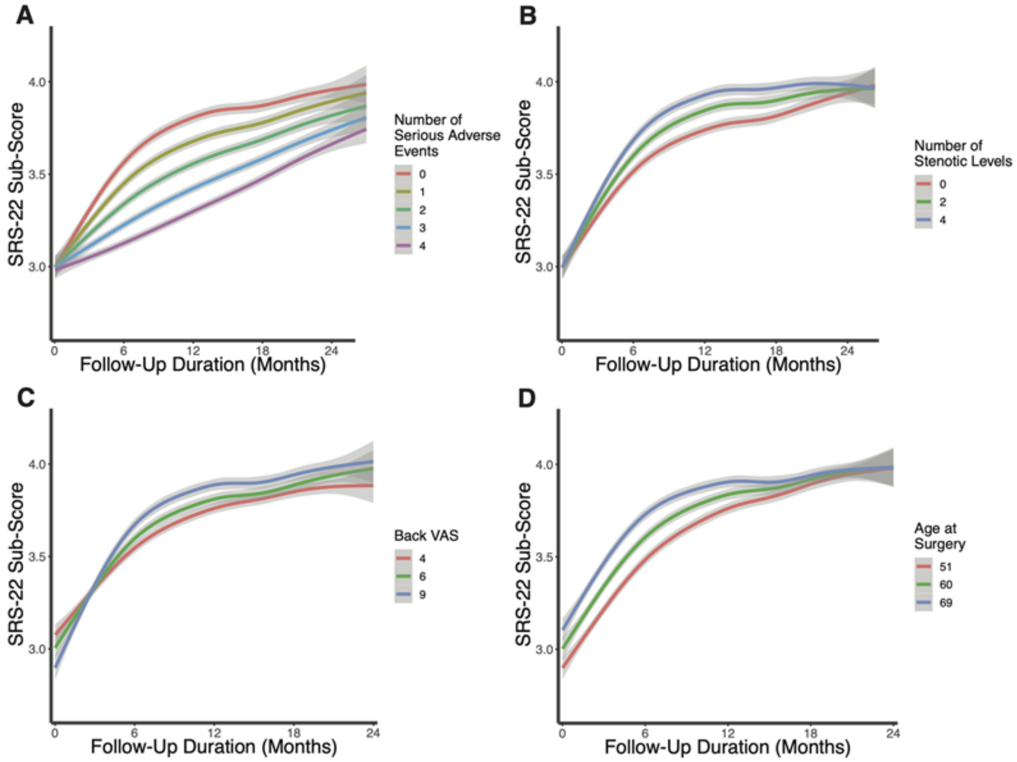

FIG. 4. Marginal effects of select SRS subscore predictors, including significant adverse events (**A**), number of stenotic levels (**B**), back VAS score (**C**), and age at surgery (**D**). Mean values and 95% confidence intervals are shown. Figure is available in color online only.

sustained improvement in ODI scores and SRS-22 subscores within 24 months of surgery, with most gains achieved by 12 months postoperatively. However, there is substantial variability in recovery trajectories, where the most and least disabled have slower rates of change and less average change. While not explaining a large degree of overall variability, other variables, such as nicotine use and significant adverse events, also significantly affected recovery trajectories for certain patients. Despite their central role in selecting surgical candidates and operative approaches, radiographic parameters explained the least variability in postoperative recovery.

Acknowledgments

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Supplemental Information

Online-Only Content

Supplemental material is available with the online version of the article.

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Conception and design: Greenberg, Kelly. Acquisition of data: Bess, Smith, Lenke, Shaffrey, Bridwell. Analysis and interpretation of data: all authors. Drafting the article: Greenberg. Critically revising the article: all authors. Reviewed submitted version of manuscript: all authors. Approved the final version of the manuscript on behalf of all authors: Greenberg. Statistical analysis: Greenberg. Administrative/technical/material support: Kelly, Bridwell. Study supervision: Kelly, Bridwell.

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