Utility of Machine Learning Algorithms in Predicting Non-home Discharge After Simultaneous Bilateral Total Knee Arthroplasty

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Abstract

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Introduction:

Simultaneous bilateral total knee arthroplasty (simBTKA) accounts for approximately 5% of all primary total knee arthroplasties [1]. Although it represents a relatively small proportion of cases, nearly 250,000 patients underwent the procedure between 2009 and 2016 alone, underscoring its continued clinical relevance. Non-home discharge, typically defined as discharge to a skilled nursing facility (SNF) or inpatient rehabilitation facility (IRF) rather than directly home, occurs more frequently after simBTKA than after staged or unilateral procedures [2] [3–6] Non-home discharge has been associated with nearly fivefold higher odds of readmission and nearly threefold higher odds of periprosthetic complications compared with home discharge, whereas home discharge appears to be the optimal strategy for minimizing complications at both 30 and 90 days postoperatively [7–9]. Patient-reported outcome data further support this distinction, as patients discharged to non-home settings have demonstrated lower rates of clinically meaningful physical improvement, worse mental health outcomes, and poorer short-term perioperative outcomes than those discharged home[9]. Non-home discharge is also a major and potentially modifiable driver of episode-of-care cost, with facility-based discharge associated with 3.9-fold greater costs than home discharge as well as greater overall healthcare utilization, including higher rates of readmission, serious adverse events, and outpatient visits. [10]

SimBTKA has been associated with substantially higher rates of non-home discharge than staged bilateral TKA. One study reports discharge to a rehabilitation facility in 46% of simBTKA patients compared with 9% of staged bilateral TKA patients [11]. This increased rate may reflect the distinct perioperative risk profile of simBTKA, including greater intraoperative blood loss and higher rates of wound, neurologic, and cardiovascular complications [12,13] Given the high prevalence of non-home discharge in this population, identifying patients at elevated risk is clinically important. In broader primary TKA populations, several patient-level factors have been associated with non-home discharge. Increasing age, higher body mass index, and higher preoperative white blood cell count have each been linked to greater odds of discharge to a skilled nursing facility or rehabilitation center [14] Other studies have identified comorbid psychiatric and neurologic conditions, including psychoses, substance abuse, neurologic

disorders, and depression, as additional predictors of non-home discharge [15], while a systematic review also found female sex to be a strong associated factor [16]. However, no study has specifically evaluated these risk factors to predict non-home discharge after simBTKA. [17]

Patients undergoing simBTKA are typically younger and have fewer comorbidities than those undergoing staged bilateral TKA, reflecting the stricter selection criteria for simultaneous surgery. Even in this healthier population, however, simBTKA has been associated with greater perioperative risk. Compared with unilateral TKA, simBTKA has been linked to higher rates of major complications, including increased blood loss, greater transfusion requirements, and more frequent cardiac and thromboembolic events [18–20]This is clinically important because perioperative transfusion has itself been associated with serious adverse events after TKA. In addition, the longer operative time, prolonged tourniquet use, bilateral lower-extremity immobility, and greater hemodynamic burden of simBTKA may further increase the risk of complications such as pulmonary embolism and stroke. Although predictors of non-home discharge, including impaired functional status, higher American Society of Anesthesiologists classification, and predischarge adverse events, have been identified in unilateral and broader arthroplasty populations, their relevance to simBTKA remains poorly defined. [21]

Machine learning (ML) is a branch of artificial intelligence that uses computational algorithms to identify complex patterns in data and generate individualized predictions. In orthopedic surgery, ML has increasingly been applied to total knee arthroplasty to predict outcomes such as complications, readmissions, length of stay, and discharge disposition, often with greater accuracy than conventional risk calculators. However, these models have been developed largely in UTKA populations, and no study to date has specifically evaluated ML-based prediction of non-home discharge after simultaneous bilateral total knee arthroplasty (simBTKA). Given the distinct perioperative burden of simBTKA and its higher baseline risk of non-home discharge, a simBTKA-specific predictive framework is needed. Accordingly, the aim of this study was to develop and validate ML models using a large national database to predict patient-specific risk of non-home discharge after simBTKA.

