Machine Learning Analysis of Patient, Implant, and Surgical Factors Associated with Acromial and Scapular Spine Fractures after Reverse Total Shoulder Arthroplasty

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Introduction:

Despite improvement in reverse shoulder arthroplasty (RSA) prosthetic design and surgical placement to mitigate complications and improve clinical outcomes, acromial (ASF) and scapula spine fractures (SSF) remain a troublesome complication. While patient risk factors are well-established, there is conflicting evidence regarding implant design and surgical placement-related factors, which are modifiable by the surgeon. With advancements in machine learning (ML) modeling, a predictive model that can handle complex relationships between predictive factors can be used to improve understanding of how features contribute to fracture risk postoperatively. Therefore, our goal is to use a gradient boosted tree model to identify factors associated with ASF and SSF after RSA.

Methods:
This is a multicenter retrospective case-control study of 6,320 RSAs from 2013 to 2019 with a minimum 3-month follow-up. The study involved 24 surgeons, from 15 U.S. institutions, who were members of the American Shoulder and Elbow Surgeons (ASES). Symptomatic ASF or SSF were identified. A gradient boosted model was used to identify patient, implant, and surgical factors associated with risk of any scapula fracture, ASFs and SSFs. Radiographic data, including the lateralization shoulder angle (LSA), distalization shoulder angle (DSA), and lateral humeral offset (LHO), were collected in a 2:1 control-to-fracture ratio in a subset of the study cohort. Model performance was assessed with and without radiographic data to assess the relative contribution of adding radiographic measurements to the models. The cohort was split to training and testing sets, respectively with a 4:1 ratio. XGBoost average information gain and Shapley Additive Explanations (SHAP) were used to evaluate the features importance. SHAP dependence plots were used to evaluate the interaction between two variables and their impact on fracture risk.

Results:
The study included 243 (3.8%) fractures (2.9% ASF and 0.9% SSF) and 6,077 no fracture controls. Including radiographic measurements improved the accuracy of all models substantially (area under the curve [AUC] of 0.98 vs. 0.76). For predicting any scapula fracture, preoperative DSA, preoperative LSA and postoperative DSA were the three most important features. The SHAP value plot (Figure 1) highlights the impact of combined patient, implant, and surgical placement features on individual predictions of fracture risk, which demonstrates that for any fracture prediction, higher preoperative LSA, higher lateral glenosphere offset, older age, lower BMI, lower preoperative DSA, inflammatory arthritis, prior surgery, inlay humeral component design, and decreased LHO were associated with higher fracture risk. A complex, non-linear association with fracture was apparent between postoperative DSA and LSA. The SHAP dependence plot (Figure 2a) further investigated the relationship between postoperative DSA, postoperative LSA, and fracture risk and found three unique clusters, including those with 1) low DSA and high LSA (highest risk for fracture), 2) moderate DSA (lowest risk for fracture), and 3) high DSA and low LSA (moderate risk for fracture). K-means clustering (Figure 2b) identified a potential target DSA range of 40-55 degrees, regardless of LSA value, to mitigate fracture risk in RSA. The ASF model results were similar to the overall fracture risk model, although high DSA did not appear to increase fracture risk. The SSF model showed a similar non-linear relationship with DSA with elevated risk at low and high DSA, yet fracture risk was more dependent on LSA than DSA, with higher postop LSA and delta LSA associated with SSF risk.

Discussion:
Our analysis revealed that a combination of baseline scapulohumeral morphology, implant design, and surgical placement factors were the most influential predictors of stress fracture. There is a complex, non-linear interaction between postoperative DSA and postoperative LSA, which contributes substantially to fracture risk and allows clustering patients into three unique risk profiles. Low postoperative DSA and high LSA comprised the highest risk cluster for ASF and SSF, moderate postoperative DSA comprised the lowest risk of ASF and SSF, and high postoperative DSA with low postoperative LSA resulted in an increased risk specifically for SSF. Additionally, postoperative distalization was more influential in predicting ASF, while lateralization was more influential for predicting SSF. Regarding implant design, high lateral offset by glenosphere was the most influential factor for increased risk of ASF and SSF, while lateral humeral offset was protective. Although patient characteristics were less influential, they also contributed to fracture risk: ASF was associated with older age, lower BMI, prior surgery, inflammatory arthritis and massive cuff tear, while SSF was associated with lower BMI and cuff tear arthropathy.

