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Prediction of suitable outpatient candidates following revision total knee arthroplasty using machine learning

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Aims
To identify variables independently associated with same-day discharge (SDD) of patients following revision total knee arthroplasty (rTKA) and to develop machine learning algorithms to predict suitable candidates for outpatient rTKA.

Methods
Data were obtained from the American College of Surgeons National Quality Improvement Programme (ACS-NSQIP) database from the years 2018 to 2020. Patients with elective, unilateral rTKA procedures and a total hospital length of stay between zero and four days were included. Demographic, preoperative, and intraoperative variables were analyzed. A multivariable logistic regression (MLR) model and various machine learning techniques were compared using area under the curve (AUC), calibration, and decision curve analysis. Important and significant variables were identified from the models.

Results
Of the 5,600 patients included in this study, 342 (6.1%) underwent SDD. The random forest (RF) model performed the best overall, with an internally validated AUC of 0.810. The ten crucial factors favoring SDD in the RF model include operating time, anaesthesia type, age, BMI, American Society of Anesthesiologists grade, race, history of diabetes, rTKA type, sex, and smoking status. Eight of these variables were also found to be significant in the MLR model.

Conclusion
The RF model displayed excellent accuracy and identified clinically important variables for determining candidates for SDD following rTKA. Machine learning techniques such as RF will allow clinicians to accurately risk-stratify their patients preoperatively, in order to optimize resources and improve patient outcomes.

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Keywords: Revision total knee arthroplasty, Same-day discharge, Machine learning

Introduction
Total knee arthroplasty (TKA), an effective intervention for patients with end-stage knee osteoarthritis, is among the fastest-growing procedures performed worldwide due to the increased longevity of the population and the burden of osteoarthritis.[1] While postoperative outcomes following TKA are generally positive, revision surgery can be required for various indications, including aseptic loosening, instability, and infection.[2] As the frequency of TKA procedures increases, the incidence of revision total knee arthroplasty (rTKA) is also rising.[3-5] Since rTKA is a more complex procedure than primary TKA, it results in relatively higher complication rates, extended hospitalization, and less satisfactory functional outcomes.[6]

Revision TKA has a median hospital length of stay (LOS) of three to five days.[7] Recent advancements in multimodal pain control, blood management techniques, and rapid recovery protocols have allowed for a shorter postoperative LOS.[8,9] This is exemplified by the recent (2021) removal of rTKA procedures from the Inpatient Only (IPO) list by the Centres for Medicare and Medicaid Services (CMS) in the USA.[10] Furthermore, recent literature

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Table I. Logistic regression analysis comparing demographic data, comorbidities, and preoperative and intraoperative variables between same-day discharge patients (zero-day length of stay) and normal discharge (two- to four-day length of stay) patients following revision total knee arthroplasty.

