

1 **Using Machine Learning to Predict Clinical Outcomes After Shoulder Arthroplasty with a**
2 **Minimal Feature Set**

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46 **Conflict of Interest Statement**

47 Vikas Kumar, Steve Overman, and Ankur Teredesai are employed by Ken Sci, Inc.
48 Christopher Roche is employed by Exactech, Inc.
49 Ryan Simovitch and Howard Routman are consultants for Exactech, Inc.
50 Pierre-Henri Flurin, Thomas Wright, and Joseph Zuckerman are consultants for Exactech, Inc. and
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55
56 **Abstract**

57 Background

58 A machine learning analysis was conducted on 5,774 shoulder arthroplasty patients to create
59 predictive models for multiple clinical outcome measures after anatomic Total Shoulder
60 Arthroplasty (aTSA) and reverse Total Shoulder Arthroplasty (rTSA). The goal of this study is to
61 compare the accuracy associated with a full feature set predictive model (e.g. full model =291
62 parameters) and a minimal feature set model (e.g. abbreviated model =19 input parameters) to
63 predict clinical outcomes in order to assess the efficacy of using a minimal feature set of inputs as
64 a shoulder arthroplasty clinical decision-support tool.

65

66 Methods

67 Clinical data from 2,153 primary aTSA patients and 3,621 primary rTSA patients were analyzed
68 using the XGBoost machine learning technique to create and test predictive models for multiple
69 outcome measures at different post-operative timepoints using a full and abbreviated model. Mean
70 absolute errors (MAE) quantified the difference between actual and predicted outcomes, and each
71 model also predicted if a patient would experience clinical improvement greater than the minimal

72 clinically important difference (MCID) and substantial clinical benefit (SCB) patient satisfaction
73 anchor-based thresholds for each outcome measure at 2-3 years after surgery.

74

75 Results

76 Across all post-operative timepoints analyzed, the full and abbreviated models had similar MAE
77 for the American Shoulder and Elbow Surgeons (ASES) (full model = ± 11.7 vs. abbreviated model
78 = ± 12.0), Constant (± 8.9 vs. ± 9.8), Global Shoulder Function (± 1.4 vs. ± 1.5), Visual Analog Scale
79 (VAS) pain (± 1.3 vs. ± 1.4), active abduction ($\pm 20.4^\circ$ vs. $\pm 21.8^\circ$), forward elevation ($\pm 17.6^\circ$ vs.
80 $\pm 19.2^\circ$), and external rotation ($\pm 12.2^\circ$ vs. $\pm 12.6^\circ$). Marginal improvements in MAE were observed
81 for each outcome measure prediction when the abbreviated model was supplemented with implant
82 size/type data and measurements of native glenoid anatomy. The full and abbreviated models each
83 effectively risk-stratified patients using only pre-operative data by accurately identifying patients
84 with improvement greater than the MCID and SCB thresholds.

85

86 Discussion

87 Our study demonstrated the full and abbreviated machine learning models achieved similar
88 accuracy to predict clinical outcomes after aTSA and rTSA at multiple post-operative timepoints.
89 These promising results demonstrate an efficient utilization of machine learning algorithms to
90 predict clinical outcomes. The use of a minimal feature set of only 19 preoperative inputs suggests
91 that this tool may be easily used during a surgical consultation to improve decision-making related
92 to shoulder arthroplasty.

93

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94 **Keywords:** Machine Learning, Predictive Outcomes Analytics, aTSA and rTSA Outcomes,

95 Shoulder Arthroplasty

96

97 **Level of Evidence:** III (retrospective comparative study)

98 **Introduction**

99 Machine learning techniques can analyze clinical and patient-reported outcome data to
100 create predictive models that can help physicians better understand their patients prior to treatment
101 by quantifying patient-specific potential for improvement associated with different treatment
102 options. The knowledge of these patient-specific outcome predictions is useful to better inform
103 shared decision-making for both the patient and surgeon.^{2,3,4,12} Machine learning models have
104 recently been used to accurately predict clinical outcomes after anatomic (aTSA) and reverse
105 (rTSA) total shoulder arthroplasty and risk-stratify patients based on predicted minimal clinically
106 important difference (MCID) and substantial clinical benefit (SCB) improvement thresholds for
107 different clinical outcome measures.¹² Deploying such a pre-operative prediction tool into clinical
108 practice offers the potential to establish more accurate expectations of patient-specific
109 improvement that can be achieved with shoulder arthroplasty, and also to align the patient and
110 surgeon on what results to expect at different post-operative timepoints. The practical limitation
111 of deploying such a tool into clinic is the large input burden often required by machine learning
112 algorithms to generate patient-specific predictions; particularly since much of that data may not be
113 routinely present in the patient's electronic medical record. As such, a prerequisite for a machine
114 learning based clinical decision-support tool is the identification of a highly predictive minimal set
115 of pre-operative inputs that can be readily-obtained as part of the normal standard of care.

116 To develop a clinical decision support tool utilizing a minimal feature set of pre-operative
117 inputs, we first conducted a machine learning analysis on a multi-center clinical database of one
118 platform shoulder prosthesis to create algorithms using the full set of pre-operative data to predict
119 post-operative outcomes of various measures, at multiple post-operative timepoints after aTSA
120 and rTSA. We developed these algorithms using a full feature set (e.g. the full model: n = 291

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121 input parameters) and in the process of doing so, we identified a minimal feature set (e.g. the
122 abbreviated model: $n = 19$ input parameters) consisting only of the most highly predictive features.
123 Therefore, the goal of this study is to quantify and compare the accuracy associated with the full
124 and abbreviated machine learning models to predict clinical outcomes after aTSA and rTSA.

125 **Methods**

126 We utilized the XGBoost²² machine learning technique to analyze a multi-center clinical
127 outcomes database of shoulder arthroplasty patients who received a single platform shoulder
128 prosthesis (Equinoxe, Exactech, Inc, Gainesville, FL) between November 2004 and December
129 2018. Every patient enrolled in this open-label clinical database provided consent. All data was
130 collected using standardized forms at each of the 30 clinical sites according to an institutional
131 review board-approved protocol (NYU IRB Study #: i05-144_MOD41). Upon completion of each
132 form, all forms are independently verified, and then are computer-scored on a secured IBM
133 database. All primary aTSA and primary rTSA patients in the database with at least 3 months of
134 follow-up were included. To ensure a homogenous dataset, patients with revisions, humeral
135 fractures, endoprostheses, and hemiarthroplasty were excluded. Primary total shoulder
136 arthroplasty patients who experienced complications and/or revisions were not excluded from this
137 analysis as those experiences contribute to the outcomes variability of the aTSA and rTSA cohorts.
138 These criteria resulted in pre-operative, intra-operative, and post-operative data from 5,774
139 patients with 17,427 post-operative follow-up visits available for analysis in this machine learning
140 study. The full database contains 291 inputs, including: demographic, diagnoses, comorbidities,
141 implant type, range of motion, radiographic findings, and clinical outcome metric scores
142 [American Shoulder and Elbow Surgeons (ASES), Constant, University of California Los Angeles
143 (UCLA), Simple Shoulder Test (SST), and Shoulder Pain and Disability Index (SPADI)],
144 including the individual questions used to derive each of these patient reported outcome scores.
145 Range of motion assessment was performed by the implanting surgeon or their surrogate and was
146 measured with a goniometer. This data was used to create predictive algorithms for the ASES,
147 Constant, Global Shoulder Function score, Visual Analog Scale (VAS) pain score, active

148 abduction, active forward elevation, and active external rotation with the arm at the side at multiple
149 timepoints after aTSA or rTSA, including: 3-6 months, 6-9 months, 1 year [9-18 months], 2-3
150 years [18-36 months], 3-5 years [36-60 months], and 5+ years [60+ months].

151

152 XGBoost was used to create the predictive algorithms for both the full and abbreviated
153 models. XGBoost is a supervised, ensemble machine learning technique of multiple-regression
154 trees that are built by iteratively partitioning the training dataset into multiple small batches using
155 a method called boosting.²² The full model utilized all 291 inputs from the database; whereas, the
156 abbreviated model utilized only a minimal feature set of 19 pre-operative inputs (Table 1) to
157 predict the Global Shoulder Function score, the VAS pain score, active abduction, forward
158 elevation, and external rotation. As described in Table 1, this minimal feature set is a selection of
159 patient demographic, diagnoses, comorbidities, pre-operative range of motion, and patient
160 responses to a few subjective questions. These specific 19 input parameters were identified using
161 domain knowledge, prevalence of the feature, uniqueness of the feature values for patients, and
162 finally the importance of features to the model. Of note, the uniqueness of a feature is computed
163 using an information theory metric known as entropy, which measures if values in feature are
164 highly uncertain and thus likely to be highly random across patients making it hard to outcomes
165 based on that feature. Also, the importance of a feature to the model was computed based on F-
166 scores determined from the XGBoost algorithm. The F-score quantifies the frequency that a
167 particular feature is used as a candidate for the split by the decision-tree algorithm.²² The
168 prevalence, entropy, and F-score were used to determine individual ranking of each feature by
169 combining into a single ranked list using Reciprocal Fusion Rank Score. When this abbreviated
170 model is supplemented with the 10 additional questions needed to calculate the pre-operative

171 ASES score and the 20 additional questions needed to calculate the pre-operative Constant score,
172 the abbreviated model can also be used to predict the ASES and Constant scores at each post-
173 operative timepoint for both aTSA and rTSA. Finally, we conducted an additional analysis which
174 supplemented the abbreviated model predictions with implant size/type data, and measurements
175 of native glenoid version and inclination (i.e. beta angle), to simulate the additional predictive
176 accuracy that could be acquired through utilization of data readily-available from CT-based pre-
177 operative planning software.

178 Similar to the methodology in our previous work,¹² this data was split 2:1 into mutually
179 exclusive datasets to build and test the predictive models using each of the full and abbreviated
180 feature sets for each outcome metric at each post-operative timepoint. A random selection of 66.7%
181 of the data defined the training cohort and the remaining 33.3% defined the validation test cohort.
182 The performance of the full and abbreviated models to predict post-operative outcomes after aTSA
183 and rTSA was quantified by the Mean Absolute Error (MAE) between the actual and predicted
184 values for each outcome measure at each post-operative timepoint in the 33.3% validation test
185 cohort. To evaluate the relative learning ability of the full and abbreviated XGBoost models, we
186 also conducted a baseline average analysis (i.e. average error associated with selecting the cohort
187 average) as the study control. Finally, a subgroup analysis was also performed using the XGBoost
188 machine learning technique for the full and abbreviated models to predict if a patient would
189 experience clinical improvement greater than the MCID¹⁹ and SCB²⁰ patient satisfaction anchor-
190 based thresholds for each outcome measure at 2-3 years follow-up. The performance of the full
191 and abbreviated models to predict if a patient will achieve the MCID and SCB improvement
192 thresholds was quantified using the classification metrics of precision (or positive predictive value,
193 which quantifies the ability of a model to not identify a negative as positive), recall (or sensitivity,

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194 which quantifies the ability of a model to identify a positive as a positive), and the area under the
195 receiver operating curve (AUROC).^{2,9,11} As data science may be new to the reader, AUROC of 0.5
196 is considered random, >0.7 is considered acceptable, >0.8 is considered good, and >0.9 is
197 considered excellent discrimination for a predictive model.^{9,11}

198 **Results**

199 The clinical data from 2,153 primary aTSA patients (7,305 visits; average follow-up=46.4
200 \pm 35.6 months) and 3,621 primary rTSA patients (10,122 visits; average follow-up=31.0 \pm 25.8
201 months) was used to build and test predictive models at each post-operative timepoint: 3-6 months
202 (aTSA=1282 and rTSA=2227 visits), 6-9 months (aTSA=658 and rTSA=1177 visits), 1 year
203 (aTSA=1451 and rTSA=2445 visits), 2-3 years (aTSA=1347 and rTSA=1882 visits), 3-5 years
204 (aTSA=1321 and rTSA=1482 visits), and 5+ years (aTSA=1246 and rTSA=909 visits). A
205 summary of demographics, diagnoses, and comorbidities for the aTSA and rTSA patient cohorts
206 are presented in Table 2. Pre-operative, post-operative, and pre-to-post-operative improvement in
207 outcomes and also complication rates for the aTSA (Table 3) and rTSA (Table 4) patient cohorts
208 at each follow-up duration are presented in Tables 3 and 4, respectively. aTSA and rTSA outcomes
209 at each follow-up duration, stratified by age and gender, are presented in the online supplemental
210 tables.

211 A comparison of the error between the actual and predicted outcomes in the validation
212 dataset demonstrates that both the full and abbreviated XGBoost models had lower MAE relative
213 to the baseline average study control MAE for all clinical outcome measure predictions, and for
214 both aTSA and rTSA at all post-operative timepoints. (Table 5) MAE associated with each aTSA
215 and rTSA outcome prediction at each post-operative timepoint are presented in the online
216 supplemental tables. As described in these tables, the prediction accuracy observed for aTSA and
217 rTSA were similar for both the full and abbreviated models; though, for both the full and
218 abbreviated models, MAE was slightly higher at early post-operative timepoints as compared to
219 later timepoints. A comparison of MAE between the full and abbreviated models demonstrates
220 that each model had similar predictive accuracy for each of the ASES (full model = \pm 11.7 vs.

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221 abbreviated model = ± 12.0), Constant (± 8.9 vs. ± 9.8), Global Shoulder Function (± 1.4 vs. ± 1.5),
222 VAS pain (± 1.3 vs. ± 1.4), active abduction ($\pm 20.4^\circ$ vs. $\pm 21.8^\circ$), forward elevation ($\pm 17.6^\circ$ vs.
223 $\pm 19.2^\circ$), and external rotation ($\pm 12.2^\circ$ vs. $\pm 12.6^\circ$) outcome measures, despite the abbreviated model
224 only utilizing a minimal feature set of pre-operative inputs to inform its predictions. Specifically,
225 across all post-operative timepoints analyzed, the average difference in MAE between the full and
226 abbreviated model predictions was ± 0.3 MAE for the ASES score (± 0.3 aTSA, ± 0.4 rTSA), ± 0.9
227 for the Constant (± 0.7 aTSA, ± 0.8 rTSA), ± 0.1 for the Global Shoulder Function (± 0.1 aTSA, ± 0.1
228 rTSA), ± 0.1 for the VAS pain (± 0.0 aTSA, ± 0.2 rTSA), $\pm 1.4^\circ$ for abduction (± 1.1 aTSA, ± 1.2
229 rTSA), $\pm 1.6^\circ$ for forward elevation (± 1.7 aTSA, ± 1.4 rTSA), and $\pm 0.4^\circ$ for external rotation (± 0.1
230 aTSA, ± 0.4 rTSA). Of note, only marginal improvements in MAE were observed for each outcome
231 measure prediction when the abbreviated model was supplemented with implant size/type data and
232 measurements of native glenoid anatomy. (Table 5)

233 The full and abbreviated model predictions for MCID improvement for each outcome
234 metric at 2-3 years follow-up is presented in Table 6. The full predictive models achieved 82-96%
235 accuracy in MCID with an AUROC between 0.75-0.97 for aTSA patients and the abbreviated
236 predictive models achieved 82-96% accuracy in MCID with an AUROC between 0.70-0.95 for
237 aTSA patients. The full predictive models achieved 91-99% accuracy in MCID with an AUROC
238 between 0.82-0.98 for rTSA patients and the abbreviated predictive models achieved 91-99%
239 accuracy in MCID with an AUROC between 0.84-0.94 for rTSA patients. Similarly, the full and
240 abbreviated model predictions for SCB improvement for each outcome metric at 2-3 years follow-
241 up is presented in Table 7. The full predictive models achieved 79-90% accuracy in SCB with an
242 AUROC between 0.74-0.90 for aTSA patients and the abbreviated predictive models achieved 76-
243 90% accuracy in SCB with an AUROC between 0.70-0.89 for aTSA patients. Finally, the full

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244 predictive models achieved 83-92% accuracy in SCB with an AUROC between 0.78-0.88 for
245 rTSA patients and the abbreviated predictive models achieved 81-90% accuracy in SCB with an
246 AUROC between 0.70-0.87 for rTSA patients.

