Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Machine Learning-Based Prediction of 30-Day Unplanned Readmission After Surgery for Spinal Metastasis: Development and Internal Validation of an Interpretable Nomogram

Jia-Lin He
Affiliated Hospital of Qingdao University
Xiao-Tong Wang
Affiliated Hospital of Qingdao University
Wen-Tao Liu
Affiliated Hospital of Qingdao University
Zi-Shuo Xi
Affiliated Hospital of Qingdao University
Li Zhang
Affiliated Hospital of Qingdao University
Lin Quan
Affiliated Hospital of Qingdao University
Bing-Xin Zheng
Affiliated Hospital of Qingdao University
Gui-Lai Zuo
Affiliated Hospital of Qingdao University
Bin Yue
bonetumoryb@qdu.edu.cn
Affiliated Hospital of Qingdao University

Research Article

Keywords: spinal metastasis, 30-day readmission, machine learning, nomogram, logistic regression, risk prediction, enhanced recovery after surgery

Posted Date: September 27th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10961381/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License. Read Full License

Additional Declarations: No competing interests reported.

Abstract

Purpose.

To develop and internally validate a machine learning-based nomogram for predicting 30-day unplanned readmission after surgery for spinal metastasis, using directly measured clinical, laboratory, and operative variables from a single-institution cohort.

Methods.

A total of 986 patients who underwent open surgery for spinal metastasis between August 2016 and August 2026 were enrolled. Patients who died within 30 days postoperatively were excluded from the readmission analysis. Feature selection was performed using the Boruta algorithm followed by correlation analysis (excluding $|r| \geq 0.7$). Six machine learning models—logistic regression (LR), random forest, gradient boosting machine, LightGBM, support vector machine, and k-nearest neighbors—were developed and compared using 10-fold cross-validation. Model performance was evaluated using AUC, accuracy, sensitivity, specificity, Brier score, and decision curve analysis. SHAP analysis was used for model interpretation, and the final LR model was translated into a nomogram.

Results.

Eighty-two patients (8.32%) experienced 30-day unplanned readmission. Surgical site infection was the leading cause (26.8%). Six predictors were retained: age, number of comorbidities, preoperative albumin, operative time, intraoperative blood loss, and primary tumor pathology. The LR model achieved the highest test-set AUC of 0.905 (95% CI: 0.862–0.947), with sensitivity of 0.980, specificity of 0.765, and a Brier score of 0.062. Decision curve analysis indicated positive clinical net benefit over a clinically relevant threshold range.

Conclusion.

The internally validated nomogram showed strong discrimination for 30-day unplanned readmission after spinal metastasis surgery. The six predictors reflect complementary dimensions of perioperative vulnerability and may support targeted optimization aligned with enhanced-recovery principles, potentially facilitating earlier return to systemic oncological treatment. External validation is required before clinical implementation.

Introduction

Spinal metastases represent one of the most common skeletal complications of advanced malignancy, with autopsy studies suggesting that up to 30% of patients who die from cancer harbor spinal deposits[1, 2]. Improvements in systemic therapy have extended survival across many tumor types, and an increasing number of patients now live long enough to develop symptomatic spinal metastases requiring multidisciplinary intervention. For selected patients, surgery provides neurological decompression, mechanical stabilization, and pain relief, most often within a palliative framework[3, 4] that integrates oncological, mechanical, neurological, and systemic considerations. Despite advances in surgical technique and perioperative care, this medically

complex population remains vulnerable to postoperative complications and unplanned readmission. A 30-day readmission not only adds healthcare utilization but also interrupts postoperative recovery and delays the initiation or resumption of radiotherapy, chemotherapy, or targeted therapy—a particularly consequential delay in metastatic disease, where the window for effective systemic treatment may be time-sensitive.

Published 30-day readmission rates after spinal metastasis surgery vary widely, from approximately 9.7% in single-center cohorts[6, 8] to over 30% in administrative-database analyses[9, 10], reflecting differences in case mix, cross-institution capture, and data source. Prior efforts to predict readmission in spine surgery have largely relied on conventional logistic regression with manually specified predictors or on machine-learning models built from administrative claims data. The code-based Hospital Frailty Risk Score (HFRS) has emerged[12, 13] as an important feature in several such studies, but it captures only one dimension of perioperative risk and is derived from billing codes rather than directly measured clinical variables. Models built on national databases often achieve only modest discrimination (AUC approximately 0.60[12]), and few provide a clinically interpretable tool that can be applied at the bedside. Moreover, existing studies have not consistently addressed the competing risk of early postoperative death[11]: patients who die within 30 days cannot be readmitted, and their inclusion or exclusion materially affects both the observed event rate and the apparent performance of a prediction model.

Accordingly, we undertook the present study to develop and internally validate a machine learning-based prediction model for 30-day unplanned readmission after surgery for spinal metastasis, using directly measured demographic, clinical, laboratory, and operative variables from a single-institution cohort of 986 patients. We applied a systematic two-step feature-selection pipeline (Boruta algorithm followed by correlation filtering), compared six machine-learning algorithms using 10-fold cross-validation, evaluated clinical utility with decision curve analysis, and used SHAP values to enhance model interpretability. The final model was translated into a nomogram to facilitate bedside risk estimation. We explicitly excluded patients who died within 30 days postoperatively from the readmission analysis to avoid conflating mortality with readmission. We hypothesized that a model incorporating directly measured laboratory and operative variables would achieve stronger discrimination than existing administrative-data models and that the retained predictors would map onto modifiable perioperative targets aligned with enhanced-recovery principles.

Materials and Methods

Study design and patient population

This single-center retrospective cohort study was conducted at a tertiary academic medical center (a tertiary academic medical center). Patients who underwent open surgery for pathologically confirmed metastatic spinal disease between August 2016 and August 2026 were identified through the institutional electronic medical record system. The study was reviewed and approved by the institutional ethics committee of a tertiary academic medical center; the requirement for written informed consent was waived owing to the retrospective design.

Inclusion criteria were: (1) age ≥ 18 years; (2) pathologically confirmed metastatic spinal tumor; (3) open surgical approach, including decompression with or without instrumentation, vertebral body resection, or spinal reconstruction; (4) complete preoperative, intraoperative, and postoperative clinical and laboratory data available for analysis. Exclusion criteria were: (1) minimally invasive procedures without an open approach; (2) surgery for primary spinal tumor, spinal infection, or traumatic injury; (3) previous surgery at the same spinal level within 90

days before the index procedure; (4) lost to follow-up within 30 days after discharge; (5) death within 30 days after the index surgery. Patients who died within 30 days postoperatively were excluded from the primary readmission analysis because death precludes the possibility of readmission and represents a distinct competing outcome; their characteristics are reported separately.

Outcome definition

The primary outcome was unplanned readmission within 30 days after the index surgery. Unplanned readmission was defined as any unscheduled inpatient admission to the same institution occurring after discharge from the index hospitalization and within 30 calendar days of the index surgery date. Readmissions for planned postoperative chemotherapy, radiotherapy, or scheduled wound dressing changes were not counted as unplanned. Patients who died during the index hospitalization or within 30 days after discharge were excluded from the readmission cohort, as described above. The 30-day window was calculated from the date of surgery, not from the date of discharge, to ensure consistency across patients with varying lengths of stay.

