Personalized Biomechanics: Computational Modeling & Simulation for Total Shoulder Arthroplasty

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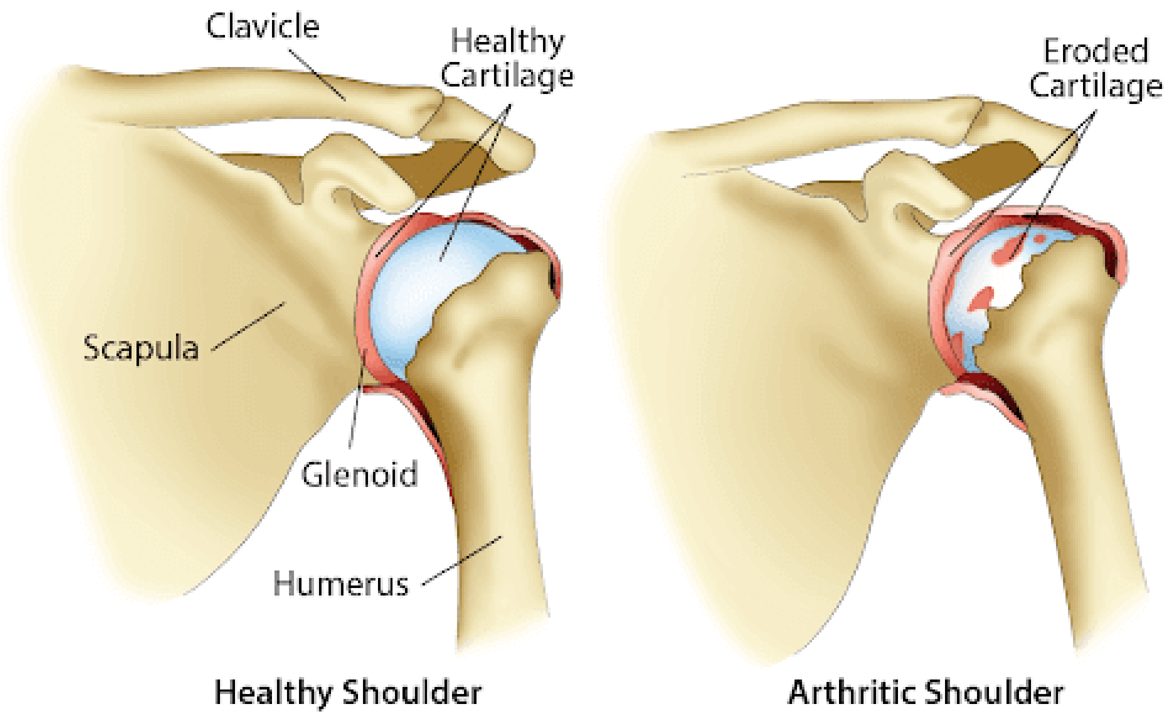
Overview

- Clinical background
- Research methods (LBO experience)
- Clinical, Cadaveric, Modeling
- MusculoSkeletal Modeling
- Finite Element Modeling
- Deep-Learning Modeling
- Populated models
- Causal Bayesian statistics
- Conclusions

Clinical background: joint degeneration



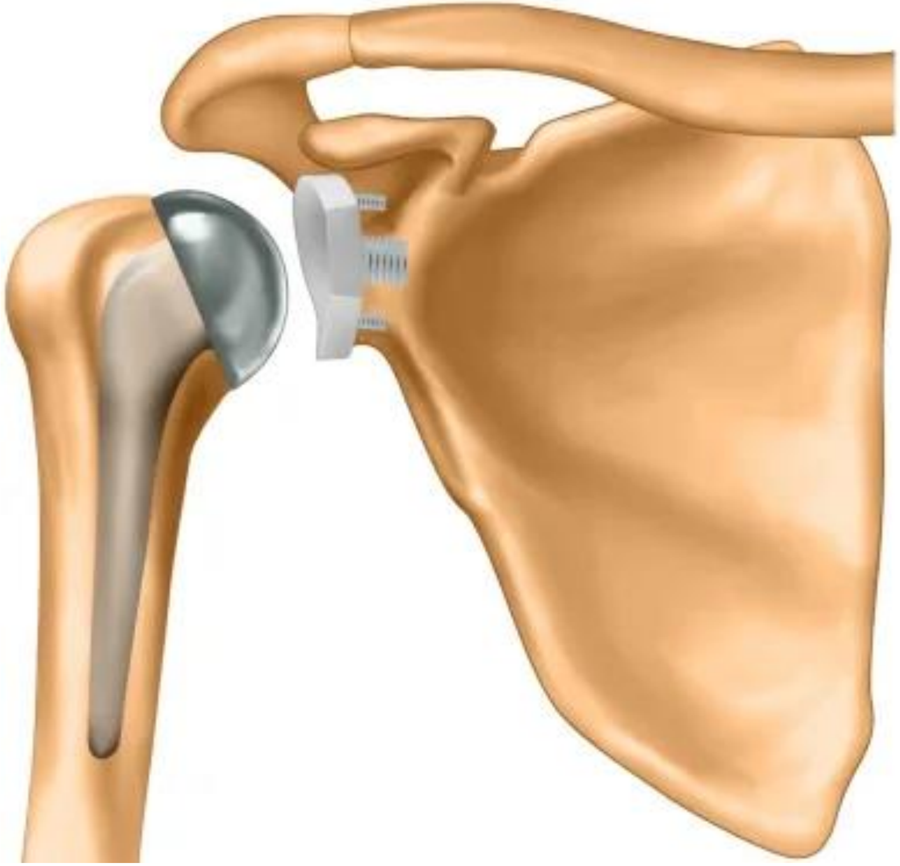
https://centenoschultz.com/condition/shoulder-arthritis/

- Osteoarthritis (OA) world's most common joint disease
- Currently no cure
- Glenohumeral osteoarthritis (GHOA) accounts for 5%–17% of patients with shoulder complaints
- Etiology of GHOA is multifactorial

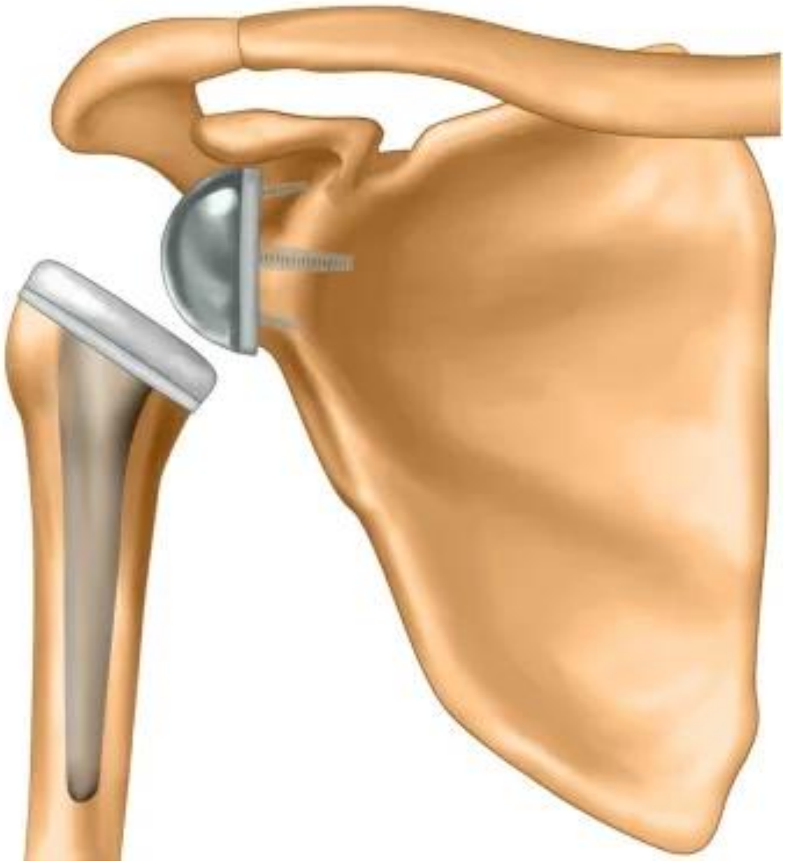
https://doi.org/10.1177/1457496920935018

Clinical background

Anatomic Total Shoulder Arthroplasty
(ATSA)



Reverse Total Shoulder Arthroplasty
(RTSA)



Sanchez-Sotelo et al., doi: 10.2174/1874325001105010106, Valsamis et al., doi: 10.1136/bmj-2023-077939

Complications of Shoulder Arthroplasty

- Meta-analysis of Bohsali et al. (2017)
  - 2006 - 2015, 122 studies, mean follow-up 40.3 months

- ATSA (3360 cases)
  - Complication rate: 10.3%
  - Most frequent: component loosening, glenoid wear, instability

- RTSA (4142 cases)
  - Complication rate: 16.1% for RTSA
  - Most frequent: instability, periprosthetic fracture, infection

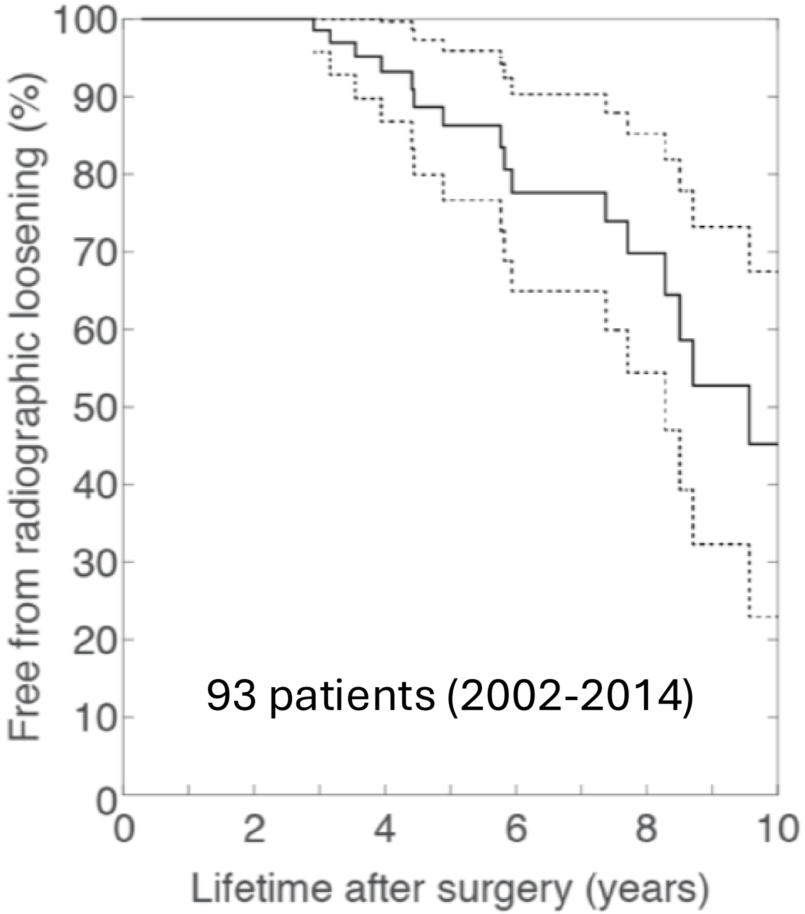
Bohsali KI, Bois AJ, Wirth MA. Complications of Shoulder Arthroplasty. J Bone Joint Surg Am. 2017 Feb 1;99(3):256–69.

