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Original Research

Machine Learning-Based Predictive Models for 90-Day Readmission of Total Joint Arthroplasty Using Comprehensive Electronic Health Records and Patient-Reported Outcome Measures

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ABSTRACT

Background: The Centers for Medicare & Medicaid Services currently incentivizes hospitals to reduce postdischarge adverse events such as unplanned hospital readmissions for patients who underwent total joint arthroplasty (TJA). This study aimed to predict 90-day TJA readmissions from our comprehensive electronic health record data and routinely collected patient-reported outcome measures.

Methods: We retrospectively queried all TJA-related readmissions in our tertiary care center between 2016 and 2019. A total of 104-episode care characteristics and preoperative patient-reported outcome measures were used to develop several machine learning models for prediction performance evaluation and comparison. For interpretability, a logistic regression model was built to investigate the statistical significance, magnitudes, and directions of associations between risk factors and readmission.

Results: Given the significant imbalanced outcome (5.8% of patients were readmitted), our models robustly predicted the outcome, yielding areas under the receiver operating characteristic curves over 0.8, recalls over 0.5, and precisions over 0.5. In addition, the logistic regression model identified risk factors predicting readmission: diabetes, preadmission medication prescriptions (ie, nonsteroidal anti-inflammatory drug, corticosteroid, and narcotic), discharge to a skilled nursing facility, and post-discharge care behaviors within 90 days. Notably, low self-reported confidence to carry out social activities accurately predicted readmission.

Conclusions: A machine learning model can help identify patients who are at substantially increased risk of a readmission after TJA. This finding may allow for health-care providers to increase resources targeting these patients. In addition, a poor response to the "social activities" question may be a useful indicator that predicts a significant increased risk of readmission after TJA.

Introduction

Total joint arthroplasty (TJA) is acknowledged as an effective procedure to reduce pain and restore function for patients with degenerative conditions of the hip and knee. As the United States population continues to age and the prevalence of obesity is increasing, the demand for this procedure has substantially increased and is projected to continue to rise through 2040 [1,2]. The Centers for Medicare & Medicaid Services (CMS) has increased efforts into improving care value through quality improvement and cost reduction for TJA and has incentivized hospitals to reduce postdischarge adverse events after TJA, such as unplanned hospital readmissions [3]. As such, CMS has encouraged health-care providers to reduce readmissions through improved patient optimization and engagement, education, and communication with respect to discharge planning [4].

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With the increase in electronic health record (EHR) adoption, considerable amounts of clinical and operational data are routinely collected. This data enable researchers to build predictive models using machine learning to refine care delivery and improve care quality. A systematic review of the literature [5] has identified several post-TJA readmission calculators, with the primary outcomes as 30-day or 90-day readmission risks, using single institution data or administrative datasets (eg, American Joint Replacement Registry). The model input variables primarily included patients' demographic and socioeconomic features, their comorbidities, and other procedure-related information available in EHR. In addition to EHR data, a growing number of health-care providers have started collecting patient-facing outcomes data, such as patient-reported outcome measures (PROMs). These outcomes reflect different aspects of health and are intended to provide comprehensive patient status, including functional, mental, and social wellness [6]. Furthermore, PROMs play a significant role in improving clinician-patient communication, patient engagement, and building relationships effectively [7].

Although a growing body of work is being done to identify ways to use PROMs upstream in the care cycle to help optimize care pathways, their ability to predict major events like readmissions has not previously been shown [8-13]. As such, the objective of this study is to develop a robust predictive model using a variety of variables (ie, demographics, socioeconomic status, care characteristics by care phases, vitals, preoperative PROMs) readily attainable from the comprehensive EHR that reflect clinicians' decision and practice. Furthermore, the risk factors highly associated with readmission were sought to establish pragmatic risk assessments of 90-day TJA readmission.

Material and methods

Patient population

This retrospective study included a cohort of patients who underwent elective primary and revision total hip arthroplasty (THA) or total knee arthroplasty (TKA) procedures (ie, excluding trauma) identified by the current procedural terminology codes (see Appendix A for the list of current procedural terminology codes). These procedures were performed by 8 fellowship-trained arthroplasty surgeons at our tertiary care, academic, safety-net institution between 2016 and 2019. The cohort was restricted to those who had visited clinics in the same network (ie, including primary care and internal medicine clinics and orthopedic clinics) before their procedure and lived in the primary service areas during the study period to avoid the potential for out-of-network hospitalizations. This restriction was intended to reduce the chance of missing unobserved readmission and underestimating readmission rates. If a patient had 2 hospitalizations over 90 days apart for surgery on a different joint, both were considered index (ie, separate) hospitalizations. After obtaining institutional review board approval, we identified 1319 unique patients with a total of 1776 surgical cases from our institutional data repository, and a total of 1590 index hospitalizations met the inclusion criteria, with 171 patients having staged separate procedures.

Outcome

The primary outcome was defined as whether a patient was readmitted for an orthopedic issue within 90 days following a THA or TKA index discharge [14]. A complication admission within 90 days after an index hospitalization was also considered as a readmission (eg, myocardial infarct, thromboembolic event). Although the CMS considers 30-day readmission and 90-day complications as quality measures for TJA [15], we unified the time window to 90 days to increase the rate of the outcome, as the previous studies frequently defined [16].

Covariates

We included different patient factors and care characteristics spanning across a patient's hospitalization journey. The timeline of the care phases (from "prior-to hospitalization" to "post-discharge" care) and the corresponding list of the variables in each category are shown in Figure 1. Specifically, using the comprehensive EHR (Epic systems, Wawona, WI), 9 categories of variables were examined: (1) demographic and socioeconomic characteristics, (2) comorbidities, (3) prior-to-hospitalization care characteristics, (4) preoperative care characteristics, (5) intraoperative care characteristics, (6) postoperative care characteristics, (7) postdischarge care characteristics, (8) hospitalization care characteristics, and (9) vitals. In addition, we investigated 3 different preoperative PROMs: Patient-Reported Outcomes Measurement Information System-10 (PROMIS-10) [17], Hip Disability and Osteoarthritis Outcome Score Joint Replacement (HOOS JR), and Knee Injury and Osteoarthritis Outcome Score Joint Replacement (KOOS JR) [18]. The PROMIS-10 was a general health measure consisting of 2 different constructs: the global physical and mental health t-scores. For our analysis, we included the composite scores from both constructs and the raw survey responses from the 10 items. We also included a single-disease-specific functional score (ie, a HOOS JR or KOOS JR composite score) depending on the type of surgery. In addition, the Risk Assessment and Prediction Tool score was included as a presurgical survey [19]. A summary of all variables can be found in Figure 1. As most variables were time-dependent, each index hospitalization was regarded as an independent sample.

A total of 104 variables were initially considered, but 5 variables including intraoperative blood sugar, discharge hemoglobin, discharge hematocrit, discharge hemoglobin a1c, and medicine reconciliation were excluded due to a high rate of missing data (ie, 50% or more). Note that the covariate set still included postoperative blood sugar and preoperative hemoglobin, and diabetes diagnosis (in the comorbidity category). Of the remaining 99 variables, 74 had missing values of less than 1%; 20 variables (ie, weight, body mass index—related variables, presurvey-related variables) had 1% to 25% missing data while 5 variables (ie, duration of surgery, hemoglobin before operation, hematocrit before operation, days between preoperative labs and operation, and Risk Assessment and Prediction Tool scores) had 25% to 36%. Missing values were imputed using the Multivariate Imputation by Chained Equation [14] method which considers the sequential conditional distributions of each missing variable during the imputation. Detailed information regarding empirical distribution of these variables by the outcome is available in Table B.1 in Appendix B. A sensitivity analysis was conducted to ensure that the imputation does not affect the main findings (see Appendix C).

After the imputation, univariate analyses were performed to identify variables strongly associated with the outcome. The two-sample *t*-test for continuous variables and chi-squared test for categorical variables were conducted. A less-strict cutoff (ie, 0.10) on *P* value was used to include as many variables as possible to allow for the examination of potential joint associations between multiple variables and the outcome [20]. Variables with test results $P < .10$ were selected as the input variables for model development.

Model performance

With the variables selected in the univariate analyses, we developed several machine learning models: (1) logistic regression