Methods

Data Source and Patient Selection

We conducted a retrospective cohort study using the American College of Surgeons National Surgical Quality Improvement Program (ACS-NSQIP) database from 2010 through 2023. Because ACS-NSQIP contains deidentified, publicly available data from more than 700 participating institutions, institutional review board approval was not required [22]. Patients undergoing simultaneous bilateral total knee arthroplasty (SBTKA) were identified using [CPT definition; e.g., two entries of CPT 27447 recorded on the same operative date, or a bilateral-specific CPT code, as applicable]. We excluded patients younger than 18 years, records with missing data for study variables, and [additional exclusions, if applicable, such as emergency cases or miscoded staged bilateral procedures]. The primary outcome was discharge disposition.

Non-home discharge was defined using the ACS-NSQIP discharge variable as discharge to a skilled nursing facility, inpatient rehabilitation facility, or another non-home destination. Home discharge served as the reference group. Of the [XX,XXX] eligible patients, 5,626 (44.1%) had non-home discharge and 7,141 (55.9%) were discharged home. Baseline demographic, comorbidity, and perioperative characteristics are presented in Table [X].

Variables

Predictor selection was limited to variables routinely available in ACS-NSQIP before surgery. These included sociodemographic characteristics (age, sex, race, ethnicity, and body mass index), baseline clinical status (American Society of Anesthesiologists [ASA] class and preoperative functional status), comorbidity profile ([e.g., diabetes, hypertension, smoking, COPD, congestive heart failure, dialysis dependence, bleeding disorders, and steroid or immunosuppressive use]), and preoperative laboratory measures (hematocrit, platelet count, white blood cell count, [additional labs if used]). To maintain a strictly preoperative prediction framework, we did not include variables that occur after surgical decision-making, such as anesthesia type, operative duration, or other intraoperative/post decision factors. The modeled endpoint was non-home discharge, defined as described above.

Model Development

Data preprocessing was performed before model fitting: continuous predictors were standardized, and categorical variables were one-hot encoded. The dataset was then split into training and test cohorts using a stratified 80:20 partition to preserve outcome balance. Given the number of candidate predictors, feature reduction was applied within the training pipeline using recursive feature elimination with a parsimonious random forest estimator to retain variables with the greatest contribution to prediction and reduce overfitting risk.

We trained four supervised machine learning models selected for prior utility in orthopaedic prediction studies: artificial neural network (ANN), histogram-based gradient boosting (HGB), random forest (RF), and k-nearest neighbors (KNN). Hyperparameters were tuned using a coarse grid-search strategy with repeated random subsampling of the training set. Model-specific tuning included learning rate, network depth/width, and training epochs for ANN; learning rate, maximum boosting iterations, and leaf complexity for HGB; number of trees and minimum leaf sample size for RF; and neighbor count plus distance metric for KNN. After tuning, each model underwent five-fold cross-validation and was subsequently evaluated on the held-out test set.

Model Performance Assessment

Model performance was assessed across three complementary dimensions: discrimination, calibration, and clinical usefulness. Discrimination was quantified using the area under the receiver operating characteristic curve (AUC), with values greater than 0.70 considered acceptable. Calibration was evaluated using calibration slope, calibration intercept, and Brier

score; optimal calibration corresponds to a slope of 1 and intercept of 0, and lower Brier scores indicate less overall prediction error.

Potential clinical usefulness was examined with decision curve analysis by estimating net benefit across a range of clinically relevant risk thresholds. Global interpretability was assessed using permutation-based feature importance, normalized to the highest-ranking predictor in the best-performing model. [If applicable: Local explanation plots were also generated to illustrate individual-level feature contributions.]

Statistical Analysis

Baseline characteristics were compared between non-home and home discharge groups. Continuous variables were analyzed using independent t t-tests or Mann–Whitney U U tests according to distributional normality (Shapiro–Wilk test). Categorical variables were compared using chi-square or Fisher exact testing, as appropriate. A two-sided significance threshold of $P < 0.05$ $P<0.05$ was used throughout. All statistical analyses and machine learning workflows were conducted in Python (Python Software Foundation) and [Anaconda/SPSS, if applicable].