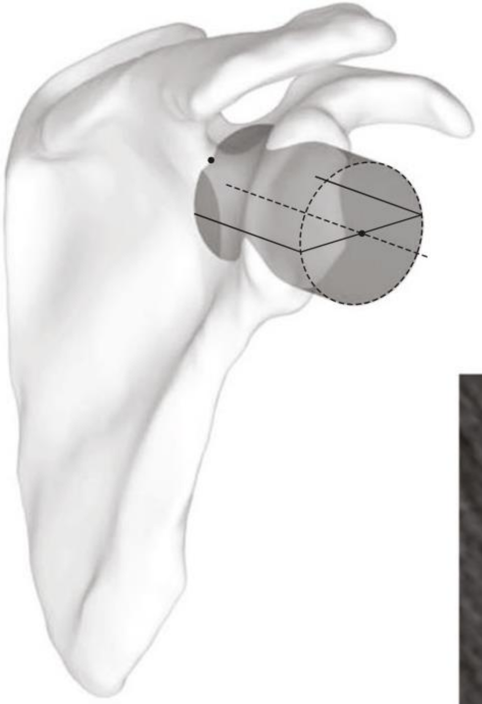
Methods to understand/reduce complications

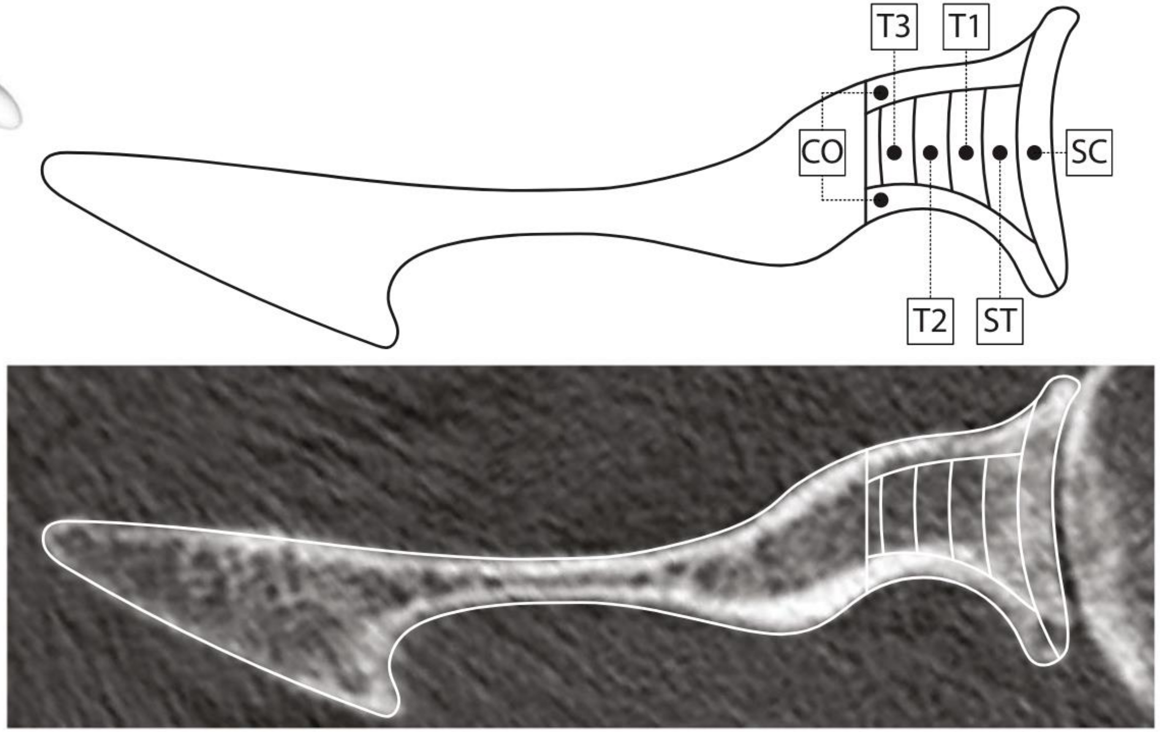
- Clinical trials (randomized multicenter double-blind)
  - Strongest evidence, but time-consuming and expensive
- Cadaveric experiments
  - Realistic anatomy and biomechanics, but not cheap, not clinical reality
- Numerical modeling
  - Fast, cheap, control all variables, but simplification, validation
- In-silico trials
  - Same as above +
  - Personalization, ethical, but requires a lot of (high-quality) data

Clinical trial example

Is preoperative glenoid bone mineral density associated with aseptic glenoid implant loosening in anatomic total shoulder arthroplasty?



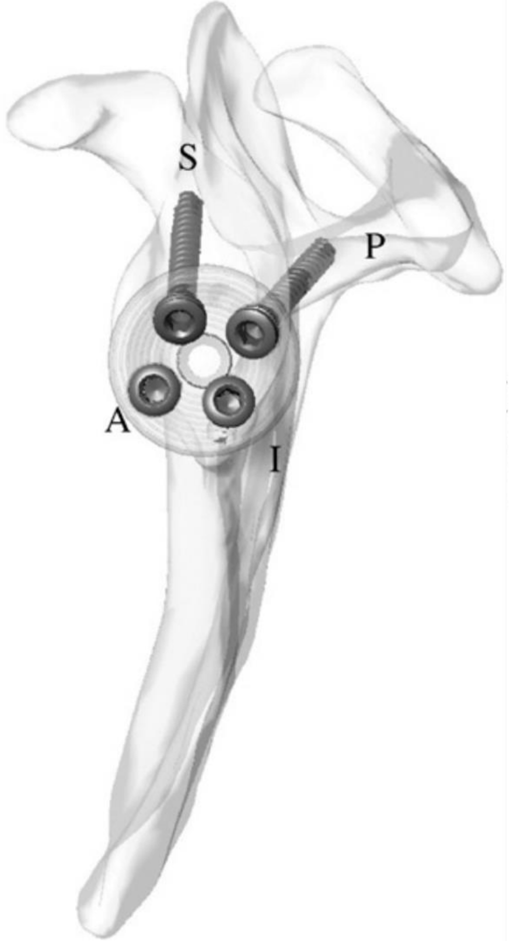


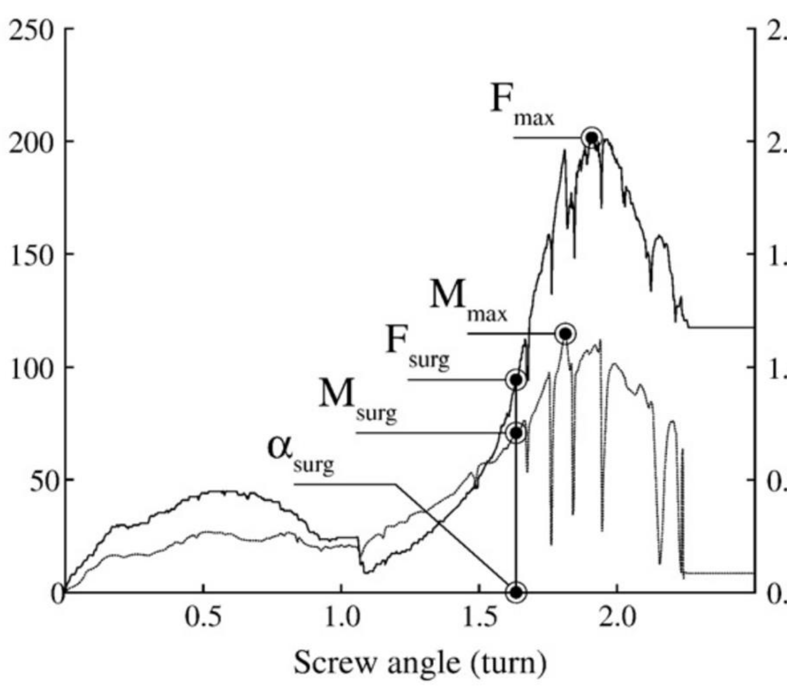


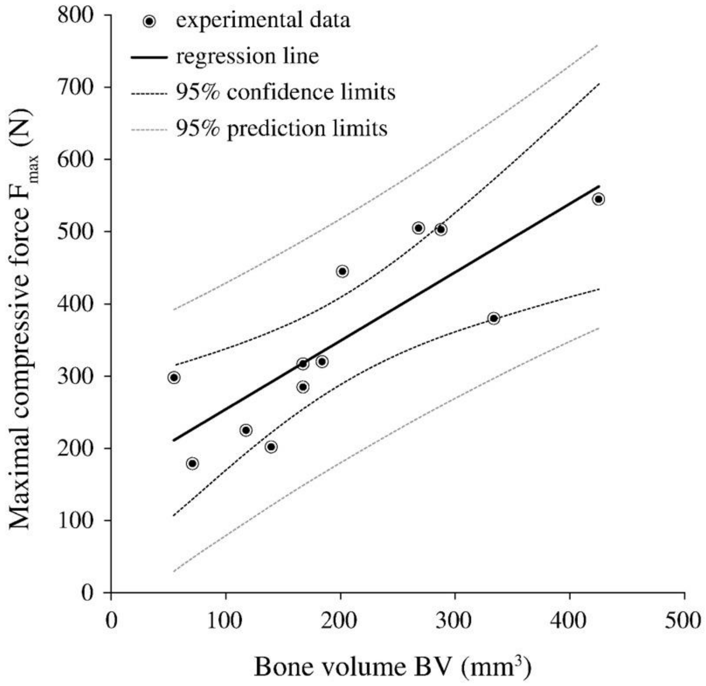
https://doi.org/10.1186/s12891-020-03892-0

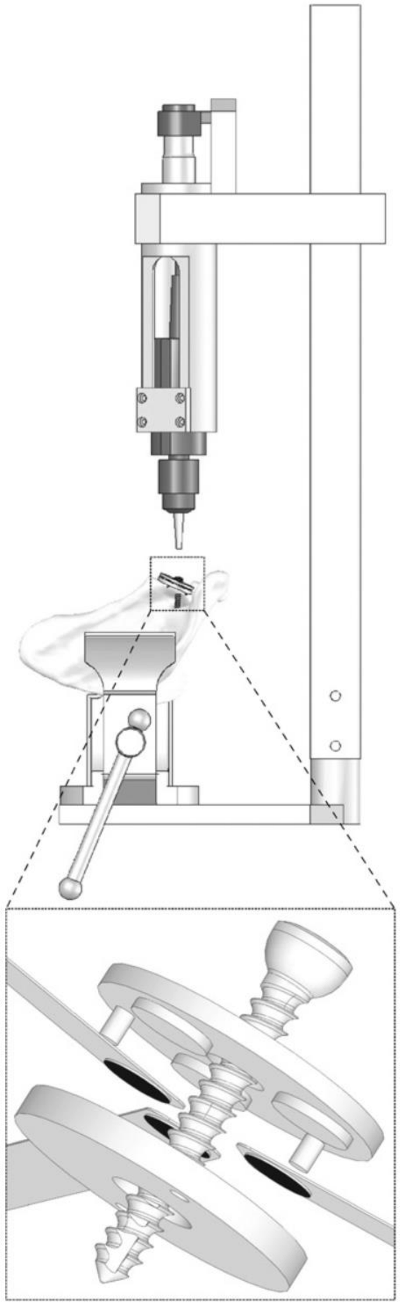
Cadaveric experiment example

Tightening force and torque of nonlocking screws in a reverse shoulder prosthesis