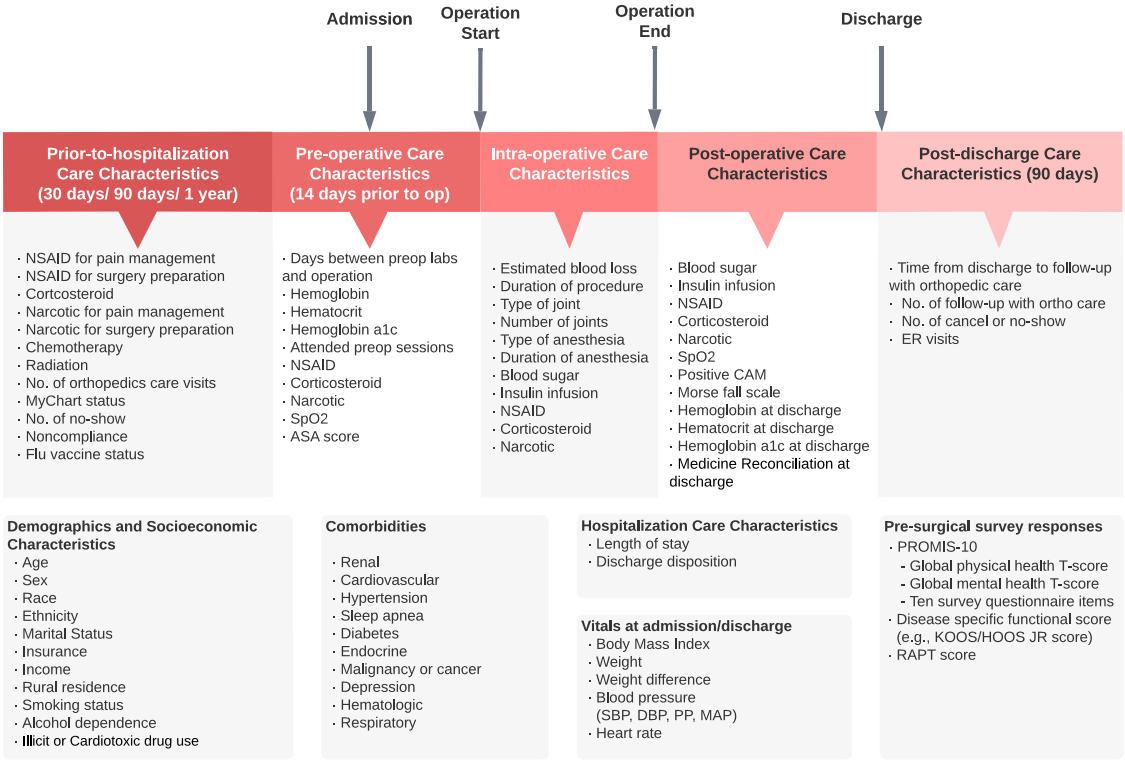

Figure 1. The list of the 10 variable categories and the timeline of the care categories. The categories related to the timeline were displayed in the first row, and the remaining categories were present in the second row. Medication prescription for pain management was defined as the medication being prescribed between 1 and 3 months prior to hospitalization, whereas one for surgery preparation was defined as the medication being prescribed within 1 month prior to hospitalization. CAM, confusion assessment method; DBP, diastolic blood pressure; ER, emergency room; HOOS, hip injury disability and osteoarthritis outcome score; KOOS, Knee Injury and Osteoarthritis Outcome score; MAP, mean arterial pressure; NSAID, nonsteroidal anti-inflammatory drugs; OP, operation; PROMIS, Patient-Reported Outcomes Measurement Information System; RAPT, Risk Assessment and Prediction Tool; SBP, systolic blood pressure.

(LR), (2) LR with the least absolute shrinkage and selection operator (Lasso) penalty, (3) polynomial and radial support vector machines, and (4) random forest (RF) to examine potential nonlinear relationships between risk factors. Furthermore, considering the class imbalance issue, (5) an RF model with oversampling and (6) a random undersampling boosting model [21] were developed.

We split the data randomly into a training set (75%) and a test set (25%). The models were built using the training set and were evaluated using the test set. We repeated the split procedure 100 times (ie, bootstrap resampling) to obtain performance ranges [22]. The metrics included the area under the receiver operating characteristic curve (AUC), precision, and recall. The curve consists of multiple pairs of false-positive and true-positive rates obtained from all possible classification thresholds. The AUC does not rely on a specific threshold and measures an aggregated performance. Both precision and recall measure true positives, but precision compares them to false positives, while recall compares them to false negatives [23]. The Matthews Correlation Coefficient (MCC) was employed to determine the optimal threshold for precision and recall since it provides a more robust and reliable evaluation than the F1 score and accuracy given a highly imbalanced outcome [24]. When the misclassification costs for positive and negative cases are unknown, the MCC considers them equal and provides a balanced assessment. In this study, the AUC and recall were mainly used for the model evaluation, assuming that a false-negative error (ie, missing a readmitted patient) costs more than a false-positive error (ie, identifying a patient who turns out not being readmitted) in the presence of case imbalance [25].

Risk factor analysis

Due to its interpretability, the LR model was used to identify robust risk factors for 90-day readmission using the entire cohort. This model can provide not only the magnitude and direction (ie, positive or negative) of the association but also the statistical significance. In addition, the Lasso model that achieved the highest performance in this study is based on the LR. For statistical efficiency, the stepwise variable selection using the Akaike information criterion was additionally conducted [26], and then we obtained the sign and magnitude of the significant risk factors based on the model after variable selection. Coefficients of variables with $P < .05$ were considered significant.

Software

Analyses were performed using R [27] version 4.0.3 and R packages including mice [28], glmnet [29], e1071 [30], randomForest [31], xgboost [32], and PROC [33].

Results

Demographics

Of the 1590 samples, females accounted for 919 (57.8%), with the majority of respondents categorizing themselves as “white” (77.7%, N = 1235). The median age was 68 (interquartile range [IQR] = 61-74). Nearly half of the patients (49.7%, N = 791) had body mass index equal to or greater than 30 at hospital admission, suggesting obesity, and 261 (16.4%) patients experienced diabetes (Table B in

Appendix B). The procedures included 910 (57.2%) TKA and 680 (42.8%) THA procedures. The average length of stay was 2 days (IQR = 1-3 days). Among the 1590 samples, only 92 (5.8%) 90-day readmissions were identified, suggesting that the samples were severely imbalanced for classification purposes (ie, most patients did not experience a readmission). There was no difference between the readmitted group (N = 92) and the non-readmitted group (N = 1498) when assessing demographics and socioeconomic characteristics (see Table A.1).

Model performance

After the missing value imputation, we identified 23 variables with a $P < .10$ as model input variables in the univariate analysis (see Table A.1), and several machine learning models including them were built and assessed based on 100 randomly sampled data sets. As illustrated in Table 1, the Lasso model outperformed the others in terms of the AUC (average = 0.862; IQR = 0.842-0.885). All the models but the support vector machine models had AUCs higher than 0.8. In addition, the cutoffs were chosen based on the MCC to calculate the recall and precision. In terms of the recall, the Lasso model yields an average of 0.566 (IQR = 0.478-0.667). This suggests that, out of all the actual readmitted instances, we expect 56.6% of them can be correctly identified by the Lasso model. The RF model with oversampling achieved a higher recall (average = 0.572; IQR = 0.478-0.667). Overall, most of the models achieved high AUCs (>0.8), recalls (>0.5), and precisions (>0.5) simultaneously.

Risk factor analysis

We conducted the stepwise variable selection to reduce multicollinearity of the 23 selected variables. The final LR model, including the variables obtained from the stepwise method, identified 9 significant variables that are listed in Figure 2. Of the significant variables, there was representation form preadmission, postdischarge, and the completed PROMs that were identified.

Episode characteristics

For preadmission characteristics, diabetes was found significant (odds ratio [OR] = 2.44, 95% confidence interval [CI] = 1.39-4.22). In addition, the following medication prescriptions prior to hospitalization were strongly associated with the readmission status: NSAID, including aspirin, for surgery preparation (OR = 3.82, 95% CI = 2.26-6.65), use of corticosteroids (OR = 6.27, 95% CI = 3.82-10.47), and use of narcotics for surgery preparation (OR = 4.47, 95% CI = 1.67-15.80). In a subgroup analysis of the NSAID prescriptions, aspirin was more prevalent in the readmitted group, while non-aspirin NSAID use (eg, ibuprofen or naproxen) was more prominent in non-readmitted patients ($P < .001$; see Table 2). Additional subgroup analysis revealed that patients who would be readmitted received more systemic corticosteroids (ie, oral or intravenous) than intra-articular (ie, triamcinolone acetonide, methylprednisolone), compared to patients who were not readmitted ($P < .001$; see Table 2). Several postdischarge care characteristics were identified as significant, including follow-up visits to orthopedics clinics more than twice (OR = 5.47, 95% CI = 3.29-9.23), one or more emergency room visits (OR = 1.77, 95% CI = 1.00-4.53), and cancel or no-show (OR = 4.48, 95% CI = 2.22-8.88) within 90 days since discharge.

Patient-reported outcome measures

The majority of PROMs, including general health (ie, PROMIS-10) and disease-specific ones (ie, the HOOS JR) did not impact the likelihood of readmission in this data set. One specific item (ie, Global09) on the PROMIS-10 was strongly predictive of the outcome. Patients who scored higher on Global09 (ie, In general, please rate how well you carry out your usual social activities and roles) were less likely to be readmitted (OR = 0.77, 95% CI = 0.60-0.97).

Discussion

A couple of features distinguish our study from the extant research in post-TJA readmission risk prediction. Because of the rapidly evolving pace of arthroplasty, outpatient TJA and same-day discharges are becoming commonplace but were not widely utilized when many existing readmission risk calculators were generated [5]. Our study was a retrospective study over a period from 2016 to 2019, which is fairly recent, and our patient cohort included many same-day patients to reflect this practice change. Also, as a single-institution study, our data are from a moderate sample size, which is sufficient to gain clinical insights, and have the advantage of having access to more granular exposure variables. Some existing models used larger sample sizes, obtained either from all-payer claims databases or long-term studies, but only contained limited set of predictors. In particular, one area of heightened interest is the sudden increase of data related to PROMs. Because it is only emerging, the use of these data to understand patients at risk of general perioperative complications is not well understood. Therefore, this study took advantage of the variety of data from EHR and PROMs at our single institution collected fairly recently.

Model performance

The inclusion of the variety of data allows us to improve machine learning model performance. Most of our models yielded

Table 1
The comparisons of model performance.