Baseline characteristics

The final study cohort consisted of 4,974 patients, of whom 2,011 (40.4%) were discharged to a non-home destination and 2,963 (59.6%) were discharged home. Patients in the non-home discharge cohort were older than those discharged home (median age: 66.0 [59.0–71.0] vs 63.0 63.0 [58.0–69.0] years, $p < 0.001$) and had a higher BMI (median: 32.85 [28.71–37.76] vs 31.56 [27.96–35.51], $p < 0.001$). Compared with the home discharge group, non-home discharge patients were more frequently male (60.9% vs 50.3%, $p < 0.001$), less frequently White (81.8% vs 88.0%, $p < 0.001$), and had similar Hispanic ethnicity (3.5% vs 3.2%, $p = 0.632$). In addition, the non-home discharge cohort had a greater proportion of partially or totally dependent functional status preoperatively (0.9% and 0.0% vs 0.5% and 0.0%, overall $p = 0.0875$), a higher prevalence of diabetes requiring either non-insulin or insulin treatment (14.4% and 4.1% vs 9.3% and 2.3%, overall $p < 0.001$), and a higher prevalence of COPD (2.5% vs 1.2%, $p = 0.00159$), while rates of smoking, bleeding disorders, congestive heart failure, renal failure, dialysis, significant weight loss, and malignancy were comparable (all $p > 0.05$). Preoperative hematocrit was lower in the non-home cohort (median: 41.40 [38.60–44.00] vs 42.20 [39.90–44.60], $p < 0.001$), whereas platelet count, white blood cell count, creatinine, sodium, and corticosteroid use were not significantly different (all $p > 0.05$). Anesthesia type differed significantly between groups (overall $p < 0.001$), with greater use of general anesthesia in non-home discharge patients (55.6% vs 42.8%), and ASA class distribution was also significantly different (overall $p < 0.001$), with a higher proportion of ASA class ≥ 3 in the non-home group (50.1% vs 35.2%). The differences in baseline characteristics stratified by discharge disposition are summarized in Table 1.

Results

Validation Performance

Four machine learning algorithms were developed to predict non-home discharge after simultaneous BTKA, including histogram gradient boosting (HGB), artificial neural network (ANN), random forest (RF), and k-nearest neighbors (Table 2). HGB achieved the highest discrimination, with an AUC of 0.75, followed by ANN and RF models, each with an AUC of 0.74, and k-nearest neighbors with an AUC of 0.73.

The ANN yielded the lowest Brier score (0.198), indicating the best overall predictive accuracy, while HGB, RF, and k-nearest neighbors produced Brier scores of 0.202, 0.203, and 0.206, respectively. Calibration metrics further suggested that the ANN was the best-calibrated model, with a slope of 1.067 and intercept of -0.024. In comparison, HGB demonstrated a slope of 1.434 and intercept of -0.182, while random forest and k-nearest neighbors demonstrated slopes of 1.228 and 1.155 and intercepts of -0.080 and -0.042, respectively.

Because HGB demonstrated the highest discriminative performance, it was selected for further evaluation. The receiver operating characteristic curve showed acceptable discrimination, with an AUC of 0.750 (Fig. X). The calibration plot demonstrated good concordance between predicted and observed probabilities. Decision curve analysis suggested modest clinical utility, with the model providing positive net benefit across a broad range of threshold probabilities relative to default strategies.

Feature importance analysis showed that BMI, age, and preoperative hematocrit were the most influential predictors of non-home discharge following simultaneous BTKA, followed by ASA class and sex. These findings suggest that discharge disposition after simultaneous BTKA is driven primarily by patient anthropometric characteristics, age, comorbidity burden, and baseline physiological status.

Discussion

In this national cohort of patients undergoing simBTKA, we developed and evaluated four machine learning models using routinely available perioperative variables to predict non-home discharge, which occurred in 40.4% of cases. Overall performance was good, with the HGB model demonstrating the best discrimination at an AUC of 0.75, while the ANN showed the best calibration, with a Brier score of 0.198, calibration slope of 1.067, and calibration intercept of -0.024. This rate of non-home discharge is consistent with prior simBTKA literature and further supports that simBTKA represents a distinct and higher-risk discharge population [11]. To our knowledge, this is the first study to apply machine learning specifically to predict non-home discharge after simBTKA, whereas prior ML-based discharge prediction models have largely been derived from unilateral or broader primary TKA populations [23] . Given the substantial risk of non-home discharge in simBTKA, accurate preoperative risk stratification may enable earlier and more targeted discharge planning, optimize resource utilization, and better align post-acute care services with anticipated patient needs [24]. Although our simBTKA-specific models