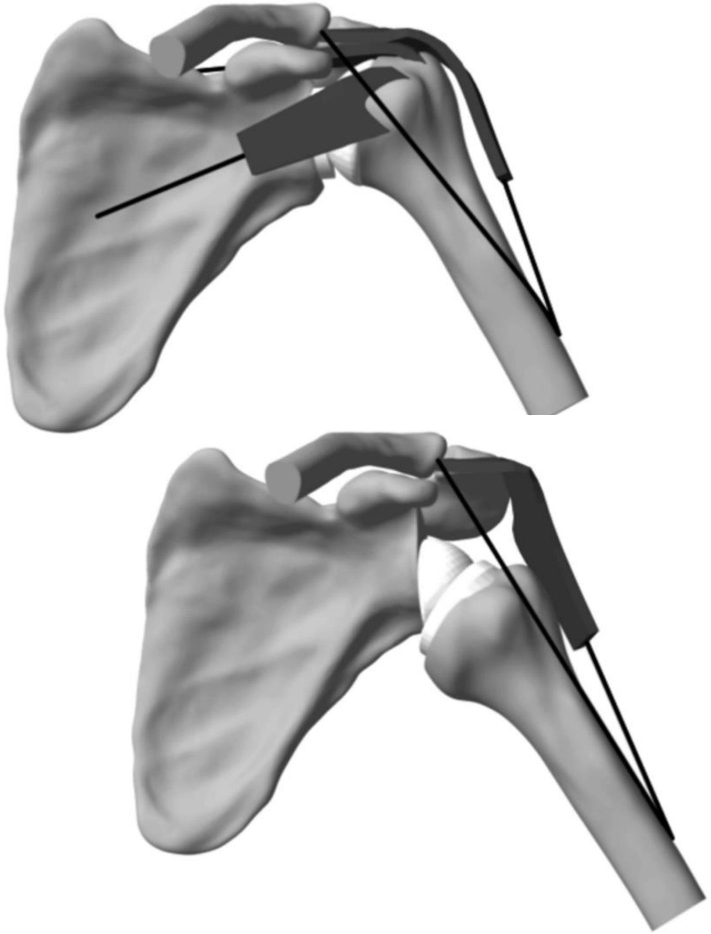


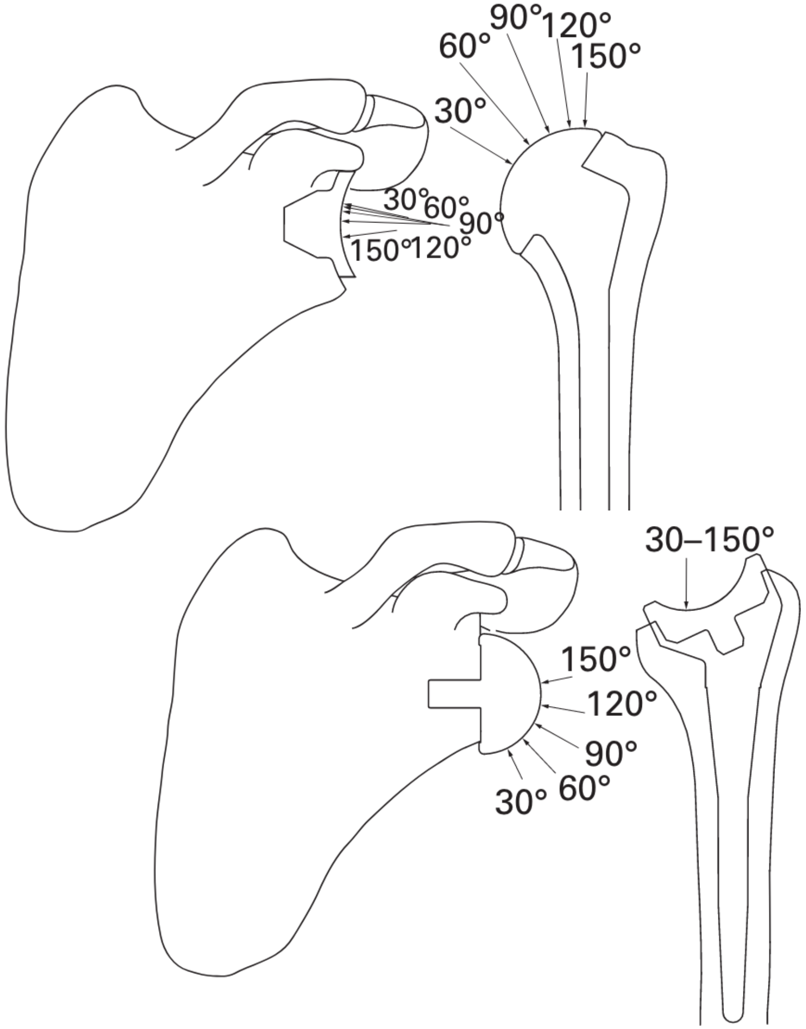


https://doi.org/10.1016/j.clinbiomech.2010.03.011

Numerical model example

Simulated joint and muscle forces in reversed and anatomic shoulder prostheses

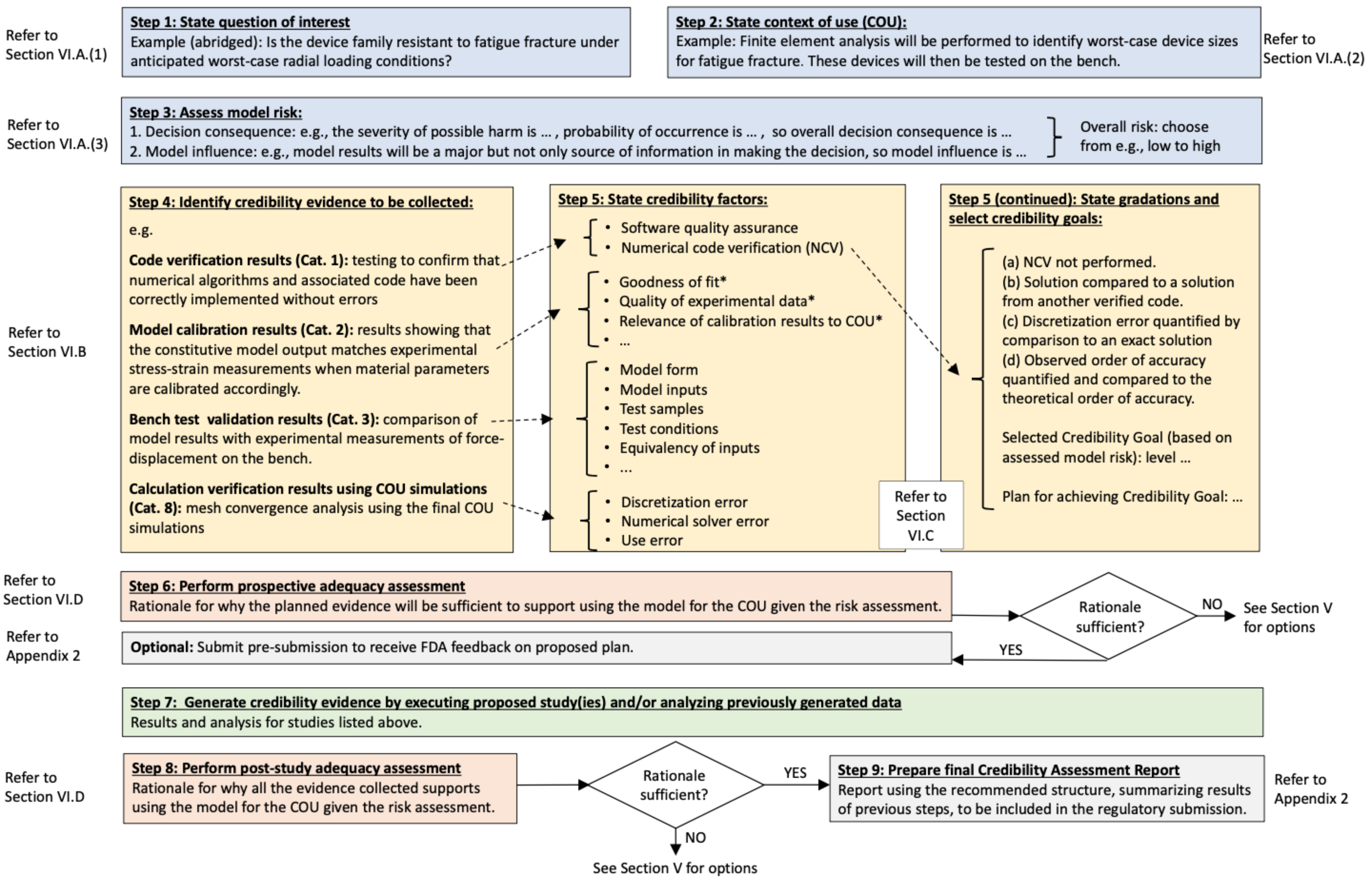




https://doi.org/10.1302/0301-620X.90B6.19708

Assessing the Credibility of Computational Modeling and Simulation in Medical Device Submissions (2023)

FDA U.S. FOOD & DRUG ADMINISTRATION
CENTER FOR DEVICES & RADIOLOGICAL HEALTH



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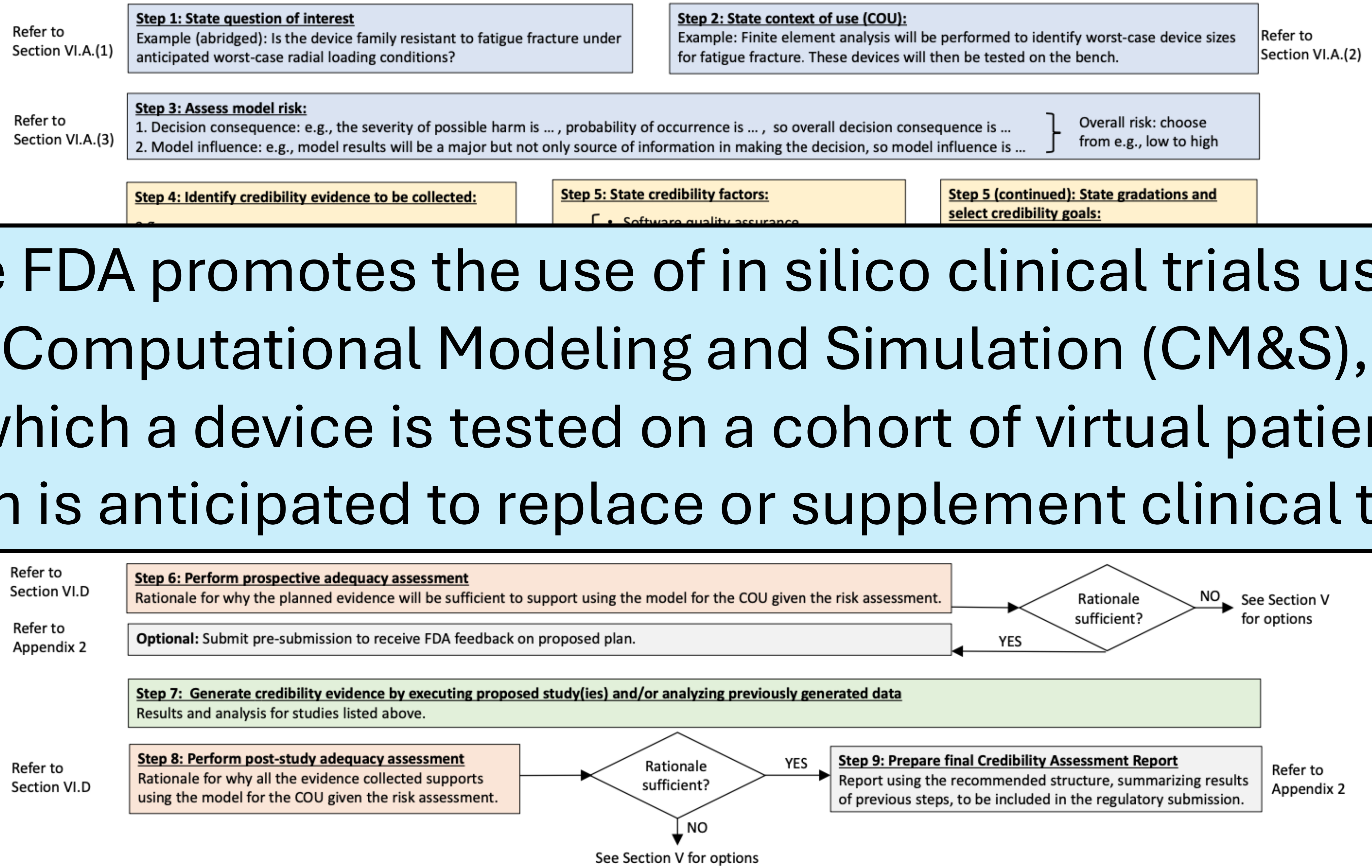


The FDA promotes the use of in silico clinical trials using Computational Modeling and Simulation (CM&S), in which a device is tested on a cohort of virtual patients, which is anticipated to replace or supplement clinical trials.

Comments on FDA recommendations

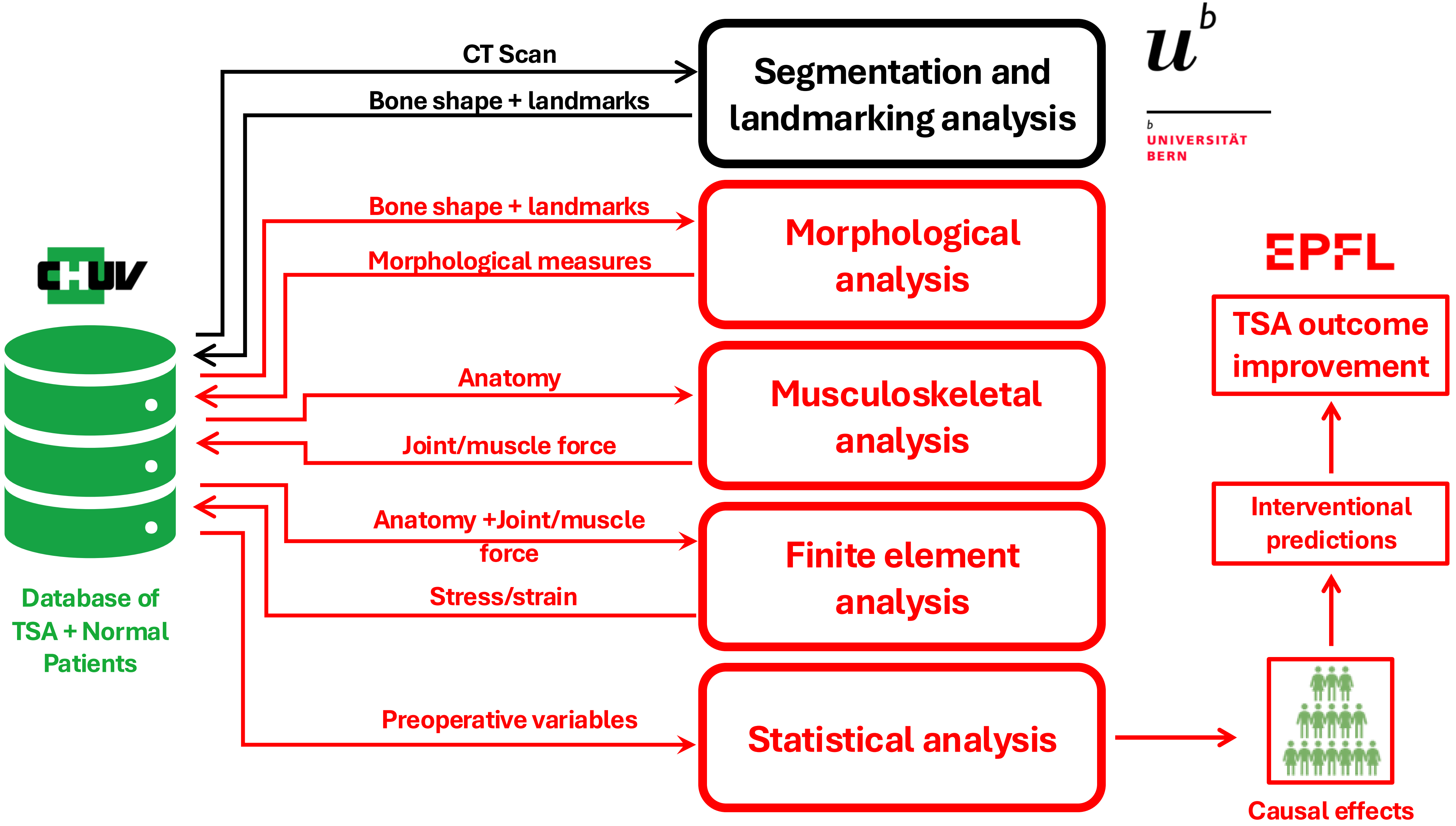
- Risk analysis
  - Uncertainty of simulation predictions
  - Potential adverse effect of false prediction
- Virtual vs real patients
  - Link with real outcome (for virtual patients)
- Link between simulated quantities and clinical quantities

