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A preoperative risk assessment tool for predicting adverse outcomes among total shoulder arthroplasty patients

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Background: With the increased utilization of Total Shoulder Arthroplasty (TSA) in the outpatient setting, understanding the risk factors associated with complications and hospital readmissions becomes a more significant consideration. Prior developed assessment metrics in the literature either consisted of hard-to-implement tools or relied on postoperative data to guide decision-making. This study

This study was reviewed by the WCG Institutional Review Board, an independent ethical review board, and an exemption was approved.

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aimed to develop a preoperative risk assessment tool to help predict the risk of hospital readmission and other postoperative adverse outcomes.
Methods: We retrospectively evaluated the 2019-2022(Q2) Medicare fee-for-service inpatient and outpatient claims data to identify primary anatomic or reserve TSAs and to predict postoperative adverse outcomes within 90 days postdischarge, including all-cause hospital readmissions, postoperative complications, emergency room visits, and mortality. We screened 108 candidate predictors, including demographics, social determinants of health, TSA indications, prior 12-month hospital, and skilled nursing home admissions, comorbidities measured by hierarchical conditional categories, and prior orthopedic device-related complications. We used two approaches to reduce the number of predictors based on 80% of the data: 1) the Least Absolute Shrinkage and Selection Operator logistic regression and 2) the machine-learning-based cross-validation approach, with the resulting predictor sets being assessed in the remaining 20% of the data. A scoring system was created based on the final regression models' coefficients, and score cutoff points were determined for low, medium, and high-risk patients.
Results: A total of 208,634 TSA cases were included. There was a 6.8% hospital readmission rate with 11.2% of cases having at least one postoperative adverse outcome. Fifteen covariates were identified for predicting hospital readmission with the area under the curve of 0.70, and 16 were selected to predict any adverse postoperative outcome (area under the curve = 0.75). The Least Absolute Shrinkage and Selection Operator and machine learning approaches had similar performance. Advanced age and a history of fracture due to orthopedic devices are among the top predictors of hospital readmissions and other adverse outcomes. The score range for hospital readmission and an adverse postoperative outcome was 0 to 48 and 0 to 79, respectively. The cutoff points for the low, medium, and high-risk categories are 0-9, 10-14, $\geq$15 for hospital readmissions, and 0-11, 12-16, $\geq$17 for the composite outcome.
Conclusion: Based on Medicare fee-for-service claims data, this study presents a preoperative risk stratification tool to assess hospital readmission or adverse surgical outcomes following TSA. Further investigation is warranted to validate these tools in a variety of diverse demographic settings and improve their predictive performance.
Level of evidence: Level III; Retrospective Cohort Design Using Large Database; Prognosis Study

Keywords: Total shoulder arthroplasty; risk stratification; predictive tool; postoperative complication; hospital readmission; mortality

An increasing number of total shoulder arthroplasties (TSAs) are conducted in an outpatient or inpatient setting but discharged on the same day of surgery.[5] There is concern over patient safety if such outpatient procedures are overutilized. This entered the spotlight in 2023 when the Bundled Payment for Care Improvement - Advanced (BPCI-A) program added outpatient TSAs to its episode definition to encourage outpatient surgeries.[7] With such financial incentives in place, there is the potential for overutilization of outpatient surgeries, which might put TSA patients at undue postoperative risk. As a result, a good understanding of the risk factors for postoperative adverse outcomes among TSA patients is needed. Such information can help guide surgeons in making both clinical and financial decisions.

An easy-to-use risk stratification tool that incorporates key risk factors and can preoperatively predict the postoperative risk of hospital admissions and other adverse outcomes could help surgeons in several ways. First, shoulder surgeons could use it to measure postoperative risk and determine if a patient would be better off receiving nonsurgical interventions. If surgical intervention is preferred, it could help a surgeon decide whether an inpatient surgery is more appropriate than an outpatient one. Finally, given a measurable risk of adverse outcomes, surgeons can plan accordingly before surgery and optimize perioperative care to minimize adverse outcomes, hospital readmission, postoperative complication, emergency room visits, and mortality. This could help improve care and mitigate unnecessary resource utilization.

