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

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IMPERIAL

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BACKGROUND & AIMS

- Simultaneous bilateral total knee arthroplasty (**simBTKA**) accounts for a small proportion of primary TKAs but remains clinically relevant.
- Compared with unilateral or staged bilateral TKA, simBTKA is associated with a **higher rate of non-home discharge**.
- Non-home discharge is important because it has been associated with:
  - higher readmission rates
  - more perioperative complications
  - worse short-term patient-reported outcomes
  - higher episode-of-care costs
- Although predictors of non-home discharge have been studied in broader arthroplasty populations, **no prior study has specifically developed machine learning models for simBTKA**.
- **Objective:** To develop and validate machine learning models to predict **non-home discharge after simBTKA** using a large national database.

STUDY DESIGN & MODEL DEVELOPMENT

We performed a retrospective cohort study using ACS-NSQIP data from 2010–2023 to develop preoperative machine learning models for prediction of non-home discharge after simBTKA. The final cohort included 4,974 patients, including 2,011 (40.4%) with non-home discharge. Candidate predictors included routinely available preoperative demographic, clinical, comorbidity, functional status, and laboratory variables. After preprocessing, the dataset was divided into stratified training and test sets. Recursive feature elimination was used to reduce overfitting and retain the most informative predictors. Four supervised machine learning algorithms were trained and compared: HGB, ANN, RF, and KNN. Hyperparameters were tuned within the training pipeline, followed by 5-fold cross-validation and final testing on the held-out dataset. Performance was assessed by discrimination, calibration, and clinical utility.

1. Cohort identification from ACS-NSQIP
2. Preoperative predictor extraction
3. Data preprocessing and feature selection
4. Training of HGB, ANN, RF, and KNN models
5. Cross-validation and held-out test evaluation
6. Comparison of model discrimination, calibration, and net benefit

RESULTS

Table 1. Baseline characteristics by discharge disposition

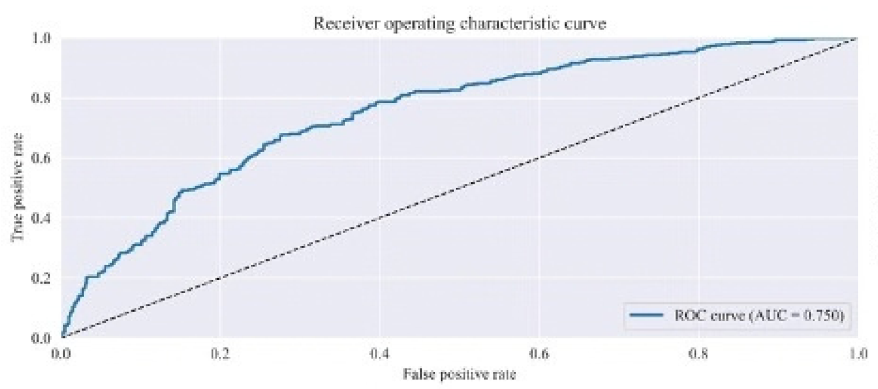
Parameter	Home discharge (n = 2963)	Non-home discharge (n = 2011)	P value
Demographics			
Age, years	63.0 (58.0–69.0)	66.0 (59.0–71.0)	**<.001**
Body mass index, kg/m²	31.6 (28.0–35.5)	32.9 (28.7–37.8)	**<.001**
Male sex	1491 (50.3)	1224 (60.9)	**<.001**
White race	2607 (88.0)	1645 (81.8)	**<.001**
Hispanic ethnicity	96 (3.2)	71 (3.5)	.632
Dependent functional status	15 (0.5)	20 (1.0)	.088
Comorbidities			
Diabetes mellitus	345 (11.6)	372 (18.5)	**<.001**
Hypertension	1402 (47.3)	703 (35.0)	**<.001**
COPD	37 (1.2)	50 (2.5)	**.002**
Current smoker	207 (7.0)	160 (8.0)	.219
Preoperative laboratory values			
Hematocrit, %	42.2 (39.9–44.6)	41.4 (38.6–44.0)	**<.001**
White cell count, ×10³/μL	6.60 (5.60–7.80)	6.60 (5.50–8.10)	.433
Creatinine, mg/dL	0.87 (0.74–1.00)	0.85 (0.71–1.00)	.191
Perioperative			
ASA class ≥ 3	1043 (35.2)	1008 (50.1)	**<.001**
General anesthesia	1267 (42.8)	1118 (55.6)	**<.001**

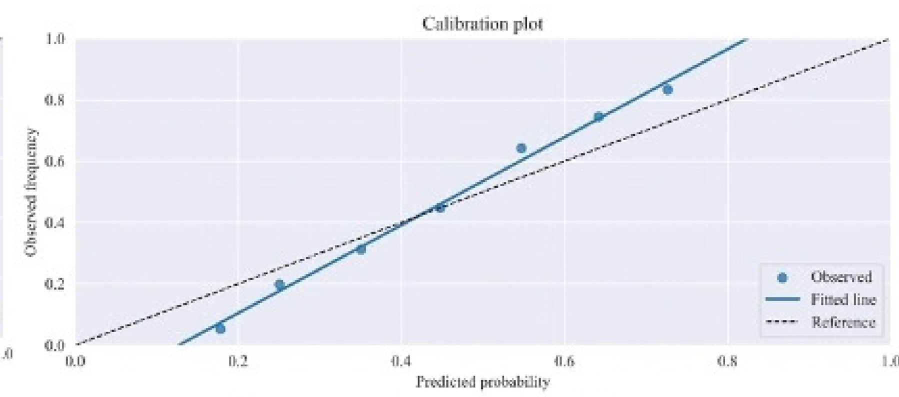
Median (IQR) for continuous variables; n (%) for categorical. Bold P values are statistically significant.