Computational modeling

- Importance of Finite Element Modeling (FEM)
- Create FEM from cadaveric data (one or few cases)
- Create FEM from patient data (one or few cases)
- Create FEM from (many) virtual/real patients

- Difficulty in automating the process for a large number of patients
- Importance of statistical methods
- Manage patient variability

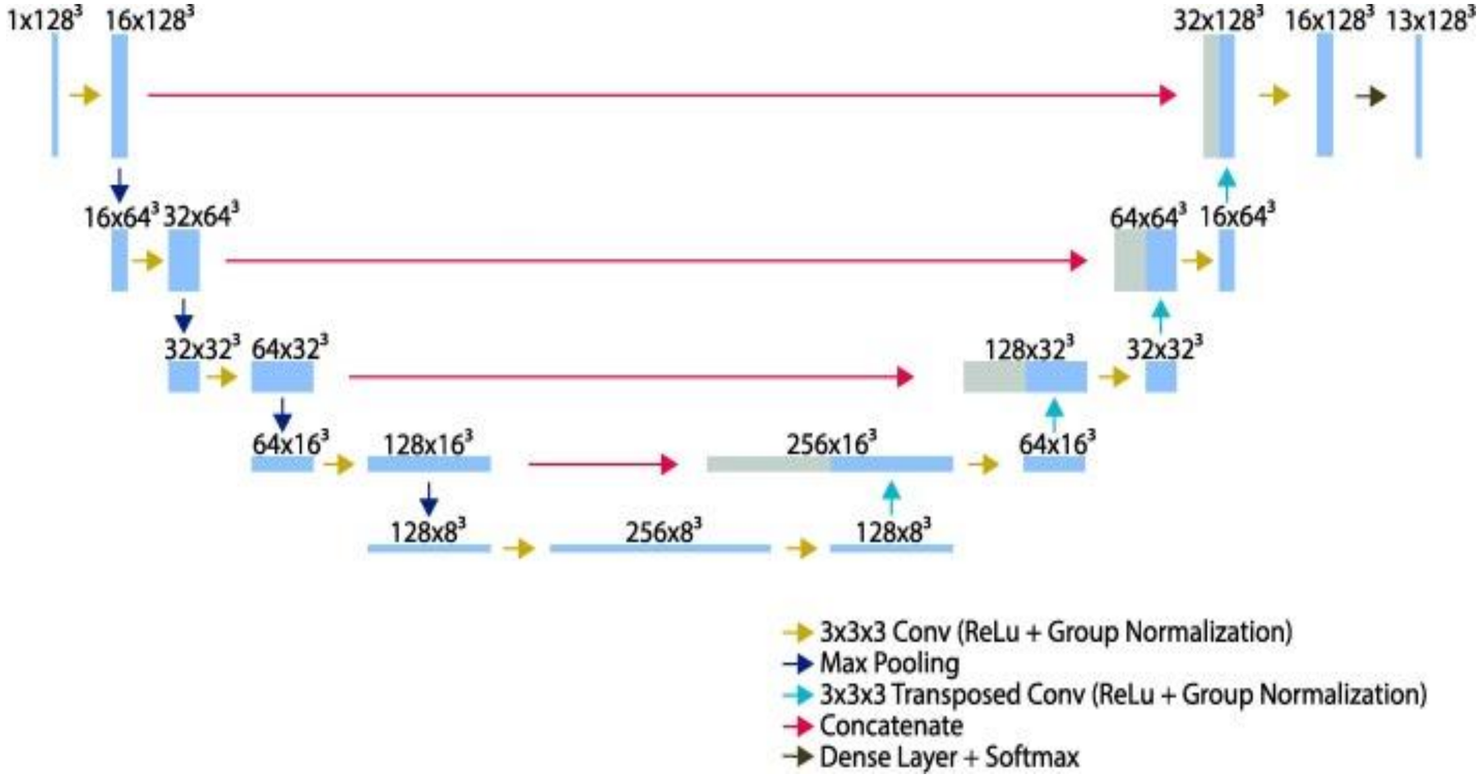
Project: Effect of preop on TSA complications

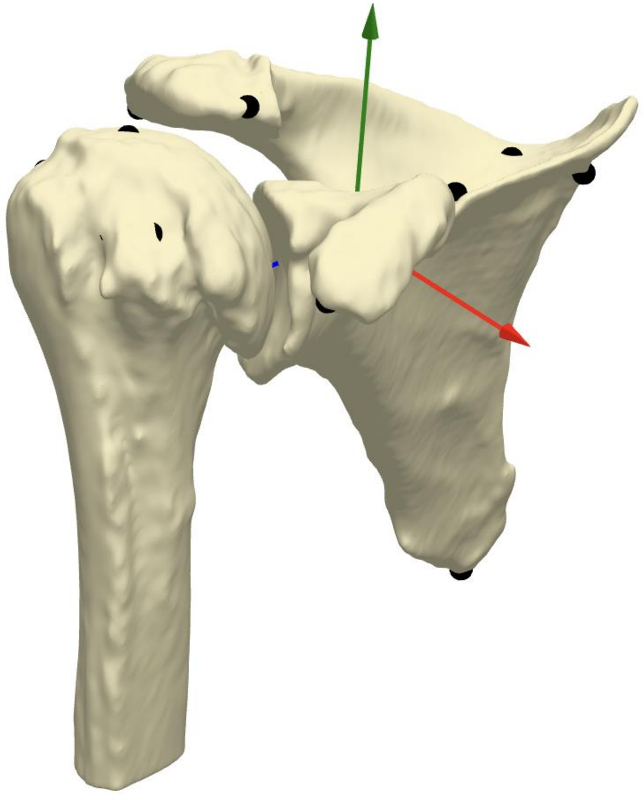


Deep Learning Model for segmentation

Preop CT scan → surface + anatomical landmarks of scapula + humerus

modified U-Net architecture for segmentation & landmark localizations

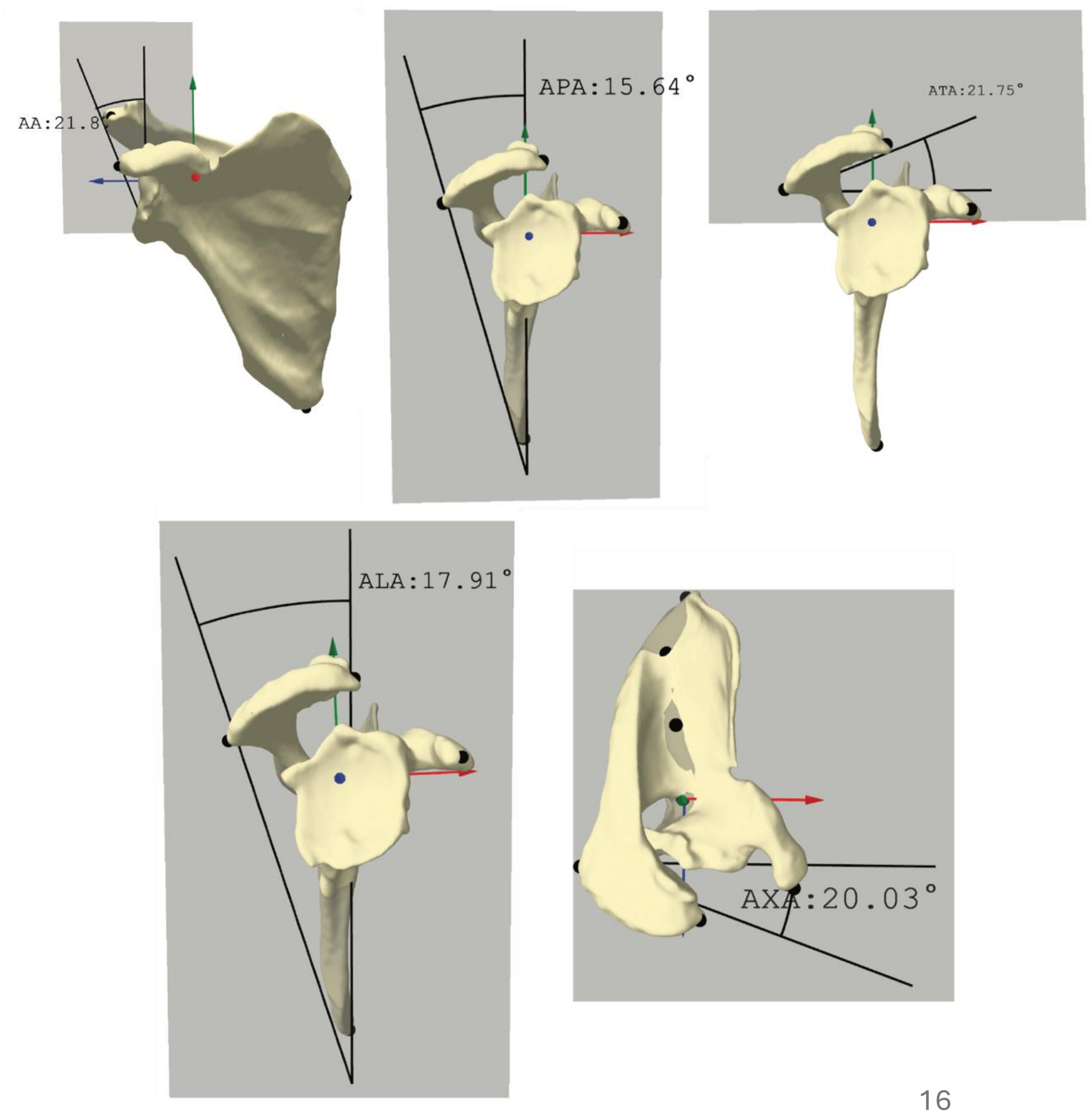




Satir et al., doi:10.1016/j.ejrad.2024.111588

Morphological analysis

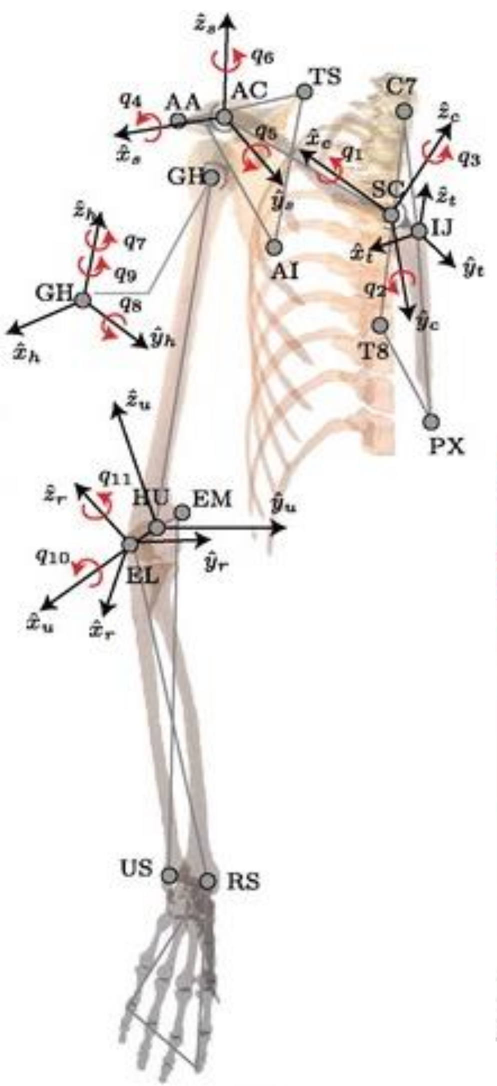
- Glenoid version angle (GVA)
- Glenoid inclination angle (GIA)
- Glenoid bone mineral density (BMD)
- Acromion angle (AA)
- Acromion posterior angle (APA)
- Acromion tilt angle (ATA)
- Acromion length angle (ALA)
- Acromion axial tilt angle (AXA)
- Rotator Cuff Degeneration
- Bone quality