Hospital readmissions are often costly, and they have been a focus of both the BPCI-A program and Medicare's Hospital Readmission Reduction Program. Under the BPCI-A program, a fixed payment is determined before episodic care of total joint arthroplasty (TJA) that spans from the index surgery to 90 days post-surgery, including hospital readmissions and postacute care. Hospital readmission, not necessarily directly related to the surgery, could easily result in large financial implications where an episode of care with hospital readmission could cost between $14,910 to $16,018,[29] $32,160 to $42,358,[18] and $10,591 to $10,914[31] after total knee arthroplasty (TKA), total hip arthroplasty (THA), and TSA, respectively. Under the Hospital Readmission Reduction Program program, hospitals with an excess readmission rate are subject to financial penalties; for example, a readmission rate of greater than 3% after a TJA can result in a $77,519 revenue loss secondary to penalties.[19]

Three previous studies developed models to predict hospital readmissions after TSA. Devana et al. used California's Office of Statewide Health Planning and Development database to examine 30-day hospital readmission in anatomic and reverse TSA patients,[9,10] resulting in an area under the curve (AUC) of 0.69 and 0.68, respectively. Arvind et al. used the National Surgical Quality Improvement Program data to predict 30-day hospital readmission and included intraoperative or postoperative risk factors in the model (AUC = 0.74).[1]

The existing prediction models for hospital readmission among TSA patients rely on machine learning and/or utilize intraoperative or postoperative risk factors. Due to the black-box nature of the machine-learning approach, these models cannot be used easily by surgeons. In addition, surgeon decision-making may rely only on preoperative information to predict adverse outcomes, and, therefore, models using intraoperative or postoperative information may be less valuable than a preoperative prediction model. Currently, there are no existing hospital readmission prediction tools for TSA patients that depend on a relatively small number of factors and offer a simple scoring system to facilitate the usage among shoulder surgeons. This study aimed to develop a streamlined parsimonious preoperative risk assessment tool to help shoulder surgeons predict the risk of hospital readmission as well as other postoperative adverse outcomes including complications, emergency room visits, and mortality. Such a tool will assist shoulder surgeons or practice managers in both clinical and financial decision-making.

Materials and methods

Data and study population

This is a retrospective analysis of the complete 2019-2022 Q2 Medicare fee-for-service inpatient and outpatient claims data. TSA procedures, including primary anatomic or reverse TSAs ies, were identified from inpatient claims using a Diagnosis Related Group code of 483 and from outpatient claims using a Current Procedural Terminology code of 23,472. The International Classification of Disease 10th Revision Procedure Coding System was used to exclude non-shoulder surgeries because Diagnosis Related Group 483 may include elbow or other upper extremity procedures. A total of 226,516 TSAs were identified, after excluding 2695 cases with either a cancer diagnosis, a missing age, or a zero or negative payment from Medicare. Since we examined outcomes 90 days postdischarge, an additional 17,882 cases were excluded because they were performed in the second quarter of 2022, resulting in a final sample of 208,634 cases.

TSA indications and outcomes

TSA indications were classified as primary osteoarthritis, rotator cuff pathology, fracture, necrosis, and other indications. We examined several adverse clinical outcomes within 90 days of discharge, including all-cause hospital readmission, postoperative complication, emergency room visit, and mortality. Postoperative complications were defined based on a publication by Carbone and colleagues,[6] including orthopedic implant-related complications (broken prosthesis, dislocation, loosening, instability, periprosthetic fracture), infections (surgical site infection, periprosthetic joint infection), and medical complications (eg, deep vein thrombosis and myocardial infarction). Emergency room visits were determined using the Medicare place of service code 23. Because hospital readmissions are often costly, we considered it as the primary outcome; we also constructed a composite outcome – the presence of any of the four outcomes within 90 days postdischarge.