Models	AUC (mean; IQR)	Threshold (mean; IQR)	Recall (mean; IQR)	Precision (mean; IQR)
Logistic regression	0.845 (0.825, 0.870)	0.342 (0.280, 0.402)	0.542 (0.423, 0.667)	0.561 (0.520, 0.640)
LASSO	0.862 (0.842, 0.885)	0.354 (0.291, 0.408)	0.566 (0.478, 0.667)	0.555 (0.495, 0.652)
SVM—polynomial	0.714 (0.705, 0.789)	0.198 (0.165, 0.239)	0.511 (0.415, 0.641)	0.701 (0.640, 0.766)
SVM—radial	0.771 (0.789, 0.839)	0.221 (0.177, 0.270)	0.551 (0.450, 0.667)	0.687 (0.619, 0.750)
Random forest	0.836 (0.819, 0.855)	0.263 (0.213, 0.307)	0.533 (0.458, 0.640)	0.637 (0.578, 0.722)
RF w/ oversampling	0.835 (0.816, 0.850)	0.258 (0.216, 0.307)	0.572 (0.478, 0.667)	0.667 (0.610, 0.727)
RUS boosting	0.835 (0.811, 0.863)	0.303 (0.243, 0.357)	0.480 (0.359, 0.602)	0.566 (0.478, 0.692)

AUC, area under the receiver operating characteristic curve; IQR, interquartile range; LASSO, least absolute shrinkage and selection operator; RF, random forest; RUS, random undersampling; SVM, support vector machines.
The 7 models were evaluated with 100 repeats. For each model, the threshold was determined by the Matthews correlation coefficient, and correspondingly, the recall and precision were obtained.

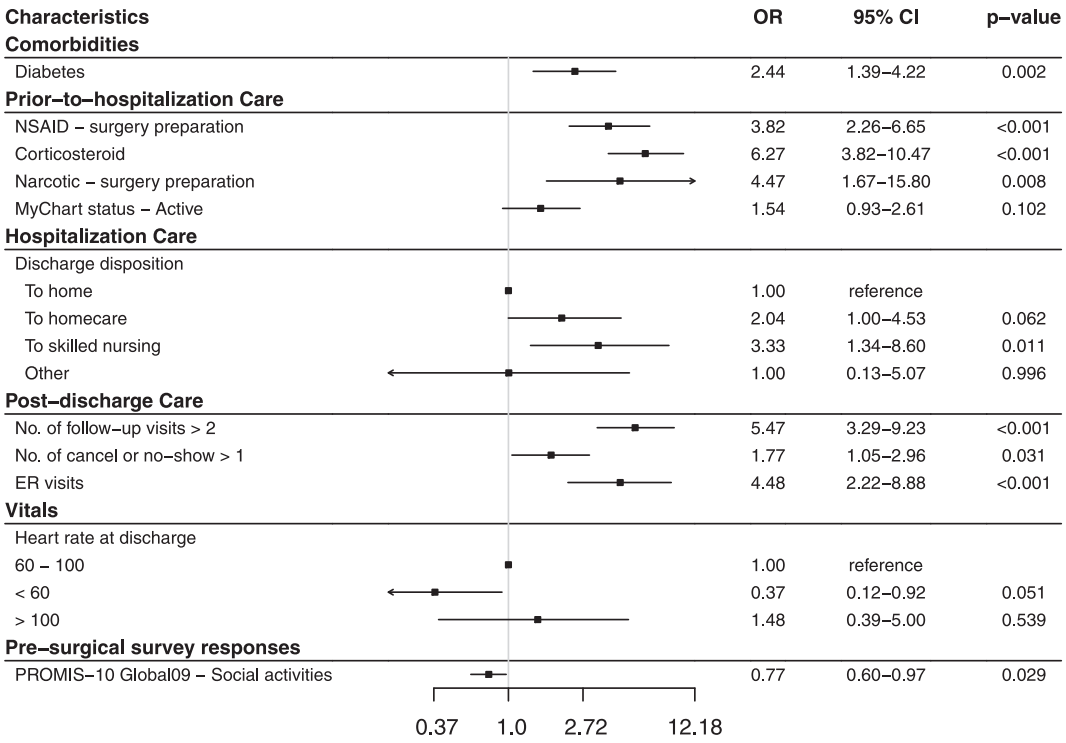

Figure 2. Forest plot of the risk factors identification associated with 90-day readmission. An odds ratio (OR) and its 95% confidence interval (CI) for each risk factor are displayed in the middle. An arrow indicates a 95% CI that exceeds the limit of the chart (the left limit = 0.37 and the right limit = 12.18). The corresponding statistics are present in the right columns. A *P*-value less than .05 indicates a significant risk factor. PROMIS-10 Global09 states, "In general, please rate how well you carry out your usual social activities and roles." ER, emergency room; NSAID, nonsteroidal anti-inflammatory drugs; PROMIS, patient-reported outcome measurement information system.

AUCs over 0.8, recalls over 0.5, and precisions over 0.5. The performances of our models were favorable, compared to AUCs (0.69-0.73) from the existing 90-day readmission prediction models [34-36]. Given the highly imbalanced distribution of the outcome (~5% readmission rate), predictive models are inclined to predict cases as not being readmitted, increasing false-negative results, and worsening the recall. Therefore, AUC might portray an overly optimistic performance of a classifier. Unfortunately, most of the existing studies only published their AUCs, and the model's performance in terms of their recall and precision was not thoroughly reported in the literature [35-38]. Nevertheless, our models were remarkably robust in correcting this bias due to imbalanced data and identifying the patients truly at a high risk of readmission, indicated by a reasonably good recall. Notably, the recall values presented herein were conservative, obtained based on maximizing MCC, that is, we do not impose that identifying the positive cases is more important than the negative cases. A different model cutoff (classifier) might be chosen to further improve recall but at the risk of reducing precision.

Risk factor identification

Among the more than 100 variables, the final model identified 9 significant risk factors. Among them, diabetes [39], discharge to a skilled nursing facility [38,40], and narcotic use [41] have been reported in the existing literature. Our data are also in line with previous work [35], which highlighted postdischarge care characteristics. Among the postdischarge care characteristics, follow-up visits to orthopedics more than twice, cancel or no-show for the follow-up appointments with orthopedic care more than once, and emergency room visit at least once were associated with 90-day readmission in our analysis. Although it is not feasible to provide preventive care based on these factors, a patient's postdischarge care journey should be carefully tracked. When a patient deviates from the pathway as mentioned earlier, their status may warrant more frequent contact and/or visits by a nurse navigator or home nurse.

In this study, we uniquely identified NSAID and corticosteroid use and patient's social independence factor. This social factor has

Table 2
The subgroup analysis for prior-to-hospitalization NSAID and corticosteroid route.

Characteristics	Readmitted patients	Non-readmitted patients	*P* value
Prior-to-hospitalization NSAID for surgery preparation	N = 64	N = 539	<.001
Only non-aspirin	12 (18.8)	448 (83.1)	
Aspirin or both	52 (81.2)	91 (16.9)	
Prior-to-hospitalization corticosteroid	N = 57	N = 277	<.001
Only intra-articular	5 (8.8)	138 (49.8)	
Systemic or both	51 (89.5)	112 (40.4)	
Unknown	1 (1.8)	27 (9.7)	

NSAID, nonsteroidal anti-inflammatory drugs.
Non-aspirin includes ibuprofen, naproxen, diclofenac, celecoxib, indomethacin, meloxicam, piroxicam, and sulindac. Intra-articular corticosteroid includes methylprednisolone and triamcinolone acetonide. Systemic corticosteroid includes dexamethasone and prednisone. Unknown includes only hydrocortisone or hydrocortisone and any intra-articular drugs.

long been recognized [42] as a predictor for postdischarge outcomes in TJA care, but our study points to the opportunity to capture this effect via a simple questionnaire routinely used to track patient's general health, the PROMIS-10, pointing to the importance of this tool for screening patients for higher resource allocation.

Regarding NSAIDs, we isolated aspirin from other NSAID drugs (eg, ibuprofen and naproxen) and found patients who were prescribed aspirin were at a high risk of readmission. We additionally built machine learning models using the "prior-to-hospitalization NSAID intake excluding aspirin" as a covariate. The prediction performances were very similar (see Table 1 and Tables D.1 and D.2 in Appendix D). This finding was surprising to the current investigators and is hard to explain based on the current knowledge of aspirin use associated with TJA surgery. Further studies may attempt to gain clarity on this finding.

Regarding corticosteroids, the investigation of their administration route suggested that those receiving systemic corticosteroid treatments, rather than an intra-articular injection, for instance, prior to hospitalization are at a high risk of readmission. Based on these findings, clinicians could determine whether and how to allocate more resources to the target patients (eg, who receive these identified medications before the hospitalizations) during or leading up to their hospitalizations. This includes potentially enlisting the help of medical co-management services or targeting closer follow-up for these patients in the perioperative period.

Finally, an association was found between the readmission and negative responses regarding social activities and roles in the PROMIS-10 preoperative survey, and this finding is aligned with the prior literature [43,44] that there is an association between social support measured by the Western Ontario and McMaster Universities Osteoarthritis Index and better clinical outcomes in TJA (ie, postoperative survey scores). Our finding also suggests that these PROMs possess the potential as predictive factors for clinical outcomes. Moreover, inputting individual survey questionnaire items in addition to the aggregated scores (ie, the global physical and mental health T-scores) helps pinpoint associations between specific risk factors and the target clinical outcome. The global mental health T-score in PROMIS-10 as the compound measure was filtered in the univariate analysis, whereas the final LR model still found PROMIS-10 Global09 regarding social activities to be significant. This could be possible due to the lack of association of the other PROMIS-10 survey responses related to social activities (ie, satisfaction with social activities and relationships) that weakens the association. Therefore, having various and more detailed PROMs can improve risk identification and correspondingly model performance. There is also an importance of encouraging patients to complete these surveys at multiple time points, including preoperatively. At our institution, we have witnessed a steady increase in response rates from the year 2016 (64.6% for PROMIS-10; 59.0% for KOOS JR; 69.1% for HOOS JR) to year 2019 (93.7% for PROMIS-10; 94.6% for KOOS JR; 86.2% for HOOS JR) and expect that these surveys will become an integral part of patients' health records and can be integrated into the existing clinical decision support system.