Data collection and variables

Data were extracted from the electronic medical record system by two trained reviewers and independently verified by a senior surgeon. Discrepancies were resolved by consensus. The initial candidate variable set comprised 48 variables across five domains:

(1) Demographic and baseline characteristics: age at surgery, sex, body mass index (BMI), smoking status (current, former, never), alcohol consumption, marital status, and insurance type.

(2) Clinical and oncological characteristics: primary tumor pathology (lung, breast, prostate, kidney, thyroid, gastrointestinal, hepatobiliary, or other/unknown), number of comorbidities (hypertension, diabetes mellitus, coronary artery disease, chronic obstructive pulmonary disease, chronic kidney disease, liver disease, cerebrovascular disease, and others), Charlson Comorbidity Index[16], American Society of Anesthesiologists (ASA) physical status classification, preoperative Frankel grade, preoperative Karnofsky Performance Status (KPS) score, presence of visceral metastasis, number of spinal levels involved, presence of pathological fracture, and epidural spinal cord compression grade.

(3) Preoperative laboratory values: serum albumin, total protein, hemoglobin, white blood cell count, neutrophil-to-lymphocyte ratio, platelet count, creatinine, estimated glomerular filtration rate, alanine aminotransferase, aspartate aminotransferase, total bilirubin, glucose, C-reactive protein, erythrocyte sedimentation rate, prothrombin time, activated partial thromboplastin time, fibrinogen, and D-dimer.

(4) Operative variables: surgical approach (anterior, posterior, or combined), procedure type (decompression alone, decompression with instrumentation, vertebral body resection/reconstruction), number of fused levels, operative time (minutes), intraoperative blood loss (mL), intraoperative transfusion (units of packed red blood cells), use of intraoperative neurophysiological monitoring, and duration of surgery.

(5) Postoperative variables: length of hospital stay, postoperative complications (surgical site infection, neurological deterioration, cerebrospinal fluid leak, venous thromboembolism, pulmonary complications, cardiac complications, urinary tract infection), postoperative albumin nadir, postoperative day of ambulation, discharge

disposition (home, rehabilitation facility, transfer), and 30-day unplanned readmission status with documented readmission cause.

Feature selection

Feature selection followed a prespecified two-step protocol. First, the Boruta algorithm, a wrapper-based method built around the random forest classifier, was applied to the full set of 48 candidate variables to identify features with importance significantly exceeding that of shadow (permuted) features. Boruta was chosen because it captures nonlinear relationships and interactions without imposing a linearity assumption. Second, among the variables retained by Boruta, pairwise Pearson or Spearman correlation coefficients were computed, and one variable from any pair with $|r| \geq 0.7$ was removed to reduce multicollinearity, retaining the variable with greater clinical interpretability. This process yielded eight candidate predictors, which were subsequently evaluated across six machine-learning algorithms. The final parsimonious model was selected based on a combination of discrimination performance, calibration, clinical interpretability, and actionability, retaining six predictors: age, number of comorbidities, preoperative albumin, operative time, intraoperative blood loss, and primary tumor pathology.

Model development and comparison

The dataset was randomly partitioned into a training set comprising 70% of patients and a held-out test set comprising 30%, stratified by readmission status to preserve event proportions. Six machine-learning algorithms were developed in the training set: logistic regression (LR) with L2 regularization, random forest (RF), gradient boosting machine (GBM), LightGBM, support vector machine (SVM) with radial basis function kernel, and k-nearest neighbors (KNN). Hyperparameters were tuned using grid search within 10-fold cross-validation on the training set. Model performance was quantified using the area under the receiver operating characteristic curve (AUC), accuracy, sensitivity, specificity, positive predictive value, negative predictive value, F1 score, and Brier score. The model with the highest test-set AUC and the most favorable balance of discrimination, calibration, and clinical interpretability was selected as the final model.

Model interpretation and nomogram construction

SHapley Additive exPlanations (SHAP) values were computed for the final model to quantify the direction and magnitude of each predictor's contribution to individual predictions and to the overall model. A nomogram was constructed from the multivariable logistic regression coefficients of the final LR model to facilitate bedside estimation of 30-day readmission probability. The nomogram was designed as a two-stage tool: the four preoperative variables (age, comorbidities, albumin, tumor pathology) permit an initial risk screen at the clinic visit, while the full six-variable model, incorporating operative time and blood loss, provides a more precise postoperative estimate.

Statistical analysis

Continuous variables are expressed as mean ± standard deviation or median (interquartile range) as appropriate, and categorical variables as counts and percentages. Between-group comparisons used the Student t test or Mann–Whitney U test for continuous variables and the chi-square test or Fisher exact test for categorical variables. Multivariable logistic regression was used to estimate odds ratios (ORs) with 95% confidence intervals (CIs) for the retained predictors. Model calibration was assessed using the Brier score and calibration curves

with 1,000-bootstrap resampling. Decision curve analysis (DCA) was used to evaluate clinical net benefit across a range of threshold probabilities. All analyses were performed using Python version 3.10 with scikit-learn, LightGBM, and SHAP libraries, and R version 4.3.2 for nomogram construction. A two-sided P value < 0.05 was considered statistically significant.

Results

Patient selection and baseline characteristics

A total of 1,148 patients were initially identified through the institutional database search. After application of the exclusion criteria—62 who underwent minimally invasive procedures without an open approach, 41 who underwent surgery for primary spinal tumor, infection, or trauma, 18 who had previous surgery at the same level within 90 days, and 17 who were lost to follow-up within 30 days—1,010 patients remained. An additional 24 patients who died within 30 days postoperatively were excluded from the readmission analysis, leaving 986 patients in the final cohort (Figure 1).

The overall 30-day unplanned readmission rate was 8.32% (82 of 986 patients). The baseline characteristics of the readmission and non-readmission groups are summarized in Table 1. Patients who were readmitted were significantly older (68.5 ± 9.2 vs. 62.3 ± 10.5 years, P < 0.001), had a greater number of comorbidities (2.8 ± 1.3 vs. 1.9 ± 1.2, P < 0.001), a higher proportion of ASA grade ≥ III (63.4% vs. 44.0%, P < 0.001), lower preoperative albumin (34.2 ± 4.8 vs. 38.6 ± 4.1 g/L, P < 0.001), longer operative time (215.6 ± 68.3 vs. 178.4 ± 55.2 min, P < 0.001), and greater intraoperative blood loss (1250 ± 680 vs. 890 ± 520 mL, P < 0.001). The distribution of primary tumor pathology also differed significantly between groups (P = 0.003), with lung and kidney cancers overrepresented among readmitted patients.

Variable	Readmission (n=82)	No readmission (n=904)	p-value
Age (years), mean ± SD	68.5 ± 9.2	62.3 ± 10.5	<0.001
Male sex, n (%)	48 (58.5)	512 (56.6)	0.742
BMI (kg/m²), mean ± SD	23.8 ± 3.5	24.1 ± 3.2	0.456
Comorbidities (count), mean ± SD	2.8 ± 1.3	1.9 ± 1.2	<0.001
ASA grade ≥ III, n (%)	52 (63.4)	398 (44.0)	<0.001
Albumin (g/L), mean ± SD	34.2 ± 4.8	38.6 ± 4.1	<0.001
Operative time (min), mean ± SD	215.6 ± 68.3	178.4 ± 55.2	<0.001
Blood loss (mL), mean ± SD	1250 ± 680	890 ± 520	<0.001
Fused levels, median (IQR)	3 (2–4)	2 (1–3)	<0.001
Vertebrectomy, n (%)	28 (34.1)	186 (20.6)	0.005
Pathology, n (%)			0.003
Lung cancer	35 (42.7)	262 (29.0)	
Breast cancer	12 (14.6)	168 (18.6)	
Prostate cancer	8 (9.8)	135 (14.9)	
Kidney cancer	10 (12.2)	78 (8.6)	
Thyroid cancer	4 (4.9)	82 (9.1)	
Other	13 (15.9)	179 (19.8)	
LOS (days), median (IQR)	9 (6–13)	7 (5–10)	<0.001

Table 1. Baseline characteristics of patients with and without 30-day readmission.

