Machine Learning Model Developed to Aid in Patient Selection for Outpatient Total Hip Arthroplasty

Columbia | Vagelos College of Physicians & Surgeons
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Research Question: Are machine learning models able to assist with preoperative patient selection for outpatient total hip arthroplasty by using patient comorbidities and demographic factors?

BACKGROUND

Total hip arthroplasty (THA), or total hip replacement, is a common elective surgical procedure that greatly restores quality of life. THA demand is increasing, but it has high costs mainly driven by hospital length of stay (LOS).[1-3] More THA procedures are performed on an outpatient basis, in which the patient has same-day discharge (LOS = 0 days).[4] Outpatient THA is as safe as inpatient THA for appropriately selected patients.[5,6] Selecting patients for outpatient THA by length of stay may help maintain cost effectiveness and good outcomes.

Machine learning (ML) is a form of artificial intelligence (AI) that learns from large datasets to build complex statistical models, which can be used to identify patterns and predict outcomes.[7,8] In orthopedic surgery, ML has been studied for classifying patients and optimizing for surgical procedures,[20] outcome predictions,[21, 22] and patient specific payment models.[23]

The purpose of this study is to develop ML models that may aid in patient selection for outpatient THA by predicting which patients, based on medical comorbidities and demographic information, may have long LOS or same-day discharge.

