Does state malpractice environment affect outcomes following spinal fusions? A robust statistical and machine learning analysis of 549,775 discharges following spinal fusion surgery in the United States

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OBJECTIVE Spine surgery is especially susceptible to malpractice claims. Critics of the US medical liability system argue that it drives up costs, whereas proponents argue it deters negligence. Here, the authors study the relationship between malpractice claim density and outcomes.

METHODS The following methods were used: 1) the National Practitioner Data Bank was used to determine the number of malpractice claims per 100 physicians, by state, between 2005 and 2010; 2) the Nationwide Inpatient Sample was queried for spinal fusion patients; and 3) the Area Resource File was queried to determine the density of physicians, by state. States were categorized into 4 quartiles regarding the frequency of malpractice claims per 100 physicians. To evaluate the association between malpractice claims and death, discharge disposition, length of stay (LOS), and total costs, an inverse-probability-weighted regression-adjustment estimator was used. The authors controlled for patient and hospital characteristics. Covariates were used to train machine learning models to predict death, discharge disposition not to home, LOS, and total costs.

RESULTS Overall, 549,775 discharges following spinal fusions were identified, with 495,640 yielding state-level information about medical malpractice claim frequency per 100 physicians. Of these, 124,425 (25.1%), 132,613 (26.8%), 130,929 (26.4%), and 107,673 (21.7%) were from the lowest, second-lowest, second-highest, and highest quartile states, respectively, for malpractice claims per 100 physicians. Compared to the states with the fewest claims (lowest quartile), surgeries in states with the most claims (highest quartile) showed a statistically significantly higher odds of a nonhome discharge (OR 1.169, 95% CI 1.139–1.200), longer LOS (mean difference 0.304, 95% CI 0.256–0.352), and higher total charges (mean difference [log scale] 0.288, 95% CI 0.281–0.295) with no significant associations for mortality. For the machine learning models—which included medical malpractice claim density as a covariate—the areas under the curve for death and discharge disposition were 0.94 and 0.87, and the R^2 values for LOS and total charge were 0.55 and 0.60, respectively.

CONCLUSIONS Spinal fusion procedures from states with a higher frequency of malpractice claims were associated with an increased odds of nonhome discharge, longer LOS, and higher total charges. This suggests that medicolegal climate may potentially alter practice patterns for a given spine surgeon and may have important implications for medical liability reform. Machine learning models that included medical malpractice claim density as a feature were satisfactory in prediction and may be helpful for patients, surgeons, hospitals, and payers.

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KEYWORDS liability; malpractice; tort; spine; surgery; claims

ABBREVIATIONS DRG = diagnosis-related group; GBC = gradient boosting classifier; GBR = gradient boosting regressor; ICD-9-CM = *International Classification of Diseases, Ninth Revision, Clinical Modification*; LOS = length of stay; MICE = multivariate imputation by chained equations; NIS = Nationwide Inpatient Sample; NPDB = National Practitioner Data Bank.

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MEDICAL malpractice adds significant costs to the US healthcare system. As of 2009, approximately \$55.6 billion (2.4% of healthcare spending) was spent on malpractice annually.¹ These costs are due to both direct costs (e.g., settlements, awards, and malpractice insurance premiums) and defensive medicine.

The medical liability (tort) system is intended to serve three functions: compensate patients injured by negligence, promote corrective justice, and deter negligence. However, critics of the US medical liability system argue that it may not lead to better healthcare quality and in addition may increase the total cost of healthcare delivery. Others suggest that the medical liability system lowers physician satisfaction, impairs the patient-physician relationship, and reduces access to care.^{2,3}

There are various methods of tort reform across the different states in the US. These include caps on noneconomic damages, medical review panels, and attorney fee limits. This has led to variable malpractice climates between the different states. By comparing health outcomes across these states, it is possible to investigate the impact of malpractice climate on patient outcomes. For instance, if the tort system deters negligence, patients may have better outcomes in malpractice climates that encourage more litigation. On the other hand, if the tort system obstructs healthcare delivery, there may be better outcomes with lower liability and increased access to care³⁻⁵ because physicians may be more willing to take on higher-risk procedures.⁶ Indeed, such investigations have been undertaken in fields such as general surgery, obstetrics and gynecology, and colorectal surgery⁷⁻⁹ and have failed to show any clear association between medical malpractice climate and patient outcomes. In neurosurgical practices—surgeons who face among the highest frequency of malpractice claims among medical specialties^{10,11}—a highly litigious medical liability climate was found to have no effect on outcomes after cranial surgery as well.¹²

Within neurosurgery, spine surgery faces the highest risk of litigation.¹³⁻¹⁵ Despite the potential relevance to this field, the association between medical malpractice climate and spine surgery outcomes remains incompletely defined.¹⁶ To this end, we examined the effect of medical liability climate on outcomes after spine surgery. We used a doubly robust, inverse-probability-weighted regression-adjustment estimator to assess 1) the impact of medical malpractice claim density on outcomes following more than half a million spinal fusion surgeries in the US and 2) the interaction between spinal fusion outcomes, claim density, and patient income. Additionally, we constructed machine learning models—including medical malpractice claim density as a covariate—in order to predict outcomes following spinal fusion surgery.