Characteristic	SDD (n = 342)	Normal discharge (n = 5,258)	p-value	Multivariable p-value	OR (95% CI)
Demographics					
Mean age, yrs (SD)	64.43 (9.87)	65.94 (9.94)	0.006	0.0024	1.02 (1.01 to 1.03)
Mean BMI, kg/m^2 (SD)	32.23 (6.27)	34.07 (7.18)	< 0.001	0.009	1.03 (1.01 to 1.05)
Sex, n (%)			0.009	0.010	
Male	160 (46.78)	2,089 (39.73)			1.51 (1.17 to 1.94)
Female	182 (53.22)	3,169 (60.27)			1
Race, n (%)			0.005		
White	296 (86.55)	4,180 (79.50)			
Black	36 (10.53)	972 (18.49)			
Asian	7 (2.05)	59 (1.12)			
Other	3 (0.87)	47 (0.89)			
Comorbidities, n (%)					
Diabetes mellitus	44 (12.87)	1,156 (21.99)	< 0.001	0.015	0.66 (0.47 to 0.93)
Smoking history	35 (10.23)	489 (9.30)	0.566		
CHF	0 (0.00)	27 (0.51)	0.184		
Hypertension	211 (61.70)	3,627 (68.89)	0.005		
Steroid use	13 (3.80)	264 (5.02)	0.313		
Bleeding disorders	11 (3.22)	173 (3.29)	0.941		
Dyspnea	12 (3.51)	351 (6.68)	0.021		
COPD	12 (3.51)	295 (5.61)	0.098		
Weight loss	0 (0.00)	22 (0.42)	0.231		
Dialysis	1 (0.29)	24 (0.46)	0.659		
Disseminated cancer	3 (0.88)	10 (0.19)	0.011		
Ascites	0 (0.00)	1 (0.02)	0.799		
Open wound/wound infection	1 (0.29)	56 (1.07)	0.168		
RBC transfusions	1 (0.29)	10 (0.19)	0.679		
Dependent functional status	1 (0.29)	178 (3.39)	0.002	0.002	0.12 (0.02 to 0.85)
Anaemia WHO class, n (%)			< 0.001		
Normal	276 (80.70)	3,400 (64.66)			1
Mild	63 (18.42)	1,565 (29.76)		0.580	0.58 (0.42 to 0.79)
Moderate/severe	3 (0.88)	293 (5.57)		< 0.001	0.20 (0.05 to 0.66)
ASA grade III to V, n (%)	168 (49.12)	3,501 (66.58)	< 0.001	0.0037	0.69 (0.54 to 0.89)
Indication, n (%)			< 0.001	< 0.001	
PJI	6 (1.75)	712 (13.54)			1
Noninfectious					17.48 (2.42 to 126.18)
Loosening	94 (27.49)	1,496 (28.45)			
Instability	81 (23.69)	630 (11.98)			
Pain	44 (12.87)	418 (7.95)			
Other	117 (34.21)	1,496 (28.45)			
Intraoperative variables					
One-component rTKA	188 (54.97)	1,394 (26.51)	< 0.001	< 0.001	1.61 (1.24 to 2.08)
Mean operating time, mins (SD)	91.30 (47.80)	144.96 (64.03)	< 0.001	< 0.001	1.02 (1.02 to 1.02)
Anaesthesia type			< 0.001		
General	161 (47.08)	3,208 (61.01)			1
Neuraxial	139 (40.64)	1,028 (19.55)		< 0.001	2.42 (1.88 to 3.14)
MAC/IV	38 (11.11)	931 (17.71)		0.014	0.62 (0.43 to 0.91)
Regional	2 (0.58)	85 (1.62)		0.498	0.61 (0.14 to 2.54)
None/Other	2 (0.58)	6 (0.11)		0.0024	15.44 (2.64 to 90.34)

ASA, American Society of Anesthesiologists; CHF, congestive heart failure; CI, confidence interval; COPD, chronic obstructive pulmonary disease; MAC/IV, monitored anesthetic care/intravenous; OR, odds ratio; PJI, periprosthetic joint infection; RBC, red blood cell; rTKA, revision total knee arthroplasty; SDD, same-day discharge; WHO, World Health Organization.

has demonstrated that outpatient rTKA with same-day discharge (SDD) is safe in carefully selected patients and case scenarios, and with appropriate patient selection, early discharge does not increase 90-day readmissions or emergency department visits.[11,12] While cardiopulmonary disease, bleeding disorders, chronic kidney disease,

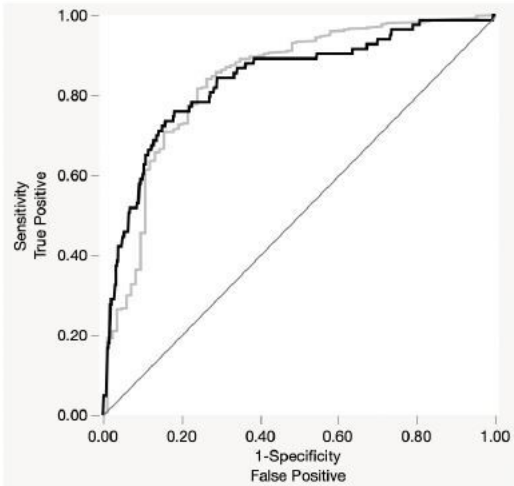

Fig. 1

Receiver operating curve of random forest training model for patients with same-day discharge (black) and without same-day discharge (gray) following revision total knee arthroplasty.