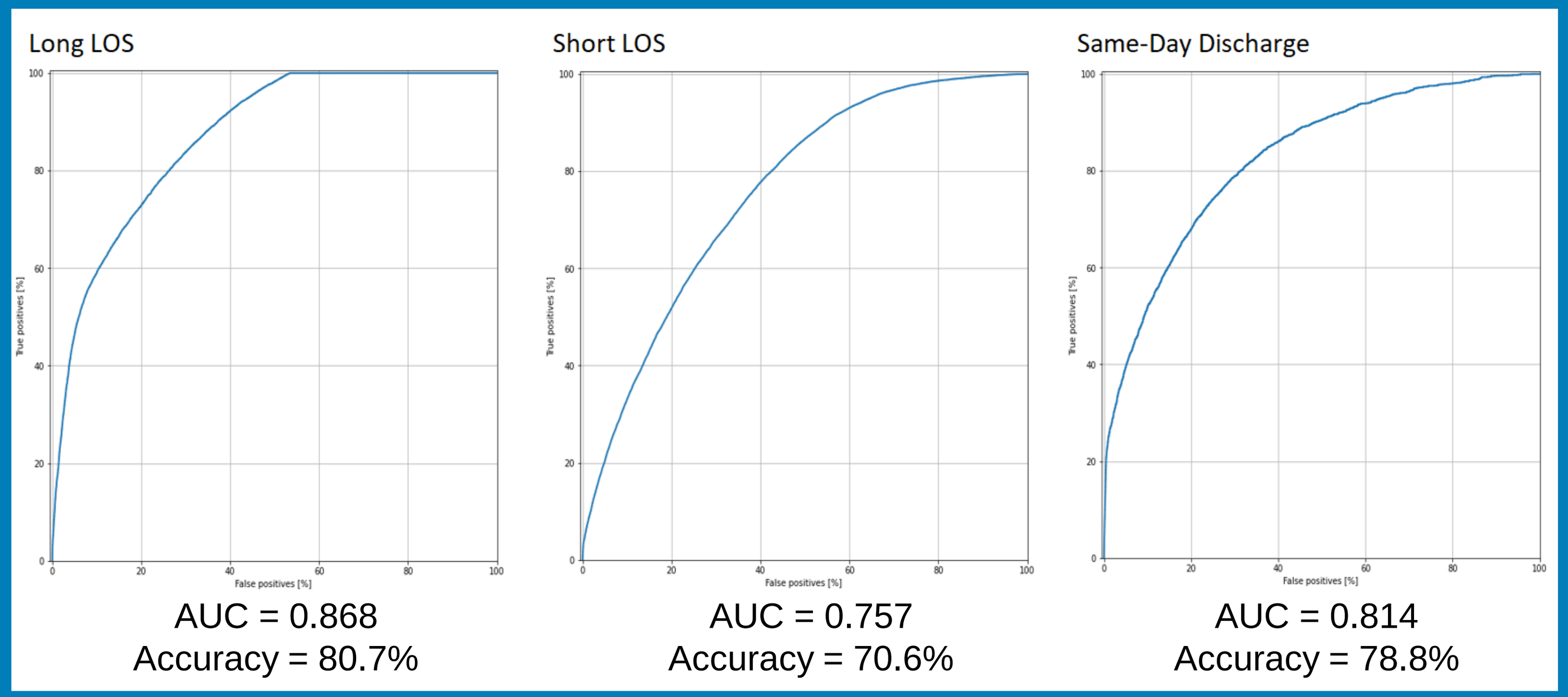
DESCRIPTION OF ORGANIZATION

The **Department of Orthopedic Surgery at New York-Presbyterian Columbia University Irving Medical Center** was formerly the New York Orthopedic Hospital, which was founded for "for the purpose of furnishing treatment to the poor, with special reference to diseases and deformities of the bones and joints requiring surgical and mechanical treatment, and for giving instruction in the same." Today, the Department of Orthopedic Surgery's missions continue through focus on patient care, research, and education.[13]

The **International Collaboration and Exchange Program** was started at Columbia University to provide opportunities for students to network and collaborate with medical students from other countries around the world. Although COVID-19 disrupted travel plans, students planned on participating in summer basic science research rotations in partner countries while experiencing the culture of the partner countries.[14]

RESULTS

Figure 1: Receiver operating characteristic (ROC) curves for machine learning models.



An AUC value of 1.0 is considered perfect discriminative ability with completely correct predictions, while 0.90 to 0.99 is considered excellent, 0.80 to 0.89 is considered good, 0.70 to 0.79 is considered fair, and 0.50 to 0.69 is considered poor.[16]

Figure 2: Odds ratios for factors associated with long LOS (left) and same-day discharge (right).