Methods

Data Source

Patient Sample—Nationwide Inpatient Sample

Using *International Classification of Diseases, Ninth Revision, Clinical Modification* (ICD-9-CM) coding (Table 1), we identified discharges from nonfederal hospitals in the US of patients who underwent spinal fusion surgery

TABLE 1. ICD-9 procedure codes used to identify patients undergoing spinal fusion surgery in the NIS between 2005 and 2010

ICD-9 Procedure Code	Description
81.00	Spinal fusion, not otherwise specified
81.01	Atlas-axis spinal fusion
81.02	Other cervical fusion of the anterior column, anterior technique
81.03	Other cervical fusion of the posterior column, posterior technique
81.04	Dorsal and dorsolumbar fusion of the anterior column, anterior technique
81.05	Dorsal and dorsolumbar fusion of the posterior column, posterior technique
81.06	Lumbar and lumbosacral fusion of the anterior column, anterior technique
81.07	Lumbar and lumbosacral fusion of the posterior column, posterior technique
81.08	Lumbar and lumbosacral fusion of the anterior column, posterior technique
81.62	Fusion or refusion of 2–3 vertebrae
81.63	Fusion or refusion of 4–8 vertebrae
81.64	Fusion or refusion of 9 or more vertebrae

between 2005 and 2010 and whose cases were recorded in the Healthcare Cost and Utilization Project (HCUP) Nationwide Inpatient Sample (NIS). The NIS is one of the largest publicly available all-payer inpatient databases in the US and contains data on more than 7 million hospital discharges each year.

Size of Malpractice Claims—National Practitioner Data Bank

The National Practitioner Data Bank (NPDB) is a identified database created by Congress with information regarding medical malpractice claims and sizes. The NPDB was queried for all malpractice claims between 2005 and 2010. The number of claims per 100 physicians was summed by state. States were ranked by the number of claims per 100 physicians and separated into 4 quartiles, namely: lowest (minimum number of claims to 1st quartile of the distribution of claims per 100 physicians); second lowest (1st quartile to 2nd quartile of the distribution of claims per 100 physicians); second highest (2nd quartile to 3rd quartile of the distribution of claims per 100 physicians); and highest (3rd quartile to maximum number of claims per 100 physicians). Minimum, 1st quartile, 2nd quartile, 3rd quartile, and maximum claims were equal to 0.00005, 0.0013, 0.0018, 0.0019, and 0.007 claims per 100 physicians, respectively. Discharges abstracted from the NIS were assigned into these four groups accordingly.

Physician Density—Area Resource File

The Area Resource File is an annual database containing information regarding the number of physicians per county per state. These frequencies were adjusted by state

population sizes to calculate the density of physicians per state, which was linked to the NIS data set for analysis.

Discharge Characteristics

We considered the following covariates: race (White, Black, Hispanic, Asian or Pacific Islander, Native American, or other); age; sex (female or male); median household income for patient's zip code (quartiles 1–4 and other as defined by the NIS¹⁷); expected primary payer (other, Medicare, Medicaid, private insurance, self-pay, or no charge); calendar year (2005–2010); number of days from admission to procedure; admission type; discharge quarter (January–March, April–June, July–September, or October–December); location/teaching status of hospital (rural, urban nonteaching, or urban teaching); physician density; hospital bed size (small, medium, or large); region of hospital (Northeast, Midwest, South, or West); congestive heart failure; Charlson Comorbidity Index;¹⁸ presence of in-hospital ICD-9 identifiable complications; and metastatic carcinoma. In addition, we considered the following covariates (not shown in Table 2): admission month, hospital state postal code; hospital FIPS (Federal Information Processing Standards) state/county code; major diagnostic category in effect on discharge date; ICD-9-CM diagnosis; Clinical Classifications Software for ICD-9-CM diagnosis classification; ICD-9-CM procedure; Clinical Classifications Software for ICD-9-CM procedures; diagnosis-related group (DRG) or Medicare Severity-DRG version used on discharge date; and DRG in use on discharge date.

Outcome Measures

We considered the following outcome measures: death (binary—dead or alive); discharge not to home (binary—not to home vs to home); length of stay (LOS; continuous); and total charges (continuous, log scale).

Statistical Analysis

Descriptive statistics, percentages, mean and SD were computed to describe characteristics of the study population. Chi-square tests for binary and categorical variables and ANOVA for continuous variables were used to evaluate the marginal relationship between covariates and categories of malpractice claims.