obesity, uncontrolled diabetes (type I or II), and dependent functional status have been shown to be predictive of SDD in primary arthroplasty, there is very limited data identifying factors that preclude SDD following rTKA.[13] Given the differences between primary and revision TKA, these factors cannot be extrapolated, and as such, accurately determining factors associated with SDD is vital to determine appropriate outpatient selection for rTKA.

Machine learning is a branch of artificial intelligence that creates complex models to iteratively improve its predictive capacity based on the quantity of data input. Through its ability to learn complicated non-linear or linear relationships, machine learning decreases bias and can provide more accurate results when compared to conventionally used logistic regression.[14] Machine learning has previously been used to predict LOS for various non-orthopaedic surgeries, but has only recently started to gain traction in orthopaedics, with one recent study using artificial neural networks to predict SDD following primary TKA.[15] However, this is the first study using machine learning techniques to predict SDD following rTKA.

The purpose of this study is to develop trained machine learning models, cross-referenced with traditional multivariable logistic regression (MLR), to determine the most important pre- and perioperative variables that may predict SDD in patients undergoing rTKA. We hypothesized that the trained models would have better accuracy when compared to MLR and will identify variables associated with increased overall health to be predictive of SDD.

Table II. Summary of model training and validation results.

Model	Training AUC	Validation AUC
MLR	0.808	0.772
RF	0.831	0.810
ANN	0.824	0.789
GBT	0.828	0.802
NB	0.819	0.792
SVM	0.811	0.778

ANN, artificial neural network; AUC, area under the curve; GBT, gradient-boosted tree; MLR, multivariable logistic regression; NB, Naïve Bayes; RF, random forest; SVM, support vector machine.

Methods

Data source. Data were obtained from the American College of Surgeons National Quality Improvement Programme (ACS-NSQIP) database from the years 2018 to 2020. ACS-NSQIP is a large clinical database that collects over 150 pre-, peri-, and postoperative variables up to 30 days following surgery at over 680 USA hospitals. Rigorous data collection and auditing by the American College of Surgeons has allowed for high-quality data with inter-reviewer reliability greater than 98%.[16]

Study population. Patients with elective, unilateral rTKA procedures and a total LOS between zero and four days were isolated in the ACS-NSQIP database using Current Procedural Terminology codes 27486 and 27487,[17] corresponding to rTKA with or without allograft one component only and revision of the femoral and entire tibial component, respectively. Patients were then categorized into two cohorts: LOS of zero days (SDD), and LOS of two to four days.

Variable selection. Baseline patient demographic data, including sex, race, age, and BMI, were collected. Patient comorbidities and preoperative variables that were collected include diabetes mellitus I and II requiring medication, dyspnea status, smoking, chronic obstructive pulmonary disease (COPD), hypertension requiring medication, chronic steroid use, > 10% weight loss in the six months preceding surgery, current need for dialysis, history of disseminated cancer, current open/ infected wound, congestive heart failure within 30 days prior to surgery, ascites within 30 days prior to surgery, history of bleeding disorder, and red blood cell (RBC) transfusions within 72 hours prior to surgery. Additionally, patient functional status (classified as either independent or partially/totally dependent), preoperative anaemia status (classified using World Health Organization (WHO) guidelines into normal, mildly anaemic, and moderate-severely anaemic), and American Society of Anesthesiologists (ASA)[18] grade (classified as either ASA grade I to II or ASA grade III to V) were collected.[19,20] Indication for rTKA was collected, and included aseptic mechanical loosening, instability, pain, and periprosthetic joint infection (PJI). Intraoperative variables were collected, including type of rTKA (single component vs all components), primary