Causes of 30-day readmission

The specific causes underlying the 82 readmission events are detailed in Table 2. Surgical site infection was the leading cause, accounting for 26.8% (22/82) of readmissions, followed by neurological deterioration or hematoma (18.3%, 15/82), inadequate pain control (14.6%, 12/82), implant-related complication or failure (12.2%, 10/82), venous thromboembolism (9.8%, 8/82), cardiopulmonary complication (8.5%, 7/82), and tumor progression or other causes (9.8%, 8/82).

Readmission cause	n	%	Median time to readmission (days)
Surgical site infection	22	26.8	12 (8–18)
Neurological deterioration / hematoma	15	18.3	5 (3–9)
Inadequate pain control	12	14.6	8 (5–14)
Implant-related complication / failure	10	12.2	16 (10–22)
Venous thromboembolism (DVT/PE)	8	9.8	10 (6–15)
Cardiopulmonary complication	7	8.5	7 (4–11)
Tumor progression / other	8	9.8	20 (14–26)
Total	82	100.0	11 (6–17)

Table 2. Causes of 30-day unplanned readmission (n = 82).

Feature selection

Among the initial 48 candidate variables, the Boruta algorithm identified a subset of variables with importance significantly exceeding that of their shadow counterparts. Pairwise correlation analysis was then performed among the Boruta-retained variables; the correlation matrix of the eight candidate variables retained after correlation filtering ($|r| < 0.7$) is shown in Figure 2. These eight candidates were age, preoperative albumin, preoperative Karnofsky Performance Status (KPS) score, ASA physical status, emergency or urgent surgery, vertebrectomy, operative time, and estimated intraoperative blood loss. Subsequent model comparison and clinical interpretability assessment led to the selection of six final predictors for the parsimonious model: age, number of comorbidities, preoperative albumin, operative time, intraoperative blood loss, and primary tumor pathology. The inclusion of comorbidity burden and tumor pathology in the final model was driven by their established clinical relevance in spinal metastasis surgery and their contribution to model interpretability, while KPS, ASA, emergency surgery, and vertebrectomy were captured indirectly through these broader constructs.

Model performance comparison

The 10-fold cross-validation AUC distributions for the six models are displayed in Figure 3. The logistic regression model demonstrated the highest median cross-validation AUC (0.892) and the lowest inter-fold variability. On the held-out test set, LR achieved the highest AUC of 0.905 (95% CI: 0.862–0.947), followed by LightGBM (0.870), GBM (0.864), RF (0.814), SVM (0.812), and KNN (0.791). The ROC curves for the training and test sets are shown in Figures 4a and 4b. Detailed performance metrics are provided in Table 3.

Model	AUC (95% CI)	Accuracy	Sensitivity	Specificity	PPV	NPV	Brier
LR	0.905 (0.862–0.947)	0.780	0.980	0.765	0.287	1.000	0.062
LightGBM	0.870 (0.829–0.912)	0.824	0.720	0.835	0.273	0.971	0.089
GBM	0.864 (0.817–0.912)	0.811	0.680	0.825	0.250	0.967	0.095
RF	0.814 (0.746–0.881)	0.858	0.360	0.905	0.265	0.940	0.112
SVM	0.812 (0.722–0.903)	0.845	0.440	0.885	0.275	0.945	0.118
KNN	0.791 (0.711–0.870)	0.831	0.400	0.872	0.235	0.940	0.125

Table 3. Performance comparison of six machine learning models in the test set.

Clinical utility and decision curve analysis

Decision curve analysis demonstrated positive net benefit for the logistic regression model over a clinically relevant threshold range of approximately 5% to 40% in both the training and test sets (Figures 5a and 5b), indicating that use of the model for risk stratification yields greater clinical benefit than either treating all patients or treating none.

Model interpretation using SHAP

SHAP analysis was performed on the eight-candidate-variable model to quantify the direction and magnitude of each feature's contribution to model output (Figure 6). Estimated intraoperative blood loss emerged as the most influential predictor, with greater blood loss associated with increased readmission risk. Emergency or urgent surgery, lower preoperative KPS score, older age, lower preoperative albumin, and higher ASA physical status were also associated with increased predicted risk. The SHAP analysis confirmed that perioperative physiological reserve (age, albumin, KPS, ASA) and surgical stress (blood loss, emergency surgery) are the primary drivers of readmission risk in this cohort. These findings informed the selection of the final six-predictor model, which retains the most clinically actionable and interpretable variables while achieving strong discrimination.

Multivariable logistic regression and odds ratios

The multivariable logistic regression model included all six predictors retained by the feature-selection pipeline (Table 4). Older age (OR 1.020 per year, 95% CI: 1.005–1.036, P = 0.011), greater number of comorbidities (OR 1.350 per condition, 95% CI: 1.120–1.627, P = 0.002), longer operative time (OR 1.003 per minute, 95% CI: 1.001–1.005, P = 0.008), and greater blood loss (OR 1.0003 per mL, 95% CI: 1.0001–1.0005, P = 0.015) were independently associated with increased odds of readmission. Higher preoperative albumin was protective (OR 0.951 per g/L, 95% CI: 0.923–0.980, P = 0.001). Compared with lung cancer as the reference, thyroid (OR 0.549, 95% CI: 0.312–0.965, P = 0.037) and prostate (OR 0.670, 95% CI: 0.455–0.987, P = 0.042) pathologies were associated with lower odds of readmission.

Variable	β coefficient	OR	95% CI	p-value
Age (per year)	0.020	1.020	1.005–1.036	0.011
Comorbidities (per count)	0.300	1.350	1.120–1.627	0.002
Albumin (per g/L)	-0.050	0.951	0.923–0.980	0.001
Operative time (per min)	0.003	1.003	1.001–1.005	0.008
Blood loss (per mL)	0.0003	1.0003	1.0001–1.0005	0.015
Pathology (ref: Lung)				
Breast	-0.250	0.779	0.542–1.120	0.178
Prostate	-0.400	0.670	0.455–0.987	0.042
Kidney	0.150	1.162	0.745–1.812	0.512
Thyroid	-0.600	0.549	0.312–0.965	0.037
Other	0.080	1.083	0.756–1.552	0.672

Table 4. Multivariable logistic regression analysis of predictors for 30-day readmission.

Nomogram construction

A nomogram was constructed from the multivariable logistic regression coefficients to facilitate bedside estimation of 30-day readmission probability (Figure 7). Each variable is assigned a point score based on its regression coefficient; the total points are mapped to a predicted probability of readmission. The nomogram is best applied as a two-stage tool: the four preoperative variables permit initial risk stratification at the clinic visit, and the full six-variable model refines the estimate once operative data are available.