Limitations

This study has important limitations that must be discussed. First, data were obtained exclusively from the study institution. A validation with a larger cohort is needed to overcome the limitation of a single-center study, which can reflect patient characteristics unique to that geographic region. Larger datasets from distributed research networks, such as the American Joint Replacement Registry [45] that contains data from multiple institutions, could be used to refine our model and ensure generalizability of the results. With respect to data quality, following the data quality assessment guideline [46], we concluded that the data source in this study provides moderate-quality data and decent sample sizes, and the data available were sufficient for our prediction purpose. However, a retrospective chart review would be preferred to the observational data this study used. In addition, missing values were imputed by the well-established technique, Multivariate Imputation by Chained Equation [28]. Although these procedures might impose additional bias, no significant impact was revealed through a sensitivity analysis that examined the effect of the missing value imputation on model performance (Table C.1 in Appendix C). Finally, the inclusion and exclusion criteria herein exclude all out-of-network readmissions. Consequently, the readmission rate was lower than that in the literature; our data had 5.8% of readmissions, whereas data in the literature had 5%-9.5% readmissions [16,35,36,47]. However, the discrepancy in readmission rate could also be attributed to the temporal and regional differences during data collection. Notably, predicting post-TJA readmission with such low readmission rates entails a class imbalance problem that might compromise machine learning models' performance [25,48]. Future work should explore advanced machine learning methods for imbalanced data.

Conclusions

Despite a low readmission rate, the machine learning models achieved a high AUC, recall, and precision simultaneously. In addition, the significant risk factors (eg, prior-to-hospitalization systemic corticosteroids) identified in this study support the recent clinical research findings and provide new insights to refine care delivery. Specifically, this study sheds light on the potential application of PROMs (eg, lack of social support) as risk predictors. Our findings can be implemented into care episodes as a part of the clinical decision support system to improve orthopedic outcomes and potentially improve risk adjustment for centers caring for safety-net patients.

Conflicts of interest

C. F. Gray is a paid consultant for Smith & Nephew Inc and is an American Academy of Orthopaedic Surgeons committee member. All other authors declare no potential conflicts of interest.

For full disclosure statements refer to https://doi.org/10.1016/j.artd.2023.101308.

CRediT authorship contribution statement

Jaeyoung Park: Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Xiang Zhong:** Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Emilie N. Miley:** Conceptualization, Data curation, Writing – review & editing, Writing – original draft. **Rachel S. Rutledge:** Conceptualization, Data curation. **Jaquelyn Kakalecik:** Conceptualization, Data curation. **Matthew C. Johnson:** Conceptualization, Data curation. **Chancellor F. Gray:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

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Table A.1
CPT codes and ICD-10 codes for total hip and knee arthroplasties.

Total joint arthroplasty	CPT codes	ICD-10 codes
Total hip arthroplasty	27120, 27125, 27130, 27132, 27134, 27137, 27138, 27090, 27091	Z96.64
Total knee arthroplasty	27440-27447, 27486-27488	Z96.65

CPT, Current Procedural Terminology; ICD-10, International Classification of Diseases, 10th Revision.

Table A.2
Characteristics and statistical tests based on the LOS categorizations.

Characteristics	LOS 0 (n = 231, 16.5%)	LOS 1 (n = 533, 38.0%)	LOS 2 (n = 370, 26.4%)	LOS 3+ (n = 267, 19.1%)	*P*-value (LOS cat. 1: 0/1-2/3+)	*P*-value (LOS cat. 2: 0/1/2+)	*P*-value (LOS cat. 3: 0/1/2/3+)
Demographics and socioeconomic characteristics							
Age, years					**<.001**	**.004**	**.002**
≤61	86 (37.2)	134 (25.1)	85 (23.0)	84 (31.5)			
62-67	69 (29.9)	151 (28.3)	98 (26.5)	74 (27.7)			
68-73	45 (19.5)	136 (25.5)	95 (25.7)	59 (22.1)			
74+	31 (13.4)	112 (21.0)	92 (24.9)	50 (18.7)			
Sex—male	105 (45.5)	263 (49.3)	135 (36.5)	114 (42.7)	.826	**.002**	.002
Race					**.002**	**.003**	**<.001**
Black	22 (9.5)	66 (12.4)	64 (17.3)	56 (21.0)			
Other	19 (8.2)	38 (7.1)	38 (10.3)	11 (4.1)			
White	190 (82.3)	429 (80.5)	268 (72.4)	200 (74.9)			
Non-Hispanic	217 (93.9)	504 (94.6)	345 (93.2)	260 (97.4)	**.088**	.830	.132
Marital status					**<.001**	**<.001**	**<.001**
Married	165 (71.4)	348 (65.3)	211 (57.0)	147 (55.1)			
Other or unknown	17 (7.4)	33 (6.2)	22 (5.9)	11 (4.1)			
Single/Divorced/Separated/Widowed	49 (21.2)	152 (28.5)	137 (37.0)	109 (40.8)			
Insurance					**<.001**	**<.001**	**<.001**
Medicaid	6 (2.6)	23 (4.3)	26 (7.0)	35 (13.1)			
Medicare	80 (34.6)	288 (54.0)	200 (54.1)	138 (51.7)			
Other	6 (2.6)	18 (3.4)	16 (4.3)	7 (2.6)			
Private or managed care	139 (60.2)	204 (38.3)	128 (34.6)	87 (32.6)			
Income					**.002**	**.002**	**.004**
<40,000	48 (20.8)	161 (30.2)	123 (33.2)	101 (37.8)			
40,000-60,000	88 (38.1)	179 (33.6)	110 (29.7)	78 (29.2)			
>60,000	95 (41.1)	193 (36.2)	137 (37.0)	88 (33.0)			
Rural	17 (7.4)	58 (10.9)	35 (9.5)	31 (11.6)	.269	.313	.374
Smoking status					**.009**	**.043**	**.034**
Current	16 (6.9)	44 (8.3)	32 (8.6)	33 (12.4)			
Former	77 (33.3)	213 (40.0)	150 (40.5)	115 (43.1)			
Never	138 (59.7)	276 (51.8)	188 (50.8)	119 (44.6)			
Alcohol dependence	9 (3.9)	17 (3.2)	12 (3.2)	15 (5.6)	.193	.642	.349
Illicit or cardiotoxic drug use	2 (0.9)	13 (2.4)	10 (2.7)	11 (4.1)	**.073**	.131	.151
Comorbidities							
Renal	1 (0.4)	7 (1.3)	12 (3.2)	17 (6.4)	**<.001**	**<.001**	**<.001**
Cardiovascular	12 (5.2)	81 (15.2)	57 (15.4)	61 (22.8)	**<.001**	**<.001**	**<.001**
Hypertension	112 (48.5)	280 (52.5)	216 (58.4)	164 (61.4)	**.015**	**.004**	**.001**
Sleep apnea	4 (1.7)	9 (1.7)	10 (2.7)	25 (9.4)	**<.001**	**.001**	**<.001**
Diabetes	22 (9.5)	65 (12.2)	62 (16.8)	62 (23.2)	**<.001**	**<.001**	**<.001**
Endocrine	2 (0.9)	3 (0.6)	7 (1.9)	11 (4.1)	**.002**	**.006**	**.002**
Malignancy or cancer	6 (2.6)	13 (2.4)	17 (4.6)	12 (4.5)	.489	.106	.213
Depression	34 (14.7)	120 (22.5)	95 (25.7)	90 (33.7)	**<.001**	**<.001**	**<.001**
Hematologic	0 (0.0)	0 (0.0)	0 (0.0)	11 (4.1)	**<.001**	**.001**	**<.001**
Respiratory	2 (0.9)	16 (3.0)	14 (3.8)	29 (10.9)	**<.001**	**<.001**	**<.001**
Prior-to-hospitalization care characteristics							
NSAID[a]—pain management	55 (23.8)	153 (28.7)	86 (23.2)	67 (25.1)	.685	.143	.244
NSAID[a]—surgery preparation	116 (50.2)	220 (41.3)	133 (35.9)	83 (31.1)	**<.001**	**<.001**	**<.001**
Corticosteroid[a]	42 (18.2)	112 (21.0)	85 (23.0)	62 (23.2)	.362	.283	.470
Narcotic[a]—pain management	37 (16.0)	136 (25.5)	109 (29.5)	90 (33.7)	**<.001**	**<.001**	**<.001**
Narcotic[a]—surgery preparation	220 (95.2)	457 (85.7)	271 (73.2)	180 (67.4)	**<.001**	**<.001**	**<.001**
Chemotherapy[a]	0 (0.0)	0 (0.0)	0 (0.0)	1 (0.4)	.119	.549	.236
Radiation[a]	0 (0.0)	1 (0.2)	1 (0.3)	2 (0.7)	.246	.447	.414
No. of orthopedics care visits[b]					**.058**	.331	.123
≤3	99 (42.9)	224 (42.0)	167 (45.1)	128 (47.9)			
4-5	94 (40.7)	212 (39.8)	141 (38.1)	80 (30.0)			

(*continued on next page*)

Table A.2 (*continued*)

