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Clinical Study

Social determinants of health and disparities in spine surgery: a 10-year analysis of 8,565 cases using ensemble machine learning and multilayer perceptron

David Shin, BS[a], Jacob Razzouk, BS[a], Jonathan Thomas, MD[b], Kai Nguyen, BS[a], Andrew Cabrera, BS[a], Daniel Bohen, BS[c], Shaina A. Lipa, MD[d], Christopher M. Bono, MD[e], Christopher I. Shaffrey, MD[f], Wayne Cheng, MD[g], Olumide Danisa, MD[h,*]

[a] *Loma Linda University School of Medicine, 11175 Campus St, Loma Linda, 92350 CA, USA*
[b] *Department of Ophthalmology, Loma Linda University, 11370 Anderson St #1800, 92354, Loma Linda, CA, USA*
[c] *Information Sciences Institute, University of Southern California, 4676 Admiral Way #1001, 90292, Los Angeles, CA, USA*
[d] *Department of Orthopaedic Surgery, Brigham and Women's Hospital, Harvard Medical School, 75 Francis St, 02115, Boston, MA, USA*
[e] *Department of Orthopaedic Surgery, Massachusetts General Hospital, Harvard Medical School, 55 Fruit St, 02114, Boston, MA, USA*
[f] *Department of Neurosurgery, Duke University Medical Center, 40 Duke Medicine Cir Suit 1554, 27710, Durham, NC, USA*
[g] *Division of Orthopaedic Surgery, Jerry L. Pettis Memorial Veterans Hospital, 11201 Benton St, 92357, Loma Linda, CA, USA*
[h] *Department of Orthopaedic Surgery, Loma Linda University Medical Center, 11234 Anderson St, 92354, Loma Linda, CA, USA*

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Abstract

BACKGROUND CONTEXT: The influence of SDOH on spine surgery is poorly understood. Historically, researchers commonly focused on the isolated influences of race, insurance status, or income on healthcare outcomes. However, analysis of SDOH is becoming increasingly more nuanced as viewing social factors in aggregate rather than individually may offer more precise estimates of the impact of SDOH on healthcare delivery.

PURPOSE: The aim of this study was to evaluate the effects of patient social history on length of stay (LOS) and readmission within 90 days following spine surgery using ensemble machine learning and multilayer perceptron.

STUDY DESIGN: Retrospective chart review.

PATIENT SAMPLE: 8,565 elective and emergency spine surgery cases performed from 2013 to 2023 using our institution's database of longitudinally collected electronic medical record information.

OUTCOMES MEASURES: Patient LOS, discharge disposition, and rate of 90-day readmission.

METHODS: Ensemble machine learning and multilayer perceptron were employed to predict LOS and readmission within 90 days following spine surgery. All other subsequent statistical analysis was performed using SPSS version 28. To further assess correlations among variables,

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*Corresponding author. Department of Orthopaedic Surgery, Loma Linda University, 25805 Barton Road A106, Loma Linda, CA, 92354, USA.

E-mail address: odanisa@yahoo.com (O. Danisa).

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Pearson's correlation tests and multivariate linear regression models were constructed. Independent sample *t*-tests, paired sample *t*-tests, one-way analysis of variance (ANOVA) with *post-hoc* Bonferroni and Tukey corrections, and Pearson's chi-squared test were applied where appropriate for analysis of continuous and categorical variables.

RESULTS: Black patients demonstrated a greater LOS compared to white patients, but race and ethnicity were not significantly associated with 90-day readmission rates. Insured patients had a shorter LOS and lower readmission rates compared to non-insured patients, as did privately insured patients compared to publicly insured patients. Patients discharged home had lower LOS and lower readmission rates, compared to patients discharged to other facilities. Marriage decreased both LOS and readmission rates, underweight patients showcased increased LOS and readmission rates, and religion was shown to impact LOS and readmission rates. When utilizing patient social history, lab values, and medical history, machine learning determined the top 5 most-important variables for prediction of LOS —along with their respective feature importances—to be insurance status (0.166), religion (0.100), ICU status (0.093), antibiotic use (0.061), and case status: elective or urgent (0.055). The top 5 most-important variables for prediction of 90-day readmission—along with their respective feature importances—were insurance status (0.177), religion (0.123), discharge location (0.096), emergency case status (0.064), and history of diabetes (0.041).

CONCLUSIONS: This study highlights that SDOH is influential in determining patient length of stay, discharge disposition, and likelihood of readmission following spine surgery. Machine learning was utilized to accurately predict LOS and 90-day readmission with patient medical history, lab values, and social history, as well as social history alone.

Keywords: Artificial intelligence; Length of stay; Machine learning; Race; Readmission; Social determinants of health; Spine surgery

Introduction

In 2011, approximately 1 million patients underwent spinal surgery, with spinal fusion with instrumentation being the most expensive procedure performed in terms of aggregate costs for hospital stays [1]. More recently in 2018, spinal fusion with instrumentation retained its position as the most expensive spinal procedure, totaling $14.1 billion in aggregate costs [2]. Frequency and costs of spinal surgeries continue to rise [3,4] and this has warranted investigation into the variability of costs as well as opportunities to diminish spending [5−8]. Patient length of stay (LOS) and readmissions have also contributed heavily to such costs [9−12] (approximately 25% to 54% of costs in lumbar spinal fusion surgery[13,14] and similar percentages in anterior cervical discectomy and fusion) [15,16]. In addition to contributing to costs, patient LOS and readmissions have been used by hospitals, insurance carriers, and medical administrators as metrics to assess the effectiveness of treatment [17,18].

The social determinants of health (SDOH) are now a focal point of interest, with evidence demonstrating how non-medical factors can affect treatment and surgical outcomes [19,20]. Spinal surgery is no exception [21], with disparities found in post-surgical satisfaction, patient reported outcome measures (PROMs), and in-hospital mortality due to race, insurance status, education level, and other socioeconomic and demographic factors [22−25]. Several studies have attempted to identify and better address the impact of social factors on spine surgery LOS and readmission rates [21,26−29]. Historically, studies have commonly focused on the isolated influences of race, insurance status, and other social factors on healthcare outcomes. Although evaluating individual social factors in isolation helps to identify important findings, social determinants of health are seldom, if ever, isolated. *Intersectionality* is the framework for studying how overlapping or intersecting social identities and related factors interact and contribute to an individual's experience [30,31]. The application of intersectionality in quantitative health disparities research has yet to be standardized, but its importance to the evaluation of healthcare inequities is clear [32,33]. The influence of SDOH on patients undergoing spine surgery is still being investigated. It is essential such analyses become increasingly more nuanced, as viewing social factors in aggregate rather than individually may offer more precise estimates of the impact of SDOH on healthcare delivery and spine surgery outcomes. The aim of this study is to evaluate the effects of patient social history on length of stay (LOS) and readmission within 90 days following spine surgery using multivariate logistic regression, ensemble machine learning, and multilayer perceptron.

Methods

Following IRB approval (blinded), we analyzed 8,565 elective and emergency spine surgeries performed from 2013 to 2023 using our institution's database of longitudinally collected electronic medical record information. Ensemble machine learning and multilayer perceptron were employed to predict LOS and readmission within 90 days following spine surgery. The following patient information was included in our analysis: patient race and ethnicity, age, sex, body mass index, smoking status, preferred language, religion, marital status, insurance coverage plan type, medical comorbidities, lab values, and discharge disposition. The following perioperative details were included in our analysis: case type (elective or emergency), add-on status, case scheduling, lab values, delay in surgery, and time in relation to the COVID-19 pandemic.