247 **Discussion**

248 The results of our 5,774 patient machine learning study demonstrate that an abbreviated
249 model utilizing a minimal feature set of only 19 pre-operative inputs provides similar accuracy as
250 the full model utilizing 291 inputs when predicting aTSA and rTSA outcomes at multiple post-
251 operative timepoints. At each post-operative timepoint, the full and abbreviated models had similar
252 MAE when predicting each outcome measure demonstrating the capability of the predictive
253 algorithms to account for outcomes variability during both the recovery period and even into mid-
254 and long-term followup as outcomes decline with age and deterioration. Additionally, no
255 differences in accuracy were observed between aTSA and rTSA outcomes predictions at any
256 timepoint for either the full or abbreviated models demonstrating the prediction algorithms were
257 equally effective for each prosthesis type. Only minor improvements in the abbreviated model
258 predictions were observed after incorporating implant size/type data and measurements of native
259 glenoid version and inclination. Furthermore, the full and abbreviated models were equally
260 effective at risk-stratifying patients using only pre-operative data, by accurately identifying
261 patients at greatest risk for poor outcomes based upon MCID thresholds (full model accuracy
262 >82%, AUROC >0.75 vs. abbreviated model accuracy >82%, AUROC >0.70), and identifying
263 patients most likely to achieve excellent outcomes based upon SCB thresholds (full model
264 accuracy >79%, AUROC >0.74 vs. abbreviated model accuracy >76%, AUROC >0.70) at 2-3
265 years follow-up for all outcome measurements.

266 Pre-operatively communicating the expected result from a proposed surgical treatment is
267 an important component of informed consent. However, few surgeons can accurately predict the
268 outcomes that a cohort of patients may achieve, nor do most know if a particular patient will do
269 better or worse (and by how much) than the “average” patient. Machine learning based predictive

270 outcomes algorithms are not a simple heuristic, rather these computational techniques analyze
271 large quantities of clinical data and consider numerous parameters to inform its evidence-based
272 outcomes predictions. As such, these predictions are clinically useful for shared decision-making
273 and can be used to more effectively communicate expected outcomes and better inform the risks
274 and benefits of a surgical procedure. For the shoulder surgeon, an evidenced-based tool that can
275 accurately predict patient-specific outcomes after aTSA and rTSA from input of only 19 patient
276 questions and active ROM measurements, has many practical applications. First, these predictions
277 can better align the surgeon's objectives for the procedure with that of the patient and establish
278 more accurate expectations of what can be achieved with shoulder arthroplasty, given each
279 patient's unique demographics, diagnoses, and comorbidities. Better alignment between the
280 patient and surgeon on what can be achieved with shoulder arthroplasty may translate to improved
281 patient satisfaction with the procedure.^{7,8,15,17} Furthermore, these predictions can aid the shoulder
282 surgeon in selecting the best technique/treatment for a particular patient based upon a comparison
283 of multiple different projected results, considering the patient's unique model inputs, as
284 exemplified in this study by the comparative aTSA and rTSA outcome predictions. When these
285 predictions are considered in a comparative manner, they function as a patient-specific tool to
286 optimize clinical outcomes for various techniques and treatment options. Additionally, considering
287 these predictions relative to the age and gender stratified outcomes for aTSA and rTSA (presented
288 online) can be used as a quality assessment metric to assess performance at each post-operative
289 timepoint. Future work should perform additional predictive analyses to compare and quantify the
290 impact of complications on model predictions, particular as it relates to false-positive predictions
291 for MCID and SCB, and also create patient-specific predictive models for complication risk
292 associated with each of the various techniques and treatment options.

293 More controversial is the use of a predictive tool to identify if a specific patient is an
294 appropriate candidate for an elective surgical treatment. The abbreviated model accurately
295 identified >82% of patients that would achieve improvement greater than the MCID threshold and
296 >76% of patients that would achieve improvement greater than the SCB threshold across all
297 outcome metrics analyzed. Furthermore, the abbreviated model algorithms were associated with
298 average MCID AUROC values of 0.82 for aTSA and 0.89 for rTSA and average SCB AUROC
299 values of 0.85 for aTSA and 0.82 for rTSA. Thus, our AUROC results suggest these predictive
300 algorithms created from a minimal feature set have on average, good (>0.8) to excellent (>0.9)
301 discrimination of patients in the validation cohort to achieve MCID and SCB improvement. While
302 these predictions can be helpful to pre-operatively identify patients who are good (or poor)
303 candidates for these elective procedures, it must be acknowledged that each patient's needs are
304 unique and different and that patient-specific requirements for pain relief and functional
305 improvement may not align with the established MCID¹⁹ or SCB²⁰ improvement thresholds. As
306 such, this tool should not define who is eligible for surgical treatment; instead, it should be used
307 to support treatment and never be misused to deny treatment.

308 Machine learning predictions using the full model, and its 291 feature inputs, have limited
309 practical application for creating a decision-support tool that can be used in the typical clinical
310 setting, due to the substantial input burden on the patient, office staff, and health care provider.
311 Fortunately, our results demonstrate that similar levels of predictive accuracy can be attained using
312 as few as 19 patient questions and active range of motion measurements. We observed minor
313 improvements in predictive accuracy when the abbreviated model was supplemented with implant
314 size/type data and measurements of native glenoid version and inclination; this additional data has
315 the potential to be seamlessly added to the model from CT-based pre-operative planning software

316 without additional input required by the office staff. While future work is necessary to create and
317 deploy the clinical software that utilizes these machine learning algorithms, the results of our study
318 objectively demonstrate the efficacy of a minimal feature set algorithm to predict aTSA and rTSA
319 outcomes at multiple post-operative timepoints. Furthermore, utilization of this minimal feature
320 set comprised of the most predictive inputs represents an opportunity for more efficient data
321 collection and resource utilization, as it is inferred from our results that the majority of the pre-
322 operative data in the full model (including the majority of the questions from the 5 outcome metrics
323 contained in the database: ASES, Constant, UCLA, SST, and SPADI) is superfluous, adding little
324 additional predictive benefit to our model. Future work can apply these machine learning
325 techniques to construct a new and more efficient shoulder arthroplasty specific patient reported
326 outcome measure that eliminates inputs of little predictive value and only utilize those patient
327 questions found to be highly predictive of post-operative outcomes and/or patient satisfaction.

328 Aside from our previous work,¹² the use of machine learning to predict outcomes after
329 shoulder arthroplasty is novel, though a few studies have recently utilized machine learning to
330 predict short-term complications after shoulder arthroplasty¹⁰ and outcomes after hip⁴ and knee^{4,23}
331 arthroplasty. Our machine learning analysis of aTSA and rTSA outcomes builds upon previous
332 work^{5,6,18-21} which used more traditional statistical techniques to compare aTSA and rTSA
333 outcomes. Our results demonstrated similar MAE between aTSA and rTSA predictions for each
334 clinical outcome measure at each post-operative timepoint; however, at earlier post-operative
335 timepoints, we observed slightly higher MAE than later timepoints, despite having more data at
336 those earlier timepoints. This finding is likely due to the greater variability in outcomes early due
337 to patients having different healing rates, and perhaps also due to different methods and utilization
338 of rehabilitation programs. As has been reported previously by Simovitch et al.²¹ and Levy et al.¹³,

339 aTSA and rTSA patients can continue to experience improvement for up to 2 years after surgery,
340 after which improvement plateaus; these findings are consistent with our own observations for
341 both aTSA and rTSA cohorts in our dataset. (Tables 3 and 4) Since machine learning algorithms
342 improve and reduce error by learning with new data, as additional clinical data is obtained, future
343 work will refine these algorithms to further reduce model MAE and improve predictive accuracy.

344 Our study has several limitations. First, our clinical outcomes database is contributed to by
345 30 different sites/surgeons, and data from each site/surgeon inevitably contains some bias. As such,
346 the derived models will also contain bias.^{1,2,14,16} To reduce collection bias and input variability, all
347 sites were trained to collect data using standardized data forms and all completed forms were
348 independently verified. Second, each of the surgeons who contributed clinical data are experienced
349 shoulder specialists who have multiple years of experience with the prosthesis utilized in this
350 study; as such, these predictions may not translate to less-experienced surgeons or those who have
351 not completed the learning curve with this platform shoulder prosthesis. Third, our clinical
352 database consists only of patients who elected to undergo shoulder arthroplasty, and those patients
353 are primarily elderly, non-Hispanic, Caucasians of European descent. For example, we do not
354 collect data on individuals who were candidates but elected to forgo surgery due to comorbid
355 illness, financial, or personal reasons. Therefore, model predictions may not be representative of
356 the outcomes achieved by patients of different demographics, regions, or ethnicity/race and model
357 predictions may be biased against patients too sick to safely undergo the procedure or patients
358 whose condition was not sufficiently degenerative to have the procedure. Fourth, our models were
359 developed from a dataset of primary aTSA and primary rTSA patients using one platform shoulder
360 prosthesis, where patients with revisions, humeral fractures, or hemiarthroplasty were excluded;
361 therefore, model predictions may not be appropriate for those excluded indications or other

362 prosthesis types or designs. Fifth, our study utilized one tree-based machine learning technique to
363 construct algorithms that quantify outcomes after shoulder arthroplasty, other techniques, such as
364 deep-learning, could achieve better predictive accuracy than XGBoost, as has been shown
365 previously¹² using the Wide and Deep²⁴ technique. Despite slight improvements in predictive
366 accuracy using Wide and Deep, we utilized XGBoost in our study because its predictions are more
367 interpretable, providing an F-score identification of the most meaningful parameters used by the
368 model. Knowledge of the model input parameters driving up/down the patient-specific predictions
369 can be clinically useful, particularly if those features are modifiable by patient. Sixth, our clinical
370 database, while extensive, contains some missing data; fortunately, XGBoost manages missing
371 values and data sparsity well and imputes missing values on its own by minimizing the error rate
372 for each tree as it learns. Finally, while we utilized a minimal feature set of 19 of the most
373 predictive features in our database, there may be other features that are more predictive and
374 clinically meaningful that were not included in full model and are not currently collected in our
375 clinical database. Future work should continue to refine the feature set to identify more clinically
376 meaningful and highly predictive parameters that minimize model MAE while also minimizing
377 the user input burden, thereby, ensuring the decision-support tool can be efficiently implemented
378 in the clinical setting.

379 **Conclusion**

380 In conclusion, we utilized a commercially available supervised machine learning technique
381 to analyze a clinical database of one platform shoulder prosthesis and constructed predictive
382 algorithms using a full model (of 291 inputs) and an abbreviated model (of 19 inputs) and attained
383 similar accuracy with each model to predict outcomes after shoulder arthroplasty at multiple post-
384 operative timepoints in our study of 2,153 primary aTSA and 3,621 primary rTSA patients. The
385 abbreviated prediction model was supplemented with implant size/type data and native glenoid
386 version and inclination measurements, which demonstrated that marginal improvements can be
387 achieved when incorporating pre-operative CT planning data. Finally, both the full and abbreviated
388 model algorithms were able to pre-operatively risk-stratify patients based upon improvement
389 predictions greater than the MCID and SCB patient-satisfaction thresholds for each outcome
390 measure analyzed in our study. These promising results demonstrate an efficient utilization of
391 machine learning algorithms to predict clinical outcomes. The use of a minimal feature set of only
392 19 preoperative inputs suggests that this tool may be easily used during a surgical consultation to
393 improve decision-making related to shoulder arthroplasty.

394 **Tables Descriptions**

395 **Table 1.** Description of the Minimal Feature Set of Pre-operative Inputs Utilized by the
396 Abbreviated Prediction Model.

397 **Table 2.** Comparison of Demographics, Diagnosis, and Comorbidities for the Primary aTSA and
398 Primary rTSA Patients in this Study

399 **Table 3.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the
400 Primary aTSA Patients Analyzed in this Study, Stratified by Follow-up Duration

401 **Table 4.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the
402 Primary rTSA Patients Analyzed in this Study, Stratified by Follow-up Duration

403 **Table 5.** Comparison of the Mean Absolute Error (MAE) Associated with each Outcome Measure
404 Prediction for the Full and Abbreviated Machine Learning Models. Note that these MAE Values
405 are a Weighted Average over each Post-operative Timepoint (3-6 months, 6-9 months, 1 year, 2-
406 3 years, 3-5 years, and 5+ years); Supplemental Tables are Included Online Reporting the MAE
407 for each Outcome Measure at each Post-operative Timepoint.

408 **Table 6.** XGBoost predictions using the full and abbreviated models for aTSA & rTSA patients
409 who experienced clinical improvement at 2-3 years follow-up greater than the MCID¹⁹ threshold
410 for multiple different outcome measures.

411 **Table 7.** XGBoost predictions using the full and abbreviated model for aTSA & rTSA patients
412 who experienced clinical improvement at 2-3 years follow-up greater than the SCB²⁰ threshold for
413 multiple different outcome measures.

414

415 **Supplemental Tables (available online)**

416 **Supplemental Table 1.** Comparison of Pre-operative, Post-operative, and Improvement in
417 Outcomes for the Primary aTSA Patients Analyzed in this Study, Stratified by Follow-up Duration,
418 Gender, and Age: Female, Age <60yrs at the time of surgery

419 **Supplemental Table 2.** Comparison of Pre-operative, Post-operative, and Improvement in
420 Outcomes for the Primary aTSA Patients Analyzed in this Study, Stratified by Follow-up Duration,
421 Gender, and Age: Female, Age 60 to <70 yrs at the time of surgery

422 **Supplemental Table 3.** Comparison of Pre-operative, Post-operative, and Improvement in
423 Outcomes for the Primary aTSA Patients Analyzed in this Study, Stratified by Follow-up Duration,
424 Gender, and Age: Female, Age 70 to <80 yrs at the time of surgery

425 **Supplemental Table 4.** Comparison of Pre-operative, Post-operative, and Improvement in
426 Outcomes for the Primary aTSA Patients Analyzed in this Study, Stratified by Follow-up Duration,
427 Gender, and Age: Female, Age \geq 80yrs at the time of surgery

428 **Supplemental Table 5.** Comparison of Pre-operative, Post-operative, and Improvement in
429 Outcomes for the Primary aTSA Patients Analyzed in this Study, Stratified by Follow-up Duration,
430 Gender, and Age: Male, Age <60yrs at the time of surgery

431 **Supplemental Table 6.** Comparison of Pre-operative, Post-operative, and Improvement in
432 Outcomes for the Primary aTSA Patients Analyzed in this Study, Stratified by Follow-up Duration,
433 Gender, and Age: Male, Age 60 to <70 yrs at the time of surgery

434 **Supplemental Table 7.** Comparison of Pre-operative, Post-operative, and Improvement in
435 Outcomes for the Primary aTSA Patients Analyzed in this Study, Stratified by Follow-up Duration,
436 Gender, and Age: Male, Age 70 to <80 yrs at the time of surgery

437 **Supplemental Table 8.** Comparison of Pre-operative, Post-operative, and Improvement in
438 Outcomes for the Primary aTSA Patients Analyzed in this Study, Stratified by Follow-up Duration,
439 Gender, and Age: Male, Age ≥ 80 yrs at the time of surgery