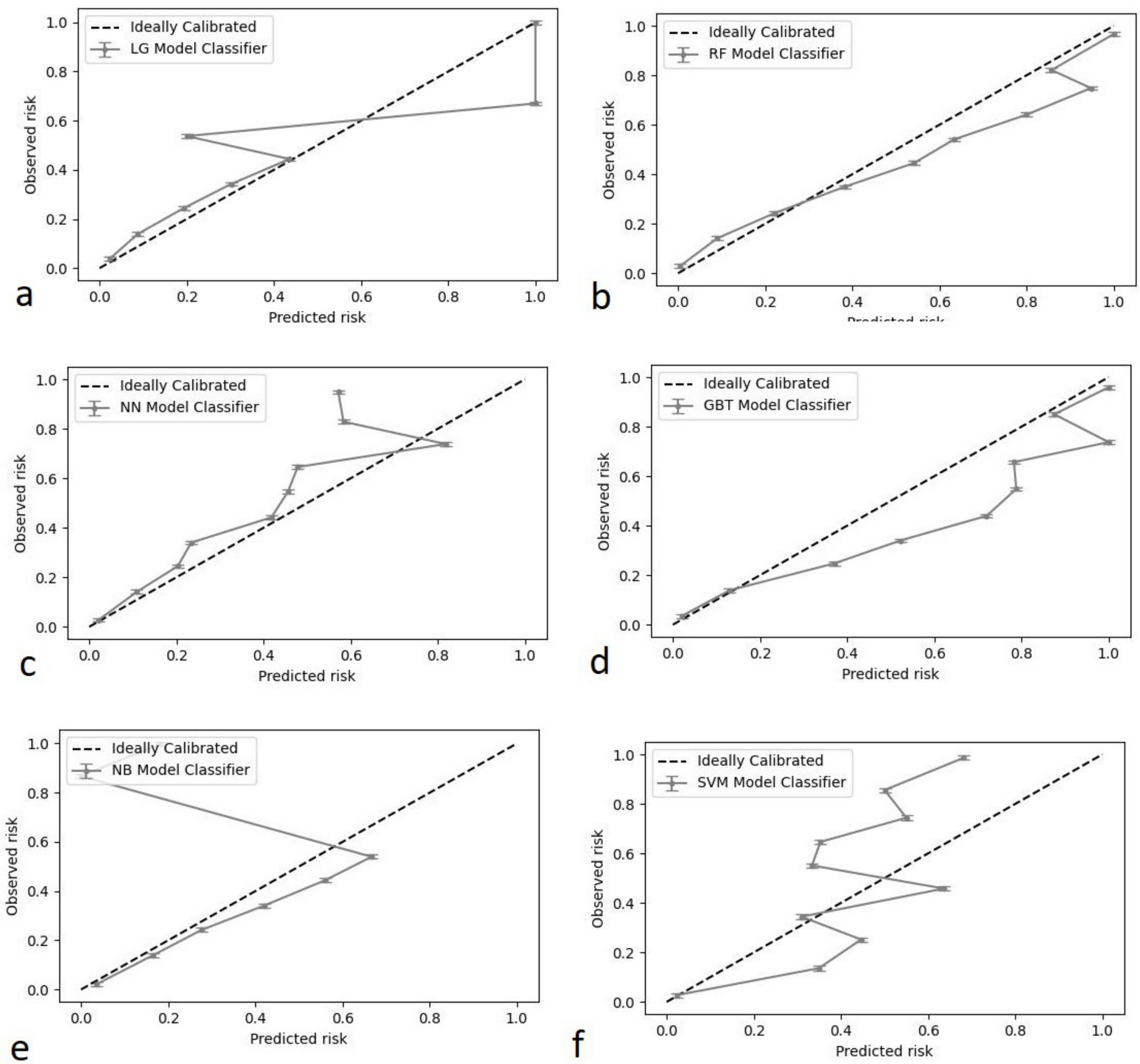

Fig. 2

Calibration curves with 95% confidence intervals for prediction of same-day discharge using a) multivariable logistic regression (LG), b) random forest (RF) regression, c) artificial neural network (NN) regression, d) gradient-boosted tree (GBT) regression, e) Naïve Bayes (NB) regression, and f) support vector machine (SVM) regression.