Artificial intelligence modeling

We constructed a deep neural network using PyTorch, with architecture and hyperparameter decisions guided by Bayesian optimization and hyperband (BOHB) multi-fidelity optimization. Meta-learning and hyperparameter optimization were used to support ensemble machine learning (EML) model construction, including 17 distinct scikit-learn classification model types, with the final model being a combination of hundreds of sub-models. Ensemble methods provide greater accuracy compared to the single-model approaches widely, yet often inappropriately used within current clinical research practices [24−26]. For each model, a stratified 70/30 train test split was used with the initial architecture search performed using Hyperopt, a Python library built for automatic model selection and hyperparameter optimization. Hyperopt uses meta-learning based on Bayesian optimization methods to provide solutions in a combined algorithm selection and hyperparameter optimization approach. Hyperopt evaluated the performance of linear regression, random forest, extra trees, stochastic gradient descent, ada boost, k-nearest-neighbors, gaussian naive bayes, bernoulli naive bayes, and multi-layer perceptron (MLP) algorithms for 10,000 iterations each. The best performing model for prediction of all outcomes was determined to be MLP. Having one model type consistently perform superior across all outcomes—as opposed to different models performing better for various outcomes—is favorable in terms of performance as it signifies the MLP model type performed well on the underlying distribution of the features, rather than performing well based on the distribution of outcomes.

Prior to AI analysis of our patient population, variables containing missing data greater than 33% were excluded from analysis. A K-nearest-neighbors (KNN) imputation method was applied to the remainder of missing data within each feature. KNN imputation utilizes related cases, or neighbors, to estimate missing data with values as close to the true value as possible. This methodology preserves feature relationships by leveraging information within the dataset [50]. To assess ML model performance, the following standard metrics were evaluated: area under the receiver operating characteristic curve (AUROC), accuracy, balanced accuracy, precision, recall, and F1 score. In determining our testing and training datasets, we utilized scikit-learn's stratified k-fold cross-validation function, with 10 folds [27]. The training data set was randomly divided into ten subsets with equally distributed classes. Of the ten folds, nine folds were used in the training process, and the remaining fold were used for model validation. This process was repeated ten times, with each of the tenfold cross-validations being used once for model validation. A single estimation was produced from the average of the ten results. We used 70% of the data for training, and the remaining 30% for model validation.

Stratified cross-validation in addition to methods built into Auto-sklearn 2.0 and Auto-PyTorch model selection processes were used to prevent instances of overfitting. Auto-sklearn 2.0 supports automatic feature pre-processing, feature selection, kernel approximation, matrix decomposition, embeddings, feature clustering, polynomial feature expansion, and methods that use a classifier for feature selection [28,29]. All subsequent statistical analysis was performed using SPSS version 28 (IBM Corporation, 2021, Armonk, NY, USA) with statistical significance defined as $p<.05$ and AUROC scores of 0.7 to 0.8 considered to be acceptable and 0.8 to 0.9 to be considered as outstanding [34]. Descriptive statistics utilized means and standard deviations (SD). Homoscedasticity was assessed using homogeneity of variance tests and regression residual plots [31]. Q-Q plots and Kolmogorov-Smirnov tests was used to assess for normality of data [32,33]. To further assess correlations among variables, Pearson's correlation tests and multivariate linear regression models were constructed. Independent sample *t*-tests, paired sample *t*-tests, one-way analysis of variance (ANOVA) with *post-hoc* Bonferroni and Tukey corrections, and Pearson's chi-squared test were applied where appropriate for analysis of continuous and categorical variables.

Results

Of the 8,565 cases included in the study, 4,164 were performed by neurosurgery and 4,401 were performed by orthopedic spine surgery. Differences in scheduling and LOS based on surgical subspecialty are listed in Table 1. The different procedure types for all 8,565 patients and the discharge disposition for 6,443 patients—the 3 most common being home, rehab facility, and skilled nursing facility—are listed in Table 2. Regarding add-on status, 1,550 were add-on cases and the remaining 7,015 were not. Regarding case length accuracy, 4,156 were under scheduled, 2,664 were overscheduled, 1,522 were accurately scheduled, and for 223 cases the case length accuracy was not listed.

The age of patients was categorized into 18-35, 36-50, 51-64, and 65+ years old. 4,112 patients were male, 4,239 were female, and for 214 this information was not available. Regarding race, 6,338 were listed as White, 725 were classified as Black, 308 were listed as Asian, 893 identified as other, and for 302 patients this data was not available. Regarding ethnicity, 2,375 identified as Hispanic or Latino, 5,886 were not Hispanic or Latino, and for 304 patients this data was not available. 7,629 patients listed English as their preferred language and the most common insurance types were public plans of Medicare and Medicaid HMO, as well

Table 1
Differences in scheduling and length of stay based on surgical specialty

	Neurosurgery		Orthopaedic spine		Mean difference	p
	Mean	SD	Mean	SD		
Day of surgery to day of discharge	6.10	9.91	5.68	5.87	0.42	**.036**
Day of admission to day of discharge	7.78	12.54	6.96	7.22	0.82	**.001**
Day of case request to day of surgery	32.20	36.09	37.12	40.84	−4.92	**<.001**
Delay in scheduled surgery start time (min)	28.58	59.23	22.90	56.21	5.68	**<.001**

p value < 0.05, indicating statistical significance.

as private PPO (Table 3 displays the languages, religions, marital statuses, and insurance plan types of the patients within this study). Regarding smoking status, 1,116 were current smokers at time of surgery, 2,485 were former smokers, 4,663 never smoked, and for 301 patients this data was not available. A complete analysis of missing data rates is listed in Table 4. Mean time from day of surgery to day of discharge, day of admission to day of discharge, day of case request to day of surgery, and delay in scheduled surgery start time were 5.84 ± 7.43 days, 7.20 ± 8.61 days, 34.72 ± 38.68 days, and 25.66 ± 57.76 minutes, respectively.

Home discharge rates

Table 5 showcases home discharge rates based on patient demographics.

Race and Ethnicity: Analyses determined that Black patients showcased lower odds of home discharge, with 49% of Black patients discharged home compared to 68% of non-Black patients (OR = 0.599, 95% CI = 0.497−0.723, p<.001). White patients had higher odds of home discharge compared to non-White patients, with 61.8% of White patients who underwent spinal surgery discharged to home (OR = 1.258, 95% CI = 1.103−1.436, p<.001). Asian patients, when compared to non-Asian patients, demonstrated lower odds of home discharge, with 53% of Asian patients discharged home compared to 61% of non-Asian patients (OR = 0.727, 95% CI = 0.539−0.981, p=.036).

Preferred language: Patients who preferred another language, compared to those who preferred English, had lower odds of home discharge (OR = 0.765, 95% CI = 0.625 −0.938, p<.010).

Insurance status: Patients who held private insurance had increased odds of home discharge, compared to those with government/public insurance (OR=2.558, 95% CI = 2.261−2.895, p<.001).

Age: the oldest age group of 65+ was associated with the lowest odds of home discharge, with 49.4% discharged home (OR = 0.499, 95% CI = 0.445−0.559, p<.001) in comparison to the other age groups.

Table 2
Procedure types and discharge locations

Procedure type	n	Discharge locations	n
Posterior cervical decompression	**271**	Home	4,133
Discectomy	2	Skilled Nursing Facility	671
Laminoplasty	87	Intermediate Care Facility	2
Laminectomy	182	Children's Hospital	6
Posterior cervical decompression and fusion	**921**	Left Against Medical Advice	15
Anterior cervical decompression and fusion	**1,134**	Short Term Hospital	63
Cervical disc Arthroplasty	**76**	Death	62
Anterior thoracolumbar fusion	**816**	Inpatient	6
ALIF	481	Federal Hospital	8
XLIF	335	Medical Facility with Hospice	4
Lumbar disc Arthroplasty	**9**	Rehab Facility	1372
Posterior thoracolumbar decompression	**2,057**	Long Term Care	75
Lumbar Microdiscectomy	230	Psychiatric Hospital	1
Laminectomy	1,827	Another Health Care Institution	4
Posterior approach thoracolumbar fusion	**2400**	Unspecified	21
Other (infection, trauma, tumor, congenital)	**881**		
Irrigation and debridement	44		
Thoracic Sympathectomy	28		
Laminectomy, tumor	200		
Laminectomy, tethered cord release	116		
Thoracolumbar Kyphoplasty with fixation	206		
Fusion, Sacroiliac Joint	52		
Cervical laminectomy with stereotactic suboccipital craniectomy for Chiari malformation	213		

p value < 0.05, indicating statistical significance.