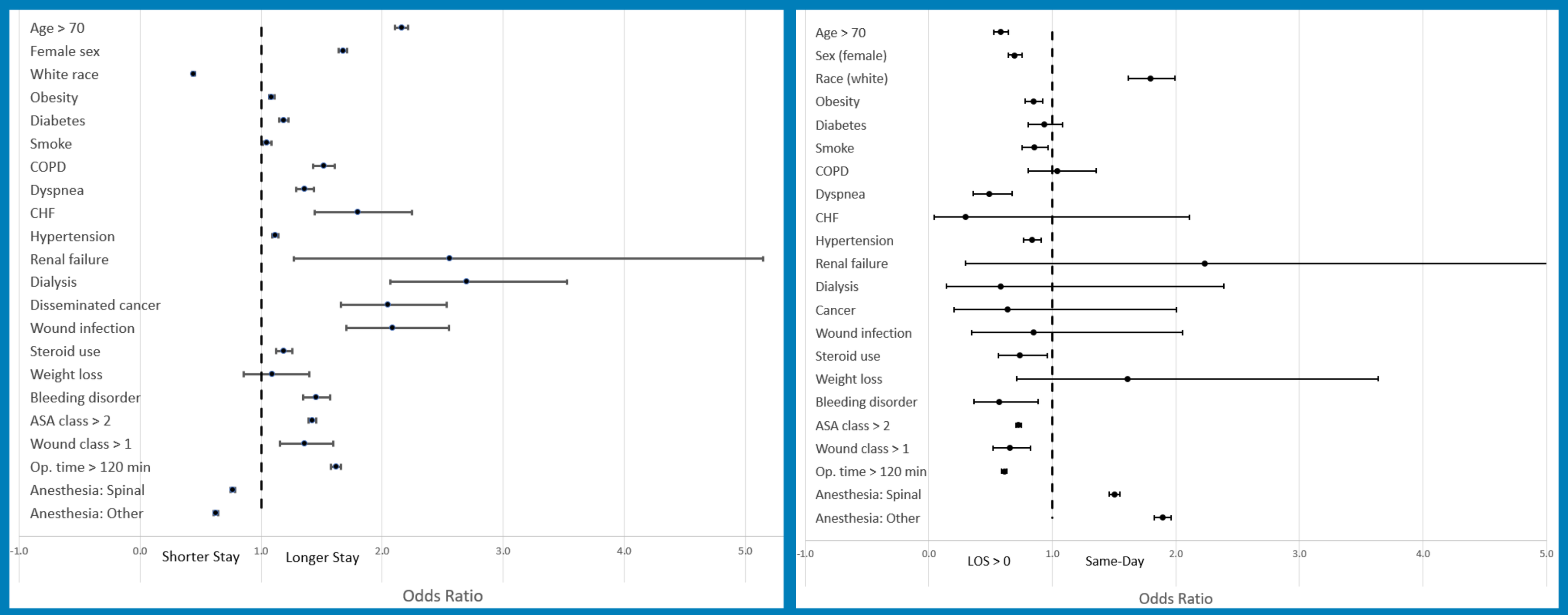


Table 1: Outcomes of cases when categorized by long LOS

Outcomes	Non-Long LOS (n = 84,770)	Long LOS (n = 68,283)	P value	All THA (n= 153,053)
Inpatient (%)	98.5%	99.2%	**< 0.001**	98.8%
Average operative time (min)	89.5	95	**< 0.001**	92.0
Prolonged operative time (%)	14.6%	20.2%	**< 0.001**	17.1%
Average LOS (days)	1.6	3.8	**< 0.001**	2.6
Any complication (%)	3.6%	15.1%	**< 0.001**	8.7%
Non-home discharge (%)	5.8%	37.0%	**< 0.001**	19.8%
Readmission (%)	3.4%	5.0%	**< 0.001**	4.2%
Reoperation (%)	1.7%	2.9%	**< 0.001**	2.3%

Table 2: Outcomes of cases when categorized by same-day discharge

Outcomes	Non-Ambulatory (n =150,432)	Ambulatory (n = 2,621)	P value	All THA (n= 153,053)
Inpatient (%)	99.1%	80.7%	**< 0.001**	98.8%
Average operative time (min)	92.1	82.4	**< 0.001**	92.0
Prolonged operative time (%)	17.3%	9.4%	**< 0.001**	17.1%
Average LOS (days)	2.6	0	**< 0.001**	2.6
Any complication (%)	8.8%	2.6%	**< 0.001**	8.7%
Non-home discharge (%)	20.0%	5.1%	**< 0.001**	19.8%
Readmission (%)	4.2%	3.2%	**0.014**	4.2%
Reoperation (%)	2.3%	2.1%	0.590	2.3%

METHODS

- This retrospective cohort study uses deidentified data from the American College of Surgeons National Surgical Quality Improvement Program (ACS-NSQIP) registry during 2010-2018.[15]
- Same-day discharge or ambulatory/outpatient THA was defined as LOS = 0 days. Short LOS patients had LOS ≤ 1 day, while long LOS patients had LOS ≥ 3 days.
- Multivariate linear regression and multivariate logistic regression analyses identified factors associated with the outcomes. All statistical analyses were conducted with Stata 16.1 (Stata Corp. – College Station, Texas, USA). Statistical significance was defined as $P < 0.05$.
- Artificial neural network (ANN) models were developed with TensorFlow Python open-source coding platform (Google Brain, Alphabet Inc. – Mountain View, California, USA). The models were trained by randomly sorting the cases into a training set (80%) and a testing set (20%).
- The model's discriminative ability (sensitivity/specificity) was evaluated with the area under the receiver operating characteristic curve (AUC). The overall model accuracy was calculated by dividing the number of correct predictions by the total sample size.

The ML model for predicting long LOS had an AUC of 0.868 and an accuracy of 80.7%. The short LOS ML model had an AUC of 0.757 and an accuracy of 70.6%. The same-day discharge ML model had an AUC of 0.814 and an accuracy of 78.8% (*Figure 1*). Age over 70, female sex, ASA Class of 3 or above, wound class of 2 or above, general anesthesia, prolonged operative time, and other comorbidities were found to increase the odds of a longer stay (*Figure 2*).

DISCUSSION

The ML models predicting long LOS and same-day discharge were considered good predictive and discriminative ability (AUC > 0.80). The model for short LOS had fair discriminative ability (AUC > 0.70). Greater numbers of comorbidities are associated with longer LOS. Non-White race was the main demographic factor found to increase odds of long LOS. These racial disparities likely reflect existing systemic inequalities in the data.[17] Predictive models may inadvertently perpetuate disparities; patients designated as higher risk may have more difficulty in being referred for THA and outpatient THA.
Limitations include lack of external validity, lack of adjustments for surgery chronology between 2010-2018, and database coding errors.

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