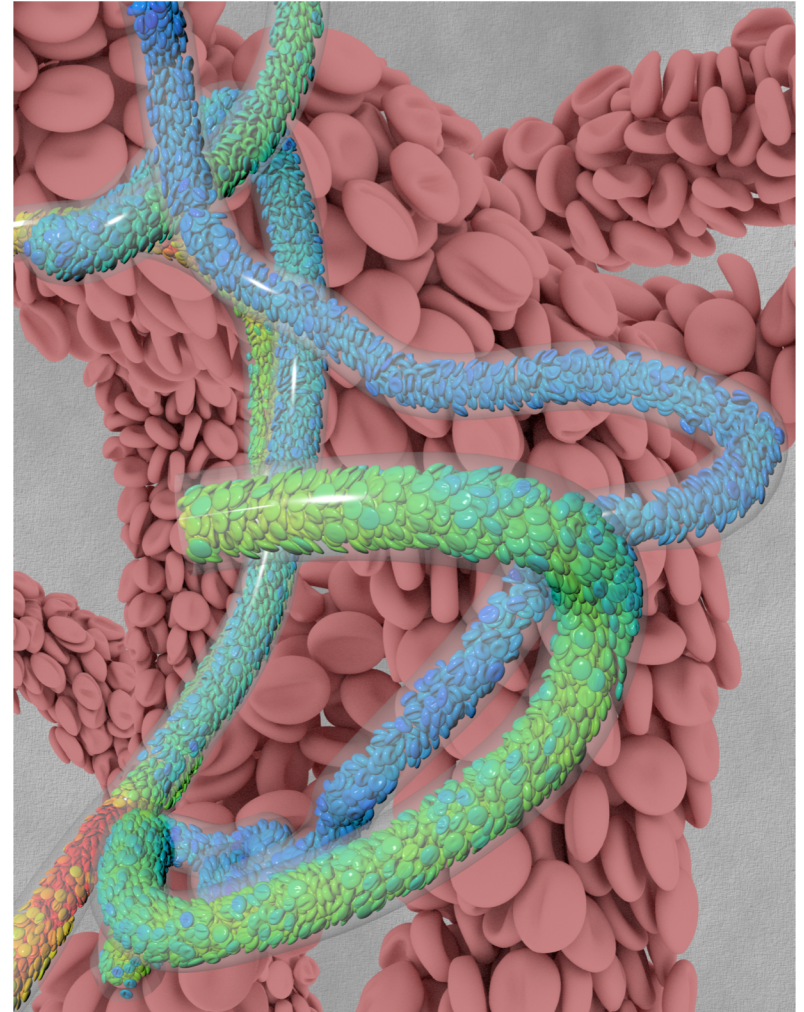




# Developing and deploying scalable, efficient, and accurate personalized flow simulations

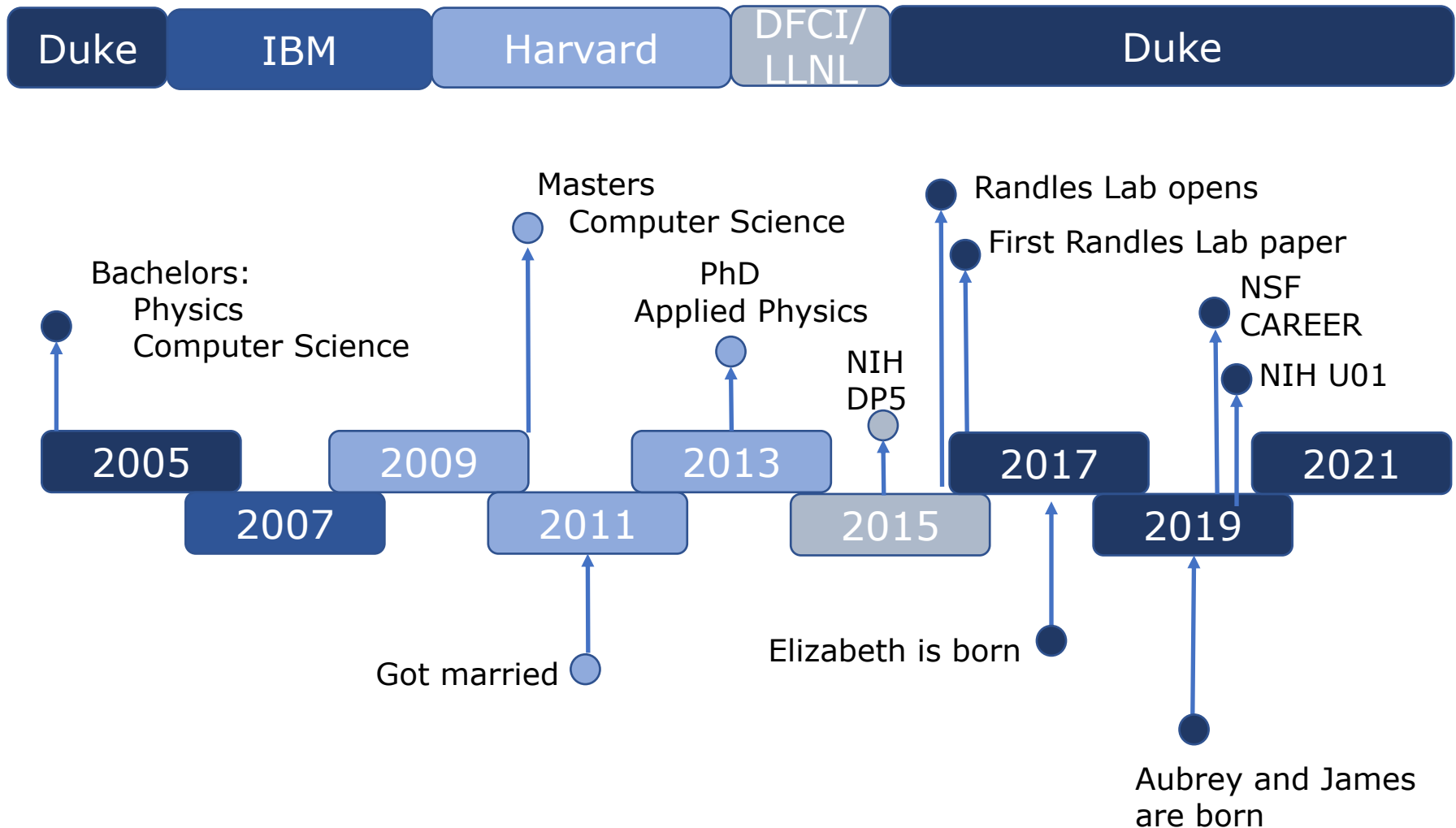
**Amanda Randles**  
Biomedical Engineering  
Duke University

**Why should you care  
about personalized  