Table 3
Patient preferred language, religion, marital status, and insurance coverage plan type

Preferred Language	n	Religion	n	Marital Status	n
Arabic	14	Apostolic Church	14	Single	2834
Bengali	1	Baptist	344	Significant Other	90
Bulgarian	3	Buddhist	37	Married	3905
Cambodian	1	Catholic	1,981	Divorced	819
Mandarin	6	Christian	2,182	Widowed	625
English	7629	Church of Jesus Christ of Latter-Day Saints	133	Primary Coverage Plan Type	n
Farsi	6	Episcopalian	25	*Private*	
Hindi	1	Greek Orthodox	13	EPO	31
Ilocano	1	Hindu	14	HMO	599
Indonesian	3	Jehovah's Witness	82	HMO POS	27
Japanese	1	Jewish	76	Indemnity	241
Korean	14	Lutheran	109	POS	89
Panjabi/Punjabi	2	Methodist	80	PPO	1107
Portuguese	1	Muslim	50	PPO POS	7
Romanian	2	Nazarene	4	*Government/Public*	
Russian	1	Nondenominational	728	CCS	107
Sign Language	4	Pentecostal	43	MCAL HMO	1457
Spanish	605	Presbyterian	47	MCR HMO	866
Tagalog	9	Protestant	419	MCR PFFS	14
Tamil	1	Seventh Day Adventist	341	MCR PPO	23
Thai	1	Atheist	21	Medicaid	2
Tonga (Nyasa)	1	Agnostic	1,311	MediCal	379
Vietnamese	19	Patient Refused to Answer	18	Medicare	1418
Not Listed	28	Not Listed	279	*Uninsured*	76

Marital status: Single, divorced, and widowed patients had decreased odds of home discharge. Our analysis revealed that 56% of single patients, 52% of divorced patients, and 54% of widowed patients were discharged home, compared to 62% for nonsingle, non-divorced, and non-widowed patients respectively (Single OR = 0.775, 95% CI = 0.684−0.879, p<.001; Divorced OR = 0.669, 95% CI = 0.556−0.791, p<.001; Widowed OR = 0.515, 95% CI = 0.424−0.625, p<.001). On the other hand, married patients had increased odds of home discharge, with 67% discharged home, compared to approximately 53% of nonmarried patients (OR = 1.784, 95% CI = 1.596−1.994, p<.001).

Hospital scheduling and length of stay based on patient social history

The length of stay (LOS) and time to surgery were assessed based on patient social history utilizing the mean difference (MD) between reference and comparison groups for different hospital scheduling characteristics. These included "day of surgery to day of discharge," "day of admission to day of discharge," "day of case request to day of surgery," and "delay in scheduled surgery start time (minutes)." Social factors that significantly impacted LOS, included, but was not limited to, race & ethnicity, preferred language, insurance status, discharge disposition, age, sex, marital status, and religion. Table 6 showcases a full breakdown of hospital scheduling and LOS based on patient social history.

Race and ethnicity: Black patients demonstrated a greater LOS compared to non-Black patients, as well as a shorter time between case requests to surgery. On the other hand, White patients had a lower LOS compared to non-White patients, but a longer time between case request to surgery and shorter delays in scheduled surgery start time. Direct comparison between Black and White patients revealed an MD of 1.14 (p=.003) for "day of surgery to day of discharge," an MD of 1.73 (p<.001) for "day of admission to day of discharge," and an MD of −4.42 (p=.016) for "day of case request to day of surgery." Additionally, when comparing Hispanic or Latino patients to non-Hispanic or Latino patients, Hispanic or Latino patients exhibited a 1 to 2 day longer LOS.

Preferred language: A greater LOS was also revealed for patients who preferred a language other than English when compared to those who preferred English, with an MD of 2.29 (p<.001) for "day of surgery to day of discharge" and an MD of 3.05 (p<0.001) for "day of admission to day of discharge," and subsequent decrease in time between case request to surgery and increase in delays in scheduled surgery start time.

Insurance status: Uninsured patients had greater LOS compared to insured patients. The MD was 4.08 (p<.001) for "day of surgery to day of discharge," 6.21 (p<.001) for "day of admission to day of discharge," and included a 17 day shorter time from case request to surgery. Additionally, government/public insured patients had a greater LOS compared to privately insured patients. The MD was 1.62 (p<.001) for "day of surgery to day of discharge" and 2.17 (p<.001) for "day of admission to day of discharge."

Discharge disposition: Patients who died postoperatively had a longer LOS by 11.84 days post-surgery and

Table 4
Missing data rates

Variable	Missing rate
Age	0.69%
Sex	2.50%
Race	3.50%
Ethnicity Hispanic	3.55%
Marital status	3.65%
Preferred language	2.62%
Religion	2.62%
Insurance type	26.23%
Ventilator use	21.67%
Vasopressor use	21.67%
Steroids	21.67%
ICU admission	21.67%
Antibiotic use	21.67%
Case status	9.79%
Smoking	3.51%
Covid	0.69%
Add on case	0.00%
Comorbid and chronic conditions	
Asthma	0.00%
Arthritis	0.00%
Scoliosis	0.00%
Hypercholesterolemia	0.00%
Osteoporosis	0.00%
Hyperlipidemia	0.00%
CHF	0.00%
COPD	0.00%
Hypertension	0.00%
Diabetes	0.00%
Cirrhosis	0.00%
End stage renal disease	0.00%
Emphysema	0.00%
Preoperative lab values	
Hemoglobin A1C	89.08%
Procalcitonin	93.34%
Lactate	86.69%
ALT	72.63%
AST	72.40%
Total bilirubin	72.41%
Albumin	72.01%
INR	64.21%
HCO3	63.87%
Sodium	43.06%
BUN	27.66%
Creatinine	27.49%
Potassium	43.08%
Glucose	38.24%
Platelets	31.58%
WBC	31.54%
Hemoglobin	31.54%
Case length	0.00%
Delay in case length	3.49%
Discharge location	26.23%

14.52 days measured from day of admission, compared to patients who lived postoperatively and were discharged. Furthermore, there was an MD of -25.65 (p<.001) for “day of case request to day of surgery” and an MD of 40.05 (p<.001) for “delay in scheduled surgery start time (minutes).” Patients discharged home had a decreased LOS, compared to those who were discharged to other locations, such as a skilled nursing facility (SNF) and rehab facility. However, patients discharged to an SNF had a longer LOS compared to other locations, and when compared to a rehab facility, had longer LOS by 1.86 and 2.66 days from post-surgery and day of admission respectively.

BMI: Underweight (BMI < 18.5 kg/m^2) patients had increased LOS compared to non-underweight patients with a MD of 5.23 (p<.001) for “day of surgery to day of discharge” and MD of 6.58 (p<.001) for “day of admission to day of discharge.”

Age: A greater LOS was found in the youngest age group of 18 to 35, compared to other age groups, as well as a decrease in time between case requests to surgery and increase in delays in scheduled surgery start time. Regarding sex, males exhibited a greater LOS, decreased time from case request to day of surgery, and increased delay in scheduled surgery start time when compared to females.