440 **Supplemental Table 9.** Comparison of Pre-operative, Post-operative, and Improvement in
441 Outcomes for the Primary rTSA Patients Analyzed in this Study, Stratified by Follow-up Duration,
442 Gender, and Age: Female, Age <60 yrs at the time of surgery

443 **Supplemental Table 10.** Comparison of Pre-operative, Post-operative, and Improvement in
444 Outcomes for the Primary rTSA Patients Analyzed in this Study, Stratified by Follow-up Duration,
445 Gender, and Age: Female, Age 60 to <70 yrs at the time of surgery

446 **Supplemental Table 11.** Comparison of Pre-operative, Post-operative, and Improvement in
447 Outcomes for the Primary rTSA Patients Analyzed in this Study, Stratified by Follow-up Duration,
448 Gender, and Age: Female, Age 70 to <80 yrs at the time of surgery

449 **Supplemental Table 12.** Comparison of Pre-operative, Post-operative, and Improvement in
450 Outcomes for the Primary rTSA Patients Analyzed in this Study, Stratified by Follow-up Duration,
451 Gender, and Age: Female, Age ≥ 80 yrs at the time of surgery

452 **Supplemental Table 13.** Comparison of Pre-operative, Post-operative, and Improvement in
453 Outcomes for the Primary rTSA Patients Analyzed in this Study, Stratified by Follow-up Duration,
454 Gender, and Age: Male, Age <60 yrs at the time of surgery

455 **Supplemental Table 14.** Comparison of Pre-operative, Post-operative, and Improvement in
456 Outcomes for the Primary rTSA Patients Analyzed in this Study, Stratified by Follow-up Duration,
457 Gender, and Age: Male, Age 60 to <70 yrs at the time of surgery

458 **Supplemental Table 15.** Comparison of Pre-operative, Post-operative, and Improvement in
459 Outcomes for the Primary rTSA Patients Analyzed in this Study, Stratified by Follow-up Duration,
460 Gender, and Age: Male, Age 70 to <80 yrs at the time of surgery

461 **Supplemental Table 16.** Comparison of Pre-operative, Post-operative, and Improvement in
462 Outcomes for the Primary rTSA Patients Analyzed in this Study, Stratified by Follow-up Duration,
463 Gender, and Age: Male, Age ≥ 80 yrs at the time of surgery

464 **Supplemental Table 17.** Comparison of Mean Absolute Error Associated with the ASES
465 Predictions with the Full and Abbreviated Machine Learning Models

466 **Supplemental Table 18.** Comparison of Mean Absolute Error Associated with the Constant
467 Predictions with the Full and Abbreviated Machine Learning Models

468 **Supplemental Table 19.** Comparison of Mean Absolute Error Associated with the Global
469 Shoulder Function Score Predictions with the Full and Abbreviated Machine Learning Models

470 **Supplemental Table 20.** Comparison of Mean Absolute Error Associated with the VAS Pain
471 Score Predictions with the Full and Abbreviated Machine Learning Models

472 **Supplemental Table 21.** Comparison of Mean Absolute Error Associated with the Active
473 Abduction (in degrees) Predictions with the Full and Abbreviated Machine Learning Models

474 **Supplemental Table 22.** Comparison of Mean Absolute Error Associated with the Active Forward
475 Elevation (in degrees) Predictions with the Full and Abbreviated Machine Learning Models

476 **Supplemental Table 23.** Comparison of Mean Absolute Error Associated with the Active External
477 Rotation (in degrees) Predictions with the Full and Abbreviated Machine Learning Models

478 **Table 1.** Description of the Minimal Feature Set of Pre-operative Inputs Utilized by the Abbreviated Prediction Model

Feature	Description and Unit	Range/Inputs
Age	Age of patient, years	18 to 115
Weight	Weight, lbs.	80 to 450
Height	Height, inches	48 to 80
Gender	Male or Female	Male or Female
Previous Shoulder Surgery?	Has the patient previously had a surgical operation on their shoulder?	Yes or No
Is surgery on the dominant shoulder?	Will the upcoming arthroplasty be on the patient's dominant shoulder?	Yes or No
Primary Diagnosis	What is the patient's diagnosis?	Osteoarthritis, Osteonecrosis, Rotator Cuff Tear, Rotator Cuff Tear Arthropathy, Rheumatoid Arthritis, and Post Traumatic Arthritis
Comorbidities	What are the patient's comorbidities?	No comorbidities, inflammatory arthritis, hypertension, heart disease, diabetes, chronic renal failure, and tobacco use
Preoperative Active Abduction	Active arm elevation in the frontal plane, degrees	0 to 180°
Preoperative Active Forward Elevation	Active arm elevation in the sagittal plane, degrees	0 to 180°
Preoperative Active External Rotation	Active lateral rotation of the arm, with the arm at the side, degrees	-90 to 90°
Preoperative Passive External Rotation	Passive lateral rotation of the arm, with the arm at the side, degrees	-90 to 90°
Preoperative Internal Rotation Score	Active medial rotation of the arm, with the arm at the side. Unitless, 8 point numeric scale with the following discreet assignments based on motion to vertebral segments: No motion = 0, hip = 1, buttocks = 2, sacrum = 3, L5 – L4 = 4, L3 – L1 = 5, T12 – T8 = 6, T7 or higher = 7.	0 to 7
Preoperative Global Shoulder Function Score	Global Shoulder Function score is patient assessment of their ability to use their shoulder prior to surgery. 11pt score (0-10), with 10 = full/normal mobility	0 to 10
Preoperative Pain on a Daily Basis (ie Visual Analog Score (VAS))	VAS pain score is the patient assessment of the pain that they experience on a daily basis prior to surgery. 11pt score (0-10), with 10 = extreme pain	0 to 10

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Preoperative Pain at Worst	Patient assessment of the worst pain that they experience on a daily basis prior to surgery. 11pt score (0-10), with 10 = extreme pain	0 to 10
Preoperative Pain when lying on your side	Patient assessment of the pain that they experience when lying on their effected side prior to surgery. 11pt score (0-10), with 10 = extreme pain	0 to 10
Preoperative Pain when touching back of neck	Patient assessment of the pain that they experience when touching back of neck prior to surgery. 11pt score (0-10), with 10 = extreme pain	0 to 10
Preoperative Pain when pushing with affected arm	Patient assessment of the pain that they experience when pushing with affected arm prior to surgery. 11pt score (0-10), with 10 = extreme pain	0 to 10

479

480 **Table 2.** Comparison of Demographics, Diagnosis, and Comorbidities for the Primary aTSA and Primary rTSA Patients in this Study

Demographics, Diagnosis, and Comorbidities	aTSA Patients	rTSA Patients
Age at Surgery	66.1 ± 9.2 yrs	72.5 ± 7.8 yrs
Gender	1111F/1027M/15Unk	2350F/1242M/29Unk
Height	66.6 ± 4.3 in	65.0 ± 4.0 in
Weight	188.9 ± 44.5 lbs	172.7 ± 41.0 lbs
Body Mass Index (BMI)	29.9 ± 6.3	28.7 ± 6.0
% Previous Shoulder Surgery	15.7%	24.7%
Surgery on Dominant Shoulder?	55.8%	62.2%
Osteoarthritis (OA) diagnosis	92.7%	53.2%
Osteonecrosis (ON) diagnosis	3.2%	2.4%
Rotator Cuff Tear (RCT) diagnosis	2.6%	39.3%
Cuff Tear Arthropathy (CTA) diagnosis	0.8%	38.4%
Rheumatoid Arthritis (RA) diagnosis	3.1%	3.5%
Post-traumatic Arthritis (PTA) diagnosis	2.1%	2.4%
No Comorbidities	35.9%	33.0%
Inflammatory Arthritis	11.7%	7.8%
Hypertension	47.4%	53.3%
Heart Disease	13.6%	16.2%

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Diabetes	12.2%	13.7%
Chronic Renal Failure	1.2%	2.0%
Tobacco use?	9.8%	7.2%

481

482

483 **Table 3.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the Primary aTSA Patients Analyzed in this
484 Study, Stratified by Follow-up Duration

aTSA Follow-up Duration	ASES (Post/Improve)	Constant (Post/Improve)	Global Shoulder Function (Post/Improve)	VAS Pain (Post/Improve)	Active Abduction (Post/Improve)	Active Forward Elevation (Post/Improve)	Active External Rotation (Post/Improve)	Adverse Event % / Revision %
Preoperative	35.7 ± 16.4	38.3 ± 14.3	4.1 ± 2.0	6.4 ± 2.1	83.1 ± 30.8	97.1 ± 32.3	19.9 ± 19.6	NA
3 – 6 months	76.5 ± 18.9 / 40.4 ± 21.4	62.3 ± 15.5 / 24.4 ± 17.1	7.2 ± 2.2 / 3.0 ± 2.8	1.7 ± 2.1 / 4.7 ± 2.7	110.2 ± 32.0 / 26.3 ± 37.2	125.4 ± 33.5 / 29.3 ± 38.0	42.6 ± 18.7 / 22.4 ± 19.7	2.1% / 1.4%
6 – 9 months	82.4 ± 17.8 / 44.5 ± 21.5	68.1 ± 14.3 / 29.1 ± 15.9	7.7 ± 2.2 / 3.5 ± 2.7	1.3 ± 1.9 / 5.0 ± 2.7	119.8 ± 31.4 / 36.5 ± 37.2	136.0 ± 30.3 / 39.0 ± 36.2	49.5 ± 18.6 / 28.2 ± 20.8	1.5% / 0.8%
1 year	85.9 ± 17.1 / 49.2 ± 20.6	71.6 ± 13.6 / 33.1 ± 15.9	8.4 ± 1.9 / 4.3 ± 2.5	1.1 ± 1.9 / 5.3 ± 2.6	127.5 ± 32.0 / 44.8 ± 37.1	143.8 ± 29.0 / 47.3 ± 35.3	51.1 ± 18.7 / 30.7 ± 20.7	2.5% / 1.4%
2 – 3 years	87.4 ± 17.1 / 51.3 ± 20.9	73.4 ± 13.8 / 35.2 ± 16.0	8.6 ± 1.9 / 4.7 ± 2.5	1.0 ± 1.9 / 5.4 ± 2.6	129.1 ± 32.1 / 45.4 ± 39.1	146.5 ± 29.1 / 48.7 ± 37.2	52.4 ± 18.8 / 33.0 ± 22.0	3.4% / 2.0%
3 – 5 years	86.2 ± 17.4 / 50.5 ± 20.4	72.8 ± 13.6 / 35.5 ± 14.7	8.6 ± 2.0 / 4.5 ± 2.6	1.1 ± 1.9 / 5.3 ± 2.6	128.4 ± 31.6 / 44.3 ± 37.9	146.8 ± 29.2 / 49.4 ± 36.2	51.5 ± 18.9 / 31.8 ± 21.7	2.6% / 2.0%
5+ years (average follow-up = 90.0 months)	81.5 ± 20.3 / 47.1 ± 23.7	68.3 ± 14.7 / 32.7 ± 16.6	8.2 ± 2.2 / 4.4 ± 2.7	1.5 ± 2.3 / 5.0 ± 2.9	120.5 ± 31.9 / 37.3 ± 38.0	141.0 ± 31.6 / 44.8 ± 37.1	46.1 ± 20.0 / 31.1 ± 22.9	5.2% / 3.4%
Full Primary aTSA Cohort								3.0%/1.9%

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486

487 **Table 4.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the Primary rTSA Patients Analyzed in this
488 Study, Stratified by Follow-up Duration

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rTSA Follow-up Duration	ASES (Post/Improve)	Constant (Post/Improve)	Global Shoulder Function (Post/Improve)	VAS Pain (Post/Improve)	Active Abduction (Post/Improve)	Active Forward Elevation (Post/Improve)	Active External Rotation (Post/Improve)	Adverse Event % / Revision %
Preoperative	34.7 ± 15.9	34.9 ± 14.4	3.7 ± 2.1	6.3 ± 2.2	72.7 ± 36.9	85.7 ± 39.3	18.5 ± 21.3	NA
3 – 6 months	73.4 ± 18.8 / 38.9 ± 20.5	58.3 ± 14.9 / 23.7 ± 16.8	6.9 ± 2.1 / 3.2 ± 2.8	1.7 ± 2.1 / 4.6 ± 2.7	104.9 ± 31.4 / 33.1 ± 39.6	120.9 ± 31.9 / 37.1 ± 42.1	28.5 ± 17.6 / 9.8 ± 21.4	3.1% / 0.7%
6 – 9 months	77.8 ± 18.1 / 41.2 ± 19.9	62.8 ± 13.7 / 28.2 ± 16.3	7.3 ± 2.0 / 3.7 ± 2.7	1.5 ± 2.0 / 4.5 ± 2.7	110.1 ± 29.7 / 39.4 ± 37.4	130.0 ± 29.1 / 46.6 ± 40.5	31.6 ± 17.7 / 13.6 ± 22.7	2.5% / 0.9%
1 year	81.2 ± 18.1 / 46.4 ± 20.7	67.0 ± 14.0 / 32.0 ± 16.2	7.9 ± 2.0 / 4.3 ± 2.6	1.3 ± 2.0 / 5.0 ± 2.7	120.6 ± 30.1 / 47.1 ± 39.7	137.8 ± 27.7 / 51.5 ± 41.2	35.7 ± 18.1 / 16.9 ± 22.2	2.3% / 1.0%
2 – 3 years	82.6 ± 18.1 / 46.7 ± 20.7	69.0 ± 13.8 / 34.1 ± 16.1	8.1 ± 1.9 / 4.4 ± 2.6	1.2 ± 2.0 / 5.0 ± 2.7	118.8 ± 30.6 / 46.5 ± 39.1	139.2 ± 26.9 / 54.2 ± 41.9	36.8 ± 17.6 / 18.8 ± 23.1	3.1% / 1.1%
3 – 5 years	82.2 ± 18.8 / 45.9 ± 21.6	68.0 ± 13.9 / 32.5 ± 15.7	8.2 ± 1.9 / 4.4 ± 2.7	1.2 ± 2.0 / 5.0 ± 2.7	117.9 ± 29.1 / 45.2 ± 39.1	137.3 ± 26.9 / 52.4 ± 41.7	36.3 ± 17.9 / 17.3 ± 23.4	2.7% / 1.3%
5+ years (average follow-up = 80.6 months)	79.9 ± 20.5 / 43.7 ± 23.5	65.7 ± 14.9 / 30.3 ± 17.3	7.9 ± 2.2 / 4.0 ± 2.9	1.4 ± 2.2 / 4.9 ± 2.9	112.3 ± 29.2 / 35.9 ± 39.6	130.7 ± 29.5 / 41.3 ± 42.9	32.3 ± 19.6 / 11.8 ± 25.3	2.5% / 1.1%
Full Primary rTSA Cohort								2.7%/1.0%

489

490

491 **Table 5.** Comparison of the Mean Absolute Error (MAE) Associated with each Outcome Measure Prediction for the Full and
 492 Abbreviated Machine Learning Models. Note that these MAE Values are a Weighted Average over each Post-operative Timepoint (3-
 493 6 months, 6-9 months, 1 year, 2-3 years, 3-5 years, and 5+ years); Supplemental Tables are Included Online Reporting the MAE for
 494 each Outcome Measure at each Post-operative Timepoint.