flow models?**





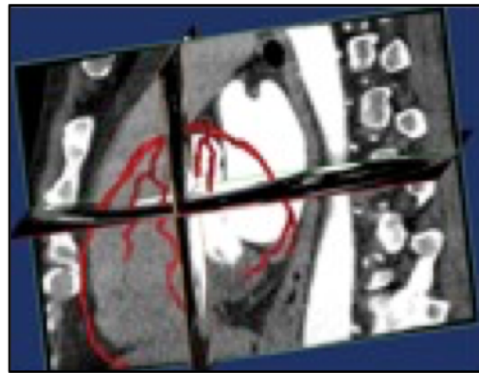
# Me in one slide



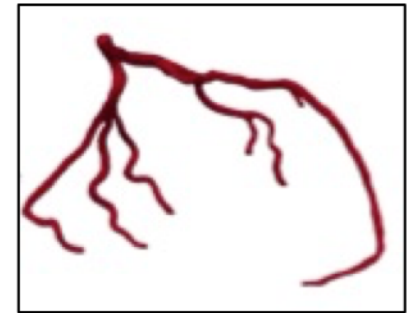
# PATIENT-SPECIFIC COMPUTATIONAL MODELS



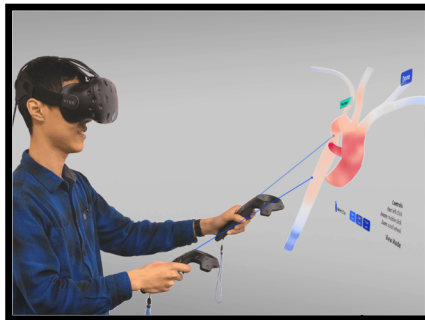
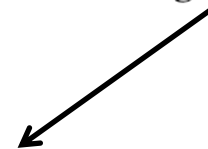
**Patient-derived  
imaging data**