demonstrated good discrimination, with AUCs ranging from 0.73 to 0.75 0.75 they may have been limited by the comparatively small simBTKA sample available for model development [25] and by incomplete capture of key clinical and social determinants of discharge disposition within national registry datasets [26]. Consistent with prior simBTKA studies identifying higher-risk clinical profiles (e.g., older age and lower preoperative hemoglobin) [27], our findings extend this evidence by demonstrating that individualized prediction of non-home discharge is feasible and clinically meaningful. Overall, this supports a practical framework for early risk identification and discharge planning after simBTKA.

Among the most clinically actionable predictors identified by our models were BMI and preoperative hematocrit, both of which may represent modifiable physiologic risk factors. Patients discharged to non-home settings had a higher median BMI than those discharged home (32.85 vs 31.56, $P < 0.001$), and BMI emerged as the most influential model feature. A study by Gwam et al. reported that for every 10% increase in BMI above the cohort mean, the odds of discharge to a skilled nursing facility and to inpatient rehabilitation increased by approximately 10% ($p < 0.001$) and 9.6% ($p < 0.001$), respectively, relative to home discharge. [28]. Higher BMI may impair early implant biomechanics; finite element data show roughly 33%–51% higher distal femoral strain and 42%–59% greater implant micromotion in high-BMI knees, potentially compromising initial fixation [29]. Clinically, this likely translates to greater perioperative morbidity, slower early mobilization and functional recovery, and higher comorbidity burden in patients with elevated BMI, collectively lowering the likelihood of safe independent home discharge. [30–32]. Preoperative hematocrit was likewise one of the strongest predictors, with lower preoperative values observed among patients discharged to non-home settings. Similarly, Gwam et al. reported that each 10% increase in preoperative hematocrit was associated with an 11% reduction in the odds of discharge to a skilled nursing facility and a 13% reduction in the odds of discharge to inpatient rehabilitation (both $p < 0.001$). Lower preoperative hematocrit likely predicts non-home discharge because it reflects reduced oxygen-carrying reserve. This reserve may be further diminished by intraoperative blood loss. Together, these factors can impair early mobilization and limit participation in physical therapy. Lower hematocrit is also associated with higher transfusion requirements and greater perioperative medical complications. Collectively, these effects may delay the functional recovery required for safe home discharge [27,33,34]. As potentially modifiable preoperative factors, BMI and hematocrit may therefore serve as practical targets for optimization strategies aimed at increasing the likelihood of home discharge after simBTKA.

In addition to these potentially modifiable factors, age, ASA class, and sex also contributed meaningfully to prediction, further contextualizing which patients may require increased postoperative support. Age was among the strongest model features, and patients discharged to non-home settings were older than those discharged home (median 66.0 vs 63.0 years, $P < 0.00$). This is consistent with prior simBTKA literature showing that older age is associated with greater rehabilitation utilization [27,35]. This likely reflects age-related declines in physiologic

reserve and baseline mobility, together with greater comorbidity burden, such that older patients often require more intensive inpatient rehabilitation while achieving slower early functional recovery, thereby delaying readiness for safe home discharge [36]. ASA class was also associated with non-home discharge, with higher-risk classifications more common in the non-home group; ASA class 3 was present in 49.0% versus 34.6%, and ASA class 4 in 1.1% versus 0.6% ($P < 0.001$). This likely reflects lower physiologic reserve and greater medical complexity, consistent with prior arthroplasty literature linking ASA score ≥ 3 to increased postoperative complications and 30-day readmission [37]. Sex contributed less strongly than age and ASA class but remained among the top model features. Men comprised 60.9% of the non-home group compared with 50.3% of the home group ($P < 0.001$). Although this differs from some unilateral TKA literature in which female sex has been associated with longer length of stay [38], prior bilateral TKA work has suggested that male patients may have higher in-hospital complication risk than female patients [39]. A plausible explanation is that, despite the female-predominant non-home discharge pattern seen in unilateral TKA, men may experience more severe postoperative complications, which in simBTKA can increase the need for supervised post-acute care and favor non-home discharge[40]. Taken together, these findings suggest that older and more medically complex patients may be less likely to achieve home discharge after simBTKA.