Prediction Error	ASES Weighted Average MAE (aTSA, rTSA)	Constant Weighted Average MAE (aTSA, rTSA)	Global Shoulder Function Weighted Average MAE (aTSA, rTSA)	VAS Pain Weighted Average MAE (aTSA, rTSA)	Active Abduction Weighted Average MAE (aTSA, rTSA)	Active Forward Elevation Weighted Average MAE (aTSA, rTSA)	Active External Rotation Weighted Average MAE (aTSA, rTSA)
Baseline Average	15.3 (15.6, 14.9)	12.5 (12.7, 12.5)	1.6 (1.6, 1.6)	1.6 (1.5, 1.6)	26.5° (26.4, 26.3)	23.0° (22.9, 23.2)	16.0° (16.2, 15.7)

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XGBoost with Full Model	11.7 (11.6, 11.8)	8.9 (9.4, 9.1)	1.4 (1.4, 1.3)	1.3 (1.2, 1.3)	20.4° (20.9, 20.1)	17.6° (18.0, 17.8)	12.2° (13.1, 11.7)
XGBoost with Abbreviated Model	12.0 (11.9, 12.2)	9.8 (10.1, 9.9)	1.5 (1.5, 1.4)	1.4 (1.2, 1.5)	21.8° (22.0, 21.3)	19.2° (19.7, 19.2)	12.6° (13.2, 12.1)
MAE Difference (Full – Abbreviated)	0.3 (0.3, 0.4)	0.9 (0.7, 0.8)	0.1 (0.1, 0.1)	0.1 (0.0, 0.2)	1.4° (1.1, 1.2)	1.6° (1.7, 1.4)	0.4° (0.1, 0.4)
XGBoost with Abbreviated Model + Implant Data	12.0 (11.7, 12.0)	9.7 (9.8, 9.8)	1.4 (1.4, 1.4)	1.3 (1.2, 1.4)	21.7° (21.9, 21.1)	19.0° (19.2, 19.1)	12.4° (13.1, 12.0)

495

496 **Table 6.** XGBoost predictions using the full and abbreviated models for aTSA & rTSA patients who experienced clinical improvement
 497 at 2-3 years follow-up greater than the MCID¹⁹ threshold for multiple different outcome measures.

MCID prediction	ASES (aTSA, rTSA)	Constant (aTSA, rTSA)	Global Shoulder Function (aTSA, rTSA)	VAS Pain (aTSA, rTSA)	Abduction (aTSA, rTSA)	Forward elevation (aTSA, rTSA)	External rotation (aTSA, rTSA)
MCID ¹⁹	13.6 (17.0, 10.3)	5.7 (12.8, -0.3)	1.4 (1.7, 1.0)	1.6 (2.7, 1.4)	7.0 (13.9, -1.9)	12.0 (23.1, -2.9)	3.0 (14.5, -5.3)
Patient percent	77.9% (72.9%, 80.6%)	71.3% (63.0%, 77.6%)	75.7% (75.5%, 75.8%)	75.3% (66.5%, 77.9%)	83.5% (78.2%, 88.7%)	79.9% (73.4%, 92.7%)	84.7% (77.8%, 90.4%)
Precision (full model)	95% (94%, 95%)	96% (97%, 98%)	94% (96%, 93%)	92% (91%, 91%)	94% (91%, 98%)	92% (87%, 99%)	95% (90%, 99%)
Recall (full model)	99% (97%, 99%)	99% (99%, 100%)	96% (95%, 98%)	98% (97%, 99%)	94% (91%, 98%)	95% (88%, 99%)	96% (93%, 99%)
Accuracy (full model)	95% (94%, 95%)	97% (96%, 99%)	92% (93%, 92%)	93% (92%, 91%)	90% (86%, 98%)	89% (82%, 99%)	95% (92%, 99%)
AUC (full model)	0.90(0.90, 0.88)	0.95 (0.97, 0.96)	0.88 (0.91, 0.87)	0.87 (0.89, 0.82)	0.83 (0.80, 0.98)	0.79 (0.75, 0.95)	0.83 (0.78, 0.95)
Precision (abbreviated model)	91% (90%, 91%)	94% (93%, 94%)	93% (94%, 91%)	91% (89%, 91%)	90% (87%, 95%)	89% (90%, 97%)	89% (85%, 94%)

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Recall (abbreviated model)	99% (97%, 99%)	99% (97%, 99%)	95% (94%, 97%)	96% (96%, 97%)	91% (89%, 95%)	95% (91%, 98%)	92% (88%, 96%)
Accuracy (abbreviated model)	93% (92%, 93%)	97% (96%, 99%)	90% (89%, 91%)	90% (88%, 92%)	84% (82%, 94%)	87% (87%, 98%)	87% (84%, 97%)
AUC (abbreviated model)	0.88 (0.87, 0.84)	0.94 (0.95, 0.93)	0.87 (0.89, 0.86)	0.87 (0.86, 0.84)	0.76 (0.72, 0.94)	0.72 (0.70, 0.89)	0.78 (0.73, 0.90)

498

499 **Table 7.** XGBoost predictions using the full and abbreviated model for aTSA & rTSA patients who experienced clinical improvement
500 at 2-3 years follow-up greater than the SCB²⁰ threshold for multiple different outcome measures.

SCB prediction	ASES (aTSA, rTSA)	Constant (aTSA, rTSA)	Global Shoulder Function (aTSA, rTSA)	VAS Pain (aTSA, rTSA)	Abduction (aTSA, rTSA)	Forward elevation (aTSA, rTSA)	External rotation (aTSA, rTSA)
SCB ²⁰	31.5 (37.6, 25.9)	19.1 (25.4, 13.6)	3.1 (3.9, 2.4)	3.2 (3.8, 2.6)	28.5 (36.1, 19.6)	35.4 (45.5, 22.3)	11.7 (20.1, 3.6)
Patient percent	66.7% (57.3%, 73.1%)	62.3% (52.8%, 71.7%)	58.8% (57.4%, 70.7%)	62.8% (61.5%, 72.5%)	64.7% (55.2%, 73.9%)	61.3% (48.4%, 75.7%)	70.1% (64.6%, 82.0%)
Precision (full model)	88% (89%, 88%)	91% (93%, 94%)	83% (91%, 91%)	85% (92%, 88%)	86% (80%, 89%)	85% (85%, 91%)	85% (79%, 92%)
Recall (full model)	93% (93%, 94%)	95% (88%, 97%)	93% (86%, 90%)	99% (92%, 97%)	86% (87%, 87%)	91% (88%, 93%)	89% (92%, 93%)
Accuracy (full model)	87% (89%, 88%)	91% (90%, 92%)	85% (87%, 86%)	86% (89%, 88%)	82% (81%, 83%)	84% (86%, 88%)	81% (79%, 88%)
AUC (full model)	0.84 (0.89, 0.81)	0.90 (0.90, 0.88)	0.84 (0.87, 0.84)	0.82 (0.86, 0.81)	0.81 (0.80, 0.78)	0.83 (0.87, 0.83)	0.76 (0.74, 0.78)
Precision (abbreviated model)	87% (88%, 86%)	90% (91%, 92%)	82% (89%, 91%)	85% (92%, 88%)	82% (76%, 84%)	78% (74%, 86%)	82% (76%, 89%)
Recall (abbreviated model)	92% (92%, 93%)	95% (88%, 97%)	93% (86%, 90%)	99% (92%, 97%)	84% (83%, 84%)	88% (81%, 91%)	88% (89%, 91%)
Accuracy (abbreviated model)	87% (89%, 88%)	90% (88%, 90%)	84% (85%, 86%)	87% (90%, 88%)	80% (79%, 81%)	81% (82%, 81%)	79% (76%, 84%)
AUC (abbreviated model)	0.82 (0.86, 0.76)	0.89 (0.89, 0.87)	0.83 (0.86, 0.83)	0.85 (0.87, 0.82)	0.72 (0.74, 0.70)	0.74 (0.78, 0.70)	0.73 (0.70, 0.76)

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501

502 **Suppl Table 1.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the Primary aTSA Patients Analyzed
 503 in this Study, Stratified by Follow-up Duration, Gender, and Age: Female, Age <60yrs at the time of surgery

aTSA Follow-up Duration	ASES (Post/Improve)	Constant (Post/Improve)	Global Shoulder Function (Post/Improve)	VAS Pain (Post/Improve)	Active Abduction (Post/Improve)	Active Forward Elevation (Post/Improve)	Active External Rotation (Post/Improve)	Adverse Event % / Revision %
Preoperative	31.1 ± 14.6	35.4 ± 14.0	4.0 ± 1.9	6.9 ± 2.0	82.1 ± 33.6	97.3 ± 37.6	20.3 ± 19.9	NA
3 – 6 months	65.7 ± 23.9 / 34.3 ± 24.6	55.0 ± 17.9 / 20.4 ± 18.5	6.5 ± 2.5 / 2.3 ± 3.1	2.9 ± 3.0 / 4.1 ± 3.3	102.7 ± 32.3 / 19.4 ± 36.4	118.3 ± 38.4 / 21.4 ± 41.6	39.8 ± 19.0 / 18.2 ± 20.2	2.9%/1.9%
6 – 9 months	68.9 ± 21.8 / 37.7 ± 23.2	58.9 ± 17.7 / 26.9 ± 20.8	6.7 ± 1.9 / 2.9 ± 2.6	2.7 ± 2.5 / 3.9 ± 2.9	105.0 ± 36.0 / 33.0 ± 43.8	125.1 ± 32.6 / 42.1 ± 43.9	43.0 ± 21.4 / 21.3 ± 23.4	5.0%/5.0%
1 year	75.0 ± 23.2 / 44.0 ± 24.1	65.2 ± 15.1 / 28.2 ± 15.8	8.1 ± 1.9 / 4.0 ± 2.3	2.1 ± 2.6 / 5.0 ± 3.2	122.4 ± 32.9 / 40.4 ± 37.7	138.7 ± 31.8 / 40.5 ± 36.6	48.7 ± 20.2 / 25.5 ± 20.7	4.9%/2.9%
2 – 3 years	82.7 ± 18.3 / 51.5 ± 20.9	68.1 ± 14.2 / 32.5 ± 16.3	8.2 ± 2.0 / 4.2 ± 2.3	1.3 ± 2.1 / 5.4 ± 2.8	124.2 ± 34.9 / 46.2 ± 43.6	146.3 ± 30.0 / 49.5 ± 38.8	51.7 ± 18.7 / 31.2 ± 22.5	5.9%/3.5%
3 – 5 years	80.3 ± 19.8 / 50.1 ± 21.4	68.7 ± 14.9 / 33.2 ± 12.5	8.0 ± 2.3 / 4.1 ± 2.4	1.8 ± 2.3 / 5.0 ± 2.6	117.2 ± 31.6 / 32.1 ± 41.0	145.6 ± 29.7 / 44.9 ± 38.8	46.6 ± 21.4 / 25.5 ± 26.4	7.3%/4.9%
5+ years	74.4 ± 20.8 / 47.5 ± 21.8	68.1 ± 18.0 / 34.9 ± 15.0	7.5 ± 2.4 / 4.1 ± 2.6	2.2 ± 2.6 / 5.1 ± 2.7	117.9 ± 33.3 / 38.9 ± 31.1	145.1 ± 38.7 / 41.5 ± 29.4	44.9 ± 19.7 / 28.0 ± 24.8	10.4%/10.4%
Primary aTSA Cohort, Female, age <60yrs at the time of surgery								5.8%/4.4%

504

505 **Suppl Table 2.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the Primary aTSA Patients Analyzed
 506 in this Study, Stratified by Follow-up Duration, Gender, and Age: Female, Age 60 to <70 yrs at the time of surgery

aTSA Follow-up Duration	ASES (Post/Improve)	Constant (Post/Improve)	Global Shoulder Function (Post/Improve)	VAS Pain (Post/Improve)	Active Abduction (Post/Improve)	Active Forward Elevation (Post/Improve)	Active External Rotation (Post/Improve)	Adverse Event % / Revision %
Preoperative	33.6 ± 15.8	35.9 ± 13.1	3.9 ± 2.0	6.6 ± 2.1	81.4 ± 30.1	95.0 ± 33.4	21.2 ± 19.7	NA
3 – 6 months	75.5 ± 17.7 / 42.5 ± 20.5	60.4 ± 14.2 / 25.7 ± 15.9	7.2 ± 2.1 / 3.2 ± 2.7	1.7 ± 2.1 / 5.0 ± 2.6	104.8 ± 32.3 / 25.8 ± 38.9	121.6 ± 35.1 / 29.1 ± 42.2	42.2 ± 19.3 / 22.7 ± 19.7	4.3%/2.5%

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6 – 9 months	80.5 ± 19.1 / 45.7 ± 23.1	66.0 ± 13.9 / 30.2 ± 16.0	7.8 ± 2.1 / 3.9 ± 2.8	1.6 ± 2.2 / 5.1 ± 2.7	120.3 ± 31.3 / 37.0 ± 39.5	137.1 ± 30.4 / 40.6 ± 38.3	52.2 ± 19.5 / 29.4 ± 21.6	3.0%/1.8%
1 year	85.9 ± 15.6 / 51.6 ± 19.2	70.1 ± 12.5 / 34.7 ± 14.1	8.5 ± 1.9 / 4.7 ± 2.4	1.0 ± 1.7 / 5.5 ± 2.4	125.9 ± 32.0 / 45.8 ± 36.9	145.2 ± 28.6 / 52.2 ± 35.8	51.5 ± 18.6 / 31.3 ± 21.6	3.9%/1.9%
2 – 3 years	85.8 ± 19.7 / 51.0 ± 23.1	70.9 ± 13.3 / 34.5 ± 15.0	8.6 ± 1.9 / 4.9 ± 2.6	1.2 ± 2.2 / 5.3 ± 2.8	128.2 ± 33.1 / 45.0 ± 40.0	147.4 ± 29.1 / 51.0 ± 38.0	55.2 ± 18.6 / 34.6 ± 22.3	4.8%/2.2%
3 – 5 years	84.5 ± 18.5 / 50.3 ± 20.7	69.9 ± 14.0 / 34.9 ± 15.8	8.4 ± 2.0 / 4.6 ± 2.6	1.2 ± 2.1 / 5.3 ± 2.6	124.8 ± 33.4 / 45.1 ± 38.3	142.5 ± 31.3 / 52.0 ± 37.4	51.5 ± 19.7 / 30.5 ± 22.4	4.0%/3.7%
5+ years	77.4 ± 23.1 / 47.0 ± 24.1	64.9 ± 15.6 / 33.0 ± 16.9	8.0 ± 2.2 / 4.8 ± 2.8	1.9 ± 2.7 / 5.1 ± 3.0	116.3 ± 32.7 / 36.4 ± 41.9	137.4 ± 35.3 / 48.2 ± 40.7	45.5 ± 21.6 / 31.2 ± 23.6	4.4%/2.8%
Primary aTSA Cohort, Female, age 60 to <70yrs at the time of surgery								4.1%/2.6%