Table 2. Machine learning model performance

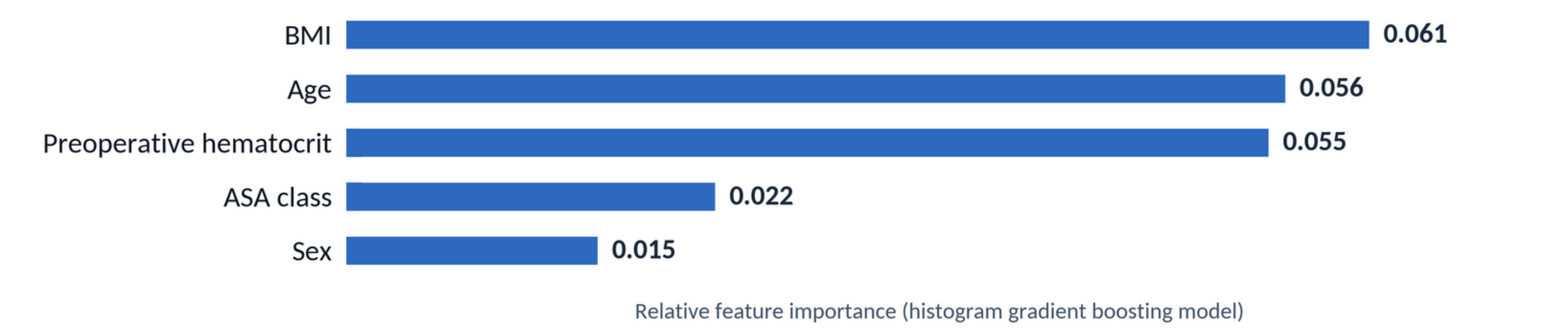
Model	AUC	Brier score	Calibration slope	Calibration intercept
Histogram gradient boosting (HGB)	**0.75**	0.202	1.434	−0.182
Artificial neural network (ANN)	0.74	**0.198**	**1.067**	**−0.024**
Random forest (RF)	0.74	0.203	1.228	−0.080
K-nearest neighbors (KNN)	0.73	0.206	1.155	−0.042

Bold = best value per metric. HGB showed the highest discrimination; ANN was best calibrated (slope nearest 1, intercept nearest 0).





Top preoperative predictors of non-home discharge



DISCUSSION & CLINICAL IMPACT

In this national cohort of patients undergoing simBTKA, non-home discharge occurred in **40.4%** of cases, consistent with prior literature and reinforcing that simBTKA represents a distinct higher-risk discharge population **[1]**. We developed and evaluated four machine learning models using routinely available preoperative variables, with **histogram gradient boosting** demonstrating the best discrimination and the **artificial neural network** showing the best calibration. To our knowledge, this is the first study to apply machine learning specifically to predict non-home discharge after simBTKA **[2]**.

The most influential predictors were **BMI, age, preoperative hematocrit, ASA class, and sex**, suggesting that discharge disposition after simBTKA is driven primarily by physiologic reserve, medical complexity, and patient anthropometrics. Among these, **BMI** and **preoperative hematocrit** may be especially clinically actionable, as prior studies have similarly linked higher BMI and lower hematocrit with increased likelihood of facility discharge after arthroplasty **[3–6]**. Older age and higher ASA class were also important contributors, consistent with prior evidence showing greater rehabilitation utilization and postoperative risk in older and more medically complex patients **[3,7–9]**.

From a clinical perspective, individualized preoperative risk prediction may help support:

- earlier discharge planning
- more informed patient counseling
- proactive involvement of case management, therapy, and caregivers
- targeted preoperative optimization of modifiable factors such as anemia and physiologic readiness **[10–18]**

At a systems level, because non-home discharge is a major driver of post-acute care use and episode-of-care cost, simBTKA-specific risk stratification may also help improve care coordination and resource allocation **[19–22]**.

LIMITATION & FUTURE WORK

- This study is limited by its **retrospective design**, with potential for 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.
- The registry also lacks granular information on enhanced recovery pathways, postoperative rehabilitation protocols, and other hospital-level factors that may influence discharge destination.
- These unmeasured clinical and social variables may partly explain the **modest model discrimination** observed.
- **External validation** was not performed, and model performance may differ across institutions and patient populations.
- Future work should focus on external validation, incorporation of social and institutional determinants, and integration of these models into clinical workflows as decision-support tools.

CONCLUSION

Machine learning-based prediction of non-home discharge after simBTKA was feasible and demonstrated acceptable performance in a large national cohort. **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 support preoperative counseling, discharge planning, and targeted optimization. Further external validation is needed before clinical implementation.

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