Marital status: Unmarried patients had a greater LOS compared to those who were married. Additionally, single patients had a greater LOS when compared to not only married patients, but also to widowed and divorced patients. Single patients, compared to widowed patients, had an MD of 1.38 (p<.001) for “day of surgery to day of discharge” and 1.62 (p<.001) for “day of admission to day of discharge.” When compared to divorced patients, they had an MD of 1.55 (p<.001) for “day of surgery to day of discharge” and 1.98 (p<.001) for “day of admission to day of discharge,” in addition to subsequent decreases in “day of case request to day of surgery” and increases in “delay in scheduled surgery start time (minutes).”

Religion: Agnostic patients had increased LOS when compared to non-agnostic patients, which included all other measured religions and atheists. For Muslim patients, a greater LOS and delay in surgery start time was found, but the LOS change postsurgery was insignificant.

Readmission within 90 days based on patient social history

794 patients were readmitted in the 90 days following their surgery, out of 8565 total patients. Table 7 shows readmission within 90 days based on patient social history.

Insurance status: Privately insured patients had lower odds of readmission compared to other types of insurance (OR: 0.595, 95% CI: 0.501−0.708, p<.001), while government/public insured patients had higher odds of readmission (OR: 1.736, 95% CI: 1.462−2.061, p<.001).

Discharge disposition: Patients discharged home had lower odds of readmission (OR: 0.459, 95% CI: 0.394−0.535, p<.001) compared to locations other than home. Patients discharged to SNF had much higher odds of readmission (OR: 2.004, 95% CI: 1.644−2.444, p<.001) than other locations, and patients discharged to rehab facility also had higher odds of readmission than locations other than rehab facilities (OR: 1.696, 95% CI: 1.441−1.995, p<.001).

Table 5
Home discharge rates based on characteristics of patient social history

Patient Characteristic	No	Yes	p	OR	95% CI
Race					
Not African American	**1,826**	**2,948**	**<.001**	**0.599**	**0.497−0.723**
African American	**246**	**238**			
Not Asian	**1,988**	**3,091**	**.036**	**0.727**	**0.539−0.981**
Asian	**84**	**95**			
Not Caucasian	**509**	**655**	**<.001**	**1.258**	**1.103−1.436**
Caucasian	**1,563**	**2,531**			
Not other	1,893	2,864	.077	1.189	0.982−1.440
Other	179	322			
Ethnicity					
Not Hispanic or Latino	1,535	2,394	.548	0.962	0.847−1.092
Hispanic or Latino	532	798			
Sex					
Female	980	1,592	.068	0.903	0.808−1.008
Male	1,109	1,626			
Smoking Status					
Never smoker	1,004	1,563	.936	1.005	0.899−1.122
Former or current smoker	1,050	1,642			
Preferred Language					
Prefers ENGLISH	**1903**	**2994**	**.010**	**0.765**	**0.625−0.938**
Prefers other language	**186**	**224**			
Marital Status					
Not single	**1,500**	**2,467**	**<.001**	**0.775**	**0.684−0.879**
Single	**589**	**751**			
Not married	**1,179**	**1,354**	**<.001**	**1.784**	**1.596−1.994**
Married	**910**	**1,864**			
Not divorced	**1,787**	**2,891**	**<.001**	**0.669**	**0.566−0.791**
Divorced	**302**	**327**			
Not widowed	**1,843**	**3,011**	**<.001**	**0.515**	**0.424−0.625**
Widowed	**246**	**207**			
Does not have significant other	2,066	3,180	.790	1.073	0.638−1.807
Has significant other	23	38			
Insurance Status					
Insured	2,139	3,244	.996	1.001	0.614−1.632
Uninsured	27	41			
Government/public	**1,665**	**1,877**	**<.001**	**2.558**	**2.261−2.895**
Private	**474**	**1,367**			
Body Mass Index					
Not underweight	1,139	1,948	.107	0.676	0.419−1.091
Underweight	32	37			
Not normal weight	**789**	**1,496**	**<.001**	**0.675**	**0.576−.792**
Normal weight	**382**	**489**			
Not overweight/preobese	799	1326	.408	1.067	0.915−1.246
Overweight/preobese	372	659			
Not class 1 obesity	**934**	**1516**	**.027**	**1.219**	**1.022−1.454**
Class 1 obesity	**237**	**469**			
Not Class 2 obesity+	**1,023**	**1,654**	**.002**	**1.383**	**1.122−1.705**
Class 2 obesity+	**148**	**331**			
Age					
Not 18−35	**1,958**	**2,878**	**.001**	**1.338**	**1.121−1.597**
18−35	**207**	**407**			
Not 35−50	**1,880**	**2,640**	**<.001**	**1.612**	**1.385−1.875**
35−50	**285**	**645**			
Not 51−64	**1,467**	**2,005**	**<.001**	**1.342**	**1.197−1.504**
51−64	**698**	**1,280**			
Not 65+	**1,190**	**2,332**	**<.001**	**0.499**	**.445−.559**
65+	**975**	**953**			

p value < 0.05, indicating statistical significance.

BMI: Underweight patients were associated with higher rates of readmission compared to non-underweight patients (OR: 3.396, 95% CI: 2.036−5.663, p<.001).

Age: Patients 35-50 had lower rates of readmission than other age groups, (OR: 0.765, 95% CI: 0.617−0.947, p<.014), while patients 65+ had higher rates of readmission

Table 6
Mean Differences (MD) in Hospital Scheduling and Length of Stay based on Patient Social History

