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Commentary: Fast and accurate surrogate of finite-element analysis: For bench to bedside, we need it now!

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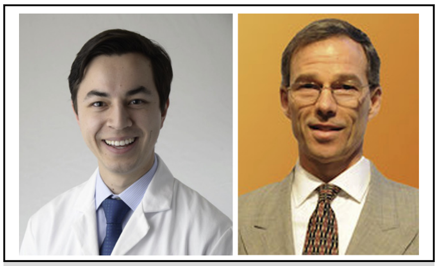

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CENTRAL MESSAGE

The 30-hour simulation for each scenario can be reduced to a few seconds using machine learning.

Yuan and colleagues[1] deserve praise for analyzing in detail thoracic endovascular aortic repair (TEVAR)-induced biomechanical changes using a finite element (FE) model based on images from a failed TEVAR in type A aortic dissection. Their article in this issue of the *Journal* shows the potential of FE modeling to predict outcomes of TEVAR and to optimize future endovascular procedures. This important work demonstrates the utility of a computational technique applied to a real-world clinical scenario. Simulation of the actual TEVAR procedure revealed that the proximal bare metal stent pushed the lamella into the false lumen and led to further stent-graft migration during deployment. An alternative landing position would have reduced the local deformation of the dissection lamella and could avoid stent-graft migration. Greater maximum principal stress (>20 kPa) was found on the lamella with deployment at the actual position, whereas the alternative strategy would have reduced the stress to <5 kPa. Importantly, Yuan and colleagues[1] point out the need for further model improvement and validation.

Two major points with their approach deserve mention. The first is that to be clinically useful, creation of an accurate FE model and interpretation of results must be done rapidly. For patients presenting with acute life-threatening conditions such as aortic dissection, even several hours to review imaging and formulate an intervention plan may become a deadly delay. Machine learning holds promise for speeding up the process by which FE model-derived results can be obtained. Liang and colleagues[2] describe a novel method using deep learning techniques as an FE model surrogate to derive aortic wall stress values. With patient-specific aortic geometry as the input, a deep neural network construct was trained on a database of more than 700 aortic geometries with FE model-derived results. An FE model simulation time of 30 minutes was reduced to a mere sub-1 second runtime and the results were within 1% error. To pave the way for translational computational techniques, a radiographic database of aortic dissection anatomy should be created for the community to use, to validate results, and to train machine-learning algorithms. The ability to obtain meaningful results within seconds to minutes would be paradigm changing for surgeons, who cannot wait hours for additional data to influence the operative plan.

Second, we advocate that uncertainty quantification and sensitivity analysis be performed on this clinical scenario model, to examine which of the input parameters results in greatest variability to the critical outcome results, in this case, aortic wall stress. Campos and colleagues[3] detail application of these techniques to a model of the left ventricle undergoing cardiac cycles. Out of several seemingly crucial parameters that are input into their model (wall thickness, myofiber orientation, passive material parameters, active stress, lumped parameter circulatory model), analysis revealed that active stress, wall thickness, and fiber direction affected ejection fraction and ventricular torsion to the greatest extent when subjected to variability.

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Drawing a parallel to the study of Yuan and colleagues, we encourage the authors to examine what factors from their study would be most critical to ensure accurate results are obtained: aortic wall thickness, dissection lamella properties, and radial force of the stent, to name a few for consideration. This will help focus attention on the most critical patient-specific data to extract for every scenario.

Researchers and clinicians united in the goal of bringing translational computational techniques into practice should be motivated to use techniques that offer the greatest-quality results on a clinically practical timeline and to understand how attention to input parameters can be optimized to provide those high-quality results.

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