anesthetic type, and operating time. All variables are defined in the ACS-NSQIP user guide.[21]

Exclusion criteria and missing data. Patients who had missing data for LOS, who underwent concurrent/additional surgical procedures, or who were readmitted within 30 days of discharge, were excluded from this study. Patients with LOS of one day were excluded from our dataset, as prior literature reports that one-day LOS in the ACS-NSQIP database includes a combination of outpatient and inpatient cases, likely as a result of discrepancies at the regional and hospital levels regarding postoperative observational care.[15,22] Other variables with missing values were imputed using multiple imputation with the missForest methodology.[23] The number of patients with missing data was as follows: LOS (n = 102); BMI (n = 584); ASA grade (n = 23); functional status (n = 47); and operating time (n = 71).

Statistical analysis. Prior to developing the machine learning models, the data were randomly divided into training (75%) and internal validation (25%) datasets. Five popular machine learning techniques, random forest (RF), artificial neural network (ANN), gradient boosted tree (GBT),

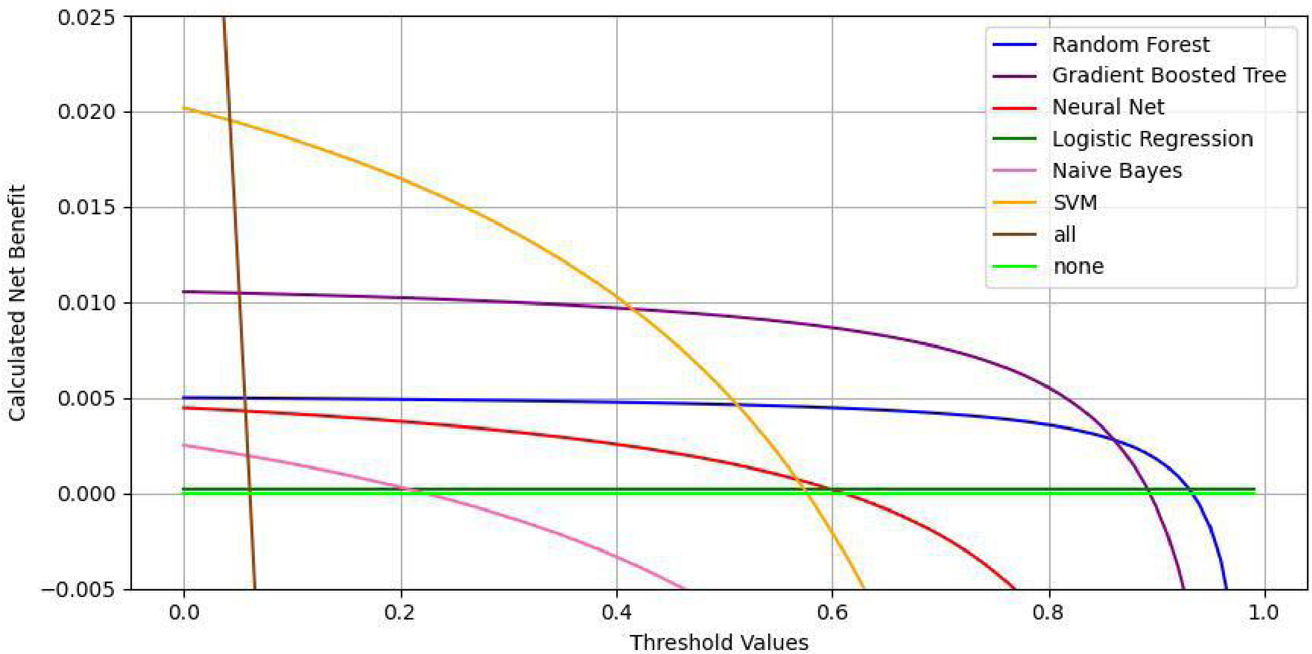

Fig. 3

Decision curve analyses showing the net benefit against the threshold probabilities based on decisions from the model outputs. The curve titled "all" represents the prediction that all patients would undergo same-day discharge (SDD). The curve titled "none" represents the prediction that all patients would not undergo SDD. SVM, support vector machine.