Patient characteristic		Day of surgery to day of discharge		Day of admission to day of discharge		Day of case request to day of surgery		Delay in scheduled surgery start time (min)	
Reference (R) group	Comparison (C) group	MD (R - C)	p	MD (R - C)	p	MD (R - C)	p	MD (R - C)	p
Race									
African American	*Not African American*	1.05	<.001	1.60	<.001	−3.98	.007	3.86	.114
Asian	*Not Asian*	−0.08	.877	−0.07	0908	−5.19	.022	1.81	.630
Caucasian	*Not Caucasian*	−0.85	<.001	−1.27	<.001	3.66	<.001	−7.45	<.001
Other	*Not Other*	0.70	.028	1.00	0010	−1.53	.277	10.53	<.001
Caucasian	*African American*	−1.14	.003	−1.73	<.001	4.42	.016	−5.12	.222
	Asian	−0.11	1.000	−0.21	1.000	5.80	.063	−3.34	1.000
	Other	−0.82	.064	−1.18	0014	2.17	.754	−11.15	<.001
African American	*Caucasian*	1.14	.003	1.73	<.001	−4.42	0016	5.12	.222
	Asian	1.03	0500	1.52	0 212	1.38	1.000	1.78	1.000
	Other	0.32	1.000	0.55	1.000	−2.24	1.000	−6.03	.375
Asian	*Caucasian*	0.11	1.000	0.21	1.000	−5.80	.063	3.34	1.000
	African American	−1.03	.500	−1.52	.212	−1.38	1.000	−1.78	1.000
	Other	−0.71	1.000	−0.97	1.000	−3.62	.972	−7.81	.420
Other	*Caucasian*	0.82	.064	1.18	.014	−2.17	.754	11.15	<.001
	African American	−0.32	1.000	−0.55	1.000	2.24	1.000	6.03	.375
	Asian	0.71	1.000	0.97	1.000	3.62	0972	7.81	.420
Ethnicity									
Hispanic or Latino	*Non-Hispanic or Latino*	1.23	<.001	1.51	<.001	−2.51	.008	5.70	<.001
Sex									
Male	*Female*	0.91	<.001	1.40	<.001	−4.75	<.001	4.77	<.001
Smoking status									
Never	*Former*	0.76	<.001	1.02	<.001	−4.14	<.001	4.13	.019
	Current	0.28	.854	0.13	1	2.42	.129	−0.28	1
Former	*Never*	−0.76	<.001	−1.02	<.001	4.14	<.001	−4.13	.019
	Current	−0.48	.232	−0.89	.024	6.56	<.001	−4.41	.106
Current	*Never*	−0.28	.854	−0.13	1	−2.42	.129	0.28	1
	Former	0.48	.232	0.89	.024	−6.56	<.001	4.41	.106
Preferred language									
Prefers other language	*Prefers English*	2.29	<.001	3.05	<.001	−4.46	.005	5.86	.027
Marital Status									
Single	*Not Single*	1.64	<.001	2.19	<.001	−5.64	<.001	5.82	<.001
Married	*Not Married*	−1.21	<.001	−1.71	<.001	2.83	<.001	−3.36	.014
Divorced	*Not Divorced*	−0.37	.200	−0.40	.259	3.82	.003	−4.12	.057
Widowed	*Not Widowed*	−0.17	.617	0.01	.980	−0.66	.650	−1.63	.502
Has significant other	*Does Not*	−0.18	.836	−0.18	.864	−0.27	.944	12.70	.041
Single	*Widowed*	1.38	.001	1.62	.002	−3.66	0.235	5.90	.288
	Married	1.80	<.001	2.46	<.001	−5.58	<.001	5.96	.003
	Divorced	1.55	<.001	1.98	<.001	−7.65	<.001	8.06	.011
	Significant Other	1.40	1.000	1.81	.839	−4.00	1.000	−8.14	1.000
Widowed	*Single*	−1.38	.001	−1.62	.002	3.66	.235	−5.90	.288
	Married	0.43	1.000	0.83	.425	−1.92	1.000	0.06	1.000
	Divorced	0.17	1.000	0.36	1.000	−3.99	.306	2.17	1.000
	Significant Other	0.02	1.000	0.19	1.000	−0.34	1.000	−14.03	.328
Married	*Single*	−1.80	<.001	−2.46	<.001	5.58	<.001	−5.96	.003
	Widowed	−0.43	1.000	−0.83	.425	1.92	1.000	−0.06	1.000
	Divorced	−0.25	1.000	−0.47	1.000	−2.08	1.000	2.11	1.000
	Significant Other	−0.40	1.000	−0.65	1.000	1.57	1.000	−14.10	.235
Divorced	*Single*	−1.55	<.001	−1.98	<.001	7.65	<.001	−8.06	.011
	Widowed	−0.17	1.000	−0.36	1.000	3.99	.306	−2.17	1.000
	Married	0.25	1.000	0.47	1.000	2.08	1.000	−2.11	1.000
	Significant Other	−0.15	1.000	−0.17	1.000	3.65	1.000	−16.20	.124
Significant other	*Single*	−1.40	1.000	−1.81	.839	4.00	1.000	8.14	1.000
	Widowed	−0.02	1.000	−0.19	1.000	0.34	1.000	14.03	.328
	Married	0.40	1.000	0.65	1.000	−1.57	1.000	14.10	.235
	Divorced	0.15	1.000	0.17	1.000	−3.65	1.000	16.20	.124

Table 6 (***Continued***)

Patient characteristic		Day of surgery to day of discharge		Day of admission to day of discharge		Day of case request to day of surgery		Delay in scheduled surgery start time (min)	
Reference (R) group	Comparison (C) group	MD (R - C)	p	MD (R - C)	p	MD (R - C)	p	MD (R - C)	p
Insurance status									
Uninsured	*Insured*	4.08	<.001	6.21	<.001	−17.01	<.001	12.17	.092
Private	*Not Private*	−1.69	<.001	−2.27	<.001	3.16	.001	−1.10	.522
Government/public	*Not Government/ Public*	1.43	<.001	1.89	<.001	−2.16	.024	0.41	.811
Uninsured	*Private*	5.15	<.001	7.65	<.001	−18.90	<.001	12.75	.245
	Government/Public	3.53	<.001	5.48	<.001	−16.05	<.001	11.88	.305
Private	*Uninsured*	−5.15	<.001	−7.65	<.001	18.90	<.001	−12.75	.245
	Government/Public	−1.62	<.001	−2.17	<.001	2.85	.009	−0.87	1.000
Government/public	*Uninsured*	−3.53	<.001	−5.48	<.001	16.05	<.001	−11.88	.305
	Private	1.62	<.001	2.17	<.001	−2.85	.009	0.87	1.000
Discharge disposition									
home	*Other than home*	−4.51	<.001	−6.13	<.001	13.47	<.001	−11.25	<.001
Died postoperatively	*Lived Postoperatively*	11.84	<.001	14.52	<.001	−25.65	<.001	40.05	<.001
SNF	*Home*	5.33	<.001	7.23	<.001	−13.98	<.001	11.42	<.001
	AMA	2.68	1.000	2.00	1.000	−1.76	1.000	6.15	1.000
	Rehab Facility	1.86	<.001	2.66	<.001	−2.58	1.000	2.64	1.000
	Other	−4.74	<.001	−7.93	<.001	13.70	<.001	−18.56	.005
	Death	−8.29	<.001	−9.72	<.001	17.02	.002	−33.09	<.001
Home	*SNF*	−5.33	<.001	−7.23	<.001	13.98	<.001	−11.42	<.001
	AMA	−2.65	1.000	−5.22	.094	12.22	1.000	−5.27	1.000
	Rehab Facility	−3.47	<.001	−4.57	<.001	11.40	<.001	−8.78	<.001
	Other	−10.07	<.001	−15.16	<.001	27.68	<.001	−29.99	<.001
	Death	−13.63	<.001	−16.94	<.001	31.00	<.001	−44.51	<.001
AMA	*SNF*	−2.68	1.000	−2.00	1.000	1.76	1.000	−6.15	1.000
	Home	2.65	1.000	5.22	.094	−12.22	1.000	5.27	1.000
	Rehab Facility	−0.82	1.000	0.66	1.000	−0.81	1.000	−3.51	1.000
	Other	−7.42	<.001	−9.93	<.001	15.47	1.000	−24.71	1.000
	Death	−10.97	<.001	−11.72	<.001	18.79	.731	−39.24	.344
Rehab facility	*SNF*	−1.86	<.001	−2.66	<.001	2.58	1.000	−2.64	1.000
	Home	3.47	<.001	4.57	<.001	−11.40	<.001	8.78	<.001
	AMA	0.82	1.000	−0.66	1.000	0.81	1.000	3.51	1.000
	Other	−6.60	<.001	−10.59	<.001	16.28	<.001	−21.20	<.001
	Death	−10.15	<.001	−12.38	<.001	19.60	<.001	−35.73	<.001
Other	*SNF*	4.74	<.001	7.93	<.001	−13.70	<.001	18.56	.005
	Home	10.07	<.001	15.16	<.001	−27.68	<.001	29.99	<.001
	AMA	7.42	<.001	9.93	<.001	−15.47	1.000	24.71	1.000
	Rehab Facility	6.60	<.001	10.59	<.001	−16.28	<.001	21.20	<.001
	Death	−3.55	.003	−1.79	1.000	3.32	1.000	−14.53	1.000
Death	*SNF*	8.29	<.001	9.72	<.001	−17.02	.002	33.09	<.001
	Home	13.63	<.001	16.94	<.001	−31.00	<.001	44.51	<.001
	AMA	10.97	<.001	11.72	<.001	−18.79	.731	39.24	.344
	Rehab Facility	10.15	<.001	12.38	<.001	−19.60	<.001	35.73	<.001
	Other	3.55	.003	1.79	1.000	−3.32	1.000	14.53	1.000
Religion									
Catholic	*Not Catholic*	0.37	.098	0.53	.052	0.18	.857	0.40	.808
Nondenominational	*Not Nondenominational*	−0.39	.047	−0.65	.006	0.42	.624	−1.50	.295
Baptist	*Not Baptist*	−0.92	.039	−1.08	.044	2.53	.198	−2.82	.388
Church of Jesus Christ of latter-day Saints	*Not Church of Jesus Christ of Latter-Day Saints*	−0.34	.666	−0.59	.535	3.12	.353	0.46	.935
Jehovah's witness	*Not Jehovah's Witness*	0.53	.560	1.31	.234	−0.40	.921	−6.52	.339
Jewish	*Not Jewish*	−0.28	.773	0.60	.614	4.59	.255	0.80	.905
Lutheran	*Not Lutheran*	−1.43	.082	−2.16	.030	3.27	.333	−5.80	.301
Methodist	*Not Methodist*	−0.91	.356	−1.29	.280	3.61	.365	−5.55	.410
Muslim	*Not Muslim*	1.45	.241	3.64	.015	−7.03	.177	20.97	.016
Protestant	*Not Protestant*	−0.23	.575	−0.65	.183	2.86	.109	2.10	.479