Characteristics	LOS 0 (n = 231, 16.5%)	LOS 1 (n = 533, 38.0%)	LOS 2 (n = 370, 26.4%)	LOS 3+ (n = 267, 19.1%)	*P*-value (LOS cat. 1: 0/1-2/3+)	*P*-value (LOS cat. 2: 0/1/2+)	*P*-value (LOS cat. 3: 0/1/2/3+)
6+	38 (16.5)	97 (18.2)	62 (16.8)	59 (22.1)			
MyChart status—active	146 (63.2)	341 (64.0)	208 (56.2)	136 (50.9)	**.007**	**.001**	**.001**
No. of no-show >1[b]	22 (9.5)	70 (13.1)	71 (19.2)	81 (30.3)	**<.001**	**<.001**	**<.001**
Noncompliance	34 (14.7)	80 (15.0)	58 (15.7)	72 (27.0)	**<.001**	**.026**	**<.001**
Flu vaccine status[b]	75 (32.5)	159 (29.8)	123 (33.2)	92 (34.5)	.604	.355	.537
Preoperative care characteristics							
Days between preoperative labs and operation	5.6 (0, 10)	4.4 (0, 8)	4.7 (0, 8)	3.5 (0, 6)	**<.001**	**.001**	**<.001**
Hemoglobin					**<.001**	**<.001**	**<.001**
Low	56 (24.2)	195 (36.6)	161 (43.5)	147 (55.1)			
Normal	174 (75.3)	336 (63.0)	207 (55.9)	120 (44.9)			
High	1 (0.4)	2 (0.4)	2 (0.5)	0 (0.0)			
Hematocrit					**<.001**	**<.001**	**<.001**
Low	59 (25.5)	229 (43.0)	174 (47.0)	151 (56.6)			
Normal	171 (74.0)	300 (56.3)	193 (52.2)	116 (43.4)			
High	1 (0.4)	4 (0.8)	3 (0.8)	0 (0.0)			
Hemoglobin a1c	4 (1.7)	10 (1.9)	16 (4.3)	12 (4.5)	.185	**.020**	**.049**
Attended preop sessions	42 (18.2)	67 (12.6)	32 (8.6)	14 (5.2)	**<.001**	**<.001**	**<.001**
NSAID	79 (34.2)	498 (93.4)	318 (85.9)	200 (74.9)	**<.001**	**<.001**	**<.001**
Corticosteroid	186 (80.5)	393 (73.7)	201 (54.3)	143 (53.6)	**<.001**	**<.001**	**<.001**
Narcotic	231 (100.0)	532 (99.8)	370 (100.0)	267 (100.0)	.759	.443	.653
ASA score >2	117 (50.6)	375 (70.4)	312 (84.3)	227 (85.0)	**<.001**	**<.001**	**<.001**
RAPT score	10.0 (9.0, 11.0)	9.3 (8.0, 11.0)	8.6 (7.0, 10.0)	8.2 (7.0, 10.0)	**<.001**	**<.001**	**<.001**
Absence of RAPT	21 (9.1)	66 (12.4)	51 (13.8)	89 (33.3)	**<.001**	**<.001**	**<.001**
Vitals							
Body mass index at admission (kg/m^2)					.469	.293	.372
<18.5	3 (1.3)	6 (1.1)	2 (0.5)	4 (1.5)			
18.5 to <25	39 (16.9)	85 (15.9)	48 (13.0)	39 (14.6)			
25 to <30	68 (29.4)	186 (34.9)	121 (32.7)	73 (27.3)			
30 to <40	93 (40.3)	205 (38.5)	149 (40.3)	111 (41.6)			
40+	28 (12.1)	51 (9.6)	50 (13.5)	40 (15.0)			
Weight (kg)							
At admission (a)	191.3 (162.0, 218.5)	197.0 (166.0, 222.7)	200.4 (162.3, 234.8)	203.8 (165.0, 239.2)	**.012**	**.011**	**.019**
Within 1 year prior to admission (b)	191.9 (163.0, 216.8)	197.3 (167.8, 224.2)	200.5 (160.0, 235.8)	203.0 (164.5, 235.6)	**.032**	**.024**	**.049**
Difference between (a) and (b)	−0.5 (−4.1, 3.4)	−0.3 (−5.4, 3.7)	−0.1 (−6.5, 4.3)	0.7 (−6.1, 6.8)	.672	.807	.847
Blood pressure (mmHg)							
Systolic BP at admission					.920	.901	.984
<120	59 (25.5)	133 (25.0)	87 (23.5)	61 (22.8)			
120 to <130	50 (21.6)	101 (18.9)	72 (19.5)	55 (20.6)			
130 to <140	52 (22.5)	122 (22.9)	83 (22.4)	58 (21.7)			
140+	70 (30.3)	177 (33.2)	128 (34.6)	93 (34.8)			
Diastolic BP at admission					.402	**.030**	**.028**
<80	153 (66.2)	363 (68.1)	288 (77.8)	190 (71.2)			
80 to <90	54 (23.4)	111 (20.8)	52 (14.1)	48 (18.0)			
90+	24 (10.4)	59 (11.1)	30 (8.1)	29 (10.9)			
Pulse pressure at admission					**.046**	**.001**	**.004**
<40	19 (8.2)	67 (12.6)	38 (10.3)	26 (9.7)			
40-60	124 (53.7)	249 (46.7)	143 (38.6)	114 (42.7)			
>60	88 (38.1)	217 (40.7)	189 (51.1)	127 (47.6)			
MAP at admission					.369	.153	.144
<70	34 (14.7)	84 (15.8)	79 (21.4)	51 (19.1)			
70-100	177 (76.6)	394 (73.9)	261 (70.5)	184 (68.9)			
>100	20 (8.7)	55 (10.3)	30 (8.1)	32 (12.0)			
SPO2 at admission <95%	20 (8.7)	59 (11.1)	30 (8.1)	31 (11.6)	.534	.531	.336
Heart rate at admission (mmHg)					**.001**	**<.001**	**<.001**
<60	28 (12.1)	81 (15.2)	41 (11.1)	22 (8.2)			
60-100	202 (87.4)	448 (84.1)	319 (86.2)	232 (86.9)			

>100	1 (0.4)	4 (0.8)	10 (2.7)	13 (4.9)			
Pre-survey responses							
PROMIS-10							
Global health T score—physical	41.7 (37.4, 44.9)	40.5 (34.9, 44.9)	37.5 (32.4, 42.3)	37.8 (32.4, 42.3)	**<.001**	**<.001**	**<.001**
Global health T score—mental	51.2 (45.8, 56.0)	49.5 (43.5, 56.0)	47.0 (41.7, 53.3)	46.5 (41.1, 50.8)	**<.001**	**<.001**	**<.001**
Survey questionnaire (1)[c]	3.5 (3.0, 4.0)	3.2 (3.0, 4.0)	3.0 (2.0, 4.0)	3.0 (2.0, 4.0)	**<.001**	**<.001**	**<.001**
Survey questionnaire (2)	3.3 (2.0, 4.0)	3.1 (2.0, 4.0)	2.7 (2.0, 3.0)	2.7 (2.0, 3.0)	**<.001**	**<.001**	**<.001**
Survey questionnaire (3)	2.7 (2.0, 3.0)	2.6 (2.0, 3.0)	2.3 (2.0, 3.0)	2.4 (2.0, 3.0)	**.006**	**<.001**	**<.001**
Survey questionnaire (4)	3.3 (3.0, 4.0)	3.3 (3.0, 4.0)	3.1 (3.0, 4.0)	3.0 (3.0, 3.0)	**<.001**	**<.001**	**<.001**
Survey questionnaire (5)	3.6 (3.0, 4.0)	3.6 (3.0, 4.0)	3.3 (3.0, 4.0)	3.3 (3.0, 4.0)	**<.001**	**<.001**	**<.001**
Survey questionnaire (6)	3.7 (3.0, 4.0)	3.5 (3.0, 4.0)	3.3 (3.0, 4.0)	3.3 (3.0, 4.0)	**<.001**	**<.001**	**<.001**
Survey questionnaire (7)	3.8 (3.0, 5.0)	3.5 (3.0, 4.0)	3.2 (2.0, 4.0)	3.2 (2.0, 4.0)	**<.001**	**<.001**	**<.001**
Survey questionnaire (8)	3.6 (3.0, 4.0)	3.4 (3.0, 4.0)	3.1 (3.0, 4.0)	3.1 (2.0, 4.0)	**<.001**	**<.001**	**<.001**
Survey questionnaire (9)	4.0 (3.0, 5.0)	3.9 (3.0, 5.0)	3.7 (3.0, 4.0)	3.6 (3.0, 4.0)	**<.001**	**<.001**	**<.001**
Survey questionnaire (10)	3.1 (2.0, 4.0)	2.8 (2.0, 4.0)	2.5 (2.0, 3.0)	2.5 (2.0, 3.0)	**<.001**	**<.001**	**<.001**
Disease specific functional score from HOOS or KOOS[d]	48.4 (42.3, 57.1)	47.8 (39.6, 57.1)	43.9 (34.2, 53.0)	43.9 (34.2, 53.0)	**.005**	**<.001**	**<.001**

BP, blood pressure; HOOS, hip injury disability and osteoarthritis outcome score; KOOS, Knee Injury and Osteoarthritis Outcome score; LOS, length of stay; cat, category; MAP, mean arterial pressure; NSAID, nonsteroidal anti-inflammatory drugs; PROMIS, Patient-Reported Outcomes Measurement Information System; RAPT, Risk Assessment and Prediction Tool.

Continuous variables are expressed as mean and interquartile range. The categorical variables are expressed in terms of n (%). A *P* value less than .1 indicates a significant difference between the 2 group and is bold.

[a] Events within 3 months prior to hospitalization.

[b] Events within 1 year prior to hospitalization.