Predictors of outcomes

To identify potential predictors of outcomes, we searched the literature and compiled a list from publications on the predictors of hospital readmissions among TJA patients,[4,13-15,17,23] the factors considered by surgeons when determining if a TJA patient can be treated as an outpatient (ie, same-day discharge),[2,11,20,26] and direct causes of TJA hospital readmissions.[27] In addition, we included the hierarchical condition categories (HCCs) used by Medicare for risk adjustment purposes.[8] The final set included 108 candidate predictors: socio-demographics (5 predictors), TSA indications (4), health care utilization in the prior 12 months (2), 83 HCCs, and other comorbidities (14). See more details in Appendix Table A.I. We did not include HCC 176 – "complications of specified implanted device or graft" – because more granular predictors were used in the models, including "fracture due to orthopedic devices," "orthopedic device mechanical complications" (eg, broken prosthesis, dislocation, loosening, instability), "superficial surgical site infection," and "deep or periprosthetic infection due to internal orthopedic devices." Since we examined primary TSAs, prior history of orthopedic device complications could be related to hemiarthroplasty or partial replacement of the same shoulder, TSA for the contralateral shoulder, or arthroplasty for other joints.

Data analysis

We used two different approaches to reducing the number of candidate predictors: a logistic regression approach using the Least Absolute Shrinkage and Selection Operator (LASSO) method[30] and a machine learning approach. LASSO imposes a penalty on the magnitude of regression coefficients and thus eliminates those that are close to zero. As the size of the penalty increases, we would obtain a more parsimonious model; an R package – "GLMNET" – was applied in the analysis.[12] In order to avoid overfitting, we randomly split the data into two files, with an 80% training file (166,851 cases) and a 20% validation file (41,783 cases). The LASSO regression was conducted in the training file, and its performance was assessed in the validation file based on AUC.

We applied a Python package – "Feature-engine" – using a logistic regression estimator and a 5-fold cross-validation method as another approach to predictor selection.[28] That is, we further randomly split the training file into 5 equal-sized subsets, used 4 of the 5 subsets to train the model and the remaining subset to validate the model, and repeated the process 4 times by rotating the validation subset. We chose a 5-fold – rather than 10-fold – cross-validation to ensure there is a reasonable number of readmissions (>2000) in each of the 5 subsets. Three feature selection algorithms were utilized: recursive feature permutation, recursive feature addition, and feature elimination, and they collectively decided which covariates were the most important and predictive. This machine learning approach added or removed a predictor based on the AUC of a 5-fold cross-validated logistic regression estimator, and the threshold for adding or removing a predictor

Table I Patient sample characteristics

Characteristics	Without a 90-day adverse outcome	With a 90-day adverse outcome	*P* value
Number of TSA cases, n (%)	185,349 (88.8)	23,285 (11.2)	N/A
Socio-demographics			
Age, yr (SD)	72.4 (6.8)	74.1 (8.2)	<.001
Female, n (%)	107,876 (58.2)	14,905 (64.0)	<.001
Dually eligible for Medicare and Medicaid, n (%)	14,437 (7.8)	3199 (13.7)	<.001
Social determinant of health, n (%)	1560 (0.8)	446 (1.9)	<.001
Primary diagnosis for TSA			
Primary osteoarthritis, n (%)	122,334 (66.0)	9350 (40.2)	<.001
Fracture, n (%)	13,452 (7.3)	7348 (31.6)	<.001
Rotator cuff pathology, n (%)	24,900 (13.4)	2438 (10.5)	<.001
Necrosis, n (%)	996 (0.5)	134 (0.6)	.48
Prior 12-mo health care utilization			
Inpatient admissions, n (%)	13,596 (7.3)	4019 (17.3)	<.001
Skilled nursing home admissions, n (%)	3244 (1.8)	1407 (6.0)	<.001
Prior 12-mo comorbidities contributing to adverse outcomes			
Acute myocardial infarction, n (%)	1571 (0.8)	571 (2.5)	<.001
Anemia, n (%)	33,964 (18.3)	8548 (36.7)	<.001
Cardio-respiratory failure and shock, n (%)	4625 (2.5)	2091 (9.0)	<.001
Chronic obstructive pulmonary disease, n (%)	23,567 (12.7)	5294 (22.7)	<.001
Congestive heart failure, n (%)	17,808 (9.6)	5238 (22.5)	<.001
Dementia, n (%)	2478 (1.3)	1117 (4.8)	<.001
Depression, n (%)	41,425 (22.3)	7410 (31.8)	<.001
Diabetes, n (%)	21,249 (11.5)	4968 (21.3)	<.001
Fracture due to orthopedic devices, n (%)	1230 (0.7)	642 (2.8)	<.001
Heart arrhythmias, n (%)	25,648 (13.8)	5676 (24.4)	<.001
Orthopedic device mechanical complications (eg, broken prosthesis, dislocation, loosening, instability), n (%)	3962 (2.1)	1168 (5.0)	<.001
Parkinson's or Huntington's Diseases, n (%)	2487 (1.3)	698 (3.0)	<.001
Pulmonary embolism, n (%)	907 (0.5)	444 (1.9)	<.001
Stroke, n (%)	1485 (0.8)	586 (2.5)	<.001
Vascular disease, n (%)	17,120 (9.2)	3911 (16.8)	<.001