Table 6 (***Continued***)

Patient characteristic		Day of surgery to day of discharge		Day of admission to day of discharge		Day of case request to day of surgery		Delay in scheduled surgery start time (min)	
Reference (R) group	Comparison (C) group	MD (R - C)	p	MD (R - C)	p	MD (R - C)	p	MD (R - C)	p
Seventh day adventist	*Not Seventh Day Adventist*	−0.42	.387	−0.01	.981	−3.18	.106	−4.26	.194
Agnostic	*Not Agnostic*	0.62	.016	0.89	.005	−2.83	.013	4.04	.033
Atheist	*Not Atheist*	−2.44	.348	−3.37	.284	−7.62	.413	−11.91	.457
Body mass index									
Underweight (BMI < 18.5 kg/m^2)	*Not Underweight*	5.23	<.001	6.58	<.001	−6.55	.079	4.84	.429
Normal weight (18.5 kg/m^2 < BMI < 24.9 kg/m^2)	*Not Normal weight*	0.78	<.001	1.26	<.001	−5.71	<.001	2.77	.153
Overweight/preobese (25.0 kg/m^2 < BMI < 29.9 kg/m^2)	*Not Overweight/ Preobese*	−0.28	.176	−0.46	0.077	1.58	0.166	−0.07	0.970
Class 1 obesity (30.0 kg/m^2 <BMI<34.9kg/m^2)	*Not Class 1 Obese*	−0.77	.001	−1.13	<.001	5.28	<.001	−3.59	.079
Class 2+ obesity (35.0 kg/m^2 < BMI)	*Not Class 2+ Obesity*	−0.56	.039	−0.75	0.025	−0.24	.873	0.07	.978
Age									
18−35	*Not 18−35*	1.58	<.001	1.78	<.001	−8.02	<.001	9.88	<.001
35−50	*Not 35−50*	−0.02	.951	0.06	.838	−2.21	.040	−2.90	.104
51−64	*Not 51−64*	−0.37	.050	−0.50	.030	2.95	<.001	0.42	.768
65+	*Not 65+*	−0.31	.111	−0.31	.189	1.80	.032	−2.79	.046

than other age groups (OR: 1.244, 95% CI: 1.067−1.452, p<.005).

Marital status: Married patients had lower odds of readmission compared to unmarried patients (OR: 0.805, 95% CI: 0.691−0.937, p<.005). Additionally, widowed patients had higher rates of readmission than nonwidowed patients (OR: 1.63, 95% CI: 1.282−2.071, p<.001).

Religion: Non-denominational patients had lower odds of readmission (OR: 0.784, 95% CI: 0.665−0.923, p<.003) compared to those who were not of the non-denominational faith.

Model performance in prediction of readmission and LOS

One ML model analyzed LOS using patient medical, lab values, and social history, while a separate ML model analyzed LOS using solely socioeconomic factors. The same was done for readmission within 90 days. Table 8 shows the model performance in prediction of readmission and LOS. Table 9 showcases the features of importance of LOS and readmission using patient social history, lab values, and medical history. Table 10 showcases the features of importance of LOS and readmission using only patient social history.

Predicting LOS based on social history alone, the ML model achieved a balanced accuracy of 0.624, an AUROC of 0.747, accuracy of 0.665, precision of 0.681, recall of 0.374, and F1 score of 0.483. Predicting readmission based on social history alone, the model achieved a balanced accuracy of 0.559, an AUROC of 0.727, accuracy of 0.862, precision of 0.582, recall of 0.134, and F1 score of 0.218.

When considering patient social history, lab values, and medical history, the top 5 most-important variables for prediction of LOS—along with their respective feature importances—were determined to be insurance status (0.166), religion (0.100), ICU status (0.093), antibiotic use (0.061), and case status: elective or urgent (0.055). This was followed by race and ethnicity, with a feature importance of 0.044. The top 5 most-important variables for prediction of 90-day readmission—along with their respective feature importances—were insurance status (0.177), religion (0.123), discharge location (0.096), emergency case status (0.064), and history of diabetes (0.041). Race and ethnicity had a feature importance of 0.018, and LOS had a feature importance of 0.010.

Discussion

We examined the impact of patient social history on length of stay (LOS) and readmission within 90 days following spinal surgery. Our findings demonstrate numerous social factors that influence LOS and readmission rates. These findings are aligned with previous research that cite race, insurance status, and discharge disposition as primary

Table 7
Readmission within 90 days based on characteristics of patient social history

Patient Characteristic	No	Yes	p	OR	95% CI
Race					
Not African American	4,125	711	.152	0.815	0.617−1.078
African American	434	61			
Not Asian	4,404	747	.818	0.951	0.619−1.461
Asian	155	25			
Not Caucasian	1,029	156	.144	1.151	0.953−1.390
Caucasian	3,530	616			
Not other	4,119	702	.610	0.933	0.716−1.216
Other	440	70			
Ethnicity					
Not Hispanic or Latino	3,414	564	.272	1.102	0.927−1.309
Hispanic or Latino	1,143	208			
Sex					
Female	2,221	382	.661	0.967	0.830−1.125
Male	2,382	396			
Smoking Status					
Never smoker	2,229	366	.423	1.064	0.914−1.240
Former or current smoker	2,323	406			
Preferred Language					
Prefers English	4,236	729	.106	0.776	0.570−1.056
Prefers other language	367	49			
Marital Status					
Not single	3,443	564	.173	1.126	0.949−1.336
Single	1,160	214			
Not Married	**2,176**	**410**	**.005**	**0.805**	**0.691−0.937**
Married	**2,427**	**368**			
Not divorced	4,051	692	.454	0.912	0.717−1.161
Divorced	552	86			
Not widowed	**4,241**	**683**	**<.001**	**1.63**	**1.282−2.071**
Widowed	**362**	**95**			
Does not have significant other	4,552	766	.297	1.398	0.742−2.635
Has significant other	51	12			
Insurance Status					
Insured	**4,665**	**790**	**.038**	**0.358**	**0.130−0.985**
Uninsured	**66**	**4**			
Other insurance	**3,074**	**601**	**<.001**	**0.596**	**0.501−0.708**
Private	**1,657**	**193**			
Other insurance	**1,723**	**197**	**<.001**	**1.736**	**1.462−2.061**
Government/public	**3,008**	**597**			
Discharge Disposition					
Discharged to location other than home	**1,725**	**441**	**<.001**	**0.459**	**0.394−0.535**
Discharged home	**2,940**	**345**			
Discharged to location other than SNF	**4,168**	**637**	**<.001**	**2.004**	**1.644−2.444**
Discharged to SNF	**506**	**155**			
Discharged to location other than rehab facility	**3,605**	**527**	**<.001**	**1.696**	**1.441−1.995**
Discharged to rehab facility	**1,069**	**265**			
Religion					
Not Catholic	3,593	592	.223	1.118	0.935−1.337
Catholic	1,010	186			
Not Nondenominational	**2,946**	**540**	**.003**	**0.784**	**0.665−0.923**
Nondenominational	**1,657**	**238**			
Not Baptist	4,378	752	.059	0.673	0.445−1.017
Baptist	225	26			
Not church of Jesus Christ of latter-day saints	4,540	762	.140	1.513	0.869−2.633
Church of Jesus Christ of latter-day saints	63	16			
Not jehovah witness	4,555	768	.545	1.236	0.623−2.453
Jehovah witness	48	10			
Not Jewish	4,557	773	.342	0.641	0.254−1.618
Jewish	46	5			
Not lutheran	4,543	767	.803	1.086	0.568−2.075
Lutheran	60	11			
Not methodist	4,559	773	.395	0.67	0.265−1.695