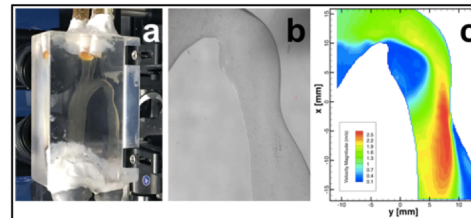
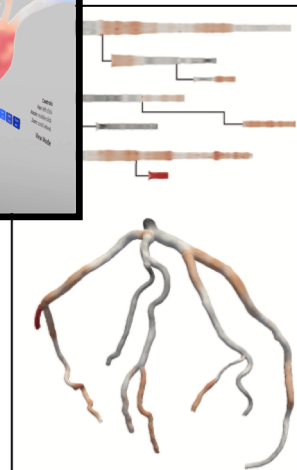
**Data Segmentation**



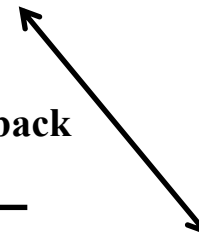
**Patient-specific  
3D geometries**



**Visualization,  
Interaction, and  
Discovery**



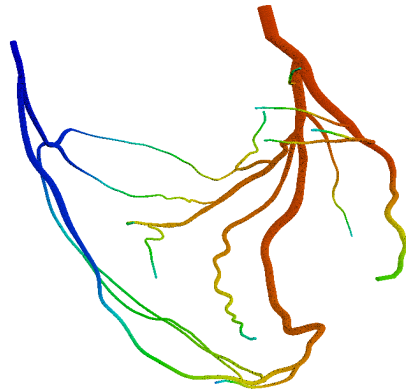
**Feedback**





# PATIENT-SPECIFIC COMPUTATIONAL MODELS

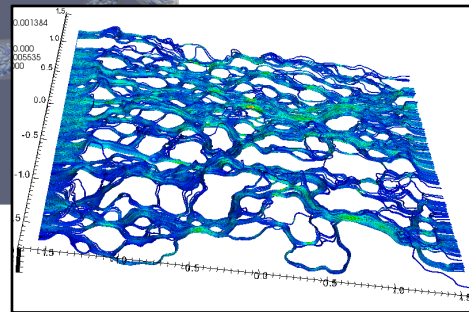
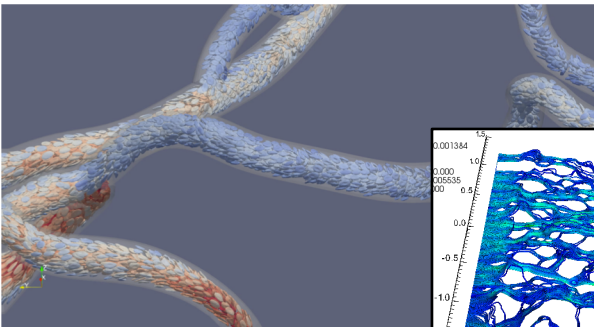
Pseudocolor  
Var. Pressure  
T.0222  
1.017  
1.011  
1.006  
1.001  
Max: 2000  
Min: 1.001



Diagnostics



Treatment Planning



Mechanistic



Massively Parallel Computing

# OUTLINE

- Impact of increase in compute capabilities
- Method overview
- Application vignettes:
  - Vascular diseases
  - Fluid structure interaction
  - Ventilator splitting model



# IMPACT OF INCREASE COMPUTE POWER



- 2005
  - 1 processor
- 2005-2008
  - Worked at IBM on the Blue Gene supercomputer
  - 65k processors



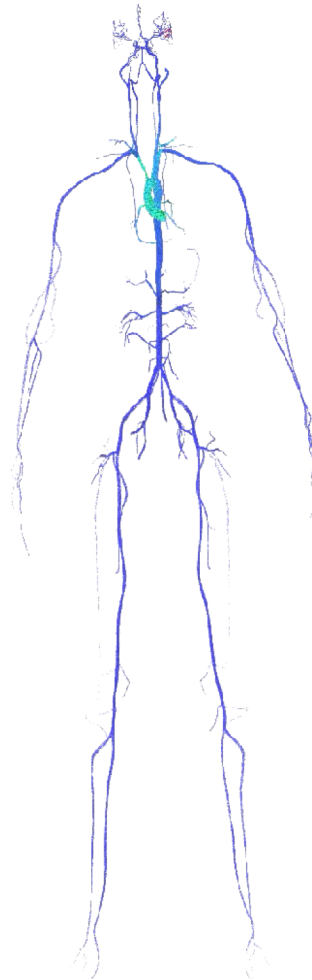
- 2009 and 2010
  - Juelich Extreme Scaling Workshops
  - ~300k processors
- 2015
  - Worked at LLNL
  - ~1.6 million processors
- 2021
  - Aurora Early Science
  - Exascale

# SIMULATIONS ARE COMPUTATIONALLY INTENSE