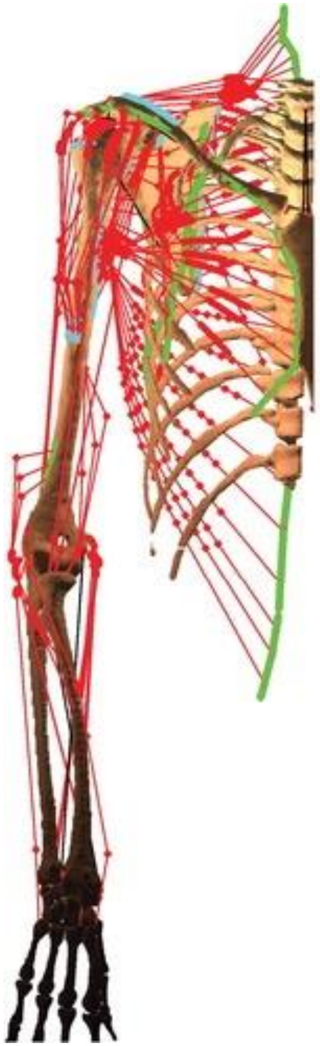


Eghbali et al., doi: 10.1002/jor.25379

MusculoSkeletal Model

A Matlab toolbox for scaled-generic modeling of shoulder and elbow



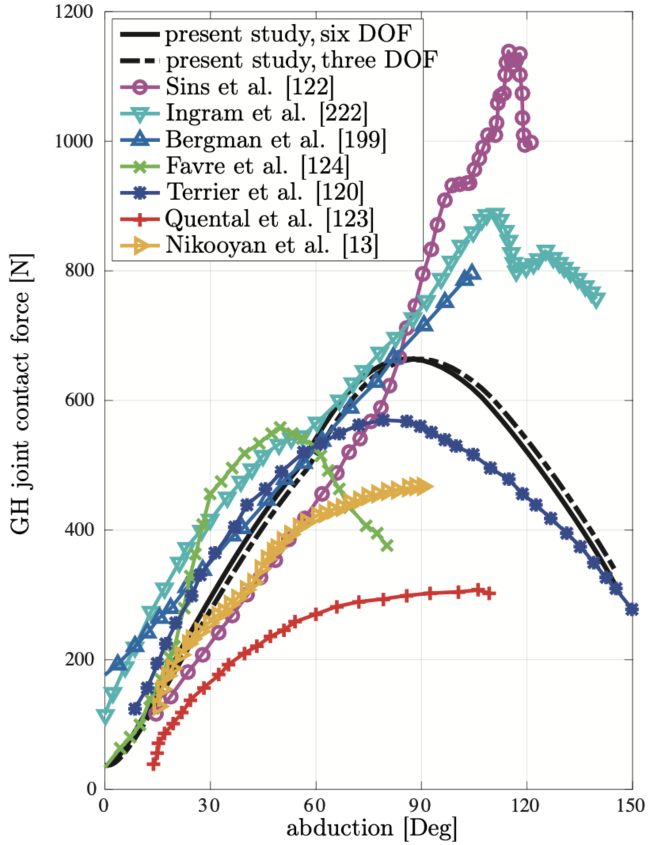


$$\min_{\tilde{\boldsymbol{f}}} \; \tilde{\boldsymbol{f}}^T P \tilde{\boldsymbol{f}}$$

$$\text{s.t.} \quad \frac{d}{dt}\left(\frac{\partial \mathscr{L}}{\partial \dot{\boldsymbol{q}}}\right) - \frac{\partial \mathscr{L}}{\partial \boldsymbol{q}} = \left[\frac{\partial \Omega}{\partial \dot{\boldsymbol{q}}} W \; \frac{\Phi_{\mathrm{TS}}}{\partial \boldsymbol{q}} \; \frac{\Phi_{\mathrm{AI}}}{\partial \boldsymbol{q}}\right] \tilde{\boldsymbol{f}}$$

$$\boldsymbol{0} \leq \tilde{\boldsymbol{f}} \leq \tilde{\boldsymbol{f}}_{\max}$$

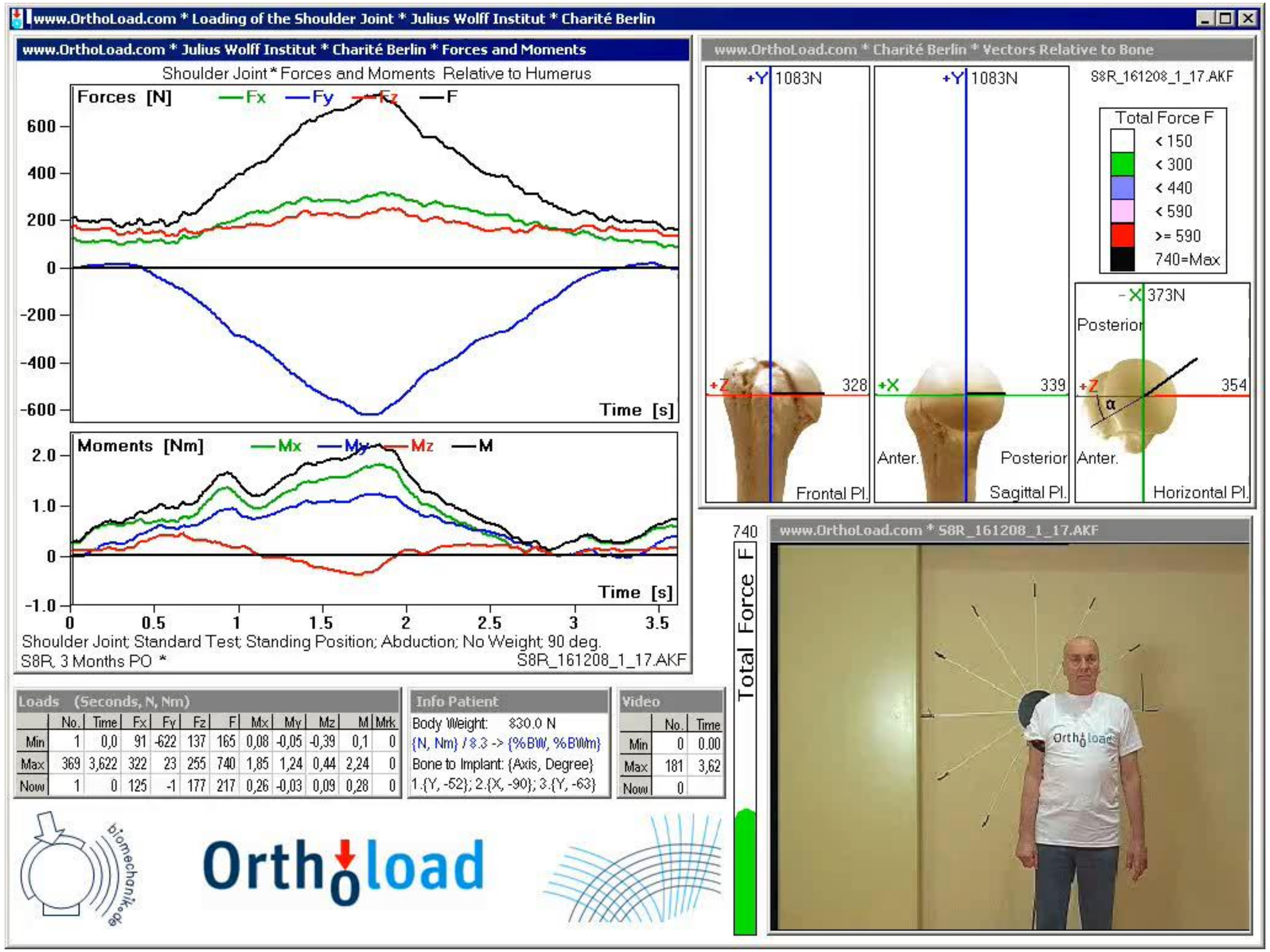
$$\boldsymbol{\psi}(\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}}, \tilde{\boldsymbol{f}}) \leq \boldsymbol{0}$$



https://www.nature.com/articles/s41598-021-99856-y

Measured joint force

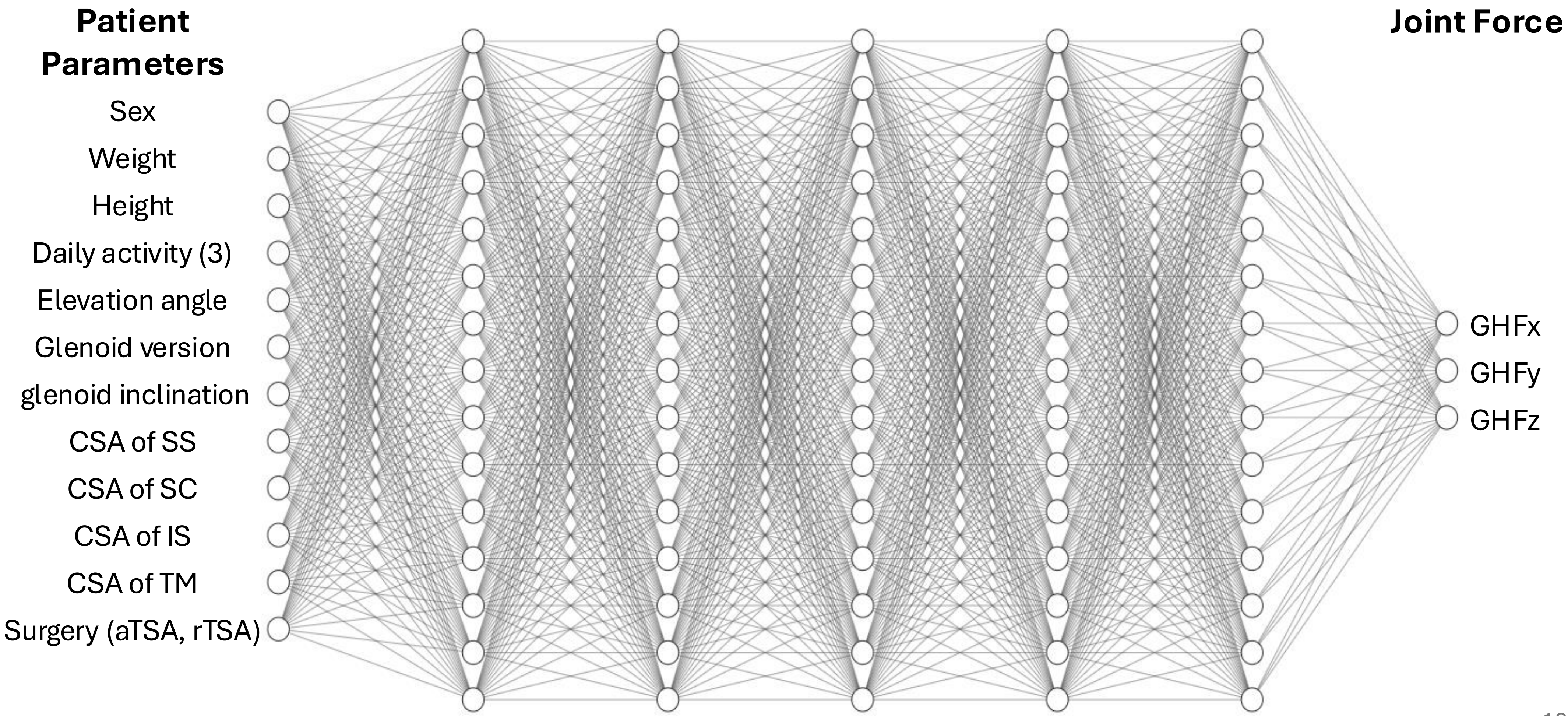
Instrumented Prosthesis



https://orthoload.com

Musculoskeletal Model → Deep Learning Model

Glenohumeral joint force prediction with deep learning



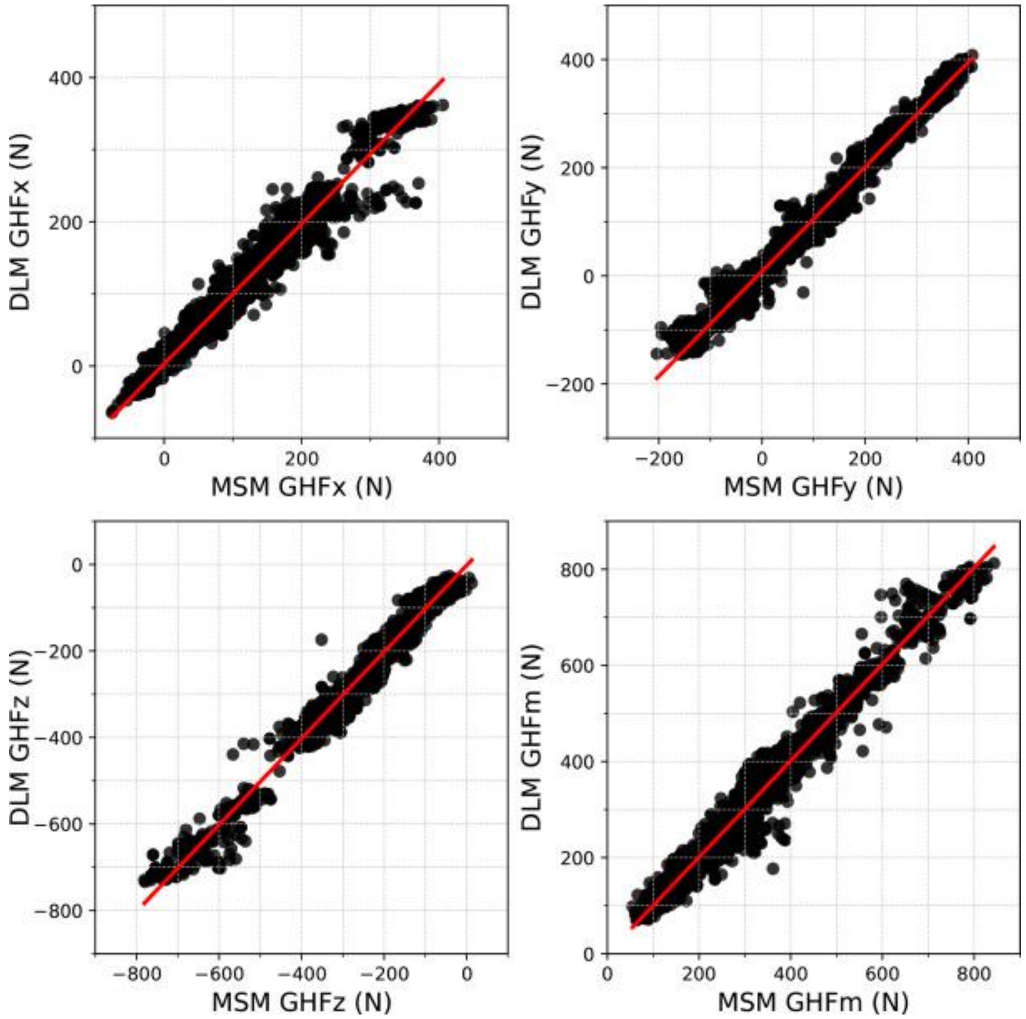
https://doi.org/10.1016/j.jbiomech.2024.111952