507

508 **Suppl Table 3.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the Primary aTSA Patients Analyzed
509 in this Study, Stratified by Follow-up Duration, Gender, and Age: Female, Age 70 to <80 yrs at the time of surgery

aTSA Follow-up Duration	ASES (Post/Improve)	Constant (Post/Improve)	Global Shoulder Function (Post/Improve)	VAS Pain (Post/Improve)	Active Abduction (Post/Improve)	Active Forward Elevation (Post/Improve)	Active External Rotation (Post/Improve)	Adverse Event % / Revision %
Preoperative	32.3 ± 14.8	35.1 ± 12.8	3.9 ± 2.0	6.7 ± 2.0	78.7 ± 30.0	93.6 ± 32.3	20.0 ± 20.4	NA
3 – 6 months	76.2 ± 19.5 / 43.6 ± 23.2	59.5 ± 15.5 / 25.8 ± 17.7	7.3 ± 2.2 / 3.2 ± 2.7	1.7 ± 2.3 / 5.0 ± 2.9	107.0 ± 33.6 / 27.8 ± 37.8	120.3 ± 37.5 / 30.3 ± 38.8	43.2 ± 19.1 / 21.8 ± 21.0	2.8%/2.4%
6 – 9 months	81.9 ± 17.1 / 49.1 ± 20.9	65.7 ± 14.3 / 30.1 ± 17.3	7.6 ± 2.2 / 3.6 ± 2.6	1.0 ± 1.5 / 5.8 ± 2.5	115.1 ± 33.7 / 37.7 ± 41.7	132.6 ± 34.8 / 39.1 ± 38.5	49.4 ± 18.4 / 28.6 ± 21.7	0.9%/0.0%
1 year	86.7 ± 14.0 / 53.8 ± 19.3	69.5 ± 13.1 / 33.8 ± 16.6	8.5 ± 1.8 / 4.5 ± 2.4	0.8 ± 1.6 / 5.8 ± 2.4	125.6 ± 33.1 / 46.4 ± 38.0	141.3 ± 30.9 / 48.3 ± 35.5	51.6 ± 18.7 / 31.1 ± 20.7	1.7%/0.7%
2 – 3 years	87.1 ± 17.4 / 55.0 ± 20.7	72.0 ± 14.5 / 37.3 ± 17.7	8.7 ± 1.7 / 4.9 ± 2.3	0.9 ± 1.8 / 5.9 ± 2.5	127.9 ± 34.1 / 49.7 ± 42.2	143.1 ± 33.8 / 48.6 ± 40.2	52.1 ± 19.9 / 32.8 ± 23.5	3.6%/2.8%
3 – 5 years	86.3 ± 16.7 / 55.7 ± 18.7	71.6 ± 13.7 / 37.9 ± 15.3	8.6 ± 2.1 / 4.7 ± 2.7	1.0 ± 1.9 / 5.9 ± 2.4	130.9 ± 32.6 / 49.9 ± 39.7	144.2 ± 32.9 / 51.4 ± 39.4	55.5 ± 18.4 / 34.3 ± 21.2	2.9%/1.6%
5+ years	82.2 ± 19.2 / 49.8 ± 25.2	66.9 ± 13.2 / 33.1 ± 14.2	8.2 ± 2.1 / 4.8 ± 2.3	1.3 ± 2.2 / 5.1 ± 3.0	120.5 ± 32.3 / 41.3 ± 36.8	138.2 ± 32.9 / 44.3 ± 36.7	46.5 ± 20.8 / 33.1 ± 26.1	1.7%/1.3%
Primary aTSA Cohort, Female, age 70 to <80yrs at the time of surgery								2.4%/1.6%

510

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511 **Suppl Table 4.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the Primary aTSA Patients Analyzed
 512 in this Study, Stratified by Follow-up Duration, Gender, and Age: Female, Age ≥80yrs at the time of surgery

aTSA Follow-up Duration	ASES (Post/Improve)	Constant (Post/Improve)	Global Shoulder Function (Post/Improve)	VAS Pain (Post/Improve)	Active Abduction (Post/Improve)	Active Forward Elevation (Post/Improve)	Active External Rotation (Post/Improve)	Adverse Event % / Revision %
Preoperative	30.4 ± 14.7	30.0 ± 12.1	3.6 ± 2.2	6.8 ± 2.1	72.4 ± 24.8	84.7 ± 28.0	16.9 ± 20.6	NA
3 – 6 months	77.4 ± 17.2 / 43.2 ± 18.0	60.8 ± 14.6 / 30.4 ± 13.9	7.1 ± 2.7 / 3.2 ± 3.2	1.6 ± 2.2 / 5.1 ± 2.6	110.6 ± 32.3 / 33.6 ± 32.7	119.0 ± 35.3 / 28.6 ± 37.6	38.7 ± 21.3 / 22.8 ± 16.9	0%/0%
6 – 9 months	86.4 ± 11.1 / 52.9 ± 18.4	61.8 ± 10.5 / 33.0 ± 16.4	8.5 ± 1.9 / 3.7 ± 2.3	0.9 ± 1.0 / 5.9 ± 2.6	110.9 ± 27.0 / 37.0 ± 22.8	117.6 ± 22.7 / 33.3 ± 28.9	43.4 ± 20.0 / 26.1 ± 17.6	0%/0%
1 year	85.3 ± 13.0 / 52.5 ± 15.3	69.0 ± 10.0 / 39.4 ± 13.8	8.6 ± 2.1 / 4.6 ± 2.1	0.7 ± 1.6 / 5.8 ± 2.6	118.3 ± 33.2 / 45.7 ± 34.4	128.6 ± 38.4 / 42.1 ± 42.4	50.3 ± 20.4 / 32.4 ± 18.6	0%/0%
2 – 3 years	84.7 ± 14.6 / 54.6 ± 20.9	68.5 ± 11.1 / 40.9 ± 16.3	8.1 ± 2.8 / 4.8 ± 2.5	0.8 ± 1.7 / 6.5 ± 2.5	123.2 ± 29.9 / 47.1 ± 32.5	136.8 ± 27.1 / 52.0 ± 29.0	54.5 ± 19.6 / 36.0 ± 23.6	0%/0%
3 – 5 years	85.1 ± 14.7 / 58.2 ± 19.0	70.4 ± 12.5 / 44.8 ± 18.4	8.3 ± 2.3 / 4.3 ± 2.5	0.6 ± 1.5 / 6.9 ± 2.1	120.2 ± 33.7 / 44.1 ± 36.4	138.3 ± 34.0 / 51.5 ± 34.5	55.1 ± 19.9 / 40.8 ± 24.7	0%/0%
5+ years	86.1 ± 16.0 / 51.5 ± 27.0	64.1 ± 11.9 / 35.4 ± 18.1	8.1 ± 1.9 / 4.4 ± 2.6	0.9 ± 1.8 / 5.3 ± 3.5	111.4 ± 28.9 / 40.7 ± 34.2	130.2 ± 32.0 / 42.4 ± 31.2	47.2 ± 17.4 / 37.6 ± 17.2	2.9%/2.9%
Primary aTSA Cohort, Female, age ≥80yrs at the time of surgery								0.4%/0.4%

513

514 **Suppl Table 5.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the Primary aTSA Patients Analyzed
 515 in this Study, Stratified by Follow-up Duration, Gender, and Age: Male, Age <60yrs at the time of surgery

aTSA Follow-up Duration	ASES (Post/Improve)	Constant (Post/Improve)	Global Shoulder Function (Post/Improve)	VAS Pain (Post/Improve)	Active Abduction (Post/Improve)	Active Forward Elevation (Post/Improve)	Active External Rotation (Post/Improve)	Adverse Event % / Revision %
Preoperative	36.4 ± 16.2	40.5 ± 13.9	4.1 ± 2.1	6.4 ± 2.1	85.5 ± 30.0	100.2 ± 30.5	16.3 ± 18.9	NA
3 – 6 months	71.9 ± 20.5 / 34.6 ± 22.4	62.0 ± 16.7 / 21.3 ± 17.9	6.8 ± 2.2 / 2.5 ± 2.5	2.3 ± 2.3 / 3.9 ± 2.7	110.4 ± 31.6 / 23.5 ± 37.2	127.9 ± 31.4 / 29.0 ± 37.3	38.9 ± 19.4 / 22.2 ± 19.8	0.5%/0.5%
6 – 9 months	79.4 ± 19.5 / 42.5 ± 21.2	69.6 ± 14.3 / 28.0 ± 14.5	7.5 ± 2.0 / 3.4 ± 2.6	1.7 ± 2.0 / 4.8 ± 2.5	121.2 ± 28.2 / 33.3 ± 34.1	140.4 ± 27.4 / 37.4 ± 32.3	45.0 ± 17.5 / 27.1 ± 18.3	0%/0%
1 year	80.4 ± 21.5 / 43.7 ± 23.2	71.2 ± 15.6 / 32.0 ± 17.0	7.9 ± 2.1 / 3.9 ± 2.8	1.7 ± 2.3 / 4.9 ± 2.7	124.7 ± 31.6 / 42.3 ± 37.3	143.3 ± 27.2 / 44.2 ± 33.6	46.9 ± 19.3 / 29.7 ± 20.9	2.9%/2.3%

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2 – 3 years	83.9 ± 17.9 /	73.8 ± 15.9 /	8.3 ± 1.9 /	1.5 ± 2.0 /	124.7 ± 32.2 /	147.1 ± 29.6 /	48.8 ± 20.0 /	2.0%/0.7%
	49.7 ± 19.6	36.8 ± 15.5	4.7 ± 2.3	5.4 ± 2.4	41.4 ± 36.6	46.5 ± 33.4	34.0 ± 21.8	
3 – 5 years	83.3 ± 19.5 /	75.5 ± 13.8 /	8.2 ± 2.1 /	1.5 ± 2.2 /	129.8 ± 30.3 /	148.0 ± 28.3 /	48.1 ± 18.4 /	1.1%/1.1%
	45.7 ± 22.2	36.2 ± 14.0	4.5 ± 2.8	5.0 ± 2.8	43.7 ± 35.9	48.3 ± 28.7	35.4 ± 21.2	
5+ years	81.5 ± 19.0 /	71.6 ± 14.5 /	7.8 ± 2.3 /	1.7 ± 2.2 /	122.1 ± 32.3 /	147.9 ± 28.9 /	44.0 ± 20.7 /	8.6%/5.9%
	46.1 ± 20.9	31.3 ± 16.7	4.1 ± 3.2	5.0 ± 2.6	34.8 ± 38.9	43.6 ± 34.5	35.4 ± 22.8	
Primary aTSA Cohort, Male, age <60yrs at the time of surgery								2.6%/1.8%

516

517 **Suppl Table 6.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the Primary aTSA Patients Analyzed
518 in this Study, Stratified by Follow-up Duration, Gender, and Age: Male, Age 60 to <70 yrs at the time of surgery

aTSA Follow-up Duration	ASES (Post/Improve)	Constant (Post/Improve)	Global Shoulder Function (Post/Improve)	VAS Pain (Post/Improve)	Active Abduction (Post/Improve)	Active Forward Elevation (Post/Improve)	Active External Rotation (Post/Improve)	Adverse Event % / Revision %
Preoperative	40.4 ± 16.8	42.4 ± 15.0	4.6 ± 2.0	6.0 ± 2.2	86.2 ± 30.1	101.2 ± 29.1	19.8 ± 18.8	NA
3 – 6 months	81.9 ± 15.7 /	68.1 ± 13.4 /	7.6 ± 2.1 /	1.3 ± 1.6 /	117.5 ± 29.1 /	132.7 ± 28.5 /	44.7 ± 16.8 /	1.4%/0.7%
	41.8 ± 19.5	25.6 ± 16.0	3.0 ± 2.7	4.9 ± 2.6	28.6 ± 35.5	32.1 ± 32.4	23.9 ± 18.2	
6 – 9 months	87.9 ± 14.1 /	72.4 ± 13.0 /	8.1 ± 2.1 /	1.0 ± 1.6 /	124.7 ± 31.6 /	140.8 ± 28.5 /	51.2 ± 16.6 /	0.7%/0%
	43.9 ± 19.9	27.6 ± 14.7	3.4 ± 2.6	4.7 ± 2.8	37.4 ± 34.7	38.9 ± 34.7	30.4 ± 19.7	
1 year	89.8 ± 15.4 /	75.9 ± 13.0 /	8.6 ± 1.9 /	0.9 ± 1.7 /	132.1 ± 30.8 /	147.9 ± 26.4 /	51.7 ± 17.9 /	1.4%/1.4%
	49.2 ± 19.5	34.1 ± 15.2	4.1 ± 2.3	5.2 ± 2.4	45.5 ± 35.9	46.4 ± 32.4	31.4 ± 19.8	
2 – 3 years	91.3 ± 14.0 /	77.7 ± 12.6 /	8.8 ± 1.8 /	0.8 ± 1.6 /	132.1 ± 29.5 /	149.3 ± 27.5 /	51.9 ± 18.4 /	1.8%/0.7%
	50.3 ± 18.5	36.1 ± 13.4	4.5 ± 2.3	5.1 ± 2.4	45.4 ± 35.6	48.6 ± 34.0	33.1 ± 20.1	
3 – 5 years	89.6 ± 15.5 /	76.8 ± 11.4 /	8.9 ± 1.7 /	1.0 ± 1.8 /	133.8 ± 28.0 /	152.3 ± 21.5 /	51.3 ± 18.2 /	0.7%/0.3%
	47.9 ± 20.0	35.2 ± 11.3	4.2 ± 2.5	4.7 ± 2.6	42.9 ± 32.4	48.8 ± 30.5	30.7 ± 19.3	
5+ years	85.9 ± 17.6 /	73.2 ± 13.6 /	8.5 ± 1.9 /	1.1 ± 1.9 /	124.8 ± 31.5 /	144.9 ± 18.4 /	48.3 ± 18.4 /	6.5%/4.0%
	46.7 ± 23.6	33.8 ± 17.4	4.2 ± 2.4	4.9 ± 2.8	37.7 ± 36.7	46.1 ± 36.1	29.3 ± 20.9	
Primary aTSA Cohort, Male, age 60 to <70yrs at the time of surgery								2.2%/1.3%

519

520 **Suppl Table 7.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the Primary aTSA Patients Analyzed
521 in this Study, Stratified by Follow-up Duration, Gender, and Age: Male, Age 70 to <80 yrs at the time of surgery

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aTSA Follow-up Duration	ASES (Post/Improve)	Constant (Post/Improve)	Global Shoulder Function (Post/Improve)	VAS Pain (Post/Improve)	Active Abduction (Post/Improve)	Active Forward Elevation (Post/Improve)	Active External Rotation (Post/Improve)	Adverse Event % / Revision %
Preoperative	41.2 ± 17.2	42.4 ± 15.7	4.4 ± 2.1	5.8 ± 2.3	89.6 ± 33.1	100.1 ± 33.6	22.1 ± 19.4	NA
3 – 6 months	82.0 ± 14.6 / 39.3 ± 18.5	66.1 ± 13.5 / 22.6 ± 18.2	7.3 ± 2.2 / 2.9 ± 3.0	1.2 ± 1.5 / 4.6 ± 2.3	115.6 ± 32.0 / 24.7 ± 39.0	128.5 ± 29.1 / 27.9 ± 38.7	45.7 ± 17.5 / 22.9 ± 20.8	0.6%/0.6%
6 – 9 months	86.6 ± 13.6 / 41.2 ± 19.6	71.9 ± 11.8 / 29.1 ± 14.3	7.8 ± 2.2 / 3.4 ± 3.0	1.1 ± 1.7 / 4.3 ± 2.8	123.2 ± 25.5 / 37.2 ± 29.6	135.6 ± 24.7 / 38.7 ± 29.5	49.2 ± 16.9 / 25.3 ± 21.4	1.3%/0%
1 year	88.9 ± 14.7 / 46.0 ± 20.3	74.4 ± 12.9 / 30.5 ± 17.1	8.6 ± 1.8 / 4.3 ± 2.5	1.0 ± 1.8 / 4.7 ± 2.9	132.8 ± 29.8 / 42.9 ± 38.4	146.4 ± 24.7 / 45.6 ± 36.6	53.4 ± 17.6 / 31.2 ± 20.9	2.4%/0.9%
2 – 3 years	89.7 ± 14.7 / 47.6 ± 21.4	75.7 ± 12.0 / 30.6 ± 18.8	8.6 ± 2.0 / 4.3 ± 2.8	0.9 ± 1.7 / 4.7 ± 2.9	133.5 ± 30.0 / 40.1 ± 38.3	146.7 ± 24.7 / 44.9 ± 39.6	51.7 ± 16.9 / 30.3 ± 21.9	4.1%/3.1%
3 – 5 years	89.9 ± 14.3 / 52.2 ± 17.9	74.3 ± 13.9 / 32.4 ± 17.4	9.0 ± 1.7 / 4.8 ± 2.3	0.7 ± 1.4 / 5.4 ± 2.3	130.7 ± 30.9 / 43.6 ± 41.4	145.5 ± 27.7 / 45.7 ± 41.9	50.1 ± 17.2 / 30.4 ± 20.3	2.5%/1.9%
5+ years	82.5 ± 20.1 / 43.2 ± 23.8	69.0 ± 14.0 / 28.6 ± 17.8	8.5 ± 2.1 / 4.0 ± 2.7	1.6 ± 2.3 / 4.6 ± 3.0	124.6 ± 28.7 / 33.5 ± 35.1	141.4 ± 27.3 / 38.7 ± 37.7	44.8 ± 18.1 / 25.9 ± 19.3	4.5%/1.9%
Primary aTSA Cohort, Male, age 70 to <80yrs at the time of surgery								2.7%/1.6%