Multivariate imputation by chained equations (MICE)¹⁹ was used to impute the missing values. The following univariate imputation techniques were used: predictive mean matching for continuous covariates; logistic regression for binary covariates; multinomial logit model for covariates with more than 2 factors; and ordered logit model for features with ordered covariates. All covariates presented before and the categories of malpractice claims were included in the analysis with MICE.

To evaluate the relationship between categories of malpractice claims and outcomes, an inverse-probability-weighted regression-adjustment estimator²⁰ was used. This estimator is known as doubly robust²¹ in the sense that unbiased results can be obtained whenever either the outcome model or the inverse-probability model is correctly specified, thus leading to more robust results. Inverse-probability weights were obtained by using a multi-

nomial logistic regression model, which modeled the relationship between categories of malpractice claims and covariates. To avoid extreme values, weights were truncated at the 95th percentile.²² To model the relationship between the four outcomes and the quartiles of malpractice claims, a multivariate logistic regression for death and discharge not to home and a multivariate linear regression for LOS and (log) total charges weighted by the inverse-probability weights were used. We used the same set of covariates for both the inverse-probability weights model and the outcome models. A sandwich estimator was used to construct 95% Wald CIs.²³ These analyses were repeated with stratification based on quartile of median household income for a patient's zip code. Statistical significance was defined as $\alpha < 0.05$. All statistical analyses were conducted in RStudio and R (versions 1.2.5001 and 3.6.3, respectively).

To predict the risk of death and discharge not to home, a gradient boosting classifier (GBC) was used. To predict the LOS in days and the (log) total charges, a gradient boosting regressor (GBR) was used. We used fivefold cross-validation to estimate prediction accuracy, mean square error, and R^2 , and we chose the best hyperparameters. We followed standard machine learning practice and randomly split the whole data set into 80% training and 20% testing data. Because death and discharge not to home outcomes were highly unbalanced (death occurred in 0.4% of the entire population under study, whereas discharge not to home occurred in 24%), we upsampled the minority class of these two outcomes in the training data set. Prediction algorithms were conducted using Python version 3.6.9.

Results

We identified 549,775 patients who underwent spinal fusion between 2005 and 2010. Of these, 495,640 had available data about frequency of malpractice claims per 100 physicians. Cohort characteristics for these 495,640 patients, stratified by malpractice claim density, can be found in Table 2. States in the highest quartile for the number of claims included Texas, Nebraska, Kansas, Oklahoma, Montana, Georgia, Louisiana, Mississippi, Iowa, Illinois, and Pennsylvania. States in the lowest quartile for the number of claims included Hawaii, Rhode Island, Connecticut, Massachusetts, New Hampshire, Vermont, Maine, Maryland, New Jersey, Alaska, and Arizona.

Table 3 reports the inverse-probability-weighted regression-adjustment estimator analyses modeling the relationships between death, discharge disposition, LOS, and total hospital charges and frequency of malpractice claims per 100 physicians. The models revealed significant associations between malpractice claim frequency per 100 physicians and discharge disposition, LOS, and total charges. Compared to spinal fusions performed in the lowest malpractice claim density states, those spinal fusions performed in states with the highest malpractice claim density had higher odds of discharge disposition not to home. Spinal fusions performed in states with higher malpractice claim density were associated with longer lengths of hospitalization. For total hospital charges, spinal fusions performed in states with higher malpractice claim density were associated with higher charges. There

TABLE 2. Cohort characteristics, stratified by quartile of number of medical malpractice claims per 100 physicians by state