From a clinical perspective, these findings suggest that machine learning-based prediction of non-home discharge after simBTKA may inform not only risk estimation but also perioperative decision-making and care coordination. In the preoperative setting, individualized risk estimates could enhance counseling by helping patients understand their expected recovery trajectory, likelihood of home discharge, and potential need for post-acute facility-based care. These predictions may also support candidacy discussions, particularly for patients with multiple risk factors, when determining whether simBTKA is the most appropriate surgical approach. For patients identified preoperatively as high risk for non-home discharge, early involvement of case management, physical therapy, social work, and family caregivers may enable more proactive discharge planning. This approach can help optimize modifiable factors, such as caregiver support and early mobilization, to facilitate safe home discharge when feasible, while allowing timely coordination of skilled nursing or inpatient rehabilitation placement when home-based recovery is not realistic [41–43]. In parallel, recognizing potentially modifiable risk factors such as low preoperative hematocrit and elevated BMI may support targeted preoperative optimization. Lower preoperative hematocrit can be addressed through structured blood-management programs (e.g., iron supplementation), which have been associated with reduced transfusion, complications, and length of stay [44,45], while multimodal prehabilitation has been shown to improve preoperative function and reduce complication rates [46,47]. Although the benefit of preoperative weight reduction remains less certain, these strategies collectively may still improve recovery and increase the likelihood of home discharge [48,49]. At a systems level, because non-home discharge is a major contributor to post-acute care utilization and episode-of-care cost [50], accurate preoperative risk stratification may help institutions anticipate discharge needs, guide preoperative optimization and patient counseling, and allocate post-acute care

resources more efficiently [51–53]. Importantly, these models should be viewed as decision-support tools that complement, rather than replace, clinical judgment, particularly because discharge disposition is also influenced by social support, insurance context, and institution-specific practice patterns that are not fully captured in national datasets.

This study has several limitations. Its retrospective design introduces the possibility of selection bias, misclassification, and residual confounding. Although ACS-NSQIP provides a large national cohort, it does not capture several important determinants of discharge disposition, including caregiver availability, home environment, insurance status, socioeconomic context, and surgeon- or institution-level discharge practices. Consequently, some predictors identified by the models may partly reflect unmeasured variation in local care pathways rather than patient-level physiologic risk alone. The registry also lacks granular information on enhanced recovery protocols, postoperative rehabilitation pathways, and other hospital-level practices that may substantially influence discharge destination after simBTKA. This is especially relevant because discharge disposition is shaped by both clinical and non-clinical factors and may partly explain the modest discrimination observed in our models. External validation was not performed, and validation in independent cohorts is needed before clinical implementation, as performance may differ across institutions, patient populations, and evolving perioperative care pathways. The identified predictor thresholds should be interpreted cautiously, as they are model-derived risk inflection points rather than clinically established abnormal cutoffs, particularly when they fall within conventionally normal ranges. Finally, these findings are specific to simultaneous bilateral TKA and should not be assumed to apply to unilateral or staged bilateral procedures, which differ in patient selection, perioperative burden, and discharge patterns.

In conclusion, machine learning-based prediction of non-home discharge after simultaneous bilateral total knee arthroplasty was feasible and demonstrated acceptable performance in a large national cohort. Among the models evaluated, histogram gradient boosting showed the best discrimination, while the artificial neural network demonstrated the best calibration. These findings suggest that simBTKA-specific risk stratification may help identify patients at increased risk of non-home discharge and could support preoperative counseling, discharge planning, and targeted optimization. Future work should focus on external validation and integration of these models into clinical workflows.

Table 1 Patient characteristics by discharge disposition

Parameter	Home discharge (n = 2963)	Non-home discharge (n = 2011)	P value
Demographics			