Naïve Bayes (NB), and support vector machine (SVM), were then applied to the training and validation datasets to predict SDD following rTKA. RF is a regression-based classification algorithm that aggregates many decision trees trained on randomly sampled subsets of a complex dataset.[24,25] When developing the RF model, a grid search was used to determine the best combination of tuning parameters, including number of trees and number of features at each split. These models were chosen based on previous machine learning studies that focused on binary classifications.[15,26] Logistic regression was also performed using independent-samples *t*-tests and Pearson's chi-squared tests to evaluate continuous and categorical variables, respectively. Statistically significant variables were then examined using MLR. All analyses were completed using Stata v. 16.1 (Stata Corp, USA). An α of 0.05 was used for statistical significance.

The predictive capacity of each model was assessed and compared using the area under the receiver operating characteristics curve (AUC), which is a measure of discrimination and is the gold-standard metric of machine-learning assessment. The receiver operating characteristic curve plots the false-positive rate on the x-axis and the true-positive rate on the y-axis. The AUC, or c-statistic, ranges from 0.5 to 1, with an AUC of 0.50 indicating that the model being studied has a 50% chance of predicting the outcome, and thus cannot distinguish between patients who did and did not undergo SDD.[27] Model performance was also measured by visually assessing calibration curves. Calibration refers to the agreement between predicted outcomes and the observed frequency of the outcome.[28] The model performs well on calibration when the curve is close to the bisector. Decision curves were further constructed in order to evaluate the models. The y-axis of the decision curve represents the net benefit, which judges whether clinical decisions have more benefit than harm, and each point on the x-axis represents a threshold probability that differentiates between patients who underwent SDD and those who did not. The model with the greatest AUC was further analyzed to determine the ten most important variables for predicting SDD, rated based on their contribution to the model.[29]

Results

Factors associated with same-day discharge following revision TKA. In total, 5,600 patients were included in the final analyses. Of these patients, 342 (6.1%) were discharged on the same day of surgery. Comparisons between patients who underwent SDD and patients who did not with regard to demographics and perioperative variables are displayed in Table I. Variables significantly associated with SDD in the MLR analysis are also displayed in Table I.

Machine learning algorithm development. The RF model had the highest AUC upon internal validation (0.810), outperforming the other models (Table II) (Figure 1). The RF model also demonstrated superior performance upon