Characteristic	Total, N = 495,640	Lowest Quartile, n = 124,425	2nd-Lowest Quartile, n = 132,613	2nd-Highest Quartile, n = 130,929	Highest Quartile, n = 107,673	p Value
Age, yrs ($\pm$ SD)	53 ($\pm$ 17)	53 ($\pm$ 16)	51 ($\pm$ 20)	54 ($\pm$ 16)	52 ($\pm$ 17)	<0.001
Women	270,290 (55)	66,537 (54)	73,710 (56)	71,229 (54)	58,814 (55)	<0.001
CCI ($\pm$ SD)	4 ($\pm$ 2)	4 ($\pm$ 2)	4 ($\pm$ 2)	4 ($\pm$ 2)	4 ($\pm$ 2)	<0.001
Congestive heart failure	3,711 (1)	990 (0.8)	1,123 (0.8)	909 (0.7)	689 (0.6)	<0.001
Metastatic carcinoma	25,109 (5)	5,745 (5)	10,189 (8)	5,882 (4)	3,293 (3)	<0.001
In-hospital, periop complication*	70,334 (14)	18,957 (15)	18,441 (14)	18,927 (14)	14,009 (13)	<0.001
Race						<0.001
White	344,754 (81)	93,207 (79)	94,891 (81)	85,270 (85)	71,386 (79)	
Black	35,434 (8)	8,877 (8)	10,899 (9)	7,691 (8)	7,967 (9)	
Hispanic	26,546 (6)	10,382 (9)	5,150 (4)	3,993 (4)	7,021 (8)	
Asian or Pacific Islander	5,226 (1)	2,575 (2)	1,261 (1)	847 (0.8)	543 (0.6)	
Native American	2,064 (0)	417 (0.4)	343 (0.3)	395 (0.4)	909 (1)	
Other	11,741 (3)	2,463 (2)	3,964 (3)	2,666 (3)	2,648 (3)	
Median household income for patient's zip code						<0.001
Quartile 1	95,751 (19)	15,360 (12)	24,144 (18)	25,037 (19)	31,210 (29)	
Quartile 2	109,364 (22)	19,734 (16)	28,266 (21)	36,653 (28)	24,711 (23)	
Quartile 3	108,862 (22)	28,111 (23)	29,256 (22)	30,546 (23)	20,949 (19)	
Quartile 4	102,849 (21)	37,646 (30)	31,530 (24)	19,524 (15)	14,149 (13)	
Other	78,814 (16)	23,574 (19)	19,417 (15)	19,169 (15)	16,654 (15)	
Expected primary payer						<0.001
Other	53,321 (11)	16,910 (14)	12,881 (10)	11,239 (9)	12,291 (11)	
Medicare	148,466 (30)	35,916 (29)	39,300 (30)	42,372 (32)	30,878 (29)	
Medicaid	37,642 (8)	9,044 (7)	12,237 (9)	9,204 (7)	7,157 (7)	
Private insurance	245,302 (49)	60,776 (49)	64,953 (49)	65,256 (50)	54,317 (50)	
Self-pay	10,021 (2)	1,641 (1)	3,176 (2)	2,481 (2)	2,723 (3)	
No charge	888 (0)	138 (0.1)	66 (0.05)	377 (0.3)	307 (0.3)	
Calendar year						<0.001
2005	68,281 (14)	20,523 (16)	16,351 (12)	16,883 (13)	14,524 (13)	
2006	74,048 (15)	20,867 (17)	20,597 (16)	17,621 (13)	14,963 (14)	
2007	87,129 (18)	21,024 (17)	29,141 (22)	20,250 (15)	16,714 (16)	
2008	82,062 (17)	19,916 (16)	21,558 (16)	23,895 (18)	16,693 (16)	
2009	92,385 (19)	20,168 (16)	27,638 (21)	23,369 (18)	21,210 (20)	
2010	91,735 (19)	21,927 (18)	17,328 (13)	28,911 (22)	23,569 (22)	
No. of days from admission to procedure ($\pm$ SD)	0.4 ($\pm$ 2)	0.5 ($\pm$ 2)	0.6 ($\pm$ 3)	0.4 ($\pm$ 2)	0.4 ($\pm$ 2)	<0.001
Admission type						<0.001
Emergency	44,292 (10)	8,364 (11)	16,896 (13)	10,391 (8)	8,641 (8)	
Urgent	38,022 (8)	4,886 (6)	8,476 (6)	11,710 (9)	12,950 (12)	
Elective	358,106 (80)	65,220 (82)	101,677 (77)	107,410 (82)	83,799 (78)	
Trauma	3,416 (1)	741 (0.9)	828 (0.6)	1,190 (0.9)	657 (0.6)	
Other	6,226 (1)	301 (0.2)	4,642 (4)	173 (0.1)	1,110 (1)	
Discharge quarter						<0.001
1st quarter, Jan–Mar	122,108 (25)	31,031 (25)	33,044 (25)	32,198 (25)	25,835 (24)	
2nd quarter, Apr–Jun	125,135 (25)	31,354 (25)	33,407 (25)	32,810 (25)	27,564 (26)	
3rd quarter, Jul–Sep	121,959 (25)	30,599 (25)	32,533 (25)	32,398 (25)	26,429 (25)	
4th quarter, Oct–Dec	126,044 (25)	31,441 (25)	33,235 (25)	33,523 (26)	27,845 (26)	

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TABLE 2. Cohort characteristics, stratified by quartile of number of medical malpractice claims per 100 physicians by state

Characteristic	Total, N = 495,640	Lowest Quartile, n = 124,425	2nd-Lowest Quartile, n = 132,613	2nd-Highest Quartile, n = 130,929	Highest Quartile, n = 107,673	p Value
Location/teaching status of hospital						<0.001
Rural	25,493 (5)	5,718 (5)	6,506 (5)	8,213 (6)	5,056 (5)	
Urban nonteaching	231,120 (47)	59,032 (48)	61,381 (46)	58,092 (44)	52,615 (50)	
Urban teaching	234,942 (48)	58,926 (48)	64,718 (49)	64,439 (49)	46,859 (45)	
Density, physicians/100,000 pop ($\pm$ SD)	1658 ($\pm$ 2945)	4434 ($\pm$ 4770)	544 ($\pm$ 534)	1145 ($\pm$ 858)	446 ($\pm$ 385)	<0.001
Bed size of hospital						<0.001
Small	67,529 (14)	16,341 (13)	14,659 (11)	10,943 (8)	25,586 (24)	
Medium	115,933 (24)	30,453 (25)	33,502 (25)	25,337 (19)	26,641 (25)	
Large	308,093 (63)	76,882 (62)	84,444 (64)	94,464 (72)	52,303 (50)	
Region of hospital						<0.001
Northeast	80,645 (16)	34,820 (28)	33,384 (25)	12,441 (10)	0 (0)	
Midwest	80,119 (16)	0 (0)	15,704 (12)	40,216 (31)	24,199 (22)	
South	216,282 (44)	22,729 (18)	41,270 (31)	68,809 (53)	83,474 (78)	
West	118,594 (24)	66,876 (54)	42,255 (32)	9,463 (7)	0 (0)	