[c] Survey questionnaire: (1) In general, how would you rate your physical health; (2) To what extent are you able to carry out your everyday physical activities; (3) How would you rate your pain on average; (4) How would you rate your fatigue on average; (5) How often have you been bothered by emotional problems such as feeling anxious, depressed, or irritable; (6) In general, would you say your health is; (7) In general, how would you rate your satisfaction with your social activities and relationships; (8) In general, would you say your quality of life is; (9) In general, how would you rate your mental health including your mood and your ability to think; (10) In general, please rate how well you carry out your usual social activities and roles.

[d] For an individual sample, only a single-disease-specific functional score (HOOS or KOOS) was included depending on the type of surgery.

Table A.3
Final model input covariates by the LOS categorization.

Characteristics	LOS cat. 1 (0/1-2/3+)	LOS cat. 2 (0/1/2+)	LOS cat. 3 (0/1/2/3+)
Demographics and socioeconomic characteristics			
Age, years	O		
Sex—male			
Race			
Non-Hispanic	O		
Marital status			
Insurance			O
Income			
Rural			
Smoking status			
Alcohol dependence			
Illicit or cardiotoxic drug use			
Comorbidities			
Renal	O	O	O
Cardiovascular	O		
Hypertension			
Sleep apnea	O	O	O
Diabetes			
Endocrine		O	O
Malignancy or cancer			
Depression	O		
Hematologic		O	O
Respiratory	O		
Prior-to-hospitalization care characteristics			
NSAID[a]—pain management		O	
NSAID[a]—surgery preparation	O		O
Corticosteroid[a]			
Narcotic[a]—pain management	O	O	
Narcotic[a]—surgery preparation	O		O
Chemotherapy[a]			
Radiation[a]			
No. of orthopedics care visits[b]			
MyChart status—active		O	
No. of no-show >1[b]	O		O
Noncompliance			
Flu vaccine status[b]			
Preoperative care characteristics			
Days between preoperative labs and operation	O		
Hemoglobin			
Hematocrit	O	O	O
Hemoglobin a1c			
Attended preoperative sessions	O	O	O
NSAID	O	O	O
Corticosteroid	O	O	O
Narcotic			
ASA score >2	O	O	O
RAPT score	O	O	O
Missing indicator of RAPT	O	O	O
Vitals			
Body mass index at admission (kg/m^2)			
Weight (kg)			
At admission (a)	O	O	O
Within 1 year prior to admission (b)			
Difference between (a) and (b)			
Blood Pressure (mmHg)			
Systolic BP at admission			
Diastolic BP at admission		O	
Pulse pressure at admission			
MAP at admission			
SPO2 at admission <95%			
Heart rate at admission (mmHg)	O	O	O
Pre-survey responses			
PROMIS			
Global health T score—physical		O	
Global health T score—mental		O	O
Survey questionnaire (1)[c]			
Survey questionnaire (2)			O
Survey questionnaire (3)			
Survey questionnaire (4)		O	
Survey questionnaire (5)			
Survey questionnaire (6)		O	O
Survey questionnaire (7)			
Survey questionnaire (8)			

Table A.3 (*continued*)

Characteristics	LOS cat. 1 (0/1-2/3+)	LOS cat. 2 (0/1/2+)	LOS cat. 3 (0/1/2/3+)
Survey questionnaire (9)			
Survey questionnaire (10)			
Disease specific functional score from HOOS or KOOS			

BP, blood pressure; HOOS, hip injury disability and osteoarthritis outcome score; KOOS, Knee Injury and Osteoarthritis Outcome score; LOS, length of stay; cat, category; MAP, mean arterial pressure; NSAID, nonsteroidal anti-inflammatory drugs; PROMIS, Patient-Reported Outcomes Measurement Information System; RAPT, Risk Assessment and Prediction Tool.

After the variable selection phases, model input covariates were identified for each outcome setting.

[a] Events within 3 months prior to hospitalization.

[b] Events within 1 year prior to hospitalization.

[c] Survey questionnaire: (1) In general, how would you rate your physical health; (2) To what extent are you able to carry out your everyday physical activities; (3) How would you rate your pain on average; (4) How would you rate your fatigue on average; (5) How often have you been bothered by emotional problems such as feeling anxious, depressed, or irritable; (6) In general, would you say your health is; (7) In general, how would you rate your satisfaction with your social activities and relationships; (8) In general, would you say your quality of life is; (9) In general, how would you rate your mental health including your mood and your ability to think; (10) In general, please rate how well you carry out your usual social activities and roles.

Table A.4
Model performance of the threshold model and the ordinal binary decomposition models for the four-category setting.

Models	Different 3 categories (LOS cat. 2: 0/1/2+)		Four categories (LOS cat. 3: LOS 0/1/2/3+)	
	Accuracy (avg., SD)	Kendall rank correlation (avg., SD)	Accuracy (avg., SD)	Kendall rank correlation (avg., SD)
Threshold model				
Ordinal regression	0.721 (0.022)	0.475 (0.038)	0.506 (0.023)	0.470 (0.034)
Ordinal decomposition models				
Logistic regression	0.637 (0.022)	0.459 (0.037)	0.535 (0.022)	0.457 (0.037)
SVM with a radial kernel	0.617 (0.025)	0.423 (0.042)	0.508 (0.024)	0.423 (0.043)
Random forest (mtry = 3)	0.632 (0.021)	0.441 (0.038)	0.541 (0.023)	0.453 (0.041)
Random forest (mtry = 4)	0.628 (0.019)	0.432 (0.034)	0.534 (0.021)	0.447 (0.034)
Random forest (mtry = 5)	0.622 (0.020)	0.425 (0.036)	0.530 (0.022)	0.445 (0.039)

avg., average; LOS, length of stay; cat., category; mtry, the numbers of variables randomly sampled as candidates at each split; SD, standard deviation; SVM, support vector machine.

Table A.5
Model performance including the indicator of procedure type for the 3 LOS categorization of interest (ie, outpatient, short stay, and prolonged stay).

Models	Accuracy (avg., IQR)	Kendall rank correlation (avg., IQR)
Threshold model		
Ordinal regression	0.714 (0.696-0.731)	0.450 (0.422-0.471)
Ordinal decomposition models		
Logistic regression	0.734 (0.717-0.749)	0.484 (0.452-0.517)
SVM with a radial kernel	0.730 (0.714-0.746)	0.450 (0.421-0.482)
Random forest (mtry = 3)	0.745 (0.726-0.762)	0.498 (0.464-0.527)
Random forest (mtry = 4)	0.743 (0.729-0.759)	0.494 (0.470-0.519)
Random forest (mtry = 5)	0.739 (0.723-0.759)	0.484 (0.456-0.511)

LOS, length of stay; avg., average; mtry, the numbers of variables randomly sampled as candidates at each split; IQR, interquartile range; SVM, support vector machine.

Table B.1
Characteristics by the outcome.

Characteristics	Total (N = 1590)	Readmission (N = 92)	No readmission (N = 1498)	*P* value
Demographics and socioeconomic characteristics (11)				
Age, year				.986
≤61	403 (25.3)	24 (26.1)	379 (25.3)	
62-67	419 (26.4)	24 (26.1)	395 (26.4)	
68-73	382 (24.0)	23 (25.0)	359 (24.0)	
74+	386 (24.3)	21 (22.8)	365 (24.4)	
Sex—male	671 (42.2)	40 (43.5)	631 (42.1)	.883
Race				.503
Black	241 (15.2)	11 (12.0)	230 (15.4)	
Other	114 (7.2)	5 (5.4)	109 (7.3)	
White	1235 (77.7)	76 (82.6)	1159 (77.4)	
Non-Hispanic	1506 (94.7)	89 (96.7)	1417 (94.6)	.514
Marital status				.401
Married	931 (58.6)	60 (65.2)	871 (58.1)	
Other or unknown	91 (5.7)	4 (4.3)	87 (5.8)	
Single/Divorced/Separated/Widowed	568 (35.7)	28 (30.4)	540 (36.0)	
Insurance				.843
Medicaid	90 (5.7)	6 (6.5)	84 (5.6)	
Medicare	894 (56.3)	51 (55.4)	843 (56.4)	
Other	47 (3.0)	4 (4.3)	43 (2.9)	
Private or managed care	557 (35.1)	31 (33.7)	526 (35.2)	
Income				.875
<40,000	499 (31.4)	27 (29.3)	472 (31.5)	
40,000-60,000	519 (32.6)	32 (34.8)	487 (32.5)	
>60,000	572 (36.0)	33 (35.9)	539 (36.0)	
Rural	166 (10.4)	9 (9.8)	157 (10.5)	.971
Smoking status				.200
Current	143 (9.0)	8 (8.7)	135 (9.0)	
Former	639 (40.2)	45 (48.9)	594 (39.7)	
Never	808 (50.8)	39 (42.4)	769 (51.3)	
Alcohol dependence	60 (3.8)	4 (4.3)	56 (3.7)	.987
Illicit or cardiotoxic drug use	45 (2.8)	3 (3.3)	42 (2.8)	1
Comorbidities (10)				
Renal	53 (3.3)	5 (5.4)	48 (3.2)	.391
Cardiovascular	276 (17.4)	21 (22.8)	255 (17.0)	.199
Hypertension	883 (55.5)	54 (58.7)	829 (55.3)	.603
Sleep apnea	67 (4.2)	5 (5.4)	62 (4.1)	.739
Diabetes	261 (16.4)	29 (31.5)	232 (15.5)	**<.001**
Endocrine	33 (2.1)	3 (3.3)	30 (2.0)	.656
Malignancy or cancer	55 (3.5)	4 (4.3)	51 (3.4)	.852
Depression	407 (25.6)	30 (32.6)	377 (25.2)	.143
Hematologic	18 (1.1)	4 (4.3)	14 (0.9)	**.013**
Respiratory	82 (5.2)	8 (8.7)	74 (4.9)	.181
Prior-to-hospitalization care characteristics (12)				
NSAID—pain management[b]	400 (25.2)	29 (31.5)	371 (24.8)	.185
NSAID—surgery preparation[a]	603 (37.9)	64 (69.6)	539 (36.0)	**<.001**
Corticosteroid[c]	334 (21.0)	57 (62.0)	277 (18.5)	**<.001**
Narcotic—pain management[b]	430 (27.0)	34 (37.0)	396 (26.4)	**.037**
Narcotic—surgery preparation[a]	1247 (78.4)	88 (95.7)	1159 (77.4)	**<.001**
Chemotherapy[b]	1 (0.1)	0 (0.0)	1 (0.1)	1
Radiation[b]	5 (0.3)	1 (1.1)	4 (0.3)	.686
No. of orthopedics care visits[d]				.369
≤3	713 (44.8)	46 (50.0)	667 (44.5)	
4-5	588 (37.0)	34 (37.0)	554 (37.0)	
6+	289 (18.2)	12 (13.0)	277 (18.5)	
MyChart status—active	900 (56.6)	61 (66.3)	839 (56.0)	**.068**
No. of no-show >1[d]	295 (18.6)	23 (25.0)	272 (18.2)	.133
Noncompliance	311 (19.6)	27 (29.3)	284 (19.0)	**.021**
Flu vaccine status[d]	518 (32.6)	25 (27.2)	493 (32.9)	.305
Pre-operative care characteristics (10)				
RAPT	8.9 (8.0, 10.0)	8.6 (7.0, 10.0)	8.9 (8.0, 10.0)	.179
Days between preoperative labs and operation	4.4 (0.0, 8.0)	4.3 (0.0, 8.0)	4.4 (0.0, 8.0)	.784
Hemoglobin				.616
Low	686 (43.1)	42 (45.7)	644 (43.0)	
Normal	896 (56.4)	49 (53.3)	847 (56.5)	
High	8 (0.5)	1 (1.1)	7 (0.5)	
Hematocrit				.425
Low	727 (45.7)	47 (51.1)	680 (45.4)	
Normal	854 (53.7)	44 (47.8)	810 (54.1)	
High	9 (0.6)	1 (1.1)	8 (0.5)	
Hemoglobin a1c	50 (3.1)	5 (5.4)	45 (3.0)	.323
Attended preoperative sessions	169 (10.6)	12 (13.0)	157 (10.5)	.549
NSAID	1238 (77.9)	70 (76.1)	1168 (78.0)	.769