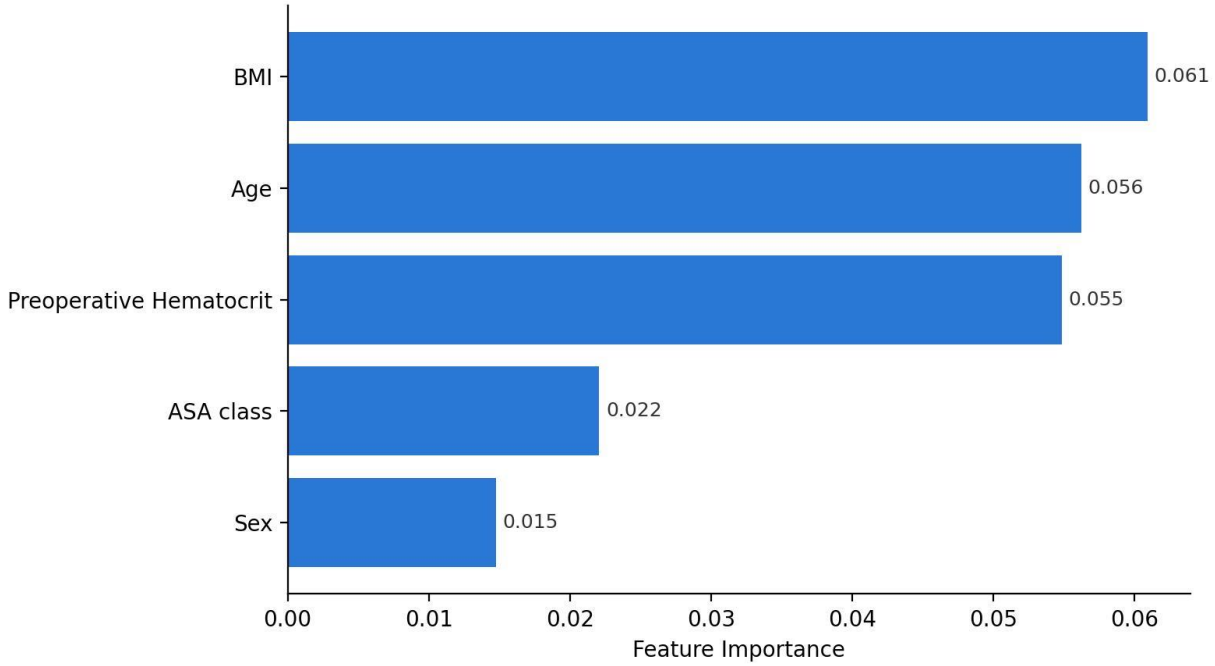
Parameter	Home discharge (n = 2963)	Non-home discharge (n = 2011)	P value
Age (years)	63.00 (58.00–69.00)	66.00 (59.00–71.00)	<.001
BMI	31.56 (27.96–35.51)	32.85 (28.71–37.76)	<.001
Sex (Men)	1491 (50.3%)	1224 (60.9%)	<.001
Race (White)	2607 (88.0%)	1645 (81.8%)	<.001
Race (Black or African American)	224 (7.6%)	265 (13.2%)	
Race (Asian)	104 (3.5%)	83 (4.1%)	
Race (American Indian or Alaska Native)	13 (0.4%)	5 (0.2%)	
Race (Native Hawaiian or Pacific Islander)	14 (0.5%)	13 (0.6%)	
Ethnicity (Hispanic)	96 (3.2%)	71 (3.5%)	0.632
Preoperative functional status (Independent)	2948 (99.5%)	1991 (99.0%)	0.0875
Preoperative functional status (Partially dependent)	15 (0.5%)	19 (0.9%)	
Preoperative functional status (Totally dependent)	0 (0.0%)	1 (0.0%)	
Comorbidities			
Smoking	207 (7.0%)	160 (8.0%)	0.219
Diabetes (No)	2618 (88.4%)	1639 (81.5%)	<.001
Diabetes (Non-insulin)	276 (9.3%)	290 (14.4%)	
Diabetes (Insulin)	69 (2.3%)	82 (4.1%)	
Hypertension	1402 (47.3%)	703 (35.0%)	<.001