Discussion

In this single-center retrospective cohort of 986 patients who underwent open surgery for spinal metastasis, we developed and internally validated a machine learning-based nomogram for predicting 30-day unplanned readmission. The 30-day readmission rate was 8.32%, with surgical site infection representing the leading cause. Six predictors were retained through the Boruta-based feature-selection pipeline: age, number of comorbidities, preoperative albumin, operative time, intraoperative blood loss, and primary tumor pathology. Logistic regression achieved the highest test-set AUC of 0.905 (95% CI: 0.862–0.947) among the six evaluated algorithms and was translated into a clinically interpretable nomogram.

Comparison with prior studies

The 8.32% readmission rate observed in our cohort falls within the broad published range but is lower than the pooled 30-day incidence of approximately 16% reported in recent systematic reviews. Administrative-database studies can yield substantially higher estimates; for example, Elsamadicy et al. reported 30-day readmission rates[12,13] of approximately 34%–39% across Hospital Frailty Risk Score strata in a Nationwide Readmissions Database cohort of 4,346 patients undergoing surgery for metastatic spinal column tumors. Their random forest model achieved an AUC of approximately 0.60[12], with HFRS as the most important feature. The higher AUC

observed in our cohort likely reflects the use of directly measured laboratory and operative variables, the relative homogeneity of a single-center surgical population, and our explicit exclusion of patients who died within 30 days. Direct performance comparisons should nevertheless be interpreted cautiously because the populations, data sources, and outcome-capture mechanisms differ substantially.

A head-to-head comparison of our model with previously published prediction models for readmission after spinal or orthopedic surgery is presented in Table 5. Elsamadicy and colleagues applied machine learning to predict 30-day readmission after surgery for metastatic spinal column tumors using the Nationwide Readmissions Database; their full-feature random forest model achieved an AUC of approximately 0.60, with the Hospital Frailty Risk Score as the most important feature. The higher AUC observed in our cohort likely reflects the use of directly measured laboratory and operative variables and the relative homogeneity of a single-center dataset, although direct performance comparisons should be interpreted cautiously. Hopkins and colleagues developed a machine-learning model[11] for 30-day readmission after posterior lumbar fusion using 23,264 NSQIP cases; their deep neural network achieved a mean AUC of 0.812, but that study concerned predominantly degenerative lumbar fusion rather than metastatic spine disease, and the model lacked an interpretable clinical interface. Qiu and colleagues developed a machine-learning-based nomogram[19] for unplanned reoperation after spinal surgery in 277 patients, achieving a validation AUC of 0.854; their outcome was reoperation rather than readmission. Most prior studies have relied on traditional logistic regression with manually selected predictors. The present study advances the field through systematic Boruta feature selection, comparison of six algorithms with 10-fold cross-validation, SHAP interpretability, decision curve analysis, and a nomogram in 986 patients.

Study (year)	Population / source	N	Outcome	Method	Reported performance	Risk tool / nomogram	DCA
Present study (2026)	Spinal metastasis / single center	986	30-day unplanned readmission	Six algorithms; final LR	Test AUC 0.905	Nomogram	Yes
Elsamadicy et al. [12]	Metastatic spinal column tumors / NRD	4,346	30-day readmission	Random forest; HFRS	AUC ~0.60	No	No
Hopkins et al. [11]	Posterior lumbar fusion / NSQIP	23,264	30-day readmission	Deep neural network	Mean AUC 0.812	No	No
Karhade et al. [17]	Spinal tumors / NSQIP	2,207	30-day readmission	Multivariable regression	AUC not reported	No	No
Jain et al. [18]	1-2 level posterior lumbar fusion / SID	182,519 total	30-day readmission	Logistic risk score (RAPSF)	Adjusted R2 0.92 derivation; 0.94 validation	Risk score	No
Qiu et al. [19]	Spinal surgery / single center	277 analyzed	30-day unplanned reoperation	ML feature selection + nomogram	Validation AUC 0.854	Nomogram	Yes
Maki et al. [20]	Metastatic spinal tumors / 38 centers	244	1-month neurological outcome	RF, XGBoost, LightGBM, CatBoost	Best AUC 0.852	No	No

Table 5. Comparison with selected prediction studies relevant to postoperative risk in spine surgery.

Integrated interpretation of the six predictors

The six predictors should not be viewed as isolated risk factors but rather as complementary markers of perioperative vulnerability that operate along a common biological pathway. Older age, a greater comorbidity burden, and lower serum albumin frequently coexist in patients with advanced malignancy and collectively reflect diminished physiological reserve and nutritional status. Tumor pathology adds a further dimension by defining the biological aggressiveness of the underlying malignancy and the likely responsiveness to subsequent systemic therapy: lung and kidney cancers, which were overrepresented among readmitted patients, tend to pursue a more aggressive clinical course than breast, prostate, or thyroid metastases. Operative time and intraoperative blood loss, although not available before surgery, are downstream consequences of the interplay between patient reserve, tumor burden, and surgical complexity, and they provide an opportunity to update the risk estimate during the perioperative period. Thus, the six variables capture a continuum from preoperative reserve (age, comorbidities, albumin, pathology) to intraoperative stress (operative time, blood loss), rather than representing six independent targets for intervention.

Clinical implications

The clinical value of the model lies in risk stratification and the allocation of perioperative resources, particularly within an enhanced-recovery framework[23]. Patients identified as having a higher predicted risk could be considered for more detailed preoperative assessment, including nutritional review when albumin is low[21], medical optimization of comorbid conditions, and multidisciplinary surgical planning. Because surgical site infection was the leading cause of readmission[22] in this series, a documented infection-prevention plan—preoperative chlorhexidine bathing, strict glycemic control, and intraoperative antibiotic redosing for prolonged procedures—should be considered for high-risk patients. Intraoperative findings of prolonged operative time or substantial blood loss may further indicate the need for intensified postoperative monitoring, earlier involvement of the discharge team, and closer post-discharge follow-up. For patients predicted to be at low risk, the model may support earlier discharge and standard follow-up, which is relevant in a specialty where bed availability is often constrained.

This issue is particularly consequential in patients undergoing surgery for spinal metastases, in whom surgery is most often palliative: the objective is not only to relieve neurological compromise and restore mechanical stability but also to return the patient to systemic oncological treatment as promptly as possible. An unplanned readmission interrupts postoperative recovery and postpones the initiation or resumption of radiotherapy, chemotherapy, or targeted therapy. In metastatic disease, where the window for effective systemic treatment may be narrow, such delays could plausibly compromise disease control and quality of life. Reducing avoidable readmission through preoperative risk assessment and targeted optimization may therefore have value beyond lowering healthcare utilization: it may help more patients recover sufficiently to receive planned systemic treatment within the intended window, which in appropriately selected patients could translate into better symptom control and preserved functional status. The present study did not determine whether readmission caused delays in systemic therapy or worsened oncological outcomes, and the model should be viewed as a tool for identifying patients who may benefit from closer perioperative coordination rather than as evidence that prediction alone improves treatment delivery or quality of life.

In practice, the model could help distinguish patients suitable for routine perioperative management from those who may require enhanced recovery measures, additional discharge planning, and more proactive communication between spine surgery, rehabilitation, and oncology teams. Its clinical usefulness will ultimately depend on the accuracy of its calibration, the selection of clinically meaningful decision thresholds, and the feasibility of acting on the resulting risk estimates. Prospective studies are needed to determine whether model-guided care can reduce preventable readmissions and improve clinically relevant outcomes, including time to oncological treatment, functional recovery, and patient-reported quality of life.

