CONFLUENT

# A Probabilistic Approach with Built-in Uncertainty Quantification for the Calibration of a Superelastic Constitutive Model from Full-field Strain Data

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# Acknowledgements


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- The findings and conclusions in this article have not been formally disseminated by the U.S. FDA and should not be construed to represent any agency determination or policy. The mention of commercial products, their sources, or their use in connection with material reported herein is not to be construed as either an actual or implied endorsement of such products by the Department of Health and Human Services.

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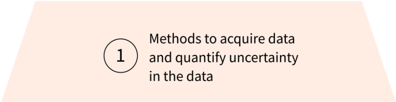

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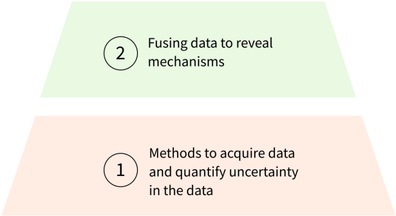

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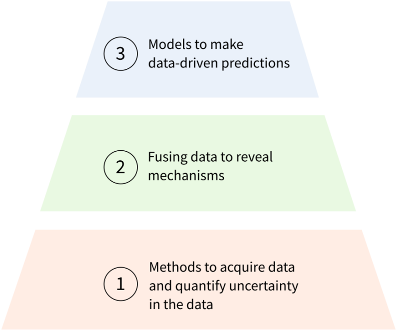

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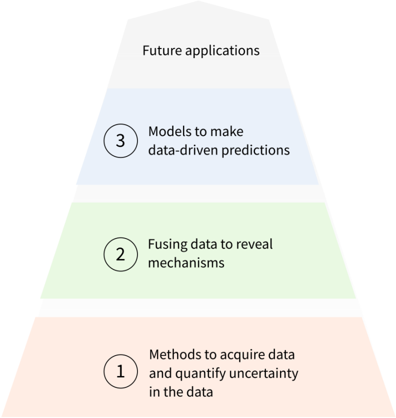

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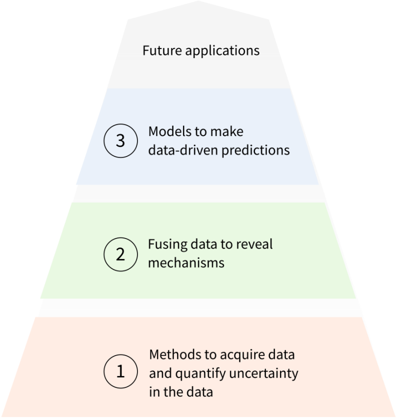

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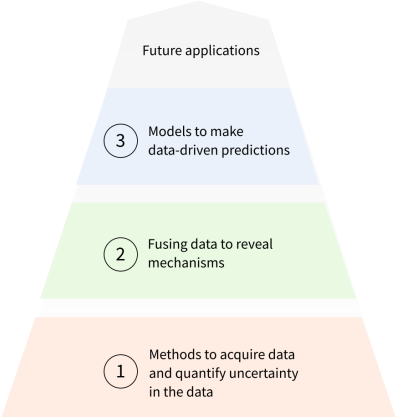
- End goal: Make data-driven prediction of implant deformation, fatigue susceptibility under in-vivo boundary condition.



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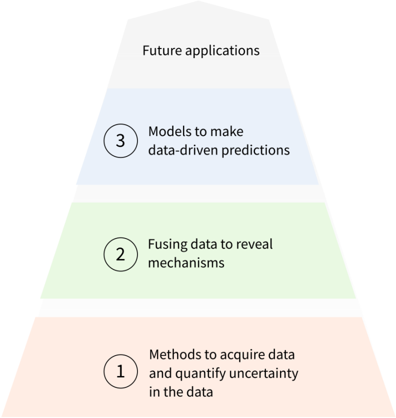

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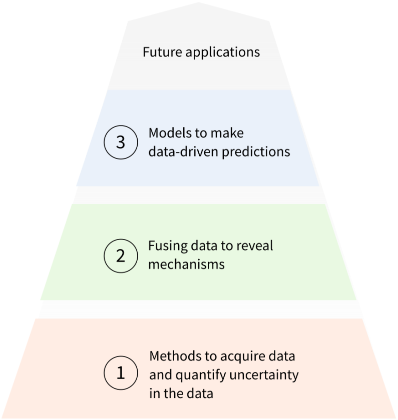