TSA, total shoulder arthroplasty.

was 0.001 unit of AUC. Each algorithm produced a list of the most important predictors and ranked them in order of importance. We then selected the variables voted by all three algorithms for our risk prediction tool. In addition, we repeated the same feature selection exercise but with a 100-decision tree random forest as our estimator; the goal was to compare the predictive performance to other approaches described above.

The final set of selected predictors from both LASSO and machine learning approaches was assessed using the validation file, and a scoring system was created based on the magnitude of regression coefficients. Covariates with a negative coefficient were multiplied by −1 before being entered into the scoring system so that the model's explanatory power is preserved and they are predictors (ie, risk factors) of adverse outcomes. Based on the distribution of the predicted probabilities, we determined the risk score cutoff points for the low (no apparent risk escalation as the risk score increases), medium (an elevated risk of up to a 50% chance of getting adverse outcomes), and high-risk patient categories (the rest of the group). This was to take full advantage of the non-linear nature of predicted probabilities of adverse outcomes and make the tool useful to clinicians and administrators.

Results

Of the 208,634 TSA cases, 11.2% had at least one adverse outcome, either hospital readmission, postoperative complication, emergency room visit, or mortality during the 90 days postdischarge (Table I). Patients with an adverse outcome were older, more likely to be female, dually eligible for both Medicare and Medicaid, have a fracture indication, issues related to social determinants of health, greater health care utilization, and comorbidities such as anemia that potentially contribute to adverse outcomes of interest.

For 90-day all-cause hospital admissions, entering all 108 predictors into a prediction model resulted in an AUC of 0.72 (Fig. 1). The LASSO approach generated 55 regression models by varying the magnitude of penalty on regression coefficients, with the number of predictors ranging from 1 to 106. Since we aimed for a parsimonious model with less than 20 predictors and to ensure the results are comparable to those based on the machine learning

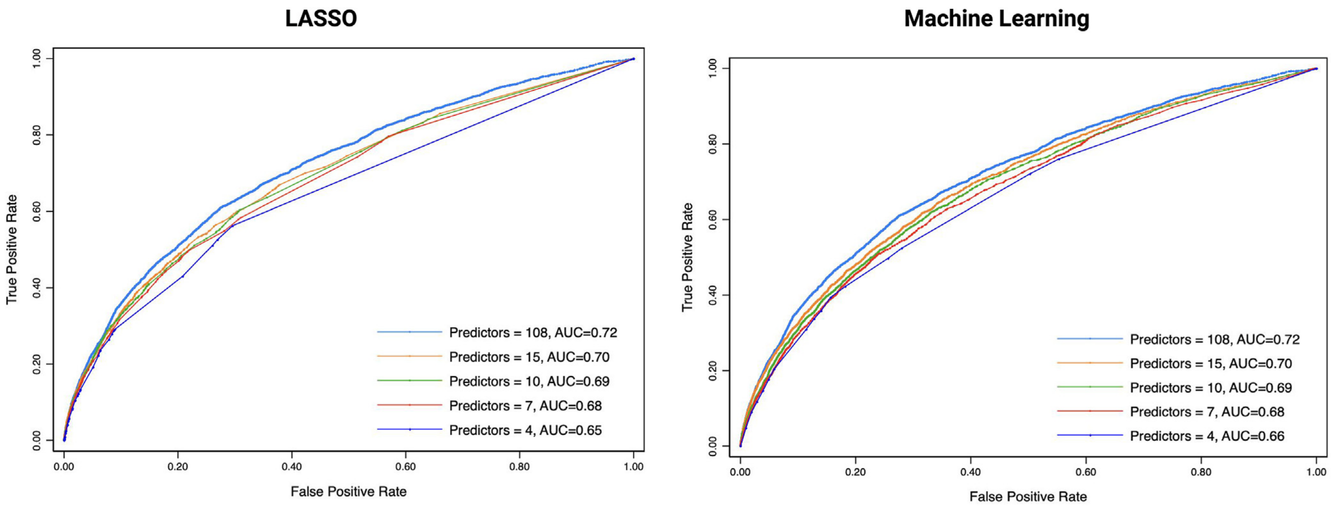

Figure 1 Model performance in predicting 90-day hospital readmissions.