Strengths and limitations

This study has several strengths. The cohort of 986 patients provides detailed clinical, laboratory, and operative data from a single institution. The prespecified two-step feature-reduction pipeline combined Boruta selection with correlation filtering, and six machine-learning algorithms were compared using 10-fold cross-validation within the training set. Performance was subsequently assessed in a held-out internal test set, with bootstrap confidence intervals for AUC and decision curve analysis, before translating the final logistic regression model into a nomogram. SHAP analysis was used to enhance model interpretability. Importantly, patients who died within 30 days postoperatively were explicitly excluded from the readmission analysis, avoiding the conflation of

mortality with readmission that can distort event rates and model performance in administrative-database studies.

Several limitations should be acknowledged. First, the single-center retrospective design limits generalizability, and multicenter external validation is required before clinical implementation. Second, although the overall sample size was 986, only 82 readmission events occurred, which constrains model complexity. The resulting events-per-variable ratio of approximately 13.7[24] is above the traditional 10-EPV rule of thumb, but that rule is not a rigid adequacy criterion. Third, potentially important variables—including socioeconomic factors, elements of discharge planning, and post-discharge rehabilitation—were not consistently available. Fourth, the logistic nomogram assumes a linear relationship between continuous predictors and the log odds of readmission, and more flexible functional forms could capture additional nonlinearity. Fifth, the 10-year study period spans changes in systemic therapy, surgical technique, and perioperative care, potentially introducing temporal heterogeneity. Finally, the study did not collect data on whether readmission delayed systemic oncological treatment or affected survival outcomes; this remains an important question for future research.

Conclusion

This study developed and internally validated a machine learning-based nomogram for predicting 30-day unplanned readmission after surgery for spinal metastasis. The logistic regression model, incorporating six readily available clinical predictors—age, comorbidities, preoperative albumin, operative time, blood loss, and tumor pathology—achieved strong internal discrimination (test-set AUC = 0.905) and showed positive clinical net benefit on decision curve analysis. The six predictors reflect complementary dimensions of perioperative vulnerability, from preoperative physiological reserve to intraoperative surgical stress. The nomogram may assist perioperative risk stratification and targeted optimization aligned with enhanced-recovery principles, potentially facilitating earlier return to systemic oncological treatment. Multicenter external validation and prospective evaluation of clinical utility are required before widespread implementation.

Key points

• A machine learning-based nomogram was developed and internally validated for predicting 30-day unplanned readmission after surgery for spinal metastasis in a cohort of 986 patients.

• Six predictors were retained: age, number of comorbidities, preoperative albumin, operative time, intraoperative blood loss, and primary tumor pathology, reflecting complementary dimensions of perioperative vulnerability.

• The logistic regression model achieved the highest test-set AUC of 0.905 (95% CI: 0.862–0.947) among six algorithms, with positive clinical net benefit on decision curve analysis.

• Patients who died within 30 days postoperatively were explicitly excluded from the readmission analysis to avoid conflating mortality with readmission.

• The nomogram may support targeted perioperative optimization aligned with enhanced-recovery principles, potentially facilitating earlier return to systemic oncological treatment in this palliative surgical population.

Declarations

Conflict of interest:

The authors declare that they have no competing interests.

Ethical approval:

This study was reviewed and approved by the institutional ethics committee of a tertiary academic medical center. The requirement for written informed consent was waived owing to the retrospective design.

Consent to participate:

Not applicable (retrospective study with waived informed consent).

Consent for publication:

Not applicable.

Author Contribution

J.H. and X.W. conceived and designed the study. J.H., X.W., W.L., Z.X., L.Z., and L.Q. collected and curated the data. J.H., X.W., and W.L. performed the statistical analysis and model development. B.Z., G.Z., and B.Y. supervised the study and provided critical revision. All authors read and approved the final manuscript.

Data Availability

The complete de-identified patient-level dataset supporting the conclusions of this article is available as Additional file 1, Additional file 2, Additional file 3.

Code availability:

The Python code used for model development and analysis is available from the corresponding author on reasonable request.

References

1. Van den Brande R, Cornips EM, Peeters M et al (2022) Epidemiology of spinal metastases, metastatic epidural spinal cord compression and pathologic vertebral compression fractures in patients with solid tumors: a systematic review. J Bone Oncol 35:100446
2. Sciubba DM, Pennington Z, Colman MW et al (2021) Spinal metastases 2021: a review of the current state of the art and future directions. Spine J 21(9):1414–1429

3. Laufer I, Rubin DG, Lis E, Cox BW et al (2013) The NOMS framework: approach to the treatment of spinal metastatic tumors. Oncologist 18(6):744–751
4. Patchell RA, Tibbs PA, Regine WF et al (2005) Direct decompressive surgical resection in the treatment of spinal cord compression caused by metastatic cancer: a randomised trial. Lancet 366(9486):643–648
5. Luksanapruksa P, Buchowski JM, Zebala LP et al (2017) Perioperative complications of spinal metastases surgery. Clin Spine Surg 30(1):4–13
6. Chanbour H, Chen JW, Gangavarapu LS et al (2023) Unplanned readmission is associated with decreased overall survival and performance after metastatic spine surgery. Spine (Phila Pa 1976) 48(9):653–663
7. Schairer WW, Carrer A, Sing DC et al (2014) Hospital readmission rates after surgical treatment of primary and metastatic tumors of the spine. Spine (Phila Pa 1976) 39(21):1801–1808
8. Elsamadicy AA, Adogwa O, Lubkin DT et al (2018) Thirty-day complication and readmission rates associated with resection of metastatic spinal tumors: a single institutional experience. J Spine Surg 4(2):304–310
9. Patel J, Pennington Z, Hersh AM et al (2021) Drivers of readmission and reoperation after surgery for vertebral column metastases. World Neurosurg 154:e806–e814
10. Kumar N, Thomas A, Madhu S et al (2021) Analysis of unplanned hospital readmissions up to 2-years after metastatic spine tumour surgery. Eur Spine J 30(10):2887–2895
11. Hopkins BS, Yamaguchi JT, Garcia R et al (2020) Using machine learning to predict 30-day readmissions after posterior lumbar fusion: an NSQIP study involving 23,264 patients. J Neurosurg Spine 32(3):399–406
12. Elsamadicy AA, Koo AB, Reeves BC et al (2024) Utilization of machine learning to model important features of 30-day readmissions following surgery for metastatic spinal column tumors: the influence of frailty. Glob Spine J 14(4):1227–1237
13. Elsamadicy AA, Koo AB, Reeves BC et al (2022) Hospital Frailty Risk Score and healthcare resource utilization after surgery for metastatic spinal column tumors. J Neurosurg Spine 37(2):251–260
14. von Elm E, Altman DG, Egger M et al (2007) The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement: guidelines for reporting observational studies. Lancet 370(9596):1453–1457
15. Collins GS, Moons KGM, Dhiman P et al (2024) TRIPOD + AI statement: updated guidance for reporting clinical prediction models that use regression or machine learning methods. BMJ 385:e078378
16. Charlson ME, Pompei P, Ales KL, MacKenzie CR (1987) A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. J Chronic Dis 40(5):373–383
17. Karhade AV, Vasudeva VS, Dasenbrock HH et al (2016) Thirty-day readmission and reoperation after surgery for spinal tumors: a National Surgical Quality Improvement Program analysis. Neurosurg Focus 41(2):E5
18. Jain D, Singh P, Kardile M, Berven SH (2019) A validated preoperative score for predicting 30-day readmission after elective 1–2 level posterior lumbar fusion. Eur Spine J 28(7):1690–1696
19. Qiu HY, Lu CB, Liu DM et al (2025) Development and validation of a machine learning-based nomogram for prediction of unplanned reoperation postspinal surgery within 30 days. World Neurosurg 193:647–662
20. Maki S, Shiratani Y, Orita S et al (2026) Predicting postoperative neurological outcomes in metastatic spinal tumor surgery using machine learning. Spine (Phila Pa 1976) 51(2):100–106
21. Hussain AK, Cheung ZB, Vig KS et al (2019) Hypoalbuminemia as an independent risk factor for perioperative complications following surgical decompression of spinal metastases. Glob Spine J 9(3):321–