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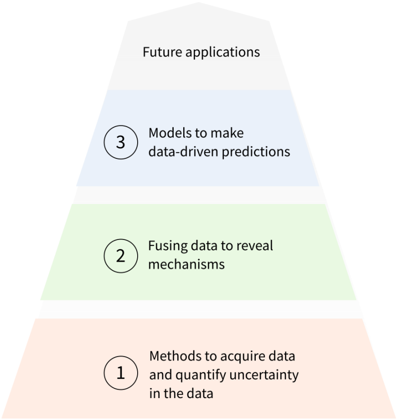

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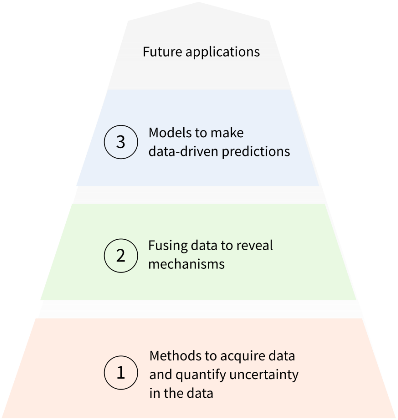

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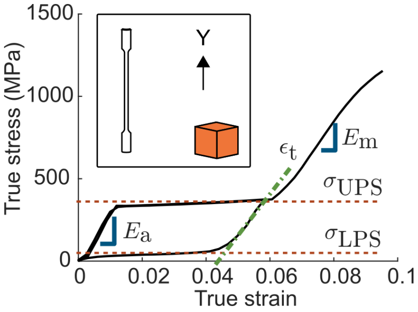
- Elastic modulus, plateau stresses, transformation strains: Material inputs for the simulation of superelastic deformation.



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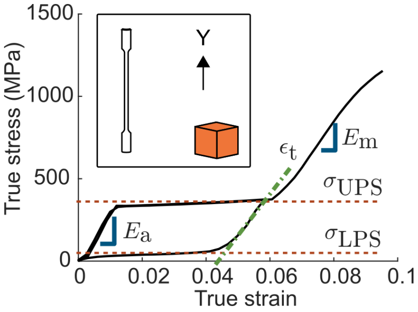

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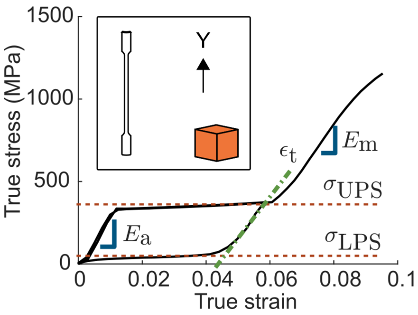


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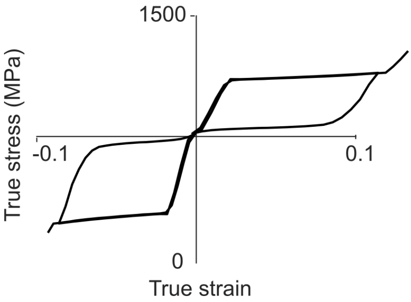
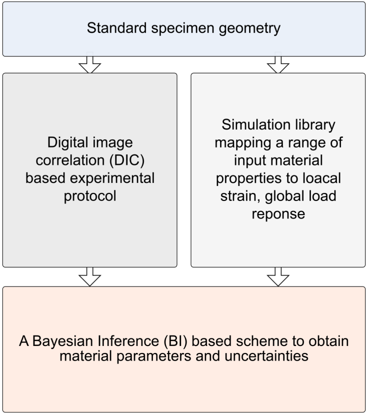



- Uncertainty in calibrated properties is rarely quantified.
- Calibration to just tensile test data does not capture tension-compression asymmetry.

# Probabilistic Calibration Methodology

- Four components of the calibration scheme:



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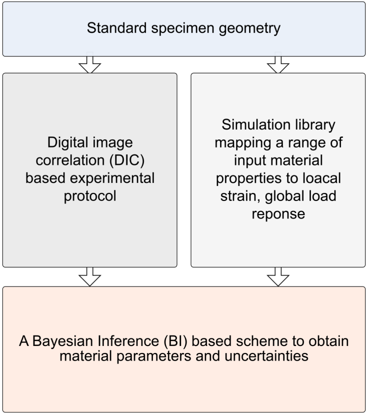