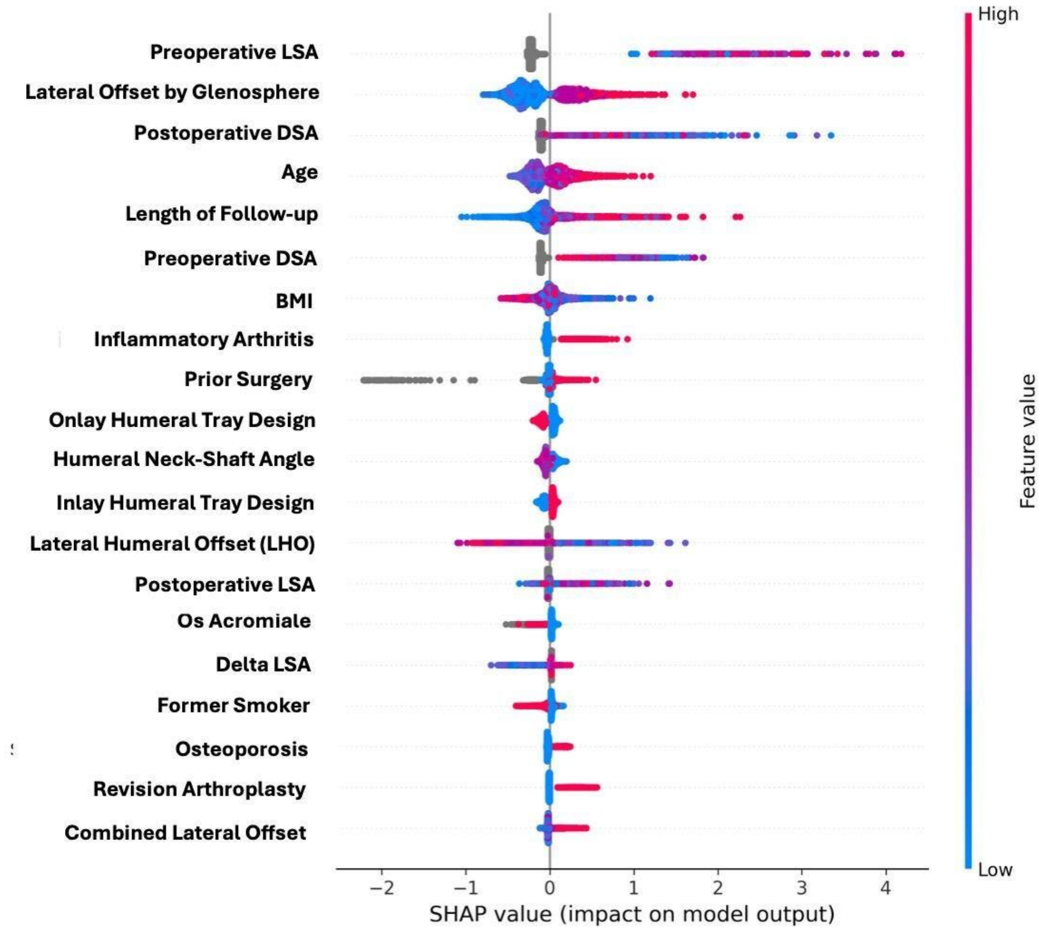

Figure 1 – Shapley additive explanation (SHAP) values plot for the gradient boosted tree model predicting any scapula fracture. Higher positive SHAP values equates to higher risk of fracture, while red color corresponds to a higher feature value (i.e. older age) and blue color corresponds to a lower feature value (i.e. younger age)

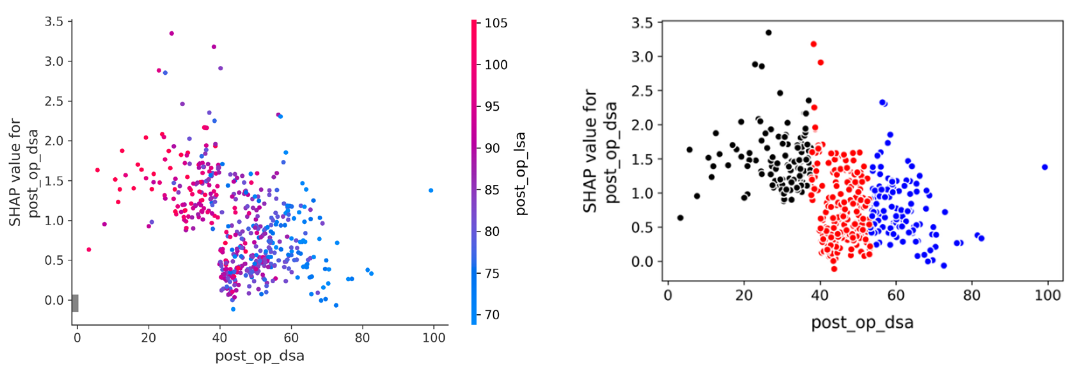

Figure 2 – a [left]) Shapley additive explanation (SHAP) dependence plot of postoperative DSA and postoperative LSA, with b [right]) k-means clustering analysis performed to identify three distinct risk categories of any scapula fracture after RSA. The highest risk group (black) is represented by low postoperative DSA and high LSA, whereas the lowest risk group (red) is represented by a moderate postoperative DSA regardless of the LSA.