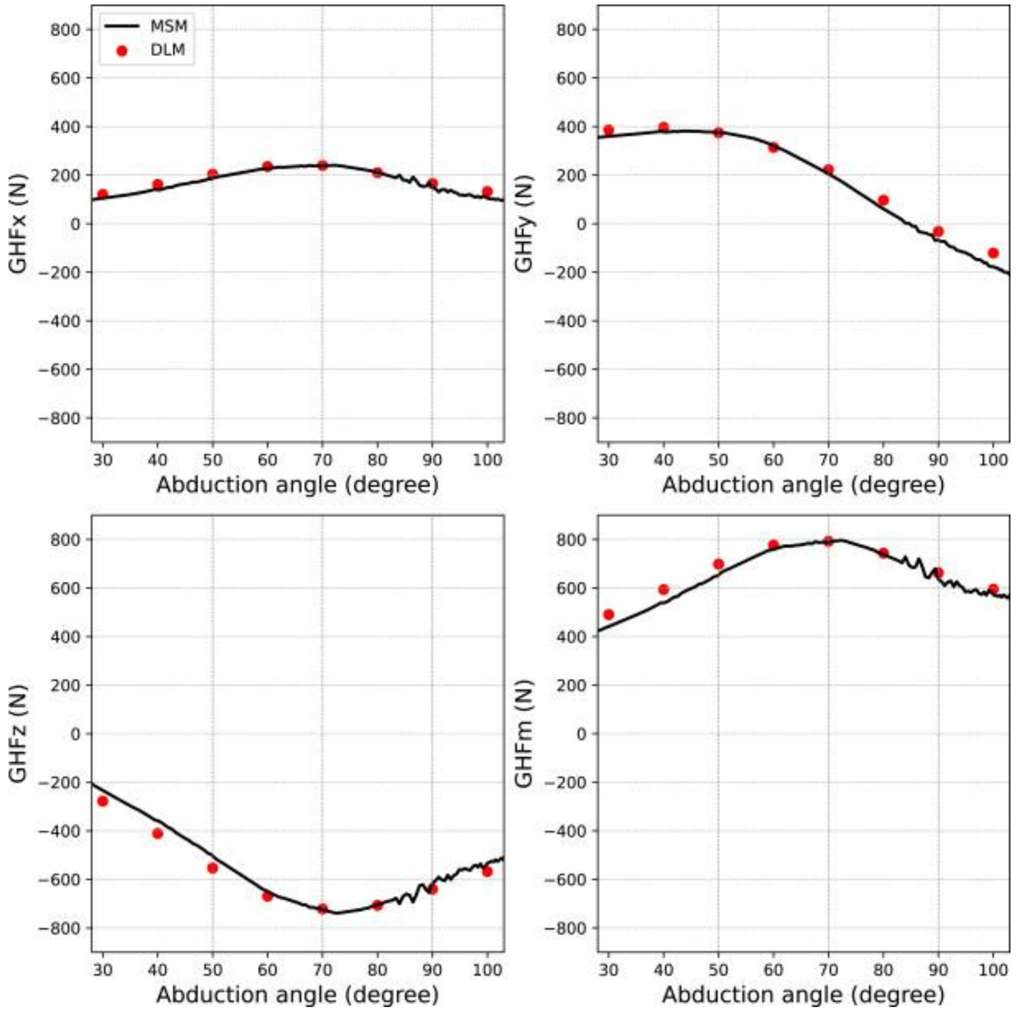
Musculoskeletal Model → Deep Learning Model

- 959 virtual subjects
  - Sampling from clinical registry with Markov-Chain-Monte-Carlo
- Training (80% of subjects)
  - Fully-connected neural network
  - Training: backpropagation algorithm, descent gradient, minimize loss function
  - Validation: hyperparameters tuning with Bayesian optimization
    - k-fold validation (k=5 → 80% training & 20% validation)

      → 7 hidden layers of 250, 20, 250, 160, 90, 90, 100 neurons
  - Monte-Carlo drop-out (to avoid overfitting)
- Testing (20% of subjects, unseen by training)
  - Evaluating model efficiency

Musculoskeletal Model → Deep Learning Model

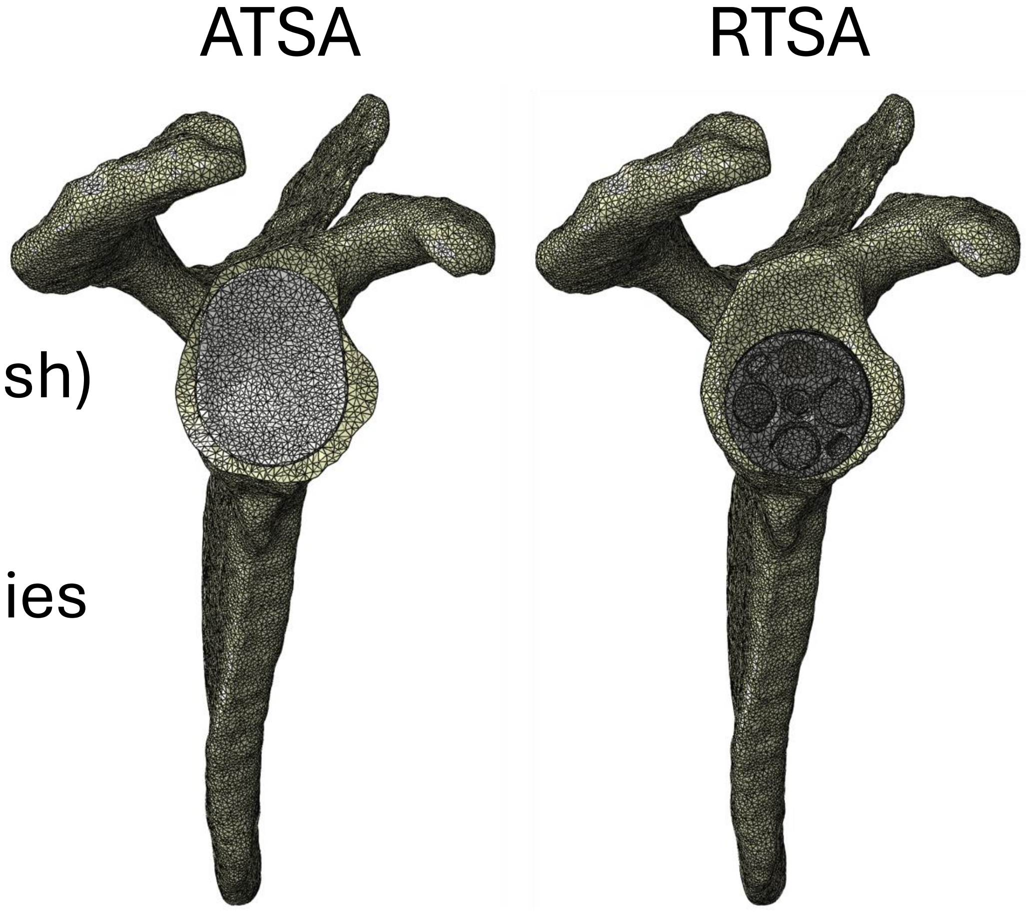




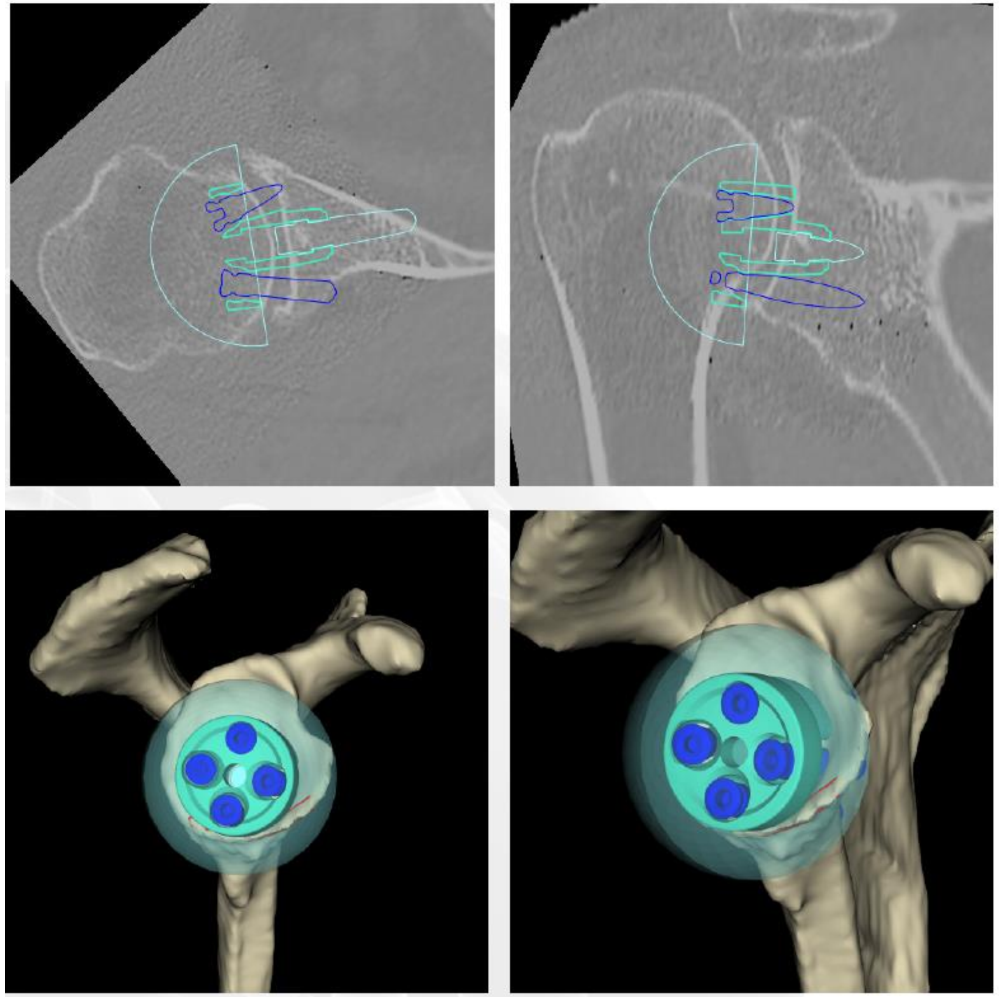
GHFm: Mean Absolute Error = 18.5 N, $R^2 = 0.97$

Automated Finite Element Model

- Bone geometry from DL segmentation
- Implant selection and positioning
  (From preoperative planning)
- Scapula and implant tetrahedral mesh (Gmsh)
- Bone reaming (PyMesh)
- Bone inhomogeneous linear elastic properties
  from preoperative CT
  (Python code)
- Force from DL MSM