522

523 **Suppl Table 8.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the Primary aTSA Patients Analyzed
524 in this Study, Stratified by Follow-up Duration, Gender, and Age: Male, Age ≥80yrs at the time of surgery

aTSA Follow-up Duration	ASES (Post/Improve)	Constant (Post/Improve)	Global Shoulder Function (Post/Improve)	VAS Pain (Post/Improve)	Active Abduction (Post/Improve)	Active Forward Elevation (Post/Improve)	Active External Rotation (Post/Improve)	Adverse Event % / Revision %
Preoperative	30.5 ± 20.0	37.6 ± 17.2	3.7 ± 2.3	7.0 ± 2.3	73.4 ± 28.1	88.0 ± 34.7	26.0 ± 16.7	NA
3 – 6 months	87.7 ± 8.9 / 56.3 ± 13.6	63.2 ± 13.4 / 34.2 ± 15.1	7.8 ± 1.9 / 4.1 ± 3.0	0.9 ± 1.2 / 6.1 ± 1.5	113.2 ± 27.0 / 42.7 ± 27.4	128.0 ± 26.6 / 37.3 ± 25.9	46.4 ± 22.5 / 17.7 ± 20.4	0%/0%
6 – 9 months	92.4 ± 9.7 / 47.3 ± 25.6	74.6 ± 14.8 / 34.1 ± 12.4	7.3 ± 3.9 / 3.1 ± 3.9	0.3 ± 0.7 / 6.1 ± 3.4	128.2 ± 32.6 / 51.6 ± 38.4	134.9 ± 34.2 / 36.9 ± 43.4	59.4 ± 22.6 / 34.2 ± 18.8	0%/0%
1 year	91.3 ± 7.2 / 55.5 ± 21.9	71.3 ± 12.1 / 35.4 ± 15.6	8.7 ± 1.2 / 5.0 ± 2.1	0.3 ± 0.6 / 7.0 ± 2.7	124.4 ± 31.4 / 54.9 ± 35.3	133.1 ± 30.4 / 53.5 ± 37.3	51.6 ± 21.7 / 29.7 ± 16.8	0%/0%
2 – 3 years	91.8 ± 11.4 / 65.4 ± 10.2	73.8 ± 11.0 / 39.1 ± 17.6	8.4 ± 2.6 / 5.6 ± 2.0	0.6 ± 1.5 / 6.5 ± 2.8	136.0 ± 32.8 / 71.3 ± 39.4	146.9 ± 25.2 / 54.7 ± 39.2	52.3 ± 21.8 / 30.6 ± 18.2	0%/0%

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3 – 5 years	89.0 ± 13.3 /	71.2 ± 11.2 /	8.8 ± 1.6 /	0.8 ± 1.7 /	120.6 ± 23.6 /	132.7 ± 26.8 /	56.8 ± 16.6 /	0%/0%
	51.6 ± 22.5	24.0 ± 20.7	5.9 ± 2.2	6.3 ± 3.2	54.0 ± 53.2	43.0 ± 55.6	34.2 ± 25.9	
5+ years*	83.6 ± 18.0	61.0 ± 12.1	8.7 ± 2.3	0.7 ± 1.6	112.5 ± 21.0	120.0 ± 20.0	55.0 ± 23.5	0%/0%
Primary aTSA Cohort, Male, age ≥80yrs at the time of surgery								0%/0%

525 *Note: Insufficient follow-up data to calculate pre-to-post improvement beyond 5yrs follow-up for this primary aTSA patient cohort

526 **Suppl Table 9.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the Primary rTSA Patients Analyzed
 527 in this Study, Stratified by Follow-up Duration, Gender, and Age: Female, Age <60yrs at the time of surgery

rTSA Follow-up Duration	ASES (Post/Improve)	Constant (Post/Improve)	Global Shoulder Function (Post/Improve)	VAS Pain (Post/Improve)	Active Abduction (Post/Improve)	Active Forward Elevation (Post/Improve)	Active External Rotation (Post/Improve)	Adverse Event % / Revision %
Preoperative	27.4 ± 15.3	28.3 ± 12.6	2.8 ± 2.3	7.2 ± 2.1	70.1 ± 34.7	77.1 ± 33.9	20.7 ± 23.2	NA
3 – 6 months	56.7 ± 21.6 /	45.2 ± 15.8 /	5.6 ± 2.3 /	3.5 ± 2.6 /	100.7 ± 36.9 /	111.0 ± 35.7 /	28.1 ± 19.6 /	2.8%/1.4%
	28.9 ± 21.9	16.0 ± 17.5	2.3 ± 3.0	3.8 ± 2.7	27.1 ± 49.4	32.9 ± 46.4	7.1 ± 25.0	
6 – 9 months	62.5 ± 23.1 /	52.7 ± 16.6 /	6.6 ± 2.3 /	3.0 ± 2.7 /	108.4 ± 30.8 /	124.2 ± 32.8 /	27.0 ± 20.7 /	4.7%/2.3%
	33.2 ± 16.3	22.3 ± 15.0	3.7 ± 2.8	4.1 ± 2.7	41.0 ± 40.8	54.0 ± 37.2	11.5 ± 24.9	
1 year	68.3 ± 23.4 /	57.1 ± 18.2 /	7.0 ± 2.3 /	2.8 ± 2.7 /	122.5 ± 33.3 /	128.5 ± 32.6 /	34.6 ± 22.0 /	0%/0%
	38.8 ± 21.0	28.1 ± 21.0	4.2 ± 2.9	4.3 ± 2.8	48.6 ± 50.1	50.6 ± 44.4	8.6 ± 24.7	
2 – 3 years	68.4 ± 25.9 /	58.7 ± 19.0 /	7.0 ± 2.4 /	2.5 ± 2.8 /	121.5 ± 40.9 /	132.8 ± 35.5 /	35.7 ± 21.7 /	5.5%/2.7%
	38.6 ± 23.3	28.2 ± 18.3	4.4 ± 3.3	4.7 ± 2.9	46.6 ± 55.9	52.3 ± 48.6	16.9 ± 24.5	
3 – 5 years	67.8 ± 23.5 /	58.1 ± 18.4 /	7.0 ± 2.1 /	2.6 ± 2.7 /	118.6 ± 34.5 /	137.6 ± 32.1 /	34.3 ± 23.4 /	2.8%/2.8%
	42.0 ± 25.7	28.7 ± 15.8	4.9 ± 3.0	4.5 ± 3.1	46.9 ± 42.1	57.6 ± 35.3	16.8 ± 23.2	
5+ years	70.3 ± 21.7 /	56.3 ± 17.8 /	6.5 ± 2.3 /	2.0 ± 2.5 /	104.8 ± 36.1 /	118.8 ± 42.1 /	21.7 ± 31.0 /	4.8%/2.4%
	40.7 ± 23.1	30.2 ± 14.2	3.8 ± 3.1	5.3 ± 2.3	39.1 ± 38.0	50.0 ± 37.2	17.2 ± 18.5	
Primary rTSA Cohort, Female, age <60yrs at the time of surgery								3.2%/1.8%

528

529 **Suppl Table 10.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the Primary rTSA Patients Analyzed
 530 in this Study, Stratified by Follow-up Duration, Gender, and Age: Female, Age 60 to <70 yrs at the time of surgery

rTSA Follow-up Duration	ASES (Post/Improve)	Constant (Post/Improve)	Global Shoulder Function (Post/Improve)	VAS Pain (Post/Improve)	Active Abduction (Post/Improve)	Active Forward Elevation (Post/Improve)	Active External Rotation (Post/Improve)	Adverse Event % / Revision %
Preoperative	32.5 ± 15.6	34.5 ± 14.0	3.9 ± 2.2	6.7 ± 2.2	75.0 ± 35.5	89.0 ± 38.5	20.1 ± 20.7	NA

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3 – 6 months	70.8 ± 19.5 / 38.5 ± 21.1	56.8 ± 15.7 / 23.4 ± 17.5	6.7 ± 2.1 / 3.0 ± 2.9	2.0 ± 2.2 / 4.7 ± 2.8	105.5 ± 32.4 / 31.9 ± 40.1	120.8 ± 33.6 / 33.9 ± 42.2	29.2 ± 17.5 / 8.3 ± 20.6	4.6%/0.6%
6 – 9 months	75.5 ± 18.1 / 41.2 ± 18.2	60.7 ± 13.6 / 26.9 ± 15.9	7.3 ± 1.8 / 3.2 ± 2.7	1.7 ± 2.0 / 4.6 ± 2.3	111.3 ± 28.5 / 38.8 ± 37.3	130.1 ± 29.5 / 46.3 ± 38.6	35.5 ± 17.3 / 15.5 ± 20.9	1.9%/1.3%
1 year	80.1 ± 19.0 / 48.1 ± 20.6	67.0 ± 14.2 / 32.7 ± 15.7	7.8 ± 2.0 / 4.1 ± 2.7	1.4 ± 2.1 / 5.3 ± 2.8	125.0 ± 32.2 / 47.5 ± 39.6	141.1 ± 27.9 / 49.1 ± 39.6	38.9 ± 18.5 / 17.9 ± 21.5	1.6%/1.0%
2 – 3 years	81.7 ± 18.0 / 49.5 ± 19.6	67.9 ± 13.8 / 35.2 ± 15.4	8.1 ± 1.8 / 4.2 ± 2.5	1.3 ± 2.1 / 5.4 ± 2.6	120.4 ± 31.6 / 46.5 ± 37.4	140.8 ± 28.0 / 53.3 ± 39.8	37.9 ± 18.4 / 18.3 ± 22.4	3.4%/1.4%
3 – 5 years	81.3 ± 19.7 / 49.1 ± 20.5	65.9 ± 15.9 / 31.5 ± 16.4	8.1 ± 2.0 / 4.4 ± 2.3	1.3 ± 2.1 / 5.5 ± 2.7	118.7 ± 31.4 / 43.3 ± 38.1	137.8 ± 29.8 / 47.6 ± 41.8	35.5 ± 17.4 / 15.8 ± 22.9	2.2%/0.9%
5+ years	77.1 ± 22.1 / 46.7 ± 21.0	65.9 ± 16.0 / 34.2 ± 14.4	7.5 ± 2.2 / 4.2 ± 2.8	1.8 ± 2.5 / 5.3 ± 3.0	111.7 ± 31.6 / 36.6 ± 35.1	134.5 ± 31.8 / 42.8 ± 38.3	33.0 ± 18.8 / 11.1 ± 21.2	2.8%/0%
Primary rTSA Cohort, Female, age 60 to <70yrs at the time of surgery								2.9%/0.9%

531

532 **Suppl Table 11.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the Primary rTSA Patients Analyzed
533 in this Study, Stratified by Follow-up Duration, Gender, and Age: Female, Age 70 to <80 yrs at the time of surgery

rTSA Follow-up Duration	ASES (Post/Improve)	Constant (Post/Improve)	Global Shoulder Function (Post/Improve)	VAS Pain (Post/Improve)	Active Abduction (Post/Improve)	Active Forward Elevation (Post/Improve)	Active External Rotation (Post/Improve)	Adverse Event % / Revision %
Preoperative	32.8 ± 15.2	33.9 ± 14.5	3.5 ± 2.1	6.5 ± 2.2	70.9 ± 37.5	85.5 ± 40.4	17.7 ± 20.9	NA
3 – 6 months	73.7 ± 18.0 / 41.5 ± 20.4	57.9 ± 14.8 / 24.4 ± 16.2	7.0 ± 2.1 / 3.4 ± 2.8	1.6 ± 2.0 / 5.0 ± 2.7	103.6 ± 32.6 / 35.3 ± 41.0	120.9 ± 33.0 / 39.2 ± 42.9	27.9 ± 17.1 / 10.5 ± 21.4	2.8%/0.7%
6 – 9 months	78.8 ± 16.7 / 44.7 ± 20.4	62.3 ± 13.1 / 28.8 ± 16.8	7.2 ± 2.0 / 3.9 ± 2.6	1.3 ± 1.9 / 4.9 ± 2.7	108.5 ± 31.2 / 40.0 ± 36.6	129.1 ± 31.2 / 46.2 ± 42.4	33.1 ± 16.8 / 15.2 ± 21.8	2.3%/0.3%
1 year	81.5 ± 16.9 / 48.6 ± 19.7	65.9 ± 13.2 / 31.4 ± 15.8	8.0 ± 1.9 / 4.4 ± 2.5	1.2 ± 1.9 / 5.3 ± 2.7	119.3 ± 29.5 / 47.6 ± 39.9	137.4 ± 28.0 / 51.7 ± 41.5	35.5 ± 17.4 / 17.4 ± 22.1	2.4%/0.7%
2 – 3 years	82.9 ± 17.2 / 48.8 ± 20.1	68.1 ± 12.7 / 34.7 ± 15.6	8.1 ± 1.9 / 4.6 ± 2.6	1.0 ± 1.9 / 5.2 ± 2.6	118.3 ± 29.3 / 49.3 ± 37.0	140.7 ± 25.5 / 58.5 ± 41.3	37.7 ± 17.3 / 20.6 ± 23.4	2.5%/0.7%
3 – 5 years	81.8 ± 17.4 / 47.7 ± 21.8	67.3 ± 12.1 / 32.2 ± 15.1	8.3 ± 1.7 / 4.6 ± 2.7	1.1 ± 1.9 / 5.3 ± 2.8	116.3 ± 27.3 / 48.3 ± 38.3	136.9 ± 26.0 / 54.9 ± 41.9	36.5 ± 17.8 / 18.0 ± 23.3	1.9%/0.4%
5+ years	78.4 ± 21.2 / 42.6 ± 25.4	63.5 ± 14.3 / 27.4 ± 18.0	7.9 ± 2.3 / 4.0 ± 3.1	1.4 ± 2.4 / 4.8 ± 3.1	110.6 ± 28.1 / 38.5 ± 40.3	129.3 ± 28.2 / 43.0 ± 43.3	31.4 ± 19.6 / 12.2 ± 26.6	0.9%/0%
Primary rTSA Cohort, Female, age 70 to <80yrs at the time of surgery								2.3%/0.5%