Table 7 (***Continued***)

Patient Characteristic	No	Yes	p	OR	95% CI
Methodist	44	5			
Not Muslim	4577	773	.791	1.139	0.436−2.974
Muslim	26	5			
Not protestant	4,350	722	.059	1.334	0.998−1.800
Protestant	253	56			
Not seventh day adventist	**4,436**	**735**	**.011**	**1.554**	**1.102−2.192**
Seventh day adventist	**167**	**43**			
Not agnostic	3,879	660	.690	0.958	0.775−1.183
Agnostic	724	118			
Not atheist	4,597	777	.990	0.986	0.119−8.202
Atheist	6	1			
Body Mass Index					
Not underweight	**2,710**	**399**	**<.001**	**3.396**	**2.036−5.663**
Underweight	**46**	**23**			
Not normal weight	1,988	311	.504	0.924	0.732−1.165
Normal weight	768	111			
Not overweight/preobese	1,850	291	.455	0.919	0.737−1.147
Overweight/preobese	906	131			
Not class 1 obesity	2,144	324	.641	1.06	0.831−1.351
Class 1 obesity	612	98			
Not class 2 obesity+	2,332	363	.455	0.894	0.666−1.199
Class 2 obesity+	424	59			
Age					
Not 18−35	4,201	698	.455	1.092	0.866−1.377
18−35	529	96			
Not 35−50	**3,901**	**683**	**.014**	**0.765**	**0.617−0.947**
35−50	**829**	**111**			
Not 51−64	2,999	523	.181	0.898	0.766−1.052
51−64	1731	271			
Not 65+	**3,089**	**478**	**.005**	**1.244**	**1.067−1.452**
65+	**1,641**	**316**			

p value < 0.05, indicating statistical significance.

contributors to spine surgery related LOS [21,35−38]. Our data demonstrates Black and Hispanic or Latino patients experience longer LOS, while White patients experience shorter LOS. Additionally, direct comparison between Black and White patients revealed approximately a one-day longer LOS after surgery, and an almost two-day longer LOS from day of admission, suggesting direct disparities between these racial groups. In terms of insurance status, our analysis found that uninsured patients had a 4 to 6 day longer LOS compared to insured patients. When directly comparing uninsured patients to privately insured patients, uninsured patients had a greater LOS of over a week from day of admission to day of discharge. Such findings indicate not only the importance of insurance in patient LOS, but also the benefits of private insurance when compared to other types.

Our findings for 90-day readmission rates showcased similarities to LOS. However, there were some irregularities and newly described relationships. While insurance status, discharge disposition, BMI, age, marital status, and religion were found to be significant variables in increasing readmission rates, race was not among these factors, which differed from some findings in current literature [13,39−41]. Privately insured patients had lower readmission rates, in line with previous findings [13], with our data showcasing how 10.4% of privately insured patients were readmitted compared to 16.56% of government/public insured patients. A notable exception, however, was that our data found uninsured patients had lower readmission rates compared to insured patients, with only 5% of uninsured patients being readmitted compared to 16% of insured patients (p<.038). However, the total uninsured data set consisted of 70

Table 8
Model performance in prediction of readmission and LOS

Modeling	AUROC	Accuracy	Balanced accuracy	Precision	Recall	F1 score
LOS − patient medical history, labs, and social history	0.859	0.684	0.714	0.579	0.894	0.703
LOS − patient social history only	0.747	0.665	0.624	0.681	0.374	0.483
Readmission - patient medical, social, and labs	0.781	0.889	0.681	0.951	0.164	0.279
Readmission - patient social only	0.727	0.862	0.559	0.582	0.134	0.218

Table 9
Features of importance for prediction of length of stay and readmission within 90 days using patient social history, lab values, and medical history

Readmission				Length of stay − patient medical, social, and labs			
Feature	Feature importance	Feature	Feature importance	Feature	Feature importance	Feature	Feature importance
Insurance status	0.177	Age	0.010	Insurance Status	0.166	Lab Value: Sodium	0.011
Religion	0.123	Preferred Language	0.010	Religion	0.100	History of Hyperlipidemia	0.011
Discharge location	0.096	History of Hyperlipidemia	0.010	ICU Status	0.093	History of Scoliosis	0.011
Case status: emergency	0.064	Lab Value: Potassium	0.010	Antibiotic Use	0.061	Readmission within 90 Days	0.010
History of diabetes	0.041	Ventilator Use	0.010	Case Status: Elective or Urgent	0.055	Length of Surgery Delay in Minutes	0.010
Case length	0.038	Lab Value: Creatinine	0.010	Race and Ethnicity	0.044	Lab Value: Platelet	0.010
Case status: elective or urgent	0.023	LOS	0.010	Case Length	0.033	Lab Value: BUN	0.010
History of ESRD	0.023	History of Arthritis	0.010	Case Status: Emergency	0.031	History of Hypercholesterolemia	0.010
Lab value: Platelet	0.021	Lab Value: Sodium	0.010	Ventilator Use	0.031	Lab Value: Creatinine	0.010
Lab value: WBC	0.021	Marital Status	0.010	Add on Status	0.028	Lab Value: Potassium	0.010
Lab value: HGB	0.020	Vasopressor Use	0.009	Marital Status	0.025	Lab Value: Glucose	0.009
Lab value: glucose	0.019	Antibiotic Use	0.009	Vasopressor Use	0.019		
Race and ethnicity	0.018	Lab Value: BUN	0.009	Preferred Language	0.018	Lab Value: HGB	0.009
History of CHF	0.018	Add on Status	0.009	Smoking Status	0.018	Age	0.009
History of osteoporosis	0.016	Length of Surgery Delay in Minutes	0.009	Steroid Use	0.017	Lab Value: WBC	0.009
History of emphysema	0.015	Smoking Status	0.009	Lab Value: Platelet	0.016	Sex	0.009
History of COPD	0.015	History of Hypertension	0.008	Lab Value: HGB	0.015	History of COPD	0.009
History of scoliosis	0.014	ICU Status	0.008	Lab Value: WBC	0.013	History of Hypertension	0.008
Time period: before or after COVID-19	0.014	Sex	0.008	History of CHF	0.011	History of Cirrhosis	0.000
History of cirrhosis	0.013			History of Arthritis	0.011	History of Diabetes	0.000
Steroid use	0.011			History of Asthma	0.011	History of Emphysema	0.000
History of hypercholesterolemia	0.011			Time Period: Before or after COVID-19	0.011	History of ESRD	0.000
History of asthma	0.011			Lab Value: Glucose	0.011	History of Osteoporosis	0.000

Table 10
Features of importance for prediction of length of stay and readmission within 90 days using patient social history only

Readmission		Length of stay − social only	
Feature	Feature importance	Feature	Feature importance
Religion	0.312	Insurance Type	0.264
Insurance type	0.199	Add on Status	0.111
Discharge location	0.129	Case Status: Emergency	0.101
Marital status	0.070	Case Length	0.092
Case status: emergency	0.062	Case Status: Elective or Urgent	0.091
Case status: elective or urgent	0.050	Religion	0.081
Case length	0.048	Marital Status	0.055
Preferred language	0.039	Race and Ethnicity	0.047
Race and ethnicity	0.020	Readmission within 90 Days	0.032
Time period: before or after COVID-19	0.012	Length of Surgery Delay in Minutes	0.030
Age	0.011	Preferred Language	0.022
Length of surgery delay in minutes	0.011	Time Period: Before or after COVID-19 Pandemic	0.021
Smoking status	0.010	Age	0.020
LOS	0.010	Smoking Status	0.017
Add on status	0.009	Sex	0.015
Sex	0.009		

patients compared to 5455 insured patients, which could plausibly account for the lower readmission rate.