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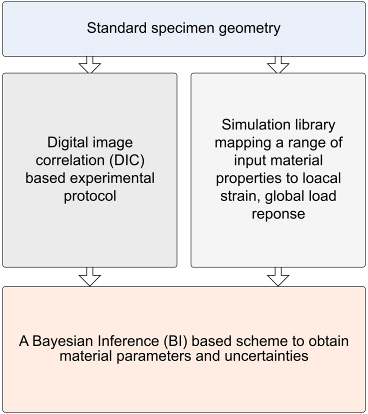

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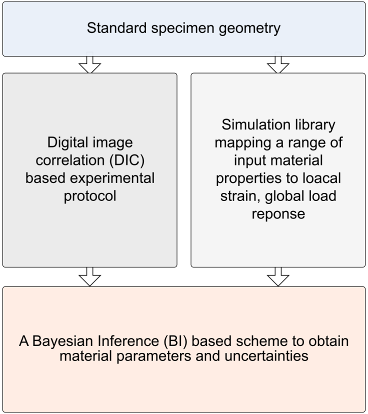

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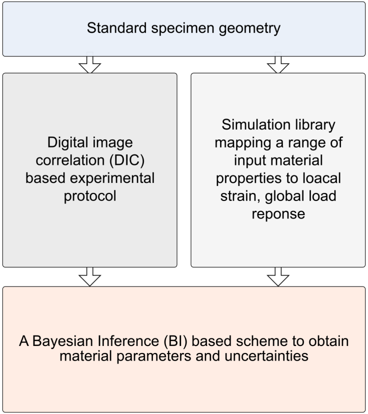

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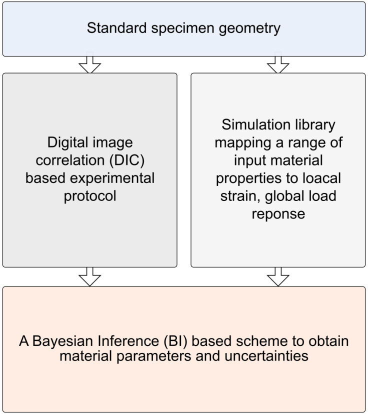

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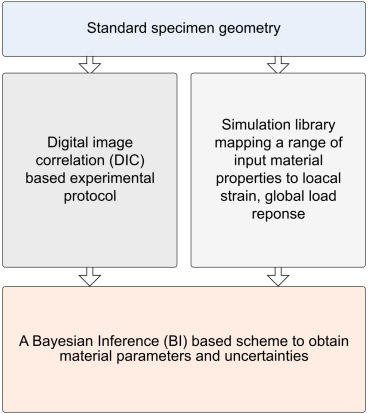
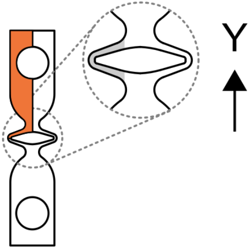



Details:

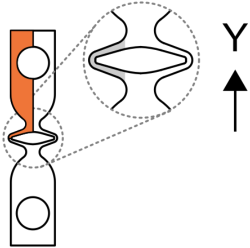
Paranjape et al. (2021). Computational Materials Science. https://doi.org/10.1016/j.commatsci.2021.110357.

- A diamond specimen geometry that produces both tensile and compressive strain fields when loaded in Y.



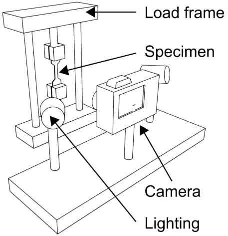
# Standardized Specimen Geometry

- A diamond specimen geometry that produces both tensile and compressive strain fields when loaded in Y.
- Shaded gray region is the area of interest.



# Protocol to Measure Surface Strain

- A digital image correlation test protocol to obtain local strain distribution and global load during a tensile test.



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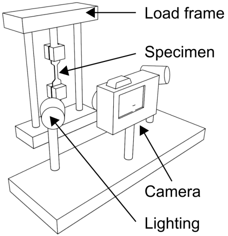