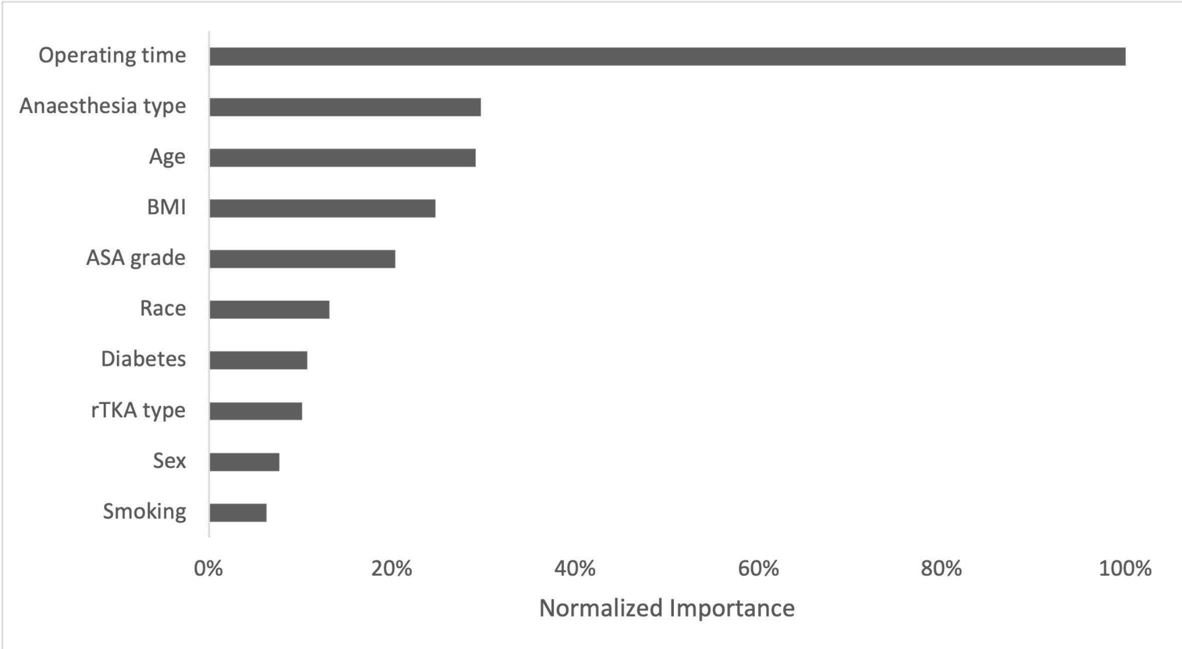

Fig. 4

Normalized importance of pre- and intraoperative factors for same-day discharge based on random forest model. Importance is the degree to which the model is dependent on the factor. ASA, American Society of Anesthesiologists; rTKA, revision total knee arthroplasty.

visual inspection of the calibration curves (Figure 2) as well as the decision curve analysis (Figure 3), in which it demonstrated a higher net benefit across the threshold values. The RF model identified operating time < 95 minutes as the most important variable for determining SDD, followed by anaesthesia type, age < 73, BMI, ASA grade, race, history of diabetes, rTKA type, sex, and smoking status (Figure 4).

Discussion

Outpatient rTKA with SDD has become more prevalent, in part due to a goal of decreasing the overall cost to the healthcare system.[11] This study applied various machine learning strategies to predict SDD following rTKA in order to identify important characteristics for appropriate outpatient selection. Among all six tested models, the RF model yielded the highest AUC in both the training (AUC 0.831) and validation (AUC 0.810) datasets, demonstrating excellent accuracy and predictability. Prior literature has found RF to be superior to other machine learning techniques in handling many factors and highly non-linear data. As such, RF appears to be the machine learning algorithm of choice in many clinical studies which use analytical databases such as ACS-NSQIP.[30,31] The results from our RF suggest that shorter operating time, anaesthesia type, age, BMI, ASA grade, race, history of diabetes, rTKA type, sex, and smoking status are most predictive of SDD following rTKA; all but race and smoking status were significant in the MLR analysis.

Operating time was a variable significantly highlighted in both RF and MLR, independent of whether the procedure was a single- or both-component revision. This finding has been previously reported by Garbarino et al,[32] who used ACS-NSQIP from 2008 to 2016 to assess the effect of operating time on in-hospital LOS in patients undergoing rTKA. They found that as operating time increases, postoperative LOS also increases, thus concluding that appropriate staffing, communication, and coordination are vital to decreasing LOS and consequently, hospital costs. This finding was also recently reported by Buller et al,[12] who conducted a matched cohort study at a single tertiary care referral centre. Furthermore, studies have found that increased operating time results in not only an increased LOS, but also increased postoperative complications such as surgical site infection, sepsis, and renal insufficiency.[33,34] As such, taking appropriate measures to increase the efficiency and limit the duration of the rTKA operation is vital to decrease hospital costs and improve patient outcomes. Additionally, our MLR analysis found indication, specifically aseptic failure, to be associated with SDD, likely due to the association of PJI with more adverse perioperative outcomes.[35] Based on our study, if the orthopaedic surgeon anticipates that the procedure will last more than 95 minutes, if the procedure is a both-component rTKA, or if the indication is PJI, they may want to consider admitting the patient to the hospital.