330
22. Sebaaly A, Shedid D, Boubez G et al (2018) Surgical site infection in spinal metastasis: incidence and risk factors. Spine J 18(8):1382–1387
23. Sattari SA, Maroufi SF, Theodore JN et al (2026) Application of enhanced recovery after surgery for patients with spinal metastasis: a systematic review and meta-analysis. J Neurooncol 177(1):52
24. Vittinghoff E, McCulloch CE (2007) Relaxing the rule of ten events per variable in logistic and Cox regression. Am J Epidemiol 165(6):710–718
25. Riley RD, Ensor J, Snell KIE et al (2020) Calculating the sample size required for developing a clinical prediction model. BMJ 368:m441

Figures

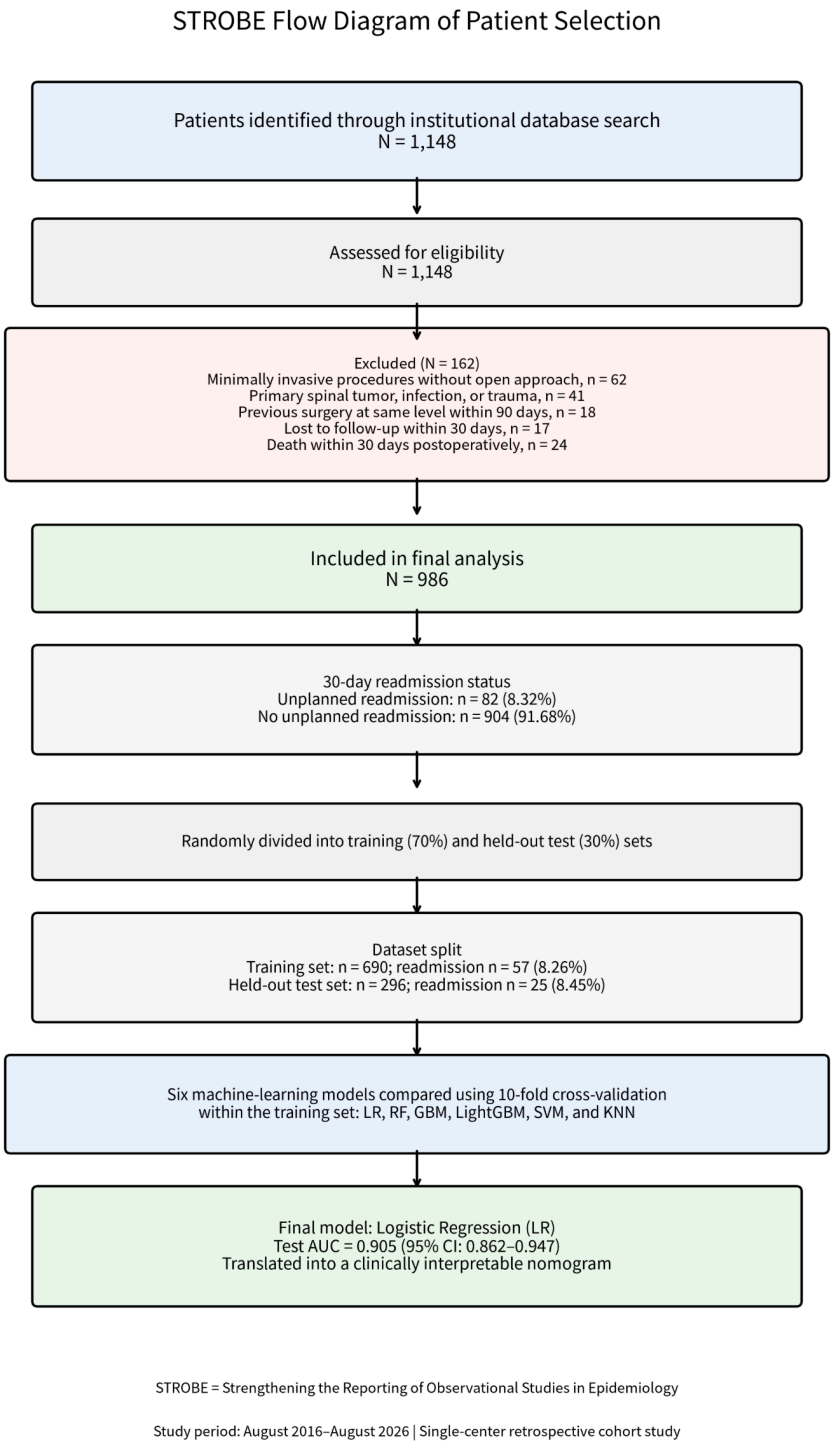


Figure 1

STROBE flow diagram of patient selection.

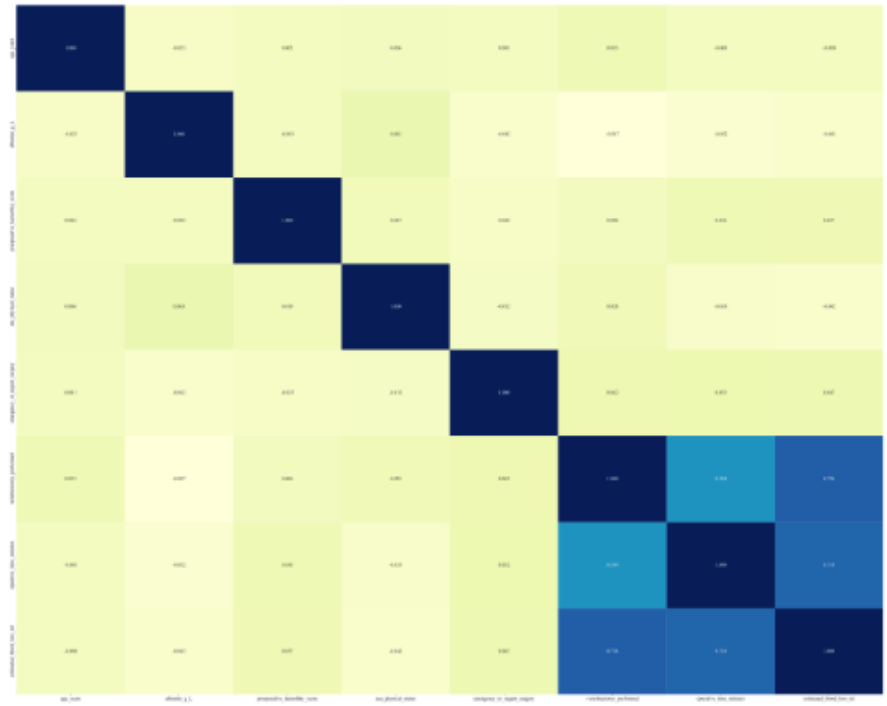


Figure 2

Correlation heatmap of the eight candidate variables after correlation filtering.