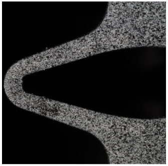

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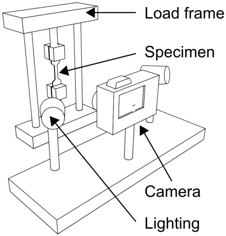
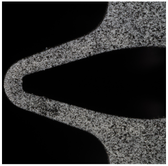
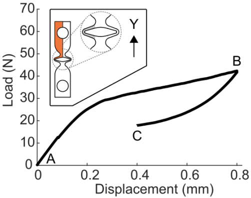
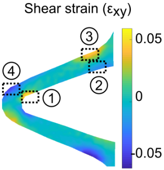
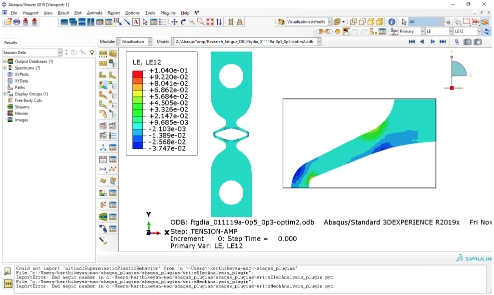




- A finite element analysis (FEA) simulation library spanning the parameter space: $E_A \in [10\,\text{GPa}, 80\,\text{GPa}]$, $E_M \in [10\,\text{GPa}, 50\,\text{GPa}]$, $\varepsilon_t \in [0.03, 0.07]$, $\sigma_{UPS} \in [100\,\text{MPa}, 600\,\text{MPa}]$, $\sigma_{LPS} \in [10\,\text{MPa}, 400\,\text{MPa}]$, and $\sigma_{CPS} \in [150\,\text{MPa}, 700\,\text{MPa}]$



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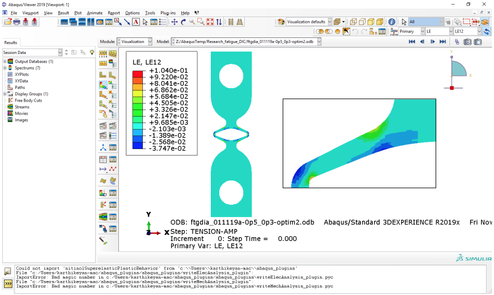
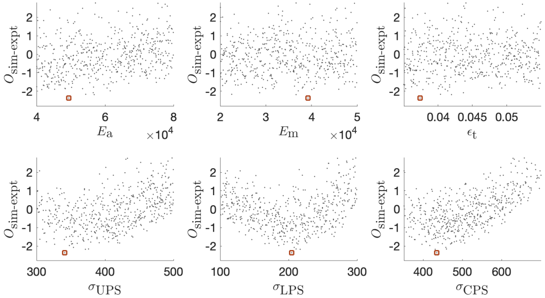
- Identical boundary conditions (BCs) as in the experimental protocol.



# Material Property Calibration: The Easy Way (a.k.a. least-squares)

- Define a quantity $Q$ based on the local strains and global load. It can be either experimentally measured ($Q^{\text{expt}}$) or obtained from simulations ($Q^{\text{sim}}$).



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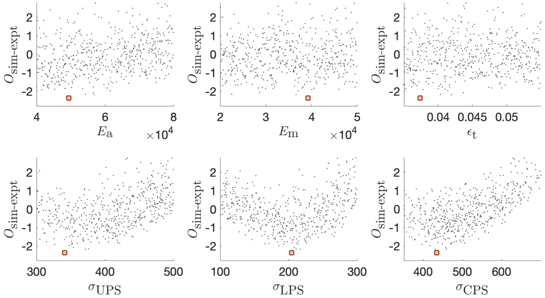
- The calibrated material parameters $m^{\text{cal}}_{\text{LSQ}}$ can be determined by performing the minimization: $m^{\text{cal}}_{\text{LSQ}} := \arg\min_m \sum_i^N w_i \left(Q_i^{\text{sim}} - Q_i^{\text{expt}}\right)^2$.



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# Material Property Calibration: Bayesian Inference

- Calculate the probability distribution (posterior) of the calibrated material parameters using Bayes' theorem and Markov Chain Monte Carlo (MCMC) sampling.
- The median material properties and their uncertainty (standard deviation) can be calculated from the posterior distribution.

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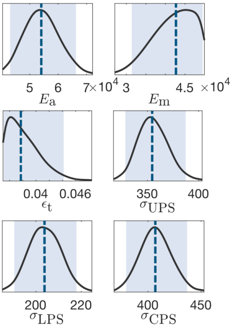
- A small library can result in a broad probability distribution irrespective of the quality of the experimental data.
- It is computationally expensive to build a very large library using the full-field FEA simulations.
- Thus, we fitted a support vector machine (SVM) regression model to predict $Q^{\text{sim}}$ for an arbitrary value of $m$.