Parameter	Home discharge (n = 2963)	Non-home discharge (n = 2011)	P value
Bleeding disorders	30 (1.0%)	30 (1.5%)	0.165
COPD	37 (1.2%)	50 (2.5%)	0.00159
Congestive heart failure	7 (0.2%)	8 (0.4%)	0.449
Renal failure	1 (0.0%)	0 (0.0%)	1
Dialysis	1 (0.0%)	2 (0.1%)	0.569
Significant weight loss	4 (0.1%)	2 (0.1%)	1
Malignancy	4 (0.1%)	4 (0.2%)	0.722
Preoperative investigations			
Hematocrit (%)	42.20 (39.90–44.60)	41.40 (38.60–44.00)	<.001
Platelet count (10^3/uL)	241.00 (205.00–283.00)	243.00 (206.00–287.00)	0.3
White blood cell (10^3/uL)	6.60 (5.60–7.80)	6.60 (5.50–8.10)	0.433
Creatinine (mg/dL)	0.87 (0.74–1.00)	0.85 (0.71–1.00)	0.191
Sodium (mmol/L)	140.00 (138.00–141.00)	140.00 (138.00–142.00)	0.0623
Preoperative medications			
Corticosteroid use	71 (2.4%)	67 (3.3%)	0.0596
Anesthesia			
Anesthesia (General)	1267 (42.8%)	1118 (55.6%)	<.001
Anesthesia (Spinal)	1130 (38.1%)	532 (26.5%)	
Anesthesia (Epidural)	86 (2.9%)	23 (1.1%)	

Parameter	Home discharge (n = 2963)	Non-home discharge (n = 2011)	P value
Anesthesia (Regional)	34 (1.1%)	25 (1.2%)	
Anesthesia (MAC/IV Sedation)	446 (15.0%)	313 (15.5%)	
ASA class			
ASA class (1)	95 (3.2%)	40 (2.0%)	<.001
ASA class (2)	1825 (61.6%)	963 (47.9%)	
ASA class (3)	1025 (34.6%)	985 (49.0%)	
ASA class (4)	18 (0.6%)	23 (1.1%)	

Table 2. Performance of Machine Learning Algorithms for Predicting Non-home Discharge

Model	AUC	Brier Score	Calibration Slope	Calibration Intercept
Histogram Gradient Boosting (HGB)	0.75	0.202	1.434	-0.182
Artificial Neural Network (ANN)	0.74	0.198	1.067	-0.024
Random Forest (RF)	0.74	0.203	1.228	-0.080
K-Nearest Neighbors (KNN)	0.73	0.206	1.155	-0.042


BMI
Age
Preoperative Hematocrit
ASA class
Sex
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Feature Importance

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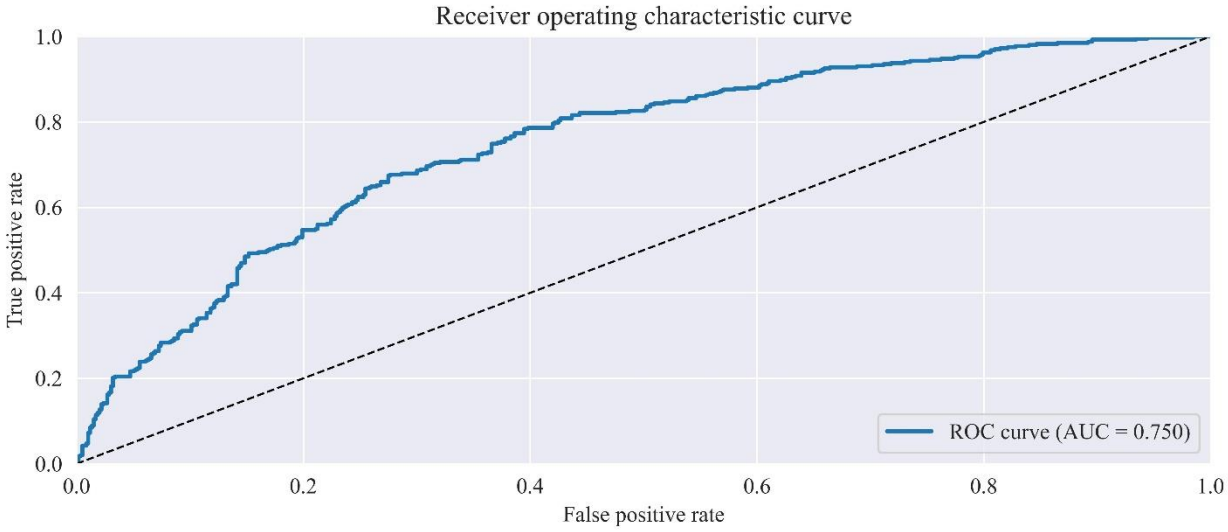
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True positive rate
False positive rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve (AUC = 0.750)