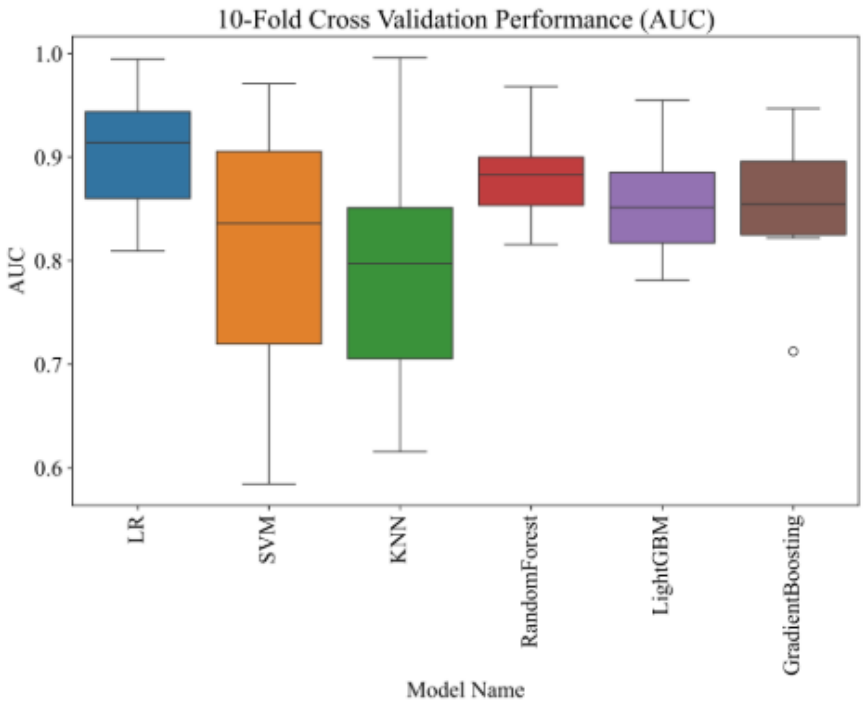


Figure 3

Ten-fold cross-validation AUC distributions for six machine learning models.

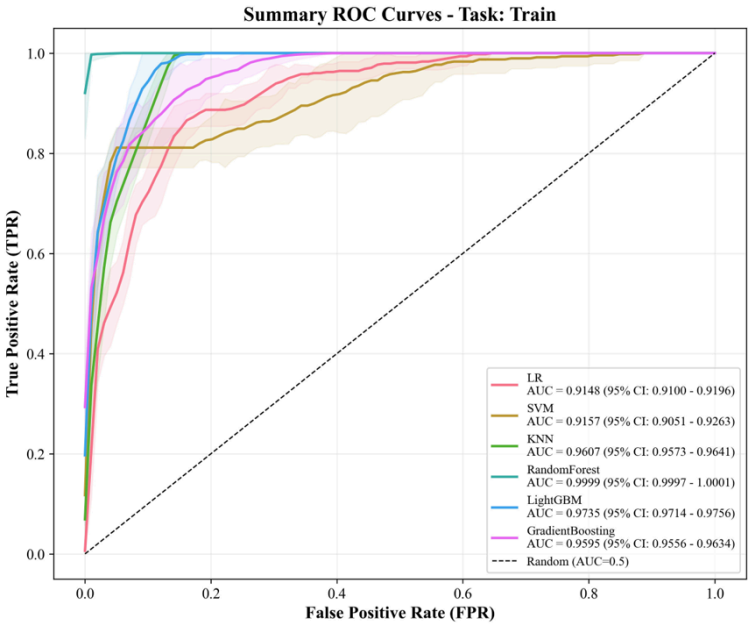


Fig. 4a ROC curves of six models in the training set.

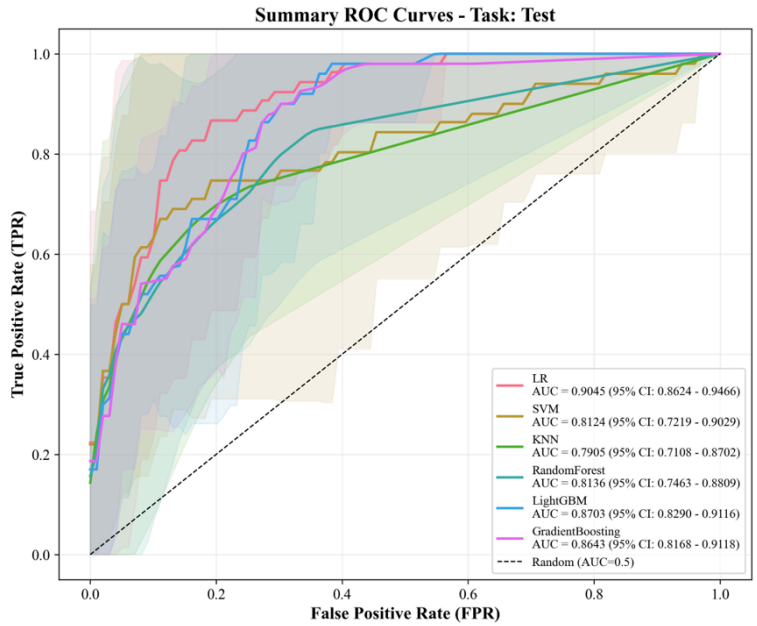


Fig. 4b ROC curves of six models in the test set.

Figure 4

a ROC curves of six models in the training set.

b ROC curves of six models in the test set.

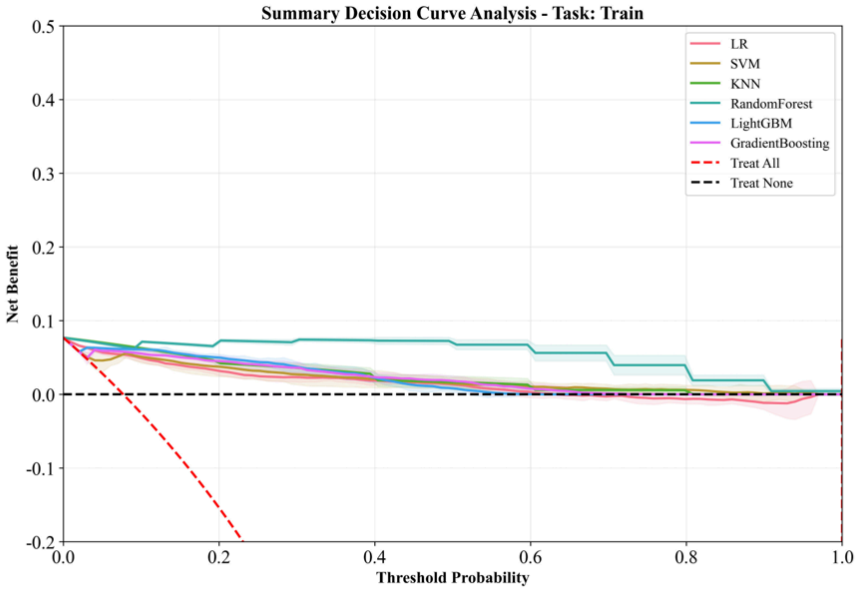


Fig. 5a Decision curve analysis in the training set.