(*continued on next page*)

Table B.1 (*continued*)

Characteristics	Total (N = 1590)	Readmission (N = 92)	No readmission (N = 1498)	*P* value
Corticosteroid	1017 (64.0)	59 (64.1)	958 (64.0)	1
Narcotic	1589 (99.9)	92 (100.0)	1497 (99.9)	1
ASA score				.738
1	11 (0.7)	1 (1.1)	10 (0.7)	
2	378 (23.8)	18 (19.6)	360 (24.0)	
3	1175 (73.9)	71 (77.2)	1104 (73.7)	
4	26 (1.6)	2 (2.2)	24 (1.6)	
Intraoperative care characteristics (13)				
Estimated blood loss	313.1 (100.0, 400.0)	339.3 (100.0, 500.0)	311.5 (100.0, 400.0)	.446
Duration of procedure, minutes				.407
≤124	503 (31.6)	26 (28.3)	477 (31.8)	
124.1-141	423 (26.6)	25 (27.2)	398 (26.6)	
141.1-172	350 (22.0)	17 (18.5)	333 (22.2)	
172.1+	314 (19.7)	24 (26.1)	290 (19.4)	
Type of joint—hip	680 (42.8)	45 (48.9)	635 (42.4)	.263
Number of joints—bilateral	26 (1.6)	0 (0.0)	26 (1.7)	.395
Type of anesthesia				
Epidural	30 (1.9)	3 (3.3)	27 (1.8)	.546
General	1085 (68.2)	67 (72.8)	1018 (68.0)	.391
Monitor anesthesia care	102 (6.4)	4 (4.3)	98 (6.5)	.539
Spinal	359 (22.6)	18 (19.6)	341 (22.8)	.559
Duration of anesthesia, minutes				.229
≤150	415 (26.1)	17 (18.5)	398 (26.6)	
150.1-167	387 (24.3)	29 (31.5)	358 (23.9)	
167.1-198	392 (24.7)	22 (23.9)	370 (24.7)	
198.1+	396 (24.9)	24 (26.1)	372 (24.8)	
Insulin infusion	19 (1.2)	3 (3.3)	16 (1.1)	.166
NSAID	173 (10.9)	10 (10.9)	163 (10.9)	1
Corticosteroid	8 (0.5)	1 (1.1)	7 (0.5)	.955
Narcotic	722 (45.4)	38 (41.3)	684 (45.7)	.480
Postoperative care characteristics (7)				
Blood sugar ≥150 mg/dL	478 (30.1)	30 (32.6)	448 (29.9)	.666
Insulin infusion	193 (12.1)	20 (21.7)	173 (11.5)	**.006**
NSAID	1298 (81.6)	79 (85.9)	1219 (81.4)	.346
Corticosteroid	51 (3.2)	8 (8.7)	43 (2.9)	**.006**
Narcotic	1374 (86.4)	84 (91.3)	1290 (86.1)	.210
Positive CAM	5 (0.3)	1 (1.1)	4 (0.3)	.686
Morse score	5.6 (3.0, 7.0)	7.0 (3.0, 7.0)	5.5 (3.0, 7.0)	.180
Hospitalization care characteristics (2)				
Length of stay, days	2.0 (1.0, 3.0)	2.7 (1.0, 3.0)	2.0 (1.0, 2.0)	.113
Discharge disposition				**.093**
Other	50 (3.1)	2 (2.2)	48 (3.2)	
To home	286 (18.0)	11 (12.0)	275 (18.4)	
To homecare	1031 (64.8)	59 (64.1)	972 (64.9)	
To skilled nursing	223 (14.0)	20 (21.7)	203 (13.6)	
Postdischarge care characteristics (4)				
Time from discharge to follow-up with orthopedic care, days				.595
≤13	427 (26.9)	29 (31.5)	398 (26.6)	
13.1-17	370 (23.3)	17 (18.5)	353 (23.6)	
17.1-38	410 (25.8)	25 (27.2)	385 (25.7)	
38.1+	383 (24.1)	21 (22.8)	362 (24.2)	
No. of follow-up visits with ortho care >2	346 (21.8)	54 (58.7)	292 (19.5)	**<.001**
No. of cancel or no-show >1	309 (19.4)	39 (42.4)	270 (18.0)	**<.001**
ER visits	107 (6.7)	20 (21.7)	87 (5.8)	**<.001**
Vitals (17)				
Body mass index at admission (kg/m^2)				**.075**
<18.5	16 (1.0)	2 (2.2)	14 (0.9)	
18.5 to <25	258 (16.2)	7 (7.6)	251 (16.8)	
25 to <30	504 (31.7)	30 (32.6)	474 (31.6)	
30 to <40	639 (40.2)	38 (41.3)	601 (40.1)	
40+	173 (10.9)	15 (16.3)	158 (10.5)	
Body mass index at discharge (kg/m^2)				.117
<18.5	14 (0.9)	2 (2.2)	12 (0.8)	
18.5 to <25	267 (16.8)	11 (12.0)	256 (17.1)	
25 to <30	496 (31.2)	26 (28.3)	470 (31.4)	
30 to <40	641 (40.3)	37 (40.2)	604 (40.3)	
40+	172 (10.8)	16 (17.4)	156 (10.4)	
Weight (kg)				
At admission (a)	197.2 (163.0, 226.5)	204.5 (167.1, 232.2)	196.8 (162.0, 226.0)	.128
Within 1 year prior to admission (b)	197.4 (162.6, 227.0)	204.3 (168.1, 235.0)	197.0 (162.4, 226.7)	.157
Difference between (a) and (b)	0.3 (−5.3, 5.0)	0.8 (−5.2, 5.0)	0.2 (−5.3, 5.0)	.763
Maximum weight gain during hospitalization	1.3 (0.0, 0.0)	2.2 (0.0, 0.0)	1.3 (0.0, 0.0)	.220
Maximum weight loss during hospitalization	0.3 (0.0, 0.0)	0.3 (0.0, 0.0)	0.3 (0.0, 0.0)	.835
Blood pressure (mmHg)				
Systolic BP at admission				.712

Table B.1 (*continued*)