Preoperative planning



```
GlenoidImplant_PartNumber;DWJ505;;DWJ505
GlenoidImplant_PerformReversedPerforation;0;;0
GlenoidImplant_PerformReversedBasePlate;Wedge;Type de platine;Wedge
GlenoidImplant_PerformReversedBasePlateIsStandard;0;;0
GlenoidImplant_PerformReversedDiameter;25;Diamètre de la platine;25 mm
GlenoidImplant_PerformReversedOffset;0;Offset de la platine;0 mm
GlenoidImplant_PerformReversedAngle;Full;Angle de la platine;Full
GlenoidImplant_PerformReversedFixation;Central Screw;Fixation;Vis centrale
GlenoidImplant_PerformReversedFixationIsCentralPost;0;;0
GlenoidImplant_PerformReversedScrewDiameter;6.5;Diamètre de vis;6.5 mm
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GlenoidImplant_PerformReversedCentralScrewPartNumber;DWJ530;;DWJ530
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GlenoidImplant_Version;-9;Rétroversion glénoïdienne;9°
GlenoidImplant_EntryPoint;(66.590668, 92.804176, 129.965637);;(66.590668, 92.804176, 129.965637)
GlenoidImplant_DrillPoint;(66.590668, 92.804176, 129.965637);;(66.590668, 92.804176, 129.965637)
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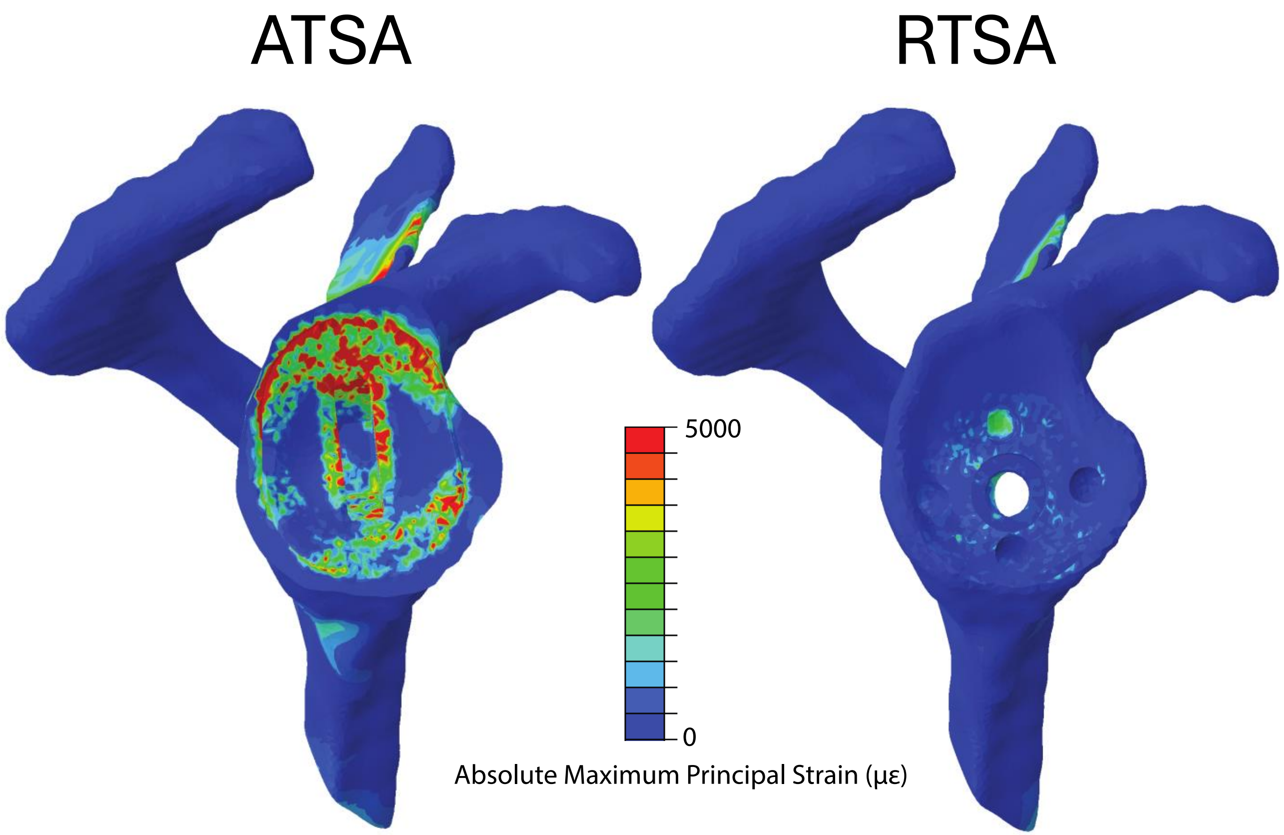
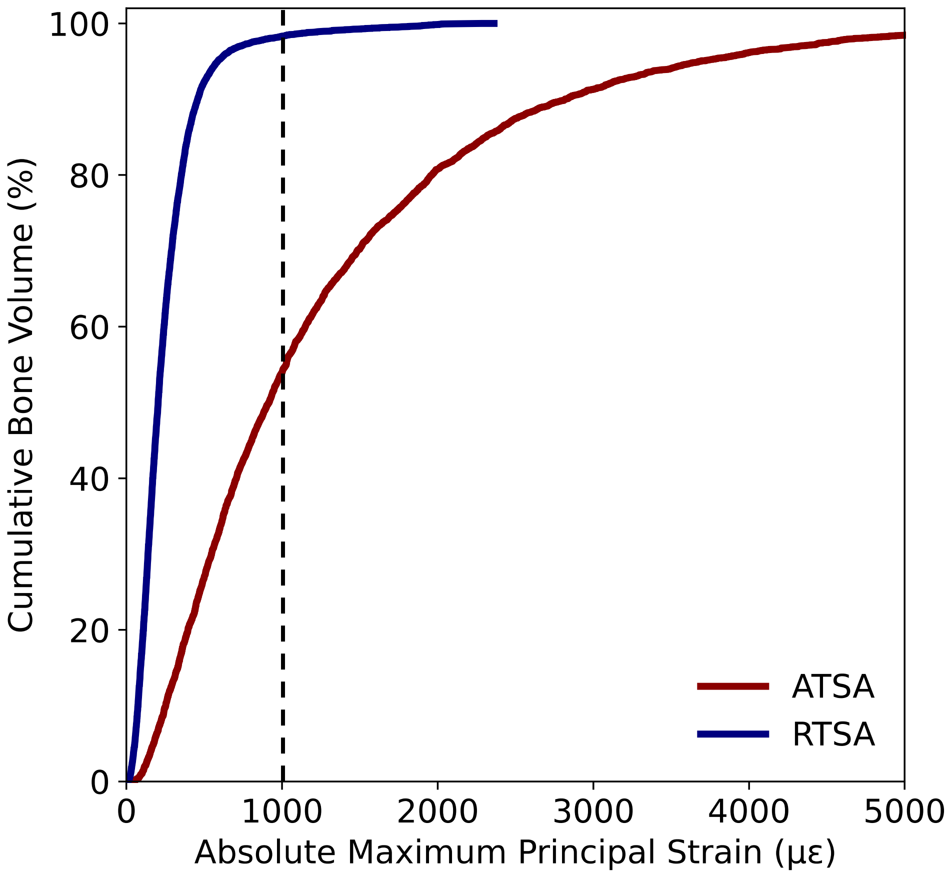
Automated Finite Element Model

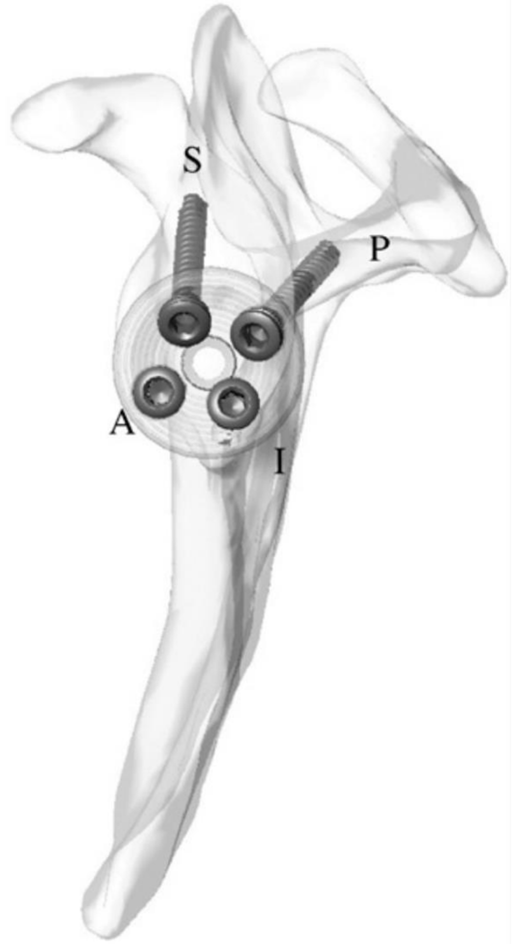




Volume Of Interest (VOI): 10 mm around the prosthesis

Effect of screws in baseplate stability

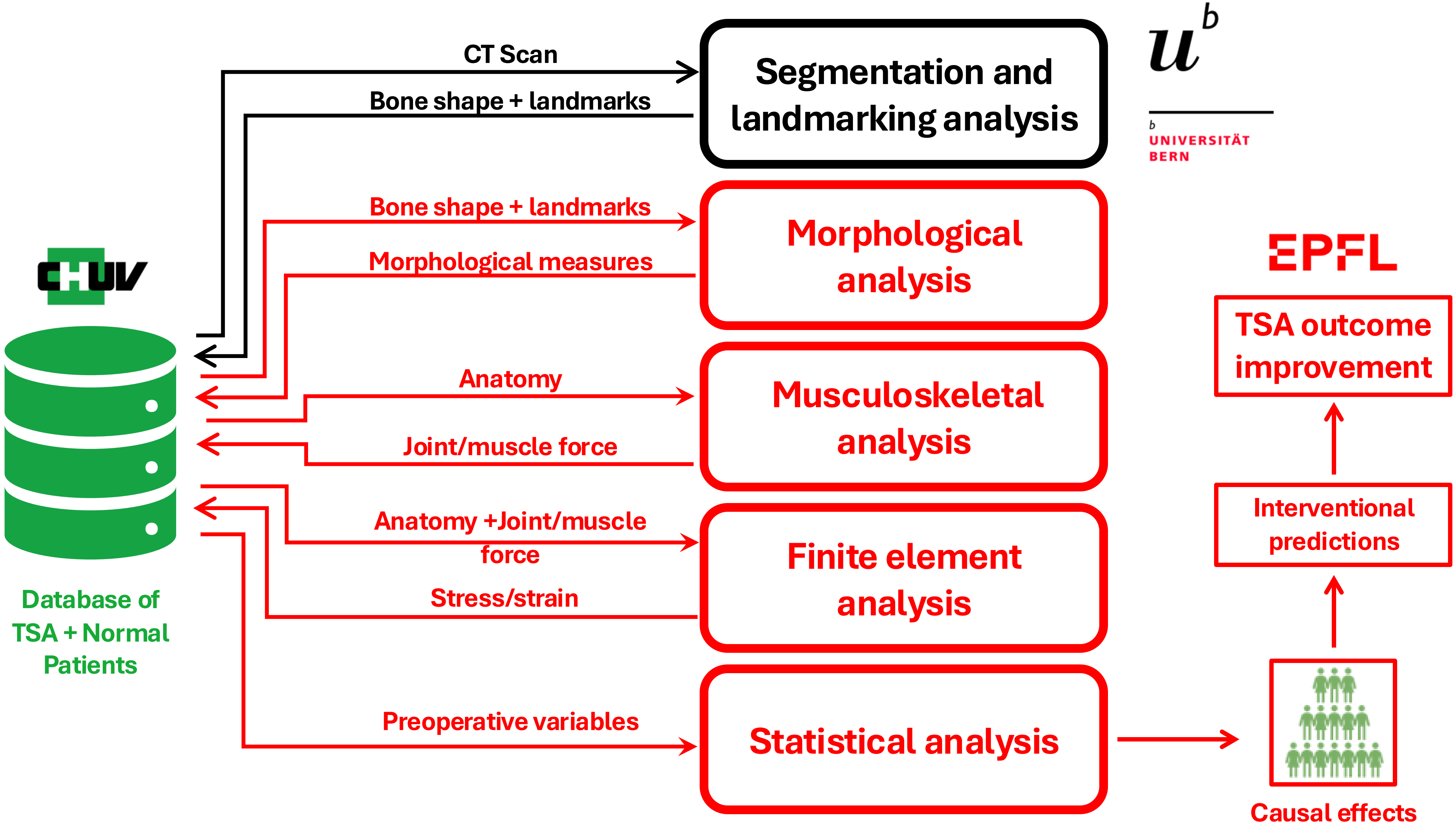
- 4 (standard) vs 2 screws (inf & sup)
- 10 patients (5 females, 56-87 years) planned for RTSA