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534 **Suppl Table 12.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the Primary rTSA Patients Analyzed
 535 in this Study, Stratified by Follow-up Duration, Gender, and Age: Female, Age ≥ 80 yrs at the time of surgery

rTSA Follow-up Duration	ASES (Post/Improve)	Constant (Post/Improve)	Global Shoulder Function (Post/Improve)	VAS Pain (Post/Improve)	Active Abduction (Post/Improve)	Active Forward Elevation (Post/Improve)	Active External Rotation (Post/Improve)	Adverse Event % / Revision %
Preoperative	31.4 \pm 14.2	30.1 \pm 12.6	3.1 \pm 2.1	6.5 \pm 2.1	60.2 \pm 30.8	71.6 \pm 35.1	13.8 \pm 19.8	NA
3 – 6 months	71.5 \pm 18.7 / 40.8 \pm 19.5	55.1 \pm 13.4 / 26.4 \pm 15.8	6.8 \pm 2.2 / 3.6 \pm 2.8	1.7 \pm 2.2 / 4.8 \pm 2.7	96.2 \pm 27.7 / 38.5 \pm 35.5	114.1 \pm 31.9 / 45.5 \pm 39.3	27.1 \pm 18.8 / 12.6 \pm 22.6	2.7%/0.8%
6 – 9 months	74.3 \pm 18.2 / 40.0 \pm 18.0	59.4 \pm 12.1 / 29.8 \pm 13.5	7.4 \pm 2.0 / 4.3 \pm 2.5	1.6 \pm 2.3 / 4.4 \pm 2.7	102.9 \pm 29.2 / 43.5 \pm 33.2	122.3 \pm 28.9 / 51.0 \pm 35.8	27.4 \pm 17.1 / 13.3 \pm 23.7	3.3%/0%
1 year	78.8 \pm 16.3 / 48.0 \pm 20.3	62.3 \pm 12.4 / 33.8 \pm 15.7	7.8 \pm 2.0 / 4.5 \pm 2.9	1.3 \pm 1.9 / 5.4 \pm 2.7	109.5 \pm 29.2 / 51.6 \pm 37.7	130.0 \pm 29.0 / 60.9 \pm 39.4	32.2 \pm 18.5 / 18.2 \pm 22.5	1.6%/0.3%
2 – 3 years	79.2 \pm 17.9 / 47.3 \pm 20.9	62.3 \pm 14.2 / 34.2 \pm 16.8	7.6 \pm 2.3 / 4.5 \pm 2.9	1.1 \pm 2.0 / 5.4 \pm 2.6	105.9 \pm 30.7 / 49.3 \pm 38.4	127.7 \pm 30.9 / 59.7 \pm 43.8	32.8 \pm 17.1 / 19.7 \pm 22.9	5.0%/0.9%
3 – 5 years	78.6 \pm 18.9 / 48.0 \pm 22.1	61.6 \pm 13.1 / 35.1 \pm 14.6	7.8 \pm 2.2 / 4.4 \pm 3.1	1.1 \pm 1.9 / 5.6 \pm 2.7	106.0 \pm 27.4 / 49.6 \pm 37.8	127.3 \pm 28.6 / 62.7 \pm 41.4	34.9 \pm 18.2 / 17.0 \pm 25.8	2.2%/0.5%
5+ years	80.7 \pm 19.1 / 45.4 \pm 26.6	61.5 \pm 14.9 / 35.2 \pm 15.9	7.8 \pm 2.4 / 3.9 \pm 3.4	1.1 \pm 2.1 / 4.9 \pm 3.3	105.2 \pm 27.9 / 44.2 \pm 35.0	120.1 \pm 35.1 / 49.6 \pm 44.6	34.2 \pm 17.0 / 21.1 \pm 25.8	4.4%/2.2%
Primary rTSA Cohort, Female, age ≥ 80 yrs at the time of surgery								3.0%/0.7%

536

537 **Suppl Table 13.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the Primary rTSA Patients Analyzed
 538 in this Study, Stratified by Follow-up Duration, Gender, and Age: Male, Age < 60 yrs at the time of surgery

rTSA Follow-up Duration	ASES (Post/Improve)	Constant (Post/Improve)	Global Shoulder Function (Post/Improve)	VAS Pain (Post/Improve)	Active Abduction (Post/Improve)	Active Forward Elevation (Post/Improve)	Active External Rotation (Post/Improve)	Adverse Event % / Revision %
Preoperative	34.2 \pm 15.5	35.7 \pm 15.2	3.5 \pm 2.2	6.1 \pm 2.1	79.7 \pm 40.6	86.8 \pm 38.9	19.1 \pm 23.8	NA
3 – 6 months	63.8 \pm 22.0 / 29.3 \pm 22.6	55.6 \pm 17.7 / 20.3 \pm 19.1	6.4 \pm 2.2 / 2.8 \pm 3.2	2.7 \pm 2.5 / 3.2 \pm 2.8	117.1 \pm 31.2 / 37.1 \pm 36.9	124.7 \pm 32.2 / 36.5 \pm 42.2	26.5 \pm 16.5 / 7.5 \pm 22.5	3.0%/0%
6 – 9 months	68.4 \pm 20.8 / 36.3 \pm 24.5	57.5 \pm 17.9 / 27.7 \pm 20.9	6.3 \pm 2.3 / 2.7 \pm 2.7	2.8 \pm 2.7 / 3.7 \pm 3.1	113.2 \pm 32.2 / 43.2 \pm 41.3	128.5 \pm 33.8 / 50.5 \pm 40.6	23.6 \pm 16.3 / 6.7 \pm 26.2	0%/0%
1 year	74.1 \pm 25.4 / 39.7 \pm 29.1	67.6 \pm 19.4 / 33.9 \pm 20.5	7.6 \pm 2.1 / 4.2 \pm 2.8	2.3 \pm 2.8 / 3.7 \pm 3.4	128.2 \pm 32.2 / 46.3 \pm 36.4	139.3 \pm 29.7 / 50.3 \pm 39.2	34.9 \pm 18.6 / 17.0 \pm 22.9	4.8%/1.6%

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2 – 3 years	78.2 ± 20.0 /	71.0 ± 16.4 /	7.9 ± 1.7 /	1.8 ± 2.1 /	132.7 ± 33.6 /	147.5 ± 25.2 /	34.5 ± 20.3 /	3.6%/3.6%
	40.2 ± 20.8	37.3 ± 17.8	4.3 ± 2.3	4.0 ± 2.3	47.5 ± 44.5	52.6 ± 44.2	18.1 ± 24.4	
3 – 5 years	73.3 ± 23.4 /	67.6 ± 20.5 /	7.4 ± 2.3 /	2.0 ± 2.5 /	123.7 ± 36.0 /	141.2 ± 33.0 /	32.7 ± 20.4 /	2.9%/2.9%
	29.6 ± 24.0	33.3 ± 19.4	4.3 ± 2.3	3.4 ± 2.5	45.5 ± 38.6	50.9 ± 38.2	27.8 ± 26.8	
5+ years	71.0 ± 23.9 /	67.2 ± 17.7 /	7.1 ± 2.8 /	2.3 ± 2.4 /	119.1 ± 37.4 /	135.4 ± 37.0 /	29.4 ± 18.0 /	3.9%/3.9%
	28.6 ± 29.1	28.4 ± 20.1	3.6 ± 2.7	3.3 ± 3.1	26.4 ± 32.0	33.4 ± 37.4	10.9 ± 26.5	
Primary rTSA Cohort, Male, age <60yrs at the time of surgery								3.3%/1.8%

539

540 **Suppl Table 14.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the Primary rTSA Patients Analyzed
541 in this Study, Stratified by Follow-up Duration, Gender, and Age: Male, Age 60 to <70 yrs at the time of surgery

rTSA Follow-up Duration	ASES (Post/Improve)	Constant (Post/Improve)	Global Shoulder Function (Post/Improve)	VAS Pain (Post/Improve)	Active Abduction (Post/Improve)	Active Forward Elevation (Post/Improve)	Active External Rotation (Post/Improve)	Adverse Event % / Revision %
Preoperative	37.8 ± 15.7	38.0 ± 14.7	3.9 ± 1.9	6.0 ± 2.2	81.5 ± 38.6	92.0 ± 38.6	16.9 ± 21.1	NA
3 – 6 months	75.9 ± 17.2 /	61.6 ± 13.9 /	7.0 ± 2.0 /	1.7 ± 1.9 /	112.0 ± 31.2 /	126.2 ± 29.6 /	29.2 ± 17.5 /	1.3%/0.4%
	37.4 ± 19.2	23.7 ± 15.2	2.9 ± 2.6	4.3 ± 2.6	30.3 ± 37.9	35.1 ± 40.6	13.0 ± 18.9	
6 – 9 months	79.7 ± 16.7 /	66.7 ± 12.4 /	7.5 ± 1.7 /	1.5 ± 1.8 /	115.4 ± 27.0 /	137.1 ± 23.4 /	29.9 ± 17.7 /	3.0%/3.0%
	41.1 ± 20.0	29.8 ± 16.1	3.6 ± 2.5	4.3 ± 2.7	35.1 ± 35.5	45.1 ± 39.5	16.2 ± 21.7	
1 year	81.6 ± 18.4 /	71.2 ± 14.0 /	7.9 ± 2.0 /	1.4 ± 1.9 /	127.2 ± 29.4 /	143.2 ± 25.6 /	35.4 ± 17.0 /	3.9%/2.8%
	43.3 ± 20.3	32.9 ± 17.5	4.1 ± 2.5	4.5 ± 2.6	44.9 ± 39.4	50.5 ± 41.7	19.0 ± 22.1	
2 – 3 years	86.8 ± 15.9 /	75.3 ± 11.9 /	8.4 ± 1.6 /	0.9 ± 1.7 /	126.2 ± 28.1 /	146.2 ± 19.5 /	35.5 ± 16.2 /	3.5%/1.3%
	48.0 ± 19.2	36.0 ± 14.8	4.6 ± 2.3	5.0 ± 2.5	44.8 ± 39.8	54.7 ± 40.4	20.0 ± 21.8	
3 – 5 years	85.6 ± 18.0 /	73.2 ± 14.0 /	8.3 ± 1.9 /	1.1 ± 2.1 /	124.6 ± 28.8 /	144.0 ± 23.7 /	36.7 ± 17.5 /	4.2%/2.4%
	45.5 ± 20.6	32.5 ± 15.2	3.9 ± 2.8	4.8 ± 2.6	38.7 ± 40.0	45.9 ± 44.7	18.4 ± 22.6	
5+ years	83.9 ± 18.7 /	69.5 ± 15.1 /	8.2 ± 1.8 /	1.2 ± 1.9 /	113.8 ± 30.5 /	133.6 ± 28.8 /	28.9 ± 17.8 /	3.5%/2.6%
	48.6 ± 20.4	28.3 ± 19.6	4.1 ± 2.4	5.3 ± 2.7	28.9 ± 43.2	34.2 ± 49.2	6.7 ± 25.4	
Primary rTSA Cohort, Male, age 60 to <70yrs at the time of surgery								3.2%/1.9%

542

543 **Suppl Table 15.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the Primary rTSA Patients Analyzed
544 in this Study, Stratified by Follow-up Duration, Gender, and Age: Male, Age 70 to <80 yrs at the time of surgery

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rTSA Follow-up Duration	ASES (Post/Improve)	Constant (Post/Improve)	Global Shoulder Function (Post/Improve)	VAS Pain (Post/Improve)	Active Abduction (Post/Improve)	Active Forward Elevation (Post/Improve)	Active External Rotation (Post/Improve)	Adverse Event % / Revision %
Preoperative	41.0 ± 16.3	39.5 ± 14.4	4.0 ± 2.1	5.6 ± 2.3	79.2 ± 38.3	92.9 ± 40.9	21.3 ± 23.2	NA
3 – 6 months	79.2 ± 16.7 / 38.8 ± 20.0	62.8 ± 13.8 / 23.5 ± 17.8	7.3 ± 1.9 / 3.2 ± 2.7	1.3 ± 1.8 / 4.4 ± 2.6	107.4 ± 28.8 / 29.9 ± 39.8	123.9 ± 29.1 / 33.5 ± 43.5	29.4 ± 17.5 / 8.0 ± 22.2	3.8%/0.8%
6 – 9 months	81.7 ± 18.1 / 37.9 ± 20.6	66.9 ± 13.5 / 26.6 ± 17.7	7.6 ± 2.0 / 3.5 ± 2.9	1.2 ± 1.9 / 4.2 ± 2.6	114.7 ± 28.6 / 35.9 ± 42.2	134.3 ± 26.8 / 41.1 ± 43.9	31.3 ± 18.8 / 9.6 ± 24.9	3.4%/1.5%
1 year	85.6 ± 17.2 / 44.4 ± 21.0	71.8 ± 12.9 / 32.2 ± 16.8	8.2 ± 1.8 / 4.1 ± 2.6	1.0 ± 1.9 / 4.6 ± 2.7	122.8 ± 27.8 / 43.3 ± 40.1	140.5 ± 24.4 / 47.1 ± 41.9	36.3 ± 18.0 / 15.3 ± 22.4	2.7%/1.2%
2 – 3 years	86.2 ± 16.5 / 43.9 ± 22.0	73.2 ± 12.3 / 32.9 ± 17.2	8.3 ± 1.8 / 4.0 ± 2.6	1.0 ± 1.9 / 4.6 ± 2.7	121.8 ± 27.6 / 42.0 ± 39.7	139.3 ± 25.4 / 45.2 ± 42.2	38.0 ± 16.9 / 15.7 ± 24.4	1.5%/1.2%
3 – 5 years	87.4 ± 17.2 / 43.5 ± 20.7	72.5 ± 11.5 / 33.3 ± 16.4	8.5 ± 1.8 / 4.4 ± 2.6	0.9 ± 1.9 / 4.4 ± 2.6	121.5 ± 27.4 / 43.2 ± 40.8	139.1 ± 23.7 / 49.7 ± 41.3	37.4 ± 16.4 / 16.1 ± 22.6	3.7%/2.2%
5+ years	85.8 ± 15.4 / 43.8 ± 20.0	71.5 ± 10.2 / 31.4 ± 17.5	8.5 ± 1.6 / 4.2 ± 2.5	1.1 ± 1.8 / 4.7 ± 2.4	118.8 ± 24.6 / 31.3 ± 42.5	135.1 ± 19.8 / 36.6 ± 42.2	36.5 ± 18.6 / 9.7 ± 26.5	2.6%/1.9%
Primary rTSA Cohort, Male, age 70 to <80yrs at the time of surgery								2.9%/1.4%

545

546 **Suppl Table 16.** Comparison of Pre-operative, Post-operative, and Improvement in Outcomes for the Primary rTSA Patients Analyzed
547 in this Study, Stratified by Follow-up Duration, Gender, and Age: Male, Age ≥80yrs at the time of surgery

rTSA Follow-up Duration	ASES (Post/Improve)	Constant (Post/Improve)	Global Shoulder Function (Post/Improve)	VAS Pain (Post/Improve)	Active Abduction (Post/Improve)	Active Forward Elevation (Post/Improve)	Active External Rotation (Post/Improve)	Adverse Event % / Revision %
Preoperative	39.9 ± 16.6	36.7 ± 13.6	4.1 ± 2.2	5.7 ± 2.3	68.5 ± 32.3	81.3 ± 35.2	21.8 ± 19.1	NA
3 – 6 months	77.1 ± 17.9 / 35.1 ± 19.9	59.3 ± 13.6 / 19.8 ± 16.8	7.1 ± 2.0 / 2.8 ± 2.6	1.7 ± 2.3 / 4.0 ± 2.8	103.9 ± 26.7 / 28.0 ± 33.8	120.4 ± 28.1 / 32.7 ± 37.1	30.2 ± 17.2 / 6.8 ± 18.8	3.0%/0.8%
6 – 9 months	85.2 ± 13.4 / 41.6 ± 17.4	65.1 ± 12.0 / 31.0 ± 13.5	8.0 ± 1.7 / 3.6 ± 2.7	0.9 ± 1.6 / 4.3 ± 2.5	109.0 ± 27.3 / 46.8 ± 33.0	129.1 ± 23.0 / 55.9 ± 32.5	33.3 ± 17.5 / 11.2 ± 19.6	0%/0%
1 year	83.9 ± 16.1 / 44.0 ± 19.9	66.4 ± 13.0 / 28.5 ± 13.4	8.0 ± 2.1 / 4.2 ± 2.5	1.1 ± 1.8 / 4.7 ± 2.6	117.0 ± 28.3 / 47.3 ± 37.6	134.6 ± 26.0 / 52.6 ± 41.6	34.5 ± 17.6 / 12.3 ± 21.8	1.6%/0.8%
2 – 3 years	83.2 ± 17.9 / 40.7 ± 20.0	68.4 ± 12.2 / 28.3 ± 14.3	8.1 ± 1.9 / 3.7 ± 2.5	1.2 ± 2.2 / 4.2 ± 2.9	115.5 ± 30.2 / 39.6 ± 36.1	135.0 ± 25.2 / 47.9 ± 37.7	37.2 ± 19.3 / 15.0 ± 19.6	3.7%/0%