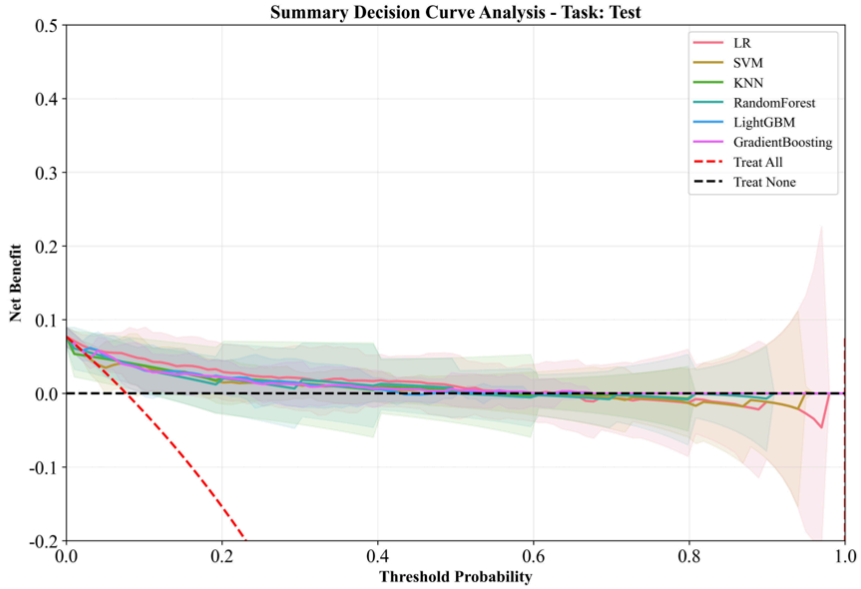


Fig. 5b Decision curve analysis in the test set.

Figure 5

a Decision curve analysis in the training set.

b Decision curve analysis in the test set.

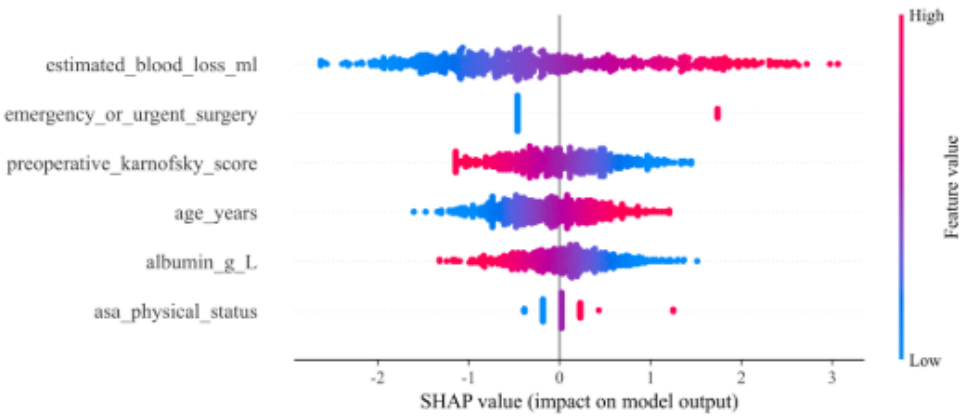


Figure 6

SHAP summary plot showing feature importance and direction of effect.

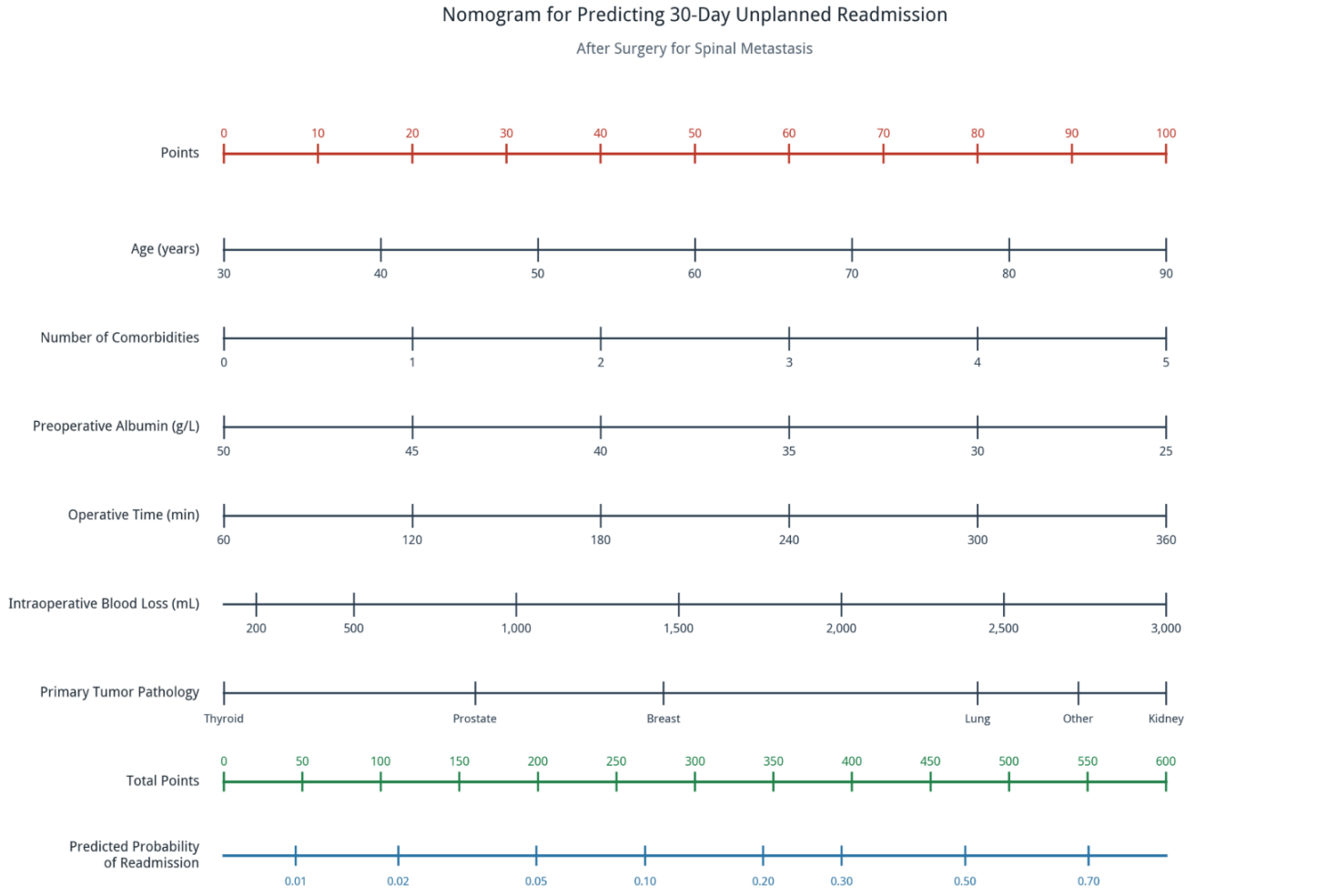


Figure 7

Nomogram for predicting 30-day unplanned readmission after spinal metastasis surgery.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Additionalfile1DataDictionary.csv
- Additionalfile2labelspinalmetastasis.csv.csv
- Additionalfile3clinicalspinalmetastasis48vars.csv.csv