# Results: Calibrated Parameters using BI + ML Approach

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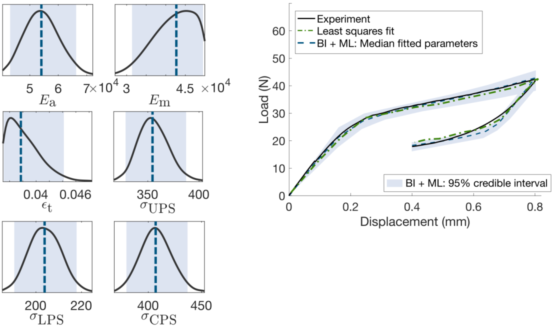


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- Top right: A comparison of the experimental data, the simulation result using the median calibrated parameters, and the 95% interval.

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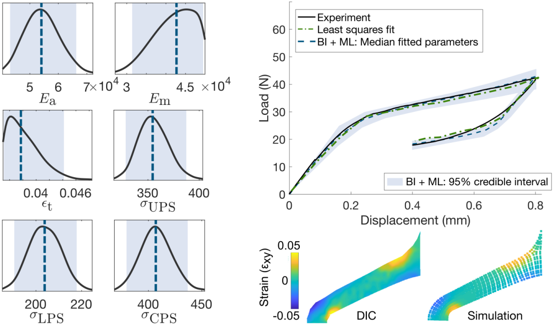
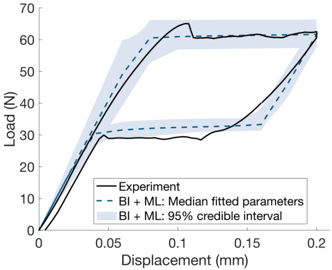



- Left: A probability distribution of the calibrated parameters obtained using tensile and DIC test data for a diamond specimen.
- Top right: A comparison of the experimental data, the simulation result using the median calibrated parameters, and the 95% interval.
- Bottom right: A comparison of the experimental strain field (DIC) and the simulated strain field from median parameters.

# Results: Simple Validation of Results

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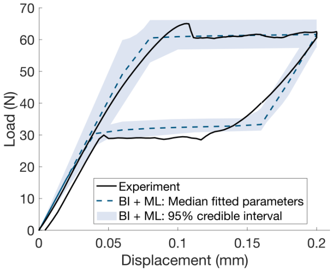


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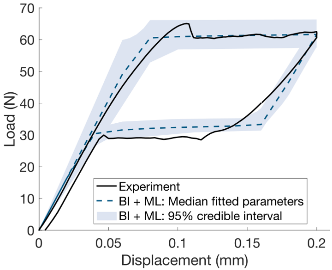


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- Diamond: Bending-dominated deformation.

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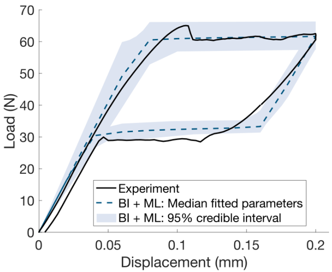


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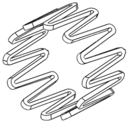
- Diamond: Bending-dominated deformation.
- Dogbone: Tension-dominated deformation.

# Results: Propagation of Uncertainty to Subsequent Simulations



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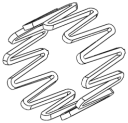

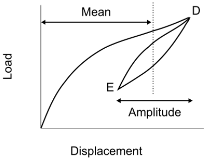


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- Cyclic BCs = {mean disp., disp. amplitude}.

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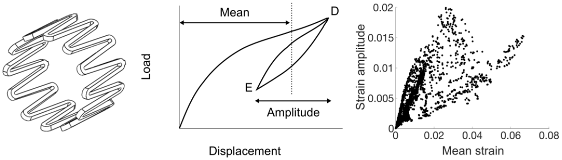


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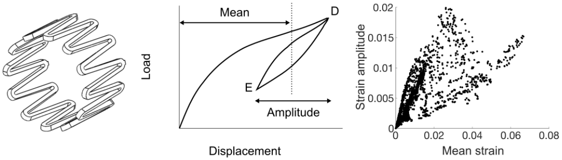


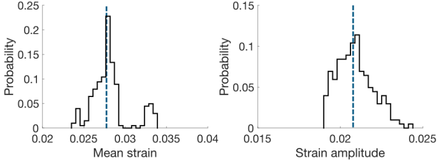


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- Probability distribution of the calibrated material properties → probability distribution of the simulated fatigue indicators.