CCI = Charlson Comorbidity Index; pop = population.

Values are presented as number (%) unless otherwise indicated.

* Complications were identified by the presence of the following ICD-9 diagnosis codes during a hospitalization: 342.00–342.92, 349.0, 349.1, 349.2, 349.31, 349.39, 349.89, 349.9, 415.11, 415.19, 415.40, 415.41, 415.42, 599.0, 900.00, 900.01, 900.02, 900.03, 900.1, 900.81, 900.82, 900.89, 900.9, 901.0, 902.0, 902.10, 902.11, 902.19, 902.40, 902.41, 902.42, 902.49, 902.50, 902.51, 902.52, 902.53, 902.54, 902.55, 902.56, 902.59, 902.87, 902.89, 902.9, 996.2, 996.40, 996.41, 996.42, 996.43, 996.44, 996.45, 996.46, 996.47, 996.49, 996.60, 996.63, 996.64, 996.66, 996.67, 996.69, 996.70, 996.75, 996.77, 996.78, 996.79, 997.00, 997.01, 997.02, 997.09, 997.1, 997.2, 997.31, 997.32, 997.39, 997.49, 997.5, 997.72, 997.79, 997.91, 997.99, 998.00, 998.01, 998.02, 998.09, 998.11, 998.12, 998.13, 998.2, 998.30, 998.31, 998.32, 998.4, 998.51, 998.59, 998.6, 998.7, 998.81, 998.83, 998.89, 998.9, 999.1, 999.2, 999.31, 999.32, 999.33, 999.34, 999.39, 999.41, 999.42, 999.49, 999.51, 999.52, 999.59, 996.60, 999.61, 999.62, 999.63, 999.69, 999.70, 999.71, 999.72, 999.73, 999.74, 999.75, 999.76, 999.77, 999.78, 999.79, 999.80, 999.81, 999.82, 999.83, 999.84, 999.85, 999.88, 999.89, 999.9.

was no significant association between malpractice claim density and mortality ($p > 0.05$).

Table 4 reports similar analyses, stratified by quartile of median household income for a patient's zip code. For those from the lowest-income zip codes, higher density of malpractice claims was associated with fewer deaths—not observed in patients from the highest-income zip codes. For discharge disposition, the association between medical malpractice claim density and outcome depended on income quartile. For those from the lowest income quartile, higher malpractice claim density was associated with discharge not to home. In contrast, for those from the highest income quartile, higher malpractice claim density was associated with discharge to home. When conducting stratified analyses, higher malpractice claim density was associated with decreased LOS (opposite in direction to the nonstratified analysis) and higher total charges (similar to the nonstratified analysis).

Table 5 shows the performance of the GBC and GBR in the test data set. Performance measures were all satisfactory except for the positive predictive value (which is the probability that, given that the algorithm predicted that a patient will die, the patient actually dies) of the machine learning algorithm for death. This is due to the fact that the class death was highly unbalanced. Careful considerations should be taken in using this algorithm to predict mortality. The most predicting feature for death was admission type,

for discharge not to home it was age, for LOS it was the number of days from admission to procedure, and for total charges (log) it was the DRG in use on the discharge date.

Discussion

In a robust analysis of more than half a million discharges for spinal fusion surgery in the US, state malpractice claim density demonstrated significant associations with multiple patient outcomes despite adjustment for various patient and hospital covariates. Patients with spinal fusions from states with a higher medical malpractice claim density had a higher odds of nonhome discharge, longer lengths of hospitalization, and higher total hospital charges compared to those with spinal fusions performed in states with fewer medical malpractice claims per 100 physicians. There was no observed association with mortality. In a subgroup analysis, the association between malpractice claim density and discharge disposition differed in directionality, however, depending on patient income. Those in the lowest income quartile were more often discharged not to home in higher claims environments, whereas those in the highest income quartile were more often discharged to home in higher claims environments. Machine learning models using medical malpractice claim density as a covariate were satisfactory in predicting outcomes following spinal fusion surgery.