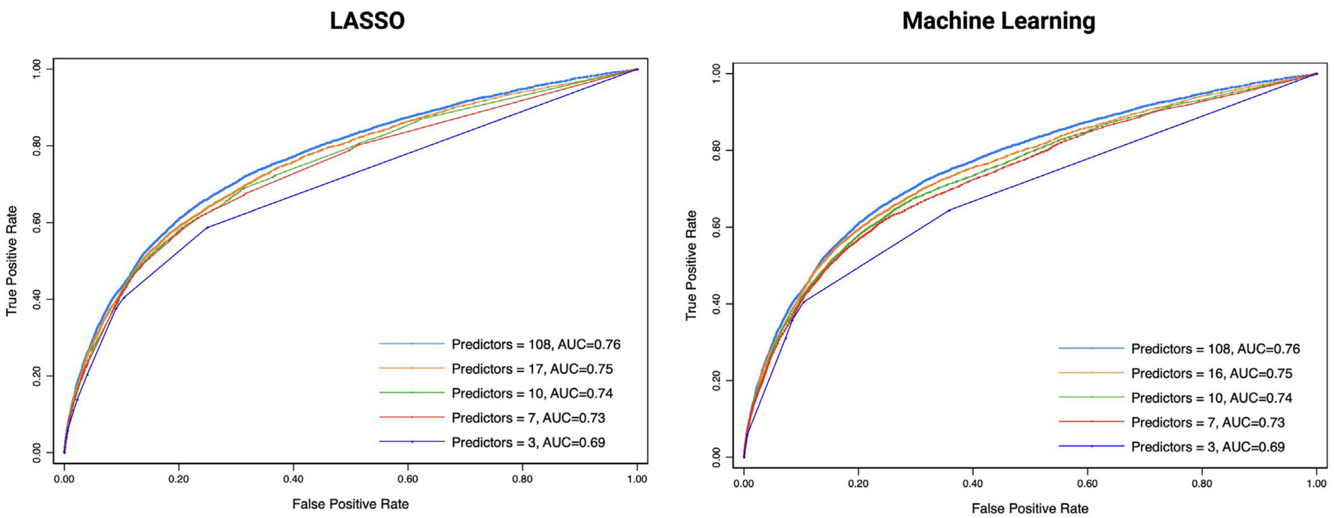

Figure 2 Model performance in predicting the 90-day composite outcome.

approach, we selectively showed the performance of four regression models with 4, 7, 10, and 15 predictors, respectively (Fig. 1, *Left Panel*). The AUC varies from 0.65 to 0.70. In comparison, the machine learning approach selected 15 predictors as the best performance model. The right panel of Fig. 1 shows nearly identical results to those from the LASSO approach, with the four models' AUC ranging from 0.64 to 0.70.

For the 90-day composite outcome, entering all 108 predictors into a prediction model resulted in an AUC of 0.76 (Fig. 2). Overall, the machine learning approach performs slightly better than the LASSO approach, although they are largely similar. When examining 3, 7, 10, and 16 predictors, the former has an AUC of 0.68-0.75 (Fig. 2, *Right Panel*), whereas the latter obtains an AUC of 0.75 using 17 predictors (Fig. 2, *Left Panel*). Overall, the predictive power of both approaches for the composite outcome is better than that for hospital readmissions.

The prediction performance of the random forest models is worse than other approaches, resulting in an AUC of 0.66 and 0.72 for hospital admissions and the composite outcome, respectively.