- Joint force at 60 degrees of abduction
- Bone volume exceeding 1000 $\mu\varepsilon$ (BVACS)
- Difference in %BVACS between 4 & 2 screw < 1%
- Results suggest safe to only use the sup. & inf. screws



Automation

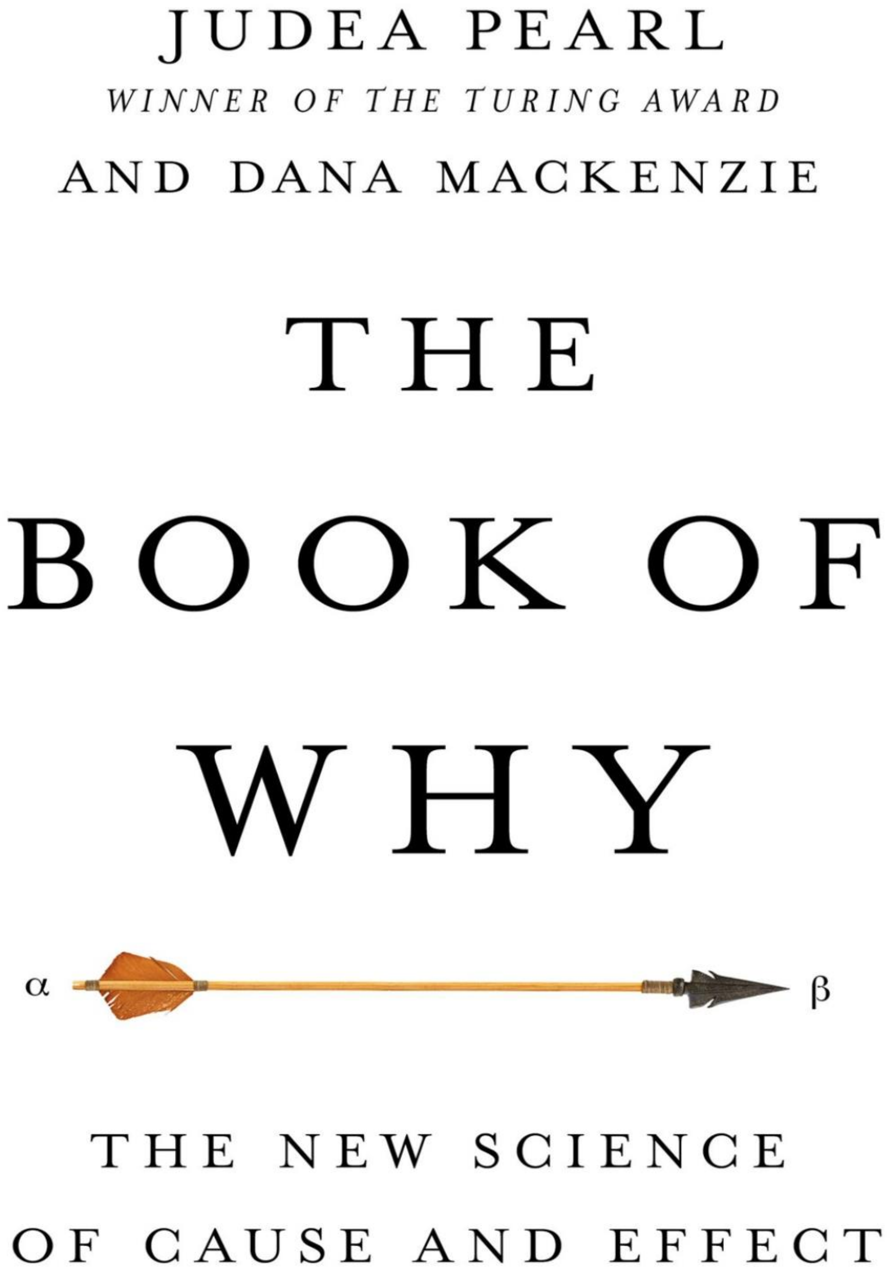
- Entire process controlled by Python workflow
  - CT, patient clinical data (sex, age, weight)
  - Deep-Learning Model → Bone and muscle anatomy, quality
  - Musculoskeletal model → Muscle and joint force
  - FE → Bone strain
  - Merge the clinical and biomechanical data of patients

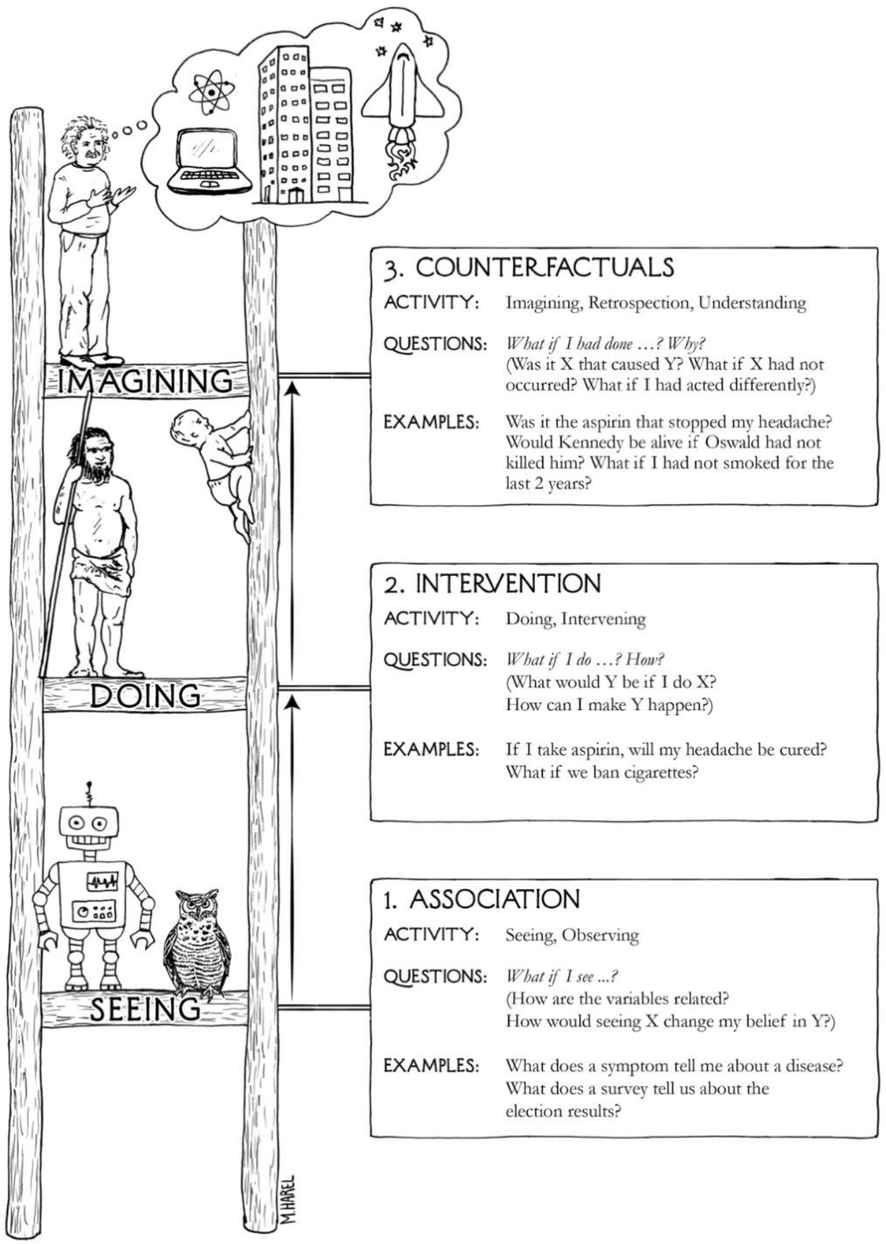
Project: Effect of preop on TSA complications



Statistics

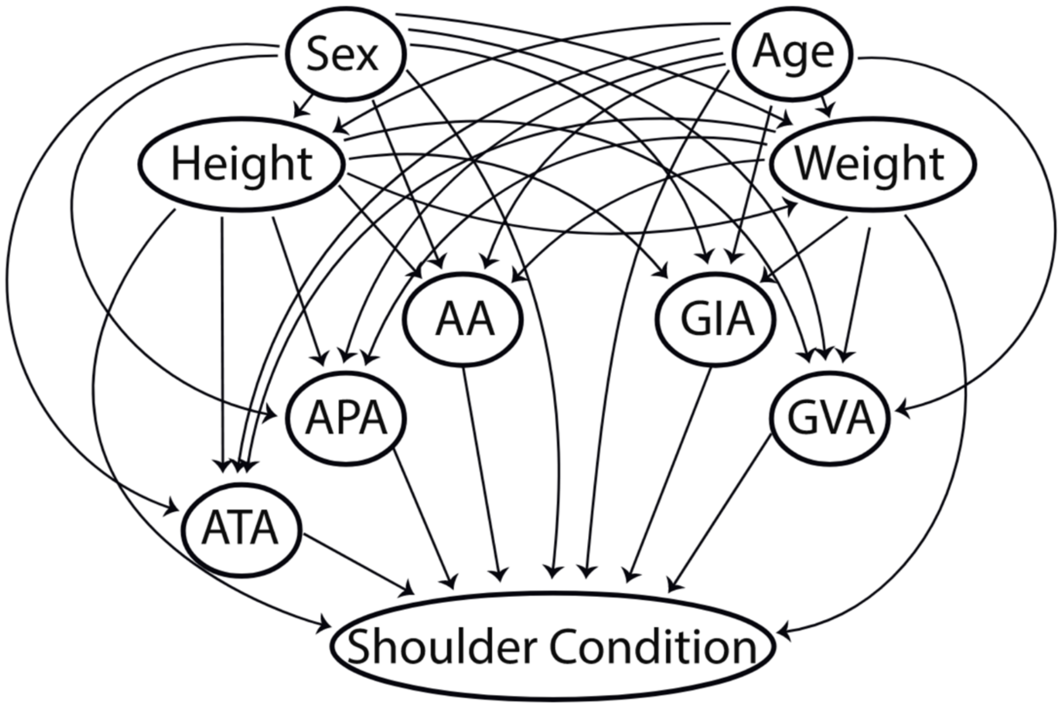
- Why?
  - Accounting for patient variability
- Association inference
  - Correlation between bone morphology/quality and mechanical strength
  - Problem of confounding variables in correctly estimating an effect
    - Both cause and effect variables dependent on a third confounding variable
- Causal inference
  - Is aging causing bone strength to decrease?
  - “Association is not causation”
  - Counterfactual “what if” questions

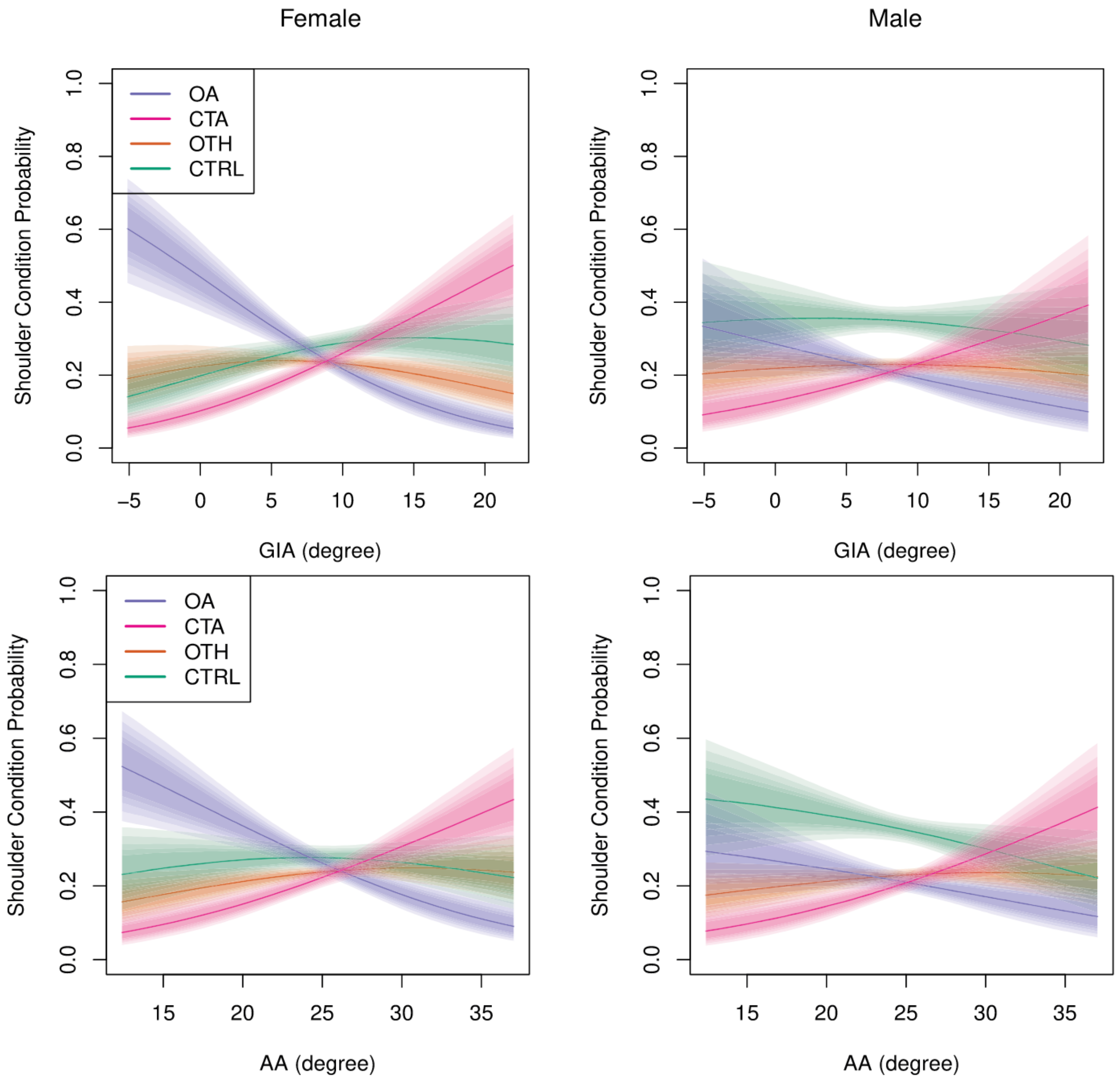




ISBN-13: 9780141982410

Causal associations between scapular morphology and shoulder condition estimated with Bayesian statistics





https://doi.org/10.1016/j.cmpb.2025.108666

Conclusion

- Computer modeling and simulation for in silico clinical trials
- Engineering background
- Link with clinical world (Surgeon, Patient, Ethics,…)
- Question-driven research
- Critical thinking