A primary goal of the medical liability system is to de-

TABLE 3. Inverse-probability-weighted regression-adjustment estimator modeling the relationships between outcomes and frequency of malpractice claims per 100 physicians

Frequency of Malpractice Claims/100 Physicians	OR (95% CI)		Linear Increase (95% CI)	
	Death	Discharge Not to Home	LOS	Total Charges (log)
Lowest quartile	Ref	Ref	Ref	Ref
2nd-lowest quartile	1.143 (0.989–1.322)	1.096 (1.068–1.124)*	0.157 (0.111–0.203)*	0.016 (0.009–0.022)*
2nd-highest quartile	0.961 (0.819–1.127)	0.948 (0.925–0.971)*	0.125 (0.080–0.170)*	0.247 (0.241–0.253)*
Highest quartile	1.041 (0.880–1.232)	1.169 (1.139–1.200)*	0.304 (0.256–0.352)*	0.288 (0.281–0.295)*

* Denotes significant relationship between frequency of malpractice claims per 100 physicians and specified outcome, compared to the reference, at $p < 0.05$.

ter negligence and reduce harm to patients. From the perspective of the patient, this may take the form of reducing complications and eliminating mortality following surgery. In our study, we found no overall association between medical malpractice climate and mortality rate following spinal fusion surgery, consistent with a prior report by Missios and Bekelis¹⁶ assessing the association between claim density and mortality following 709,951 patients undergoing spine surgery whose cases were recorded in the NIS. In their study, the authors reported that states with a higher frequency of malpractice claims also showed higher hospital charges. Notably, the authors used multivariable logistic regression and excluded missing variables from the analysis entirely by using listwise deletion, introducing bias. Missing data—a noteworthy problem in large, administrative data sets—can result in an under- or overestimation

of treatment effects,^{24–26} depending on the mechanism of missingness, and may limit statistical power.²⁷ To address this potential issue, we used MICE and a doubly robust inverse-probability-weighted regression-adjustment estimator in order to rigorously assess the association between malpractice claim density and mortality. In doing so, we provide evidence supporting Missios and Bekelis's finding that medical malpractice claim density does not significantly associate with mortality. This is consistent with investigations outside of spine surgery,^{9,28} including cranial neurosurgery.¹² A review by Minami et al. in 2014 did not find that the threat of litigation improved physician adherence to quality indicators or led to better outcomes.²⁸ Similarly, a review of 20 studies across nonobstetrical care and 16 studies in obstetrics by Mello et al. found little evidence to suggest that liability risk leads to better outcomes.⁹ In fact,

TABLE 4. Inverse-probability-weighted regression-adjustment estimator modeling the relationships between outcomes and frequency of malpractice claims per 100 physicians, stratified by income quartile

Income Quartile	Frequency of Malpractice Claims/100 Physicians	OR (95% CI)		Linear Increase (95% CI)	
		Death	Discharge Not to Home	LOS	Total Charges (log)
Lowest income quartile	Lowest quartile	Ref	Ref	Ref	Ref
	2nd-lowest quartile	1.031 (0.785 to 1.356)	1.169 (1.111 to 1.230)*	−0.308 (−0.494 to −0.121)*	−0.308 (−0.333 to −0.284)*
	2nd-highest quartile	0.524 (0.384 to 0.714)*	1.037 (0.987 to 1.089)	−0.237 (−0.411 to −0.063)*	0.17 (0.149 to 0.191)*
	Highest quartile	0.611 (0.458 to 0.817)*	1.048 (0.999 to 1.099)	−0.358 (−0.529 to −0.187)*	0.050 (0.030 to 0.071)*
2nd-lowest income quartile	Lowest quartile	Ref	Ref	Ref	Ref
	2nd-lowest quartile	1.440 (1.089 to 1.905)*	1.107 (1.054 to 1.164)*	0.021 (−0.160 to 0.201)	−0.128 (−0.149 to −0.106)*
	2nd-highest quartile	0.716 (0.541 to 0.948)*	0.985 (0.943 to 1.029)	−0.293 (−0.423 to −0.162)*	0.098 (0.080 to 0.117)*
	Highest quartile	0.984 (0.728 to 1.329)	0.926 (0.883 to 0.971)*	0.206 (0.064 to 0.347)*	0.243 (0.224 to 0.262)*
2nd-highest income quartile	Lowest quartile	Ref	Ref	Ref	Ref
	2nd-lowest quartile	0.907 (0.687 to 1.196)	0.991 (0.946 to 1.038)	−0.137 (−0.294 to 0.019)	0.003 (−0.018 to 0.025)
	2nd-highest quartile	0.506 (0.387 to 0.663)*	0.794 (0.762 to 0.827)*	0.061 (−0.075 to 0.197)	0.359 (0.342 to 0.377)*
	Highest quartile	0.738 (0.555 to 0.980)	0.993 (0.947 to 1.040)	−0.012 (−0.165 to 0.141)	0.184 (0.166 to 0.203)
Highest income quartile	Lowest quartile	Ref	Ref	Ref	Ref
	2nd-lowest quartile	1.237 (0.930 to 1.646)	0.950 (0.906 to 0.996)*	−0.251 (−0.415 to −0.088)*	−0.018 (−0.042 to 0.005)
	2nd-highest quartile	0.745 (0.535 to 1.037)	0.83 (0.791 to 0.871)*	−0.082 (−0.235 to 0.072)	0.422 (0.399 to 0.444)*
	Highest quartile	0.819 (0.572 to 1.173)	0.866 (0.822 to 0.913)*	−0.267 (−0.441 to −0.094)*	0.256 (0.235 to 0.277)*

* Denotes significant relationship between frequency of malpractice claims per 100 physicians and specified outcome, compared to the reference, at $p < 0.05$.