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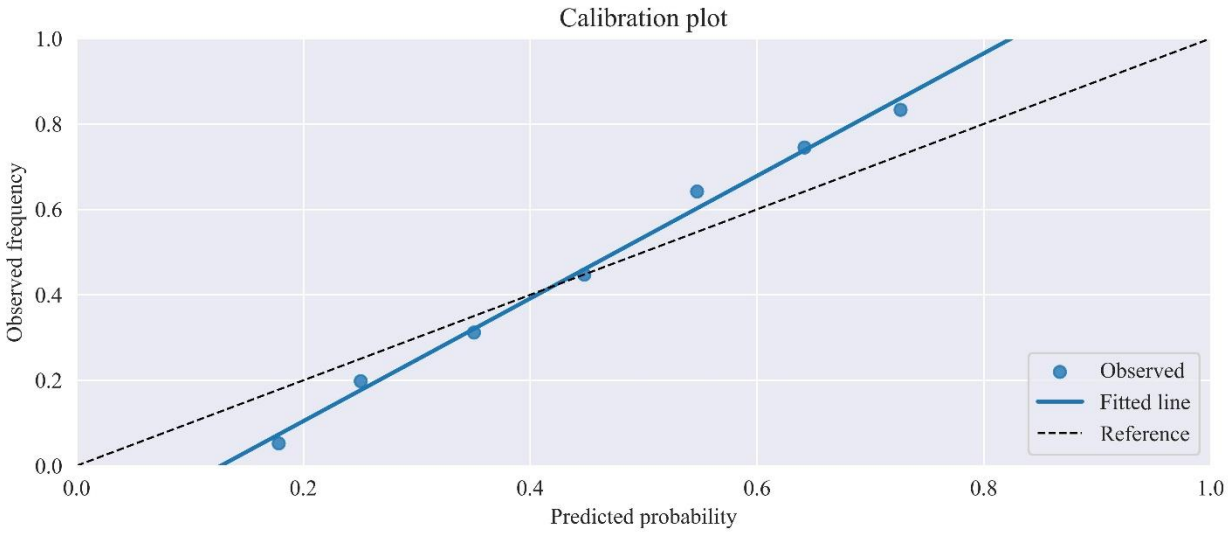

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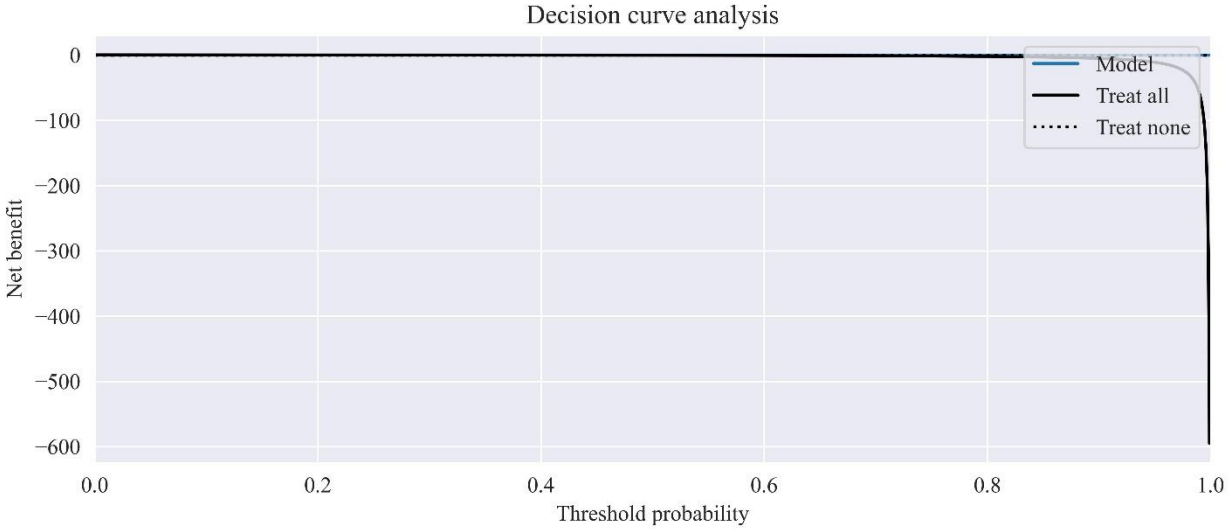

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