# Summary and Future Work

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- The quantified uncertainties in the material parameters can be propagated to the results of subsequent simulations.

# Probabilistic Approach to Local Property Determination

- The Bayesian material property determination approach is extensible to other testing methods.

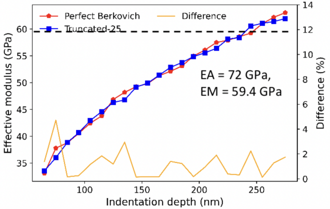
## Oliver-Pharr method applied in SMA

Oliver-Pharr equation,

$$\sqrt{A} = \frac{S}{\beta E_r}$$

β = 1.1667 for Berkovich indenter;
$E_r$ is reduced modulus,

$$\frac{1}{E_r} = \frac{(1-\nu^2)}{E} + \frac{(1-\nu_i^2)}{E_i}$$




- SMA used has a moduli as, EA = 72 GPa, EM = 59.4 GPa.
- The contact area is not well determined.

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2

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- Indentation: Tool to probe local material response.

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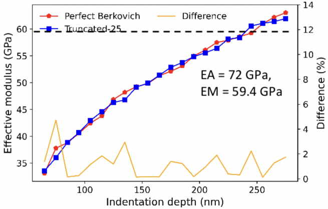


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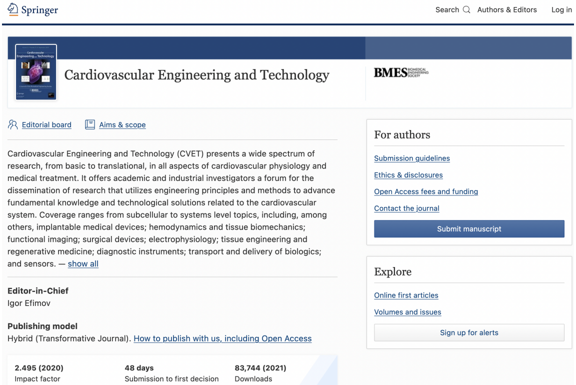
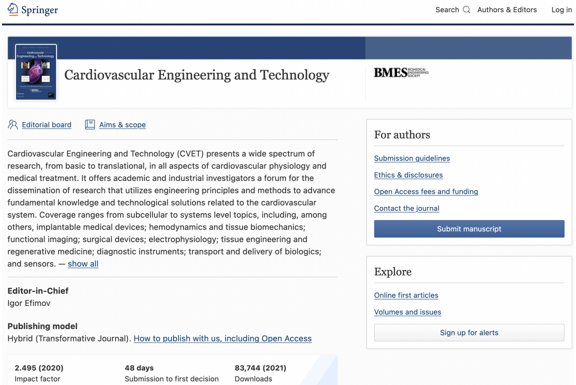
# Fatigue: Shift from Deterministic to Probabilistic Approach

- Heart Valve Collaboratory (HVC): A community of practitioners to develop a consensus on heart valve (NiTi and other metals) durability assessment.



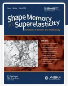
# Fatigue: Shift from Deterministic to Probabilistic Approach

- Heart Valve Collaboratory (HVC): A community of practitioners to develop a consensus on heart valve (NiTi and other metals) durability assessment.
- Stay tuned for HVC special issue in Cardiovascular Engineering and Technology journal in 2023.



# Data Science: One of Many Tools for Advancing Nitinol Implant Design

Springer



## Shape Memory and Superelasticity

Advances in Science and Technology

Journal home > Journal updates > Call for Papers for Special Issue on Nitinol Me...

## Call for Papers for Special Issue on Nitinol Medical Devices

The journal *Shape Memory and Superelasticity* is organizing a special issue dedicated to Nitinol medical devices. This issue will address scientific and engineering topics that relate to the durability and the function of cardiovascular implants manufactured from Nitinol. Certain examples of such topics include fatigue properties, influence of processing on device performance, and interaction between cardiovascular physiology and the Nitinol material.

The journal is soliciting original research articles that broadly fall in the scope of this special issue. Typical research articles will be approximately 8 journal pages in length. Longer papers can be accommodated with permission from the guest editors.

Srinidhi Nagaraja and Harshad Paranjape will be guest editors in this special issue. Please inform both guest editors if interested in submitting an article to this special issue by January 14, 2022 .

Thank you

https://bit.ly/smst2022

## Calibration of SE Model

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