We found that the type of anaesthesia, specifically neuraxial anaesthesia, was also significant in both RF and

MLR. Neuraxial anaesthesia results in decreased operating time, LOS, and postoperative complications such as surgical site infection in both primary and revision TKA.[15,36,37] This is likely due to sympathetic blockade and consequent reduced blood loss.[38,39] Therefore, increased utilization of neuraxial anaesthesia may improve patient outcomes and decrease LOS associated with rTKA.

BMI, age, anaemia status, ASA grade, sex, and history of diabetes were also identified from the RF model and considered significant predictors of SDD following rTKA by MLR analysis. These variables have been previously reported on in the context of primary TKA. Specifically, Wei et al[15] found that upon using ANN to predict SDD following primary TKA, preoperative sodium, BMI, age, anaesthesia type, operating time, race, and anaemia status were key factors. Thus, accounting for these characteristics and delaying surgery until modifiable risk factors such as BMI have been addressed may greatly benefit the patient.

Worldwide, the incidence of rTKAs is projected to increase rapidly.[5] Consequently, selecting patients suitable for outpatient rTKA has become increasingly relevant. Our study used many variables, including demographics, comorbidities, and perioperative factors, to determine the ideal candidate for outpatient rTKA. Several studies have previously shown the advantages of machine learning techniques such as RF and ANN to study risk assessment for various orthopaedic procedures, such as delirium in geriatric patients following hip fracture fixation and postoperative complications following lumbar spine fusion.[26,40] Moreover, these techniques have also shown promise in predicting SDD following procedures such as laminectomy surgery and primary total knee and total hip arthroplasties.[15,41,42] However, to the best of our knowledge, this is the first study applying RF and ANN to predict SDD following rTKA. This study adds to the existing literature regarding the utilization of various machine learning techniques to predict complications and SDD following common orthopaedic procedures. Physicians can apply these machine learning models to aid in appropriate patient selection for outpatient rTKA and engage in shared decision-making with patients. Furthermore, implementation of the important variables identified in this study may be used to optimize patients perioperatively.

Our study has limitations. First, our analyses may be biased by the retrospective nature of this study; however, this approach allowed for a large sample size, greatly improving the accuracy of the models tested.[43] Second, as with any database study, we are limited by the number of variables included in the dataset and the quality of the dataset. However, ACS-NSQIP is a large dataset with many variables, and previous studies have found it to be of high quality, with high inter-reviewer reliability.[16] This minimizes bias, allowing us to accurately distinguish between patients with SDD and patients with inpatient hospitalizations. Third, the application of machine learning to medicine is still relatively novel, and although several features were selected as important by the RF model, the exact nature of their importance is difficult to interpret. However, in this study, we have also provided the analyses from traditionally used MLR for cross-reference, allowing for greater clarification as to the importance of certain variables. It is recommended that surgeons use all published information on rTKA for appropriate decision-making. Finally, external validation of these models in a dataset that is not obtained through NSQIP is warranted.

In summary, the machine learning techniques developed in this study, especially RF, displayed excellent accuracy for the prediction of SDD following rTKA. Once cross-referenced with conventional MLR, the most predictive variables included operating time, BMI, age, and type of anaesthesia. With the rising emphasis on value-based care, outpatient surgical practice is rapidly expanding across all healthcare subspecialties.[44,45] Incorporating models such as these can allow orthopaedic surgeons to accurately risk-stratify their patients preoperatively to achieve the most optimal outcomes.

Take home message

- This study identified important perioperative factors integral in determining same-day discharge of patients following revision total knee arthroplasty (rTKA).
- Machine learning techniques can accurately predict patients suitable for outpatient rTKA.
- Using these techniques, surgeons can engage in shared decision-making with patients to develop an effective strategy for management.

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