Characteristics	Total (N = 1590)	Readmission (N = 92)	No readmission (N = 1498)	*P* value
<120	390 (24.5)	25 (27.2)	365 (24.4)	
120 to <130	314 (19.7)	17 (18.5)	297 (19.8)	
130 to <140	348 (21.9)	23 (25.0)	325 (21.7)	
140+	538 (33.8)	27 (29.3)	511 (34.1)	
Systolic BP at discharge				.777
<120	700 (44.0)	38 (41.3)	662 (44.2)	
120 to <130	366 (23.0)	25 (27.2)	341 (22.8)	
130 to <140	235 (14.8)	12 (13.0)	223 (14.9)	
140+	289 (18.2)	17 (18.5)	272 (18.2)	
Diastolic BP at admission				.964
<80	1407 (88.5)	82 (89.1)	1325 (88.5)	
80 to <90	142 (8.9)	8 (8.7)	134 (8.9)	
90+	41 (2.6)	2 (2.2)	39 (2.6)	
Diastolic BP at discharge				.105
<80	1137 (71.5)	70 (76.1)	1067 (71.2)	
80 to <90	297 (18.7)	10 (10.9)	287 (19.2)	
90+	156 (9.8)	12 (13.0)	144 (9.6)	
Pulse pressure at admission				.271
<40	172 (10.8)	6 (6.5)	166 (11.1)	
40-60	696 (43.8)	46 (50.0)	650 (43.4)	
>60	722 (45.4)	40 (43.5)	682 (45.5)	
Pulse pressure at discharge				.637
<40	158 (9.9)	7 (7.6)	151 (10.1)	
40-60	749 (47.1)	42 (45.7)	707 (47.2)	
>60	683 (43.0)	43 (46.7)	640 (42.7)	
MAP at admission				.146
<70	287 (18.1)	23 (25.0)	264 (17.6)	
70-100	1148 (72.2)	63 (68.5)	1085 (72.4)	
>100	155 (9.7)	6 (6.5)	149 (9.9)	
Map at discharge				.255
<70	380 (23.9)	26 (28.3)	354 (23.6)	
70-100	1149 (72.3)	65 (70.7)	1084 (72.4)	
>100	61 (3.8)	1 (1.1)	60 (4.0)	
Heart rate at admission (mmHg)				**.010**
<60	197 (12.4)	5 (5.4)	192 (12.8)	
60-100	1360 (85.5)	82 (89.1)	1278 (85.3)	
>100	33 (2.1)	5 (5.4)	28 (1.9)	
Heart rate at discharge (mmHg)				.549
<60	113 (7.1)	4 (4.3)	109 (7.3)	
60-100	1402 (88.2)	83 (90.2)	1319 (88.1)	
>100	75 (4.7)	5 (5.4)	70 (4.7)	
Presurvey responses (13)				
PROMIS				
Global health T score—physical	38.9 (34.9, 42.3)	36.9 (32.4, 42.3)	39.0 (34.9, 42.3)	**.004**
Global health T score—mental	48.1 (43.5, 53.3)	47.2 (41.1, 53.3)	48.2 (43.5, 53.3)	.263
Global01[e]	3.4 (3.0, 4.0)	3.2 (3.0, 4.0)	3.4 (3.0, 4.0)	**.008**
Global02	3.2 (3.0, 4.0)	3.0 (2.0, 4.0)	3.3 (3.0, 4.0)	**.025**
Global03	3.1 (2.0, 4.0)	2.9 (2.0, 4.0)	3.1 (2.0, 4.0)	**.057**
Global04	3.7 (3.0, 5.0)	3.8 (3.0, 5.0)	3.7 (3.0, 5.0)	.737
Global05	3.3 (2.2, 4.0)	3.3 (2.8, 4.0)	3.3 (2.2, 4.0)	.842
Global09	2.7 (2.0, 3.0)	2.4 (2.0, 3.0)	2.7 (2.0, 3.0)	**.002**
Global06	2.8 (2.0, 4.0)	2.6 (2.0, 3.0)	2.9 (2.0, 4.0)	**.013**
Global10	3.5 (3.0, 4.0)	3.3 (3.0, 4.0)	3.5 (3.0, 4.0)	.218
Global08	3.2 (3.0, 4.0)	3.0 (2.0, 3.0)	3.2 (3.0, 4.0)	**.016**
Global07	2.5 (2.0, 3.0)	2.4 (2.0, 3.0)	2.5 (2.0, 3.0)	.254
JR Score from KOOS and HOOS	45.5 (36.4, 54.8)	44.2 (34.2, 55.1)	45.6 (36.4, 54.8)	.406

NSAID, nonsteroidal anti-inflammatory drugs; CAM, confusion assessment method; ER, emergency room; PROMIS, Patient-Reported Outcomes Measurement Information System; KOOS, Knee Injury and Osteoarthritis Outcome score; HOOS, hip injury disability and osteoarthritis outcome score.
Continuous variables are expressed as mean and interquartile range. The categorical variables are expressed in terms of n (%). A *P* value less than .05 indicates a significant difference between the 2 group and is bold.

[a] Events within 1 month prior to hospitalization.
[b] Events between 1 month and 3 months prior to hospitalization.
[c] Events within 3 months prior to hospitalization.
[d] Events within 1 year prior to hospitalization.
[e] Global01: In general, would you say your health is; Global02: In general, would you say your quality of life is; Global03: In general, how would you rate your physical health; Global04: In general, how would you rate your mental health including your mood and your ability to think; Global05: In general, how would you rate your satisfaction with your social activities and relationships; Global06: To what extent are you able to carry out your everyday physical activities; Global07: How would you rate your pain on average; Global08: How would you rate your fatigue on average; Global09: In general, please rate how well you carry out your usual social activities and roles; Global10: How often have you been bothered by emotional problems such as feeling anxious, depressed, or irritable.

Table C.1
Sensitivity analysis using different imputed samples.

Models	AUC (mean; IQR)	Threshold (mean; IQR)	Recall (mean; IQR)	Precision (mean; IQR)
Logistic regression	0.862 (0.841, 0.887)	0.363 (0.299, 0.415)	0.620 (0.538, 0.705)	0.569 (0.500, 0.645)
LASSO	0.868 (0.850, 0.892)	0.359 (0.298, 0.413)	0.619 (0.548, 0.705)	0.578 (0.518, 0.650)
SVM—polynomial	0.717 (0.709, 0.782)	0.218 (0.177, 0.267)	0.511 (0.426, 0.609)	0.667 (0.608, 0.750)
SVM—radial	0.778 (0.796, 0.851)	0.220 (0.188, 0.271)	0.612 (0.523, 0.714)	0.697 (0.643, 0.762)
Random forest	0.856 (0.840, 0.872)	0.254 (0.218, 0.292)	0.622 (0.548, 0.732)	0.672 (0.622, 0.750)
RF w/ oversampling	0.854 (0.838, 0.872)	0.280 (0.239, 0.324)	0.546 (0.406, 0.667)	0.630 (0.558, 0.734)
RUS boosting	0.85 (0.828, 0.876)	0.297 (0.242, 0.345)	0.534 (0.427, 0.647)	0.611 (0.548, 0.714)

AUC, area under the receiver operating characteristic curve; IQR, interquartile range; LASSO, least absolute shrinkage and selection operator; RF, random forest; RUS, random undersampling; SVM, support vector machines.
The 7 models were compared with 100 repeats.

Table D.1
Model performance comparison of new models replacing the covariate general NSAID intake with "NSAID intake excluding aspirin."

Models	AUC (mean; IQR)	Threshold (mean; IQR)	Recall (mean; IQR)	Precision (mean; IQR)
Logistic regression	0.845 (0.826, 0.872)	0.244 (0.148, 0.309)	0.543 (0.448, 0.648)	0.560 (0.500, 0.659)
LASSO	0.856 (0.842, 0.877)	0.181 (0.114, 0.215)	0.585 (0.500, 0.680)	0.601 (0.552, 0.695)
SVM—polynomial	0.714 (0.701, 0.781)	0.147 (0.072, 0.105)	0.494 (0.387, 0.609)	0.690 (0.629, 0.764)
SVM—radial	0.769 (0.787, 0.837)	0.176 (0.094, 0.159)	0.530 (0.444, 0.644)	0.679 (0.629, 0.744)
Random forest	0.825 (0.811, 0.843)	0.164 (0.114, 0.191)	0.573 (0.435, 0.704)	0.696 (0.644, 0.794)
RF w/ oversampling	0.825 (0.810, 0.845)	0.225 (0.179, 0.267)	0.601 (0.500, 0.693)	0.712 (0.673, 0.758)
RUS boosting	0.823 (0.799, 0.848)	0.688 (0.566, 0.839)	0.510 (0.391, 0.652)	0.631 (0.570, 0.741)

AUC, area under the receiver operating characteristic curve; IQR, interquartile range; LASSO, least absolute shrinkage and selection operator; NSAID, nonsteroidal anti-inflammatory drug; RF, random forest; RUS, random undersampling; SVM, support vector machines.
The 7 models were evaluated with 100 repeats. For each model, the threshold was determined by the Matthews correlation coefficient, and correspondingly, the recall and precision were obtained.

Table D.2
Risk factors identification associated with 90-day readmission from a new model replacing general NSAID intake with "NSAID intake excluding aspirin."

Characteristics	OR	*P* value
Comorbidities		
Diabetes	2.443	.001
Prior-to-hospitalization care		
NSAID without aspirin—surgery preparation	2.607	<.001
Corticosteroid	6.324	<.001
Narcotic—surgery preparation	5.106	.004
MyChart status—active	1.472	.138
Hospitalization care		
Discharge disposition (ref: To home)		
To homecare	2.088	.054
To skilled nursing	3.366	.010
Other	1.026	.977
Postdischarge care		
No. of follow-up visits >2	5.370	<.001
No. of cancel or no-show >1	1.772	.030
ER visits	3.957	<.001
Vitals		
Heart rate at discharge (ref: 60-100)		
<60	0.384	.056
>100	1.783	.364
Presurgical survey responses		
PROMIS-10 Global 09—social activities	0.764	.024

ER, emergency room; NSAID, nonsteroidal anti-inflammatory drugs; OR, odds ratio; PROMIS, patient-reported outcome measurement information system.
A *P* value less than .05 indicates a significant risk factor. PROMIS-10 Global09 states, "In general, please rate how well you carry out your usual social activities and roles."