TABLE 5. Performance of the GBC and GBR in the test data set

Performance Measure*	GBC		GBR		
	Death	Discharge Not to Home	Performance Measure*	LOS	Total Charges (log)
Accuracy	0.86	0.79	R ²	0.55	0.60
PPV (precision)	0.03	0.59			
NPV	0.99	0.91			
Sensitivity (recall)	0.89	0.77			
Specificity	0.86	0.79			
AUC	0.94	0.87			

AUC = area under the curve; NPV = negative predictive value; PPV = positive predictive value.

* The higher the better. GBC for death resulted in the following best hyper-parameters: *n_estimators* = 1000, *learning_rate* = 0.01, *max_features* = 10, *max_depth* = 10; GBC for discharge not to home: *n_estimators* = 1000, *learning_rate* = 0.1, *max_features* = 3, *max_depth* = 10; GBR for LOS: *n_estimators* = 1000, *learning_rate* = 0.1, *max_features* = 10, *max_depth* = 10; and GBR for total charges: *n_estimators* = 1000, *learning_rate* = 0.1, *max_features* = 10, *max_depth* = 10.

we detected a significant association between high medical malpractice claim density and higher odds of nonhome discharge, which has not been described in spine surgery previously. This is supported by a previous investigation following 189,103 cranial neurosurgical procedures, in which the authors found a similar association between nonhome discharge and higher claim density. The association is probably multifactorial and may be a result of risk-adverse discharge practices favoring discharge to acute rehabilitation or a skilled nursing facility—as opposed to home or home with home healthcare—for borderline patients.

Similarly to Missios and Bekelis, we found that states with a higher frequency of malpractice claims also showed longer hospitalizations and higher total charges following spinal fusion surgery (the latter despite adjustment for LOS).¹⁶ Higher malpractice awards and premiums have been linked to higher medical spending,²⁹ which is likely to be driven by defensive medicine.^{3,12,30,31} Indeed, the costs of defensive medicine among orthopedic surgeons have been estimated at more than US\$2 billion per year.³² A large part of this is probably driven by “assurance behavior,” such as performing excess tests, diagnostic procedures, consultations, and imaging. To this point, in a study by Studdert et al. in which the authors surveyed 824 emergency medicine, general surgery, orthopedic surgery, neurosurgery, obstetrics/gynecology, and radiology physicians, 43% of physicians in states with high malpractice claims reported ordering imaging purely for defensive medicine.³¹ Importantly, this finding—total charges increasing with higher malpractice claim density—remained when stratifying patients by income level and despite adjustment for covariates such as race, insurance, comorbidity, the presence of in-hospital complications, and LOS. In the modern era of value-based care provision,^{33–35} defensive medicine—driven by the threat of medical malpractice—may be another significant driver of cost and systematic reduction of value.

Interestingly, we observed that the associations observed between malpractice claim density and outcomes demonstrated a statistical interaction with patient income. First, we observed that the directionality of the association between discharge disposition and medical malpractice claim density differed depending on income. For lower-income patients, higher malpractice claim density was associated with nonhome discharge. Conversely, for higher-income patients, higher malpractice claim density was associated with home discharge. This may reflect concerns about home support and resources for lower-income patients. Second, when conducting stratified analyses, higher malpractice claim density was associated with decreased LOS, opposite in direction to the nonstratified analysis in which higher malpractice claim density was associated with increased LOS. This finding suggests that the interaction between malpractice claim density and income is negative, and the magnitude of the effect of income on LOS is greater than the main effect of malpractice claim density on LOS. Last—in contrast to the overall analysis—for those from the lowest income quartiles, spinal fusions in patients from states with higher malpractice claim frequency were associated with decreased mortality. This may reflect the “cherry-picking” of healthier patients and lower-risk procedures in low-income patients. This may be an additional impediment to surgical care that may be pursued further in future investigations.