In terms of BMI, 33% of underweight patients were readmitted, compared to approximately 13% of patients of all other BMIs. Underweight patients also demonstrated increased LOS, while obese patients demonstrated lower LOS and did not seem to possess significantly different readmission rates. This relationship could possibly connect to literature that suggests obesity may not always adversely influence long-term surgical outcomes [46,47], and an underweight BMI is a risk factor for poor surgical outcomes [48,49].

Additionally, our study investigated relationships that have not been precisely determined by previous research, such as how LOS differs based on relationship status and religion [39]. Marital status, both current and past, seemed to correlate with a shorter LOS. Married patients did not exhibit a statistically significant (p=1.000) lower LOS when compared to those who were divorced or widowed, and single patients had a longer LOS compared to divorced and widowed patients. In terms of readmission, married patients had lower odds of readmission compared to unmarried patients, with 16% of unmarried patients being readmitted compared to 13% of married patients (p<.001). Additionally, widowed patients had higher rates of readmission compared to nonwidowed patients. While religion was shown to impact LOS and readmission rates, effects seemed to fluctuate depending on the different types of religious affiliation and was not uniform between LOS and readmission. Research has shown that a patient's religious beliefs significantly impact their lifestyle choices and behaviors, such as dietary restrictions, alcohol and tobacco use, and accepting medical recommendations [51]. One study found that patients with stronger religious beliefs had fewer complications and shorter LOS after undergoing heart surgery [52]. However, an additional study found a significant positive association between dimensions of religiousness and surgical fear [53]. The associations demonstrated in the literature, in conjunction with our results and religion's impact on machine learning model performance, highlight the importance of religion in a healthcare setting. Given that numerous patients rely on their faith during challenging healthcare choices [54], it is essential for professionals to place an emphasis on cultural and social competence and customize their assessment and care according to patients' religious and spiritual convictions.

Analyses also revealed that patients with a longer LOS from day of admission and post-surgery were associated with a shorter time from case request to day of surgery, and a longer delay in scheduled surgery start time. This relation was found to be consistent with most variables in which LOS increased, such as race, insurance status, discharge disposition, BMI, and relationship status. We hypothesize that this relationship could arise from patients with worse overall health or more clinically complex cases requiring more immediate surgery as well as more intensive pre-surgical care that contributed to delays in start time.

Home discharge location also contributed to LOS and readmission rates, similarly to previous findings [42−45]. Patients who were discharged home demonstrated shorter LOS and lower readmission rates, and patients discharged to SNF had longer LOS and higher readmission rates than those discharged to rehab facilities. However, we also found discharge disposition to be significantly affected by patient social history. Black patients exhibited lower odds of home discharge while White patients had higher odds, indicating a potential disparity in post-operative care and support systems. The influence of language preference on discharge disposition also underscores the importance of effective communication in post-operative care. Additionally, insurance status emerged as a crucial factor, with privately insured patients being more likely to be discharged home. Married patients also exhibited higher odds of home discharge, compared to non-single patients, suggesting supporting social networks may facilitate better post-operative care arrangements.

Machine learning

Utilizing ensemble machine learning and multilayer perceptron, we employed machine learning to predict LOS and readmission within 90 days following spine surgery. The AUROC was 0.859 for predicting LOS with patient social history, as well as medical and lab information. However, when only taking into account patient social history, the AUROC score of 0.747 was still acceptable. Additionally, the AUROC was 0.781 for predicting readmission with patient social history, as well as medical and lab information. However, when only considering patient social history, the AUROC score was 0.727. Despite the undeniable importance of medical and lab information in evaluating surgical outcomes [55,56], when given both medical information and social history, the artificial intelligence modeling made accurate predictions of LOS and readmission based on social history alone, as well as ranked the importance of certain social factors above patient medical information.

Our model listed insurance status and religious status as the most important features, when given access to patient medical and lab information when predicting both LOS and readmission. When considering just social history, insurance type and religion remained the top 2 factors for readmission. In predicting LOS, insurance type retained its position as most important, but religion dropped down to 5th most important, suggesting religion might be of most value when considered in conjunction with medical factors.

Limitations

This study is one of the most comprehensive to date in terms of the variety of social factors analyzed in determining the effects on both LOS and readmission rates. However, this study is not without limitations. Our data was collected from a single academic center. Factors specific to the institution such as policies, local practices, and geographical location may introduce confounding to its generalizability. Furthermore, all spine surgeries were considered in our analysis without controlling for different types of spinal surgery. This may be seen as both a strength and weakness: while the surgeries analyzed were heterogeneous, the fact that disparities remained evident adds credence to the underlying influence of SDOH on LOS and readmission. Despite this, a lack of stratification of the invasiveness or type of surgery could limit our findings due to the possible relationship between type of surgery and patient demographics, such as certain demographics receiving more invasive surgeries on average. An additional limitation was the lack of consideration of preoperative disposition. While our analysis demonstrated a strong correlation between postoperative discharge disposition and LOS and readmission rates, a better understanding of where patients were admitted from could showcase additional implications. Finally, sample sizes between compared groups were occasionally skewed, which could result in certain contradictory findings. Controlling for these limitations could also modulate for the lack of significance of race and preferred language on readmission rates.

Conclusion

Insurance status, discharge disposition, BMI, marital status, and religion were shown to be associated with increased LOS and 90-day readmission rates after spine surgery. Race and ethnicity was shown to significantly increase LOS, but our study showed an insignificant association with 90-day readmission rates. Discharge disposition was also affected by socioeconomic factors, with race and ethnicity, preferred language, insurance status, age, and marital status all contributing to higher rates of discharge to home. Machine learning was utilized to accurately predict LOS and readmission with patient medical history, lab values, and social history, as well as social history alone. Insurance status and religion were ranked as more important than any other aspect of medical history, lab values, or other social factors in predicting LOS and readmission. Such findings showcase the effect of social determinants of health in spine surgery outcomes and highlight the need for targeted interventions to ensure equitable postoperative care for patients. Future research may focus on viewing social factors in aggregate rather than individually to offer more precise estimates of the impact of SDOH on outcomes.

Availability of data and material

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Supplemental Figure 1. Prediction of Readmission within 90 Days

Supplemental Figure 2. Prediction of LOS

Supplemental Figure 3. Calibration Curve for Readmission within 90 Days

Supplemental Figure 4. Calibration Curve for LOS

Declaration of competing interest

One or more of the authors declare financial or professional relationships on ICMJE-TSJ disclosure forms.

CRediT authorship contribution statement

David Shin: Writing − review & editing, Writing − original draft, Validation, Resources, Investigation, Formal analysis, Conceptualization. **Jacob Razzouk:** Writing − review & editing, Writing − original draft, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jonathan Thomas:** Writing − review & editing, Software, Project administration, Formal analysis, Data curation. **Kai Nguyen:** Writing − original draft, Validation, Resources, Project administration, Formal analysis, Data curation. **Andrew Cabrera:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing − original draft, Writing − review & editing. **Daniel Bohen:** Writing − review & editing, Writing − original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation. **Shaina A. Lipa:** Writing − review & editing, Supervision, Project administration, Conceptualization. **Christopher M. Bono:** Writing − review & editing, Supervision, Project administration, Formal analysis, Conceptualization. **Christopher I. Shaffrey:** Writing − review & editing, Supervision, Project administration, Formal analysis, Conceptualization. **Wayne Cheng:** Writing − review & editing, Supervision, Resources, Project administration, Conceptualization.

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Supplementary materials

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