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3 – 5 years	87.9 ± 12.6 /	72.2 ± 9.7 /	8.8 ± 1.5 /	0.7 ± 1.4 /	121.8 ± 27.1 /	136.5 ± 23.5 /	41.1 ± 20.2 /	3.6%/1.8%
	43.4 ± 16.5	30.9 ± 14.2	4.6 ± 2.3	4.7 ± 2.3	43.6 ± 37.5	49.1 ± 34.9	15.1 ± 23.6	
5+ years	82.5 ± 26.2 /	67.9 ± 19.2 /	8.5 ± 2.3 /	1.3 ± 2.6 /	121.1 ± 32.1 /	137.5 ± 28.8 /	43.0 ± 23.3 /	4.5%/0%
	27.6 ± 20.9	27.8 ± 12.4	3.8 ± 2.7	3.1 ± 3.0	42.3 ± 34.5	53.2 ± 37.7	21.4 ± 16.3	
Primary rTSA Cohort, Male, age ≥80yrs at the time of surgery								2.5%/0.6%

548

549 **Suppl Table 17.** Comparison of Mean Absolute Error Associated with the ASES Predictions with the Full and Abbreviated Machine
550 Learning Models

ASES Predictions	MAE (aTSA, rTSA) 3-6 months	MAE (aTSA, rTSA) 6-9 months	MAE (aTSA, rTSA) 1yr	MAE (aTSA, rTSA) 2-3yrs	MAE (aTSA, rTSA) 3-5yrs	MAE (aTSA, rTSA) 5+yrs	Weighted Average MAE (aTSA, rTSA)
Baseline Average	14.5 (14.9, 14.3)	14.4 (14.8, 14.1)	14.5 (14.8, 13.9)	15.8 (15.9, 15.0)	16.1 (16.2, 16.0)	16.9 (16.9, 16.9)	15.3 (15.6, 14.9)
XGBoost with Full Model	12.2 (12.9, 11.8)	12.2 (12.9, 12.0)	11.8 (11.1, 11.9)	11.1 (10.3, 11.7)	11.1 (10.8, 11.3)	12.2 (11.9, 12.5)	11.7 (11.6, 11.8)
XGBoost with Abbreviated Model	12.4 (13.0, 12.0)	12.4 (13.0, 12.1)	12.3 (11.5, 12.5)	11.5 (10.8, 12.1)	11.3 (11.0, 11.5)	12.4 (12.2, 12.7)	12.0 (11.9, 12.2)
MAE Difference (Full – Abbreviated)	0.2 (0.1, 0.2)	0.2 (0.1, 0.1)	0.5 (0.4, 0.6)	0.4 (0.1, 0.2)	0.2 (0.2, 0.2)	0.2 (0.3, 0.2)	0.3 (0.3, 0.4)
XGBoost with Abbreviated Model + Implant Data	12.4 (12.9, 12.09)	12.4 (12.9, 12.0)	12.2 (11.4, 12.4)	11.4 (10.6, 11.9)	11.2 (10.9, 11.4)	12.4 (12.0, 12.6)	12.0 (11.7, 12.0)

551

552 **Suppl Table 18.** Comparison of Mean Absolute Error Associated with the Constant Predictions with the Full and Abbreviated Machine
553 Learning Models

Constant Predictions	MAE (aTSA, rTSA) 3-6 months	MAE (aTSA, rTSA) 6-9 months	MAE (aTSA, rTSA) 1yr	MAE (aTSA, rTSA) 2-3yrs	MAE (aTSA, rTSA) 3-5yrs	MAE (aTSA, rTSA) 5+yrs	Weighted Average MAE (aTSA, rTSA)
Baseline Average	13.1 (13.8, 13.0)	12.6 (13.6, 12.5)	12.4 (12.4, 12.4)	12.3 (12.3, 12.3)	12.3 (12.1, 12.5)	12.3 (12.1, 12.4)	12.5 (12.7, 12.5)

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XGBoost with Full Model	10.1 (10.8, 10.0)	9.3 (10.1, 9.2)	9.2 (9.2, 9.2)	8.3 (8.2, 8.7)	7.9 (7.6, 8.2)	8.5 (8.2, 8.9)	8.9 (9.4, 9.1)
XGBoost with Abbreviated Model	10.3 (10.9, 10.1)	10.0 (10.9, 10.0)	10.3 (10.3, 10.2)	9.4 (9.3, 9.9)	9.0 (8.7, 9.7)	9.4 (9.1, 9.6)	9.8 (10.1, 9.9)
MAE Difference (Full - Abbreviated)	– 0.2 (0.1, 0.1)	0.7 (0.8, 0.8)	0.9 (1.1, 1.0)	1.1 (1.1, 1.2)	1.1 (1.1, 1.5)	0.9 (1.1, 0.7)	0.9 (0.7, 0.8)
XGBoost with Abbreviated Model + Implant Data	10.2 (10.9, 10.0)	10.0 (10.8, 9.9)	10.1 (10.2, 10.0)	9.2 (9.2, 9.8)	9.0 (8.7, 9.6)	9.3 (9.1, 9.5)	9.7 (9.8, 9.8)

554

555 **Suppl Table 19.** Comparison of Mean Absolute Error Associated with the Global Shoulder Function Score Predictions with the Full
556 and Abbreviated Machine Learning Models

Shoulder Function Prediction	MAE (aTSA, rTSA) 3-6 months	MAE (aTSA, rTSA) 6-9 months	MAE (aTSA, rTSA) 1yr	MAE (aTSA, rTSA) 2-3yrs	MAE (aTSA, rTSA) 3-5yrs	MAE (aTSA, rTSA) 5+yrs	Weighted Average MAE (aTSA, rTSA)
Baseline Average	1.6 (1.5, 1.7)	1.6 (1.6, 1.7)	1.5 (1.5, 1.4)	1.5 (1.5, 1.5)	1.4 (1.4, 1.5)	1.7 (1.8, 1.7)	1.6 (1.6, 1.6)
XGBoost with Full Model	1.4 (1.3, 1.5)	1.5 (1.4, 1.5)	1.3 (1.4, 1.2)	1.4 (1.4, 1.3)	1.2 (1.2, 1.2)	1.5 (1.5, 1.4)	1.4 (1.4, 1.3)
XGBoost with Abbreviated Model	1.5 (1.4, 1.6)	1.5 (1.4, 1.6)	1.5 (1.6, 1.3)	1.4 (1.5, 1.4)	1.4 (1.4, 1.4)	1.5 (1.6, 1.5)	1.5 (1.5, 1.4)
MAE Difference (Full - Abbreviated)	– 0.1 (0.1, 0.1)	0.0 (0.0, 0.1)	0.2 (0.2, 0.1)	0.0 (0.1, 0.1)	0.2 (0.2, 0.2)	0.0 (0.1, 0.1)	0.1 (0.1, 0.1)
XGBoost with Abbreviated Model + Implant Data	1.4 (1.4, 1.5)	1.5 (1.4, 1.6)	1.4 (1.5, 1.2)	1.4 (1.5, 1.4)	1.3 (1.3, 1.3)	1.5 (1.5, 1.5)	1.4 (1.4, 1.4)

557

558 **Suppl Table 20.** Comparison of Mean Absolute Error Associated with the VAS Pain Score Predictions with the Full and Abbreviated
559 Machine Learning Models

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VAS Pain Prediction	MAE (aTSA, rTSA) 3-6 months	MAE (aTSA, rTSA) 6-9 months	MAE (aTSA, rTSA) 1yr	MAE (aTSA, rTSA) 2-3yrs	MAE (aTSA, rTSA) 3-5yrs	MAE (aTSA, rTSA) 5+yrs	Weighted Average MAE (aTSA, rTSA)
Baseline Average	1.6 (1.4, 1.6)	1.8 (1.7, 1.8)	1.4 (1.4, 1.5)	1.4 (1.4, 1.5)	1.5 (1.4, 1.5)	1.9 (1.9, 1.8)	1.6 (1.5, 1.6)
XGBoost with Full Model	1.3 (1.4, 1.5)	1.3 (1.2, 1.4)	1.2 (1.1, 1.3)	1.2 (1.1, 1.3)	1.2 (1.2, 1.2)	1.4 (1.4, 1.4)	1.3 (1.2, 1.3)
XGBoost with Abbreviated Model	1.4 (1.4, 1.6)	1.3 (1.2, 1.4)	1.5 (1.3, 1.6)	1.3 (1.2, 1.5)	1.4 (1.4, 1.4)	1.5 (1.6, 1.5)	1.4 (1.2, 1.5)
MAE Difference (Full - Abbreviated)	0.1 (0.0, 0.1)	0.0 (0.0, 0.0)	0.3 (0.2, 0.3)	0.1 (0.1, 0.2)	0.2 (0.2, 0.2)	0.1 (0.2, 0.1)	0.1 (0.0, 0.2)
XGBoost with Abbreviated Model + Implant Data	1.4 (1.4, 1.6)	1.3 (1.1, 1.3)	1.4 (1.3, 1.6)	1.2 (1.2, 1.4)	1.3 (1.3, 1.3)	1.5 (1.5, 1.5)	1.3 (1.2, 1.4)

560

561 **Suppl Table 21.** Comparison of Mean Absolute Error Associated with the Active Abduction (in degrees) Predictions with the Full and
562 Abbreviated Machine Learning Models

Abduction (°) Prediction	MAE (aTSA, rTSA) 3-6 months	MAE (aTSA, rTSA) 6-9 months	MAE (aTSA, rTSA) 1yr	MAE (aTSA, rTSA) 2-3yrs	MAE (aTSA, rTSA) 3-5yrs	MAE (aTSA, rTSA) 5+yrs	Weighted Average MAE (aTSA, rTSA)
Baseline Average	26.0 (26.5, 25.9)	26.3 (26.5, 26.1)	27.0 (26.3, 27.3)	28.3 (28.0, 28.1)	24.6 (24.4, 25.0)	26.3 (27.0, 24.0)	26.5 (26.4, 26.3)
XGBoost with Full Model	21.4 (22.4, 20.9)	22.0 (21.9, 22.9)	21.7 (21.2, 21.9)	19.6 (20.0, 18.2)	18.5 (18.0, 19.0)	18.1 (19.2, 16.6)	20.4 (20.9, 20.1)
XGBoost with Abbreviated Model	23.1 (23.9, 22.5)	23.4 (23.4, 23.2)	23.0 (23.0, 23.3)	20.2 (20.5, 19.7)	20.2 (20.1, 20.3)	19.8 (20.3, 18.8)	21.8 (22.0, 21.3)
MAE Difference (Full - Abbreviated)	1.5 (1.5, 1.6)	1.4 (1.5, 0.3)	1.3 (1.8, 1.4)	0.8 (0.5, 1.5)	1.7 (2.1, 1.3)	1.7 (1.1, 2.2)	1.4 (1.1, 1.2)
XGBoost with Abbreviated Model + Implant Data	22.9 (23.8, 22.2)	23.2 (23.2, 23.2)	23.0 (22.9, 23.1)	20.0 (20.3, 19.6)	20.0 (19.9, 20.2)	19.8 (20.1, 18.8)	21.7 (21.9, 21.1)

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563

564 **Suppl Table 22.** Comparison of Mean Absolute Error Associated with the Active Forward Elevation (in degrees) Predictions with the
565 Full and Abbreviated Machine Learning Models

Forward Elevation (°) Prediction	MAE (aTSA, rTSA) 3-6 months	MAE (aTSA, rTSA) 6-9 months	MAE (aTSA, rTSA) 1yr	MAE (aTSA, rTSA) 2-3yrs	MAE (aTSA, rTSA) 3-5yrs	MAE (aTSA, rTSA) 5+yrs	Weighted Average MAE (aTSA, rTSA)
Baseline Average	24.9 (24.9, 24.9)	24.3 (24.5, 24.0)	22.6 (22.7, 22.4)	20.9 (20.0, 22.0)	21.4 (21.2, 22.7)	23.7 (24.0, 23.2)	23.0 (22.9, 23.2)
XGBoost with Full Model	20.5 (20.5, 20.4)	20.3 (20.4, 20.0)	17.4 (17.9, 17.0)	15.4 (15.0, 17.5)	15.2 (15.2, 15.3)	15.7 (16.1, 15.0)	17.6 (18.0, 17.8)
XGBoost with Abbreviated Model	21.9 (21.9, 21.9)	21.9 (22.0, 21.4)	19.0 (19.1, 18.7)	17.8 (17.5, 18.9)	16.9 (16.9, 17.0)	16.2 (16.9, 16.1)	19.2 (19.7, 19.2)
MAE Difference (Full - Abbreviated)	1.4 (1.4, 1.5)	1.6 (1.6, 1.4)	1.6 (1.2, 1.7)	2.4 (2.5, 1.4)	1.7 (1.7, 1.7)	0.5 (0.8, 1.1)	1.6 (1.7, 1.4)
XGBoost with Abbreviated Model + Implant Data	21.8 (21.8, 21.8)	21.8 (21.9, 21.4)	18.9 (19.1, 18.6)	17.0 (16.9, 17.8)	16.9 (16.9, 16.9)	16.2 (16.9, 16.1)	19.0 (19.2, 19.1)

566

567 **Suppl Table 23.** Comparison of Mean Absolute Error Associated with the Active External Rotation (in degrees) Predictions with the
568 Full and Abbreviated Machine Learning Models

External Rotation (°) Prediction	MAE (aTSA, rTSA) 3-6 months	MAE (aTSA, rTSA) 6-9 months	MAE (aTSA, rTSA) 1yr	MAE (aTSA, rTSA) 2-3yrs	MAE (aTSA, rTSA) 3-5yrs	MAE (aTSA, rTSA) 5+yrs	Weighted Average MAE (aTSA, rTSA)
Baseline Average	15.6 (15.5, 15.7)	15.9 (15.9, 16.0)	15.6 (15.6, 15.2)	15.5 (16.0, 14.3)	17.0 (17.2, 16.7)	17.0 (17.9, 16.8)	16.0 (16.2, 15.7)
XGBoost with Full Model	12.3 (12.2, 12.3)	12.9 (13.1, 12.6)	12.7 (13.9, 12.0)	12.0 (13.0, 11.6)	12.2 (12.9, 11.7)	10.3 (11.1, 9.2)	12.2 (13.1, 11.7)
XGBoost with Abbreviated Model	12.8 (12.8, 12.8)	13.0 (13.2, 13.0)	12.9 (13.9, 12.4)	12.2 (13.3, 12.1)	12.9 (13.0, 12.3)	11.9 (12.5, 11.0)	12.6 (13.2, 12.1)

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MAE Difference (Full Abbreviated)	-	0.5 (0.6, 0.5)	0.1 (0.1, 0.4)	0.2 (0.0, 0.4)	0.2 (0.3, 0.5)	0.7 (0.1, 0.6)	1.6 (1.4, 1.8)	0.4 (0.1, 0.4)
XGBoost with Abbreviated Model Implant Data	+	12.3 (12.3, 12.2)	12.9 (13.2, 13.0)	12.8 (13.0, 12.2)	11.9 (13.1, 11.7)	12.8 (13.0, 12.2)	11.9 (12.5, 11.0)	12.4 (13.1, 12.0)

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