Neurosurgeons may be particularly sensitive to the medical malpractice environment, because they are the most likely physicians to be sued.¹⁰ In a survey of neurosurgeons, a majority (64%) reported that malpractice claims were a major burden, with many substantially altering their practice due to liability concerns, such as by eliminating high-risk procedures.³⁰ In another survey not specific to neurosurgeons, 42% of respondents reported that they had restricted their practice due to litigation concerns, including eliminating high-risk procedures and avoiding medically complex patients or patients perceived to be litigious.³¹ Within neurosurgery, spine surgery faces the highest risk of litigation.^{13–15} This avoidance of high-risk but necessary procedures may result in a barrier or delay to important care, resulting paradoxically in harm to patients. Our data suggest that this may be a particular concern in lower-income patients. Tort reform, of great interest to multiple stakeholders, including patients, surgeons, payers, hospitals, and policymakers, may have the potential to mitigate these access barriers, decrease costs, and improve care. Tort reform laws have already been linked to decreases in excess imaging use.³⁶ Another series of studies examining the relatively recent tort reform in Texas found that reform increased the number of physicians per capita in 20 of 22 trauma service areas.⁴ They also found that the reform lowered annual lawsuits by more than 50%.³⁷ However, this was also accompanied by increases in medical board complaints, disciplinary action, and license revocations,³⁸ underscoring other mechanisms for corrective justice. In the states we found to have the lowest frequency of malpractice claims, a number of different tort reform measures have been enacted, such as damage caps (Hawaii, Massachusetts, Maine, Maryland, New Jersey, Alaska); joint liability reform (Hawaii, Con-

necticut, New Hampshire, New Jersey, Alaska, Arizona); collateral source reform (Rhode Island, Connecticut, Massachusetts, Maine, New Jersey, Alaska, Arizona); and limiting attorney fees (Hawaii, Connecticut, Massachusetts, New Hampshire, Maine, New Jersey, Alaska).³⁹

The significant associations between medical malpractice claim density and outcomes following spinal fusion surgery suggests that modeling of death, discharge disposition, LOS, and hospital charges would not be optimal without inclusion of claim density as a variable—something that has been unmodeled previously. Using robust machine learning techniques, we found it possible to predict death and discharge disposition with areas under the curve of 0.94 and 0.87, respectively, following spinal fusion surgery by using data contained within the NIS, NPDB, and Area Resource File. Similarly, models predicting LOS and total charges performed with R^2 values of 0.55 and 0.60, respectively. These high-performing models may be leveraged by multiple stakeholders,⁴⁰ including patients, surgeons, hospital administrators, case managers planning discharge, and payers. For patients and surgeons the models may aid in the surgical decision-making process and perioperative planning. For hospital administrators and case managers planning discharge, these models may aid in efficient resource allocation.⁴¹ For payers, these models may inform reimbursement patterns.⁴² Machine learning modeling has been increasingly applied to spinal outcomes.^{40,43,44} With the addition of new features—such as medicolegal climate—machine learning approaches will only improve in their predictive capacity. Although our statistical analyses provide evidence demonstrating an association between malpractice claims and discharge-level parameters (death, LOS, discharge disposition, and charges), our machine learning analyses suggest that we can predict these parameters with reasonable accuracy by using algorithms trained with a large data set. Therefore, leveraging machine learning with a large data set provides powerful predictive tools for treating patients optimally based on patient and environmental characteristics—including malpractice claim density—that are readily reported. Machine learning methods, such as the GBC and GBR used in our analysis, allow us to predict discharge-level parameters by modeling complex variables' interactions. This avoids relying on stringent and sometimes wrong assumptions such as those required of standard regression models. By using flexible methods, we achieve better predictions of these parameters.

Limitations

This investigation relies on data sourced from an administrative data set and thus holds the inherent limitations. Additionally, the study uses data from 2005 to 2010 (years in which discharges in the NIS were identifiable by state). State designation was required to link discharges to state malpractice claim frequency and practitioner density. Therefore, it is possible that a hypothetical analysis with more recent information may yield different findings. Ultimately, however, with the latest available nationally representative data set, our study shows that the frequency of malpractice claims by state is associated with disparate outcomes following spinal fusion procedures in the US. Additionally, the NPDB—despite consideration as

the most comprehensive database on medical malpractice payments in the US^{16,29}—is not without several limitations. The NPDB provides information on the frequency of malpractice claim payments on behalf of physicians in general. Therefore, information is not known about the frequency of claims that were not paid and claim payments on behalf of spine surgeons specifically.

Conclusions

Spinal fusion procedures from states with a higher frequency of medical malpractice claims were associated with increased odds of nonhome discharge, longer lengths of hospitalization, and higher total charges despite adjustment for various covariates. Patient income demonstrates a significant interaction with these associations, with lower-income patients yielding a correlation between higher frequency of malpractice claims, and lower mortality and claim density exerting opposing associations with discharge disposition depending on patient income. This suggests that the frequency of malpractice claims, serving as a proxy for medicolegal climate, may alter practice patterns for spine surgeons. This may have important implications for healthcare and tort reform. Machine learning models including medical malpractice claim density were satisfactory in prediction and may be leveraged for preoperative decision-making, resource allocation, and reimbursement.

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