Table II illustrates the final set of predictors based on the machine learning approach which performs as well as or slightly better than the LASSO approach. Since having a primary osteoarthritis or rotator cuff indication is negatively associated with adverse outcomes, their opposites (ie, a nonosteoarthritis or nonrotator cuff indication) are used as predictors in the scoring systems. Having an advanced age (eg, ≥85), a TSA indication other than primary osteoarthritis, anemia, and a history of orthopedic device mechanical complication or fracture due to orthopedic devices

Table II Selected predictors and scores for 90-day hospital readmissions and the 90-day composite outcome based on the machine learning approach

Predictors	Hospital readmission score	Composite outcome score
Age: 65-74 (reference)		
<65	2	1
75-84	1	2
≥85	5	6
Dual eligibility	–	2
TSA indication		
Nonosteoarthritis indication	4	3
Nonrotator cuff indication	2	–
Fracture	–	13
Anemia	4	4
Congestive heart failure	2	3
Heart arrhythmias (atrial fibrillation, ventricular tachycardia)	2	2
Cardio-respiratory failure and shock	3	4
Vascular disease (embolism, thrombosis, atherosclerosis)	2	–
Stroke	–	6
Pulmonary embolism	–	10
Chronic obstructive pulmonary disease	2	–
Diabetes	2	–
Acute renal failure	–	5
Depression	2	1
Dementia	–	4
Parkinson's or Huntington's Disease	3	3
Fracture due to orthopedic devices	7	6
Orthopedic device mechanical complications (eg, broken prosthesis, dislocation, loosening, instability)	4	4
Inpatient admission in the previous 12 mo	1	–

TSA, total shoulder arthroplasty.
Note: "–" means not applicable. The score range for hospital readmission and the composite outcome is 0 to 48 and 0 to 79, respectively. The cutoff points for the low, medium, and high-risk categories are 0-9, 10-14, ≥15 for hospital readmissions, and 0-11, 12-16, ≥17 for the composite outcome. For a TSA patient, users can check if these predictors exist prior to the surgery and sum the scores associated with existing predictors.
Note: "–" means not applicable. The score range for hospital readmission and the composite outcome is 0-48 (optimal cutoff = 7) and 0-79 (optimal cutoff = 6), respectively. For a TSA patient, users can check if these predictors exist prior to the surgery and sum the scores associated with existing predictors. Hospital readmission (or an adverse outcome) is expected if the total score for hospital readmission (or the composite outcome) is greater than (7 or 6).

are among the key contributors to hospital readmissions. In predicting the composite outcome, advanced age, a fracture indication, and a history of stroke, pulmonary embolism, or fracture due to orthopedic devices play an important role.

The score range for hospital readmission and the composite outcome is 0-48 and 0-79, respectively. The AUC based on the score is 0.69 and 0.75 for hospital readmission and the composite outcome, respectively, slightly lower than or similar to those based on the final models fitted in the validation file. Fig. 3 shows the trajectories of the risk of adverse outcomes and contrasts the actual and predicted probabilities. The model typically underpredicts when the actual risk is low and vice versa. Based on the predicted probabilities, the risk score cutoff points for the low, medium, and high-risk categories are 0-9, 10-14, ≥15 for hospital readmissions, and 0-11, 12-16, ≥17 for the composite outcome.

Discussion

This study utilized Medicare data to develop a preoperative parsimonious risk stratification tool to predict hospital readmissions and adverse outcomes among TSA patients within 90 days postdischarge. These tools achieved moderate predictive power (AUC 0.70 and 0.75) for hospital readmission and the overall postoperative outcome (including the presence of any hospital readmission, postoperative complication, emergency room visit, and mortality). A scoring system was developed to facilitate their use in practice. Equipped with such information, surgeons would be able to determine whether the benefit of a surgical intervention outweighs its potential adverse consequences, whether an outpatient TSA is appropriate, and the best options to plan perioperative care accordingly.

To utilize the tools, shoulder surgeons could go through the checklist and compute a score for hospital readmission and adverse outcomes. For example, an 86-year-old patient with diabetes and heart arrhythmia would have a total score of 9 based on the hospital readmission model (5 points for age ≥85, 2 for diabetes, and 2 for heart arrhythmia), which is larger than the threshold of 7. As a result, the patient is at a higher risk to get readmitted within 90 days postdischarge, and a surgeon may consider such hospital readmission risk before surgery. Patients who have a history of fracture due to an orthopedic device are also at a higher risk to be rehospitalized after TSA because the predictor has a score of 7, reaching the threshold already. Similarly, to predict any of the four adverse outcomes (hospital readmission, postoperative complication, emergency room visit, or mortality), a score can be assigned to TSA patients. In particular, if a patient meets any of the following: being 85 years or older, having a TSA indication of fracture, or a history of stroke, pulmonary embolism, or fracture due to orthopedic devices, s/he is at an increased risk to have at

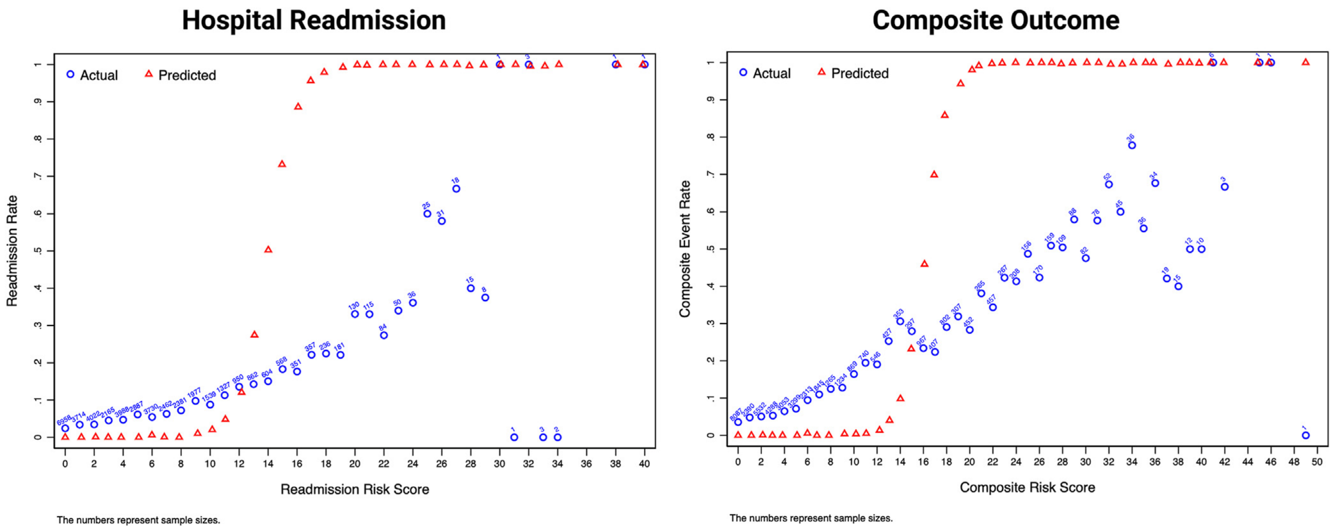

Figure 3 Hospital readmission and composite outcome based on readmission and composite risk score.

least one of these undesirable outcomes as each predictor has a score of 6 (the threshold) or above.

The majority of predictors aligned for both hospital readmission and overall adverse outcome. However, there were some differences between the driving predictors for each model. For example, prior inpatient readmission within 12 months was a predictor for readmission postoperatively, however, not selected for other adverse outcomes. On the other hand, a history of dementia, stroke, pulmonary embolism, or acute renal failure all act as predictors of an adverse outcome, but do not contribute as risk factors for hospital readmission.

It is not surprising that a history of fracture due to orthopedic devices predicts hospital readmissions among TSA patients. These patients have an underlying medical condition (eg, osteopenia) that has already led to fracture, which is often treated in an inpatient setting, and prior fracture is associated with an increased incidence of periprosthetic fracture following joint arthroplasty.[33] For the same reason, it is a key predictor of other postoperative adverse events as well.

Interestingly, a shoulder arthroplasty performed for a fracture indication was associated with a very high risk of adverse outcome postoperatively with a score of 13 (above the cutoff of adverse surgical outcome of 6). These patients are often admitted through the emergency room due to trauma, have concomitant injuries, and have higher acuity. This is consistent with work by Khazzam et al. showing a high risk of postoperative complications following arthroplasty for fracture at 15.4% in the initial 30 days postoperatively.[21] Further investigation into factors to mitigate this increased complication risk in the fracture population is indicated.

A history of pulmonary embolism is another important predictor of adverse outcomes that has a score of 10, the presence of which indicates an adverse outcome rate of almost 20%. The incidence rate of pulmonary embolism after TSAs is about 0.9%,[26] but it indicates patients may have other associated medical conditions that could lead to adverse outcomes. Pulmonary embolism is also often considered by surgeons as one of the factors to determine whether a TSA patient can be discharged on the same day of surgery.

Primary osteoarthritis is the most prevalent TSA indication in our study cohort, and it is a predictor in both models. Osteoarthritis patients tend to be healthier on average than those with other indications for shoulder arthroplasty (fracture, rotator cuff arthropathy, or avascular necrosis) and have less risk of being readmitted to a hospital. That is, it is a protective factor. The scoring system uses a "non-osteoarthritis" indication so that it is a risk factor, comparable to other predictors.

Our model resulted in an AUC of 0.70 for hospital readmission, which is largely consistent with similar models developed for hip and knee arthroplasty. Seven studies developed prediction models for hospital readmissions within 30 or 90 days after TKA and THA.[3,13,14,17,24,25,32] The performance of these models ranged from 0.66 to 0.76. In addition, two studies examined hospital readmission among TKA patients only (AUC = 0.59 and 0.82, respectively)[16,22] and 1 evaluated THA patients only (AUC = 0.72)[23]; the two TKA-only models had a wider variation in performance due possibly to the use of data from a single institution.

In general, prediction models utilizing intraoperative or postoperative information have better performance than those using preoperative information only. It is conceivable that more information leads to greater accuracy. For example, among the six studies that predict hospital readmissions among TKA and THA patients, four of them used intraoperative or postoperative information and had an average AUC of 0.72,[13,17,25,32] whereas the remaining two studies using preoperative information only had an average AUC of 0.66.[14,24] Among the three studies on TSAs, the average AUC of 1 study using postoperative information achieved an AUC of 0.74,[1] but the other two studies based on preoperative information had an average AUC of 0.69.[9,10] Our study relies on preoperative information only and results in an AUC of 0.70 for hospital readmission, consistent with prior studies on TSAs. Compared to a tool utilizing postoperative factors, a tool utilizing only preoperative factors has the advantage of providing surgeons with planning information that is actionable before surgical intervention.

Compared to the traditional regression approach (eg, logistic regressions), machine learning does have some advantages in model performance. This was confirmed by the three studies on post-TSA hospital readmissions,[1,9,10] although it is not universally true.[16] Also, in our analysis, the performance of the LASSO approach is nearly identical to that of machine learning.

However, the downside of machine-learning-based models is that they are hard to use by surgeons because of their black-box nature – making it unclear to surgeons which predictors are used. We adopted a slightly different approach: we used machine learning to select the core features (or predictors), which allowed us to develop tools based on a relatively small number of predictors. In addition, we developed a scoring system for these tools so they are manageable by surgeons for preoperative planning purposes; and electronic medical record systems are typically able to incorporate such tools to further reduce such burden on surgeons.

We utilized multiple years of Medicare fee-for-service inpatient and outpatient data to develop tools for predicting hospital readmissions and other adverse outcomes after TSAs. To our knowledge, this is the largest prediction tool development study for TSAs in terms of sample size – 208,634 surgical cases. Previous studies used either state-level claims data or single-institution data, with a sample size of 10,302 or less.[1,9,10] Nevertheless, our study is subject to several limitations. First, Medicare fee-for-service data do not include those enrolled in Medicare Advantage plans, whose hospital readmission patterns may be different due to managed care.

Second, Medicare claims have limited information. For example, patient functional status, the American Society of Anesthesiologists physical status classification, and social support are not available in the data, limiting the models' predictive power. Third, our conclusions may not be generalizable to commercially insured TSA patients since Medicare beneficiaries are a different population. In addition, we were unable to examine patient satisfaction or other patient-reported outcomes due to a lack of such data. Lastly, the retrospective nature of the study allowed us to create this model, yet its validity is not certain and would be better assessed using a prospective study design.

Conclusion

Using multiple years of Medicare fee-for-service claims data, we developed preoperative risk stratification tools to assess for hospital readmission or adverse surgical outcomes following TSA. These tools have the potential to assist surgeons in preoperative patient counseling. Further investigation is warranted to validate these tools in a variety of diverse demographic settings and improve their predictive performance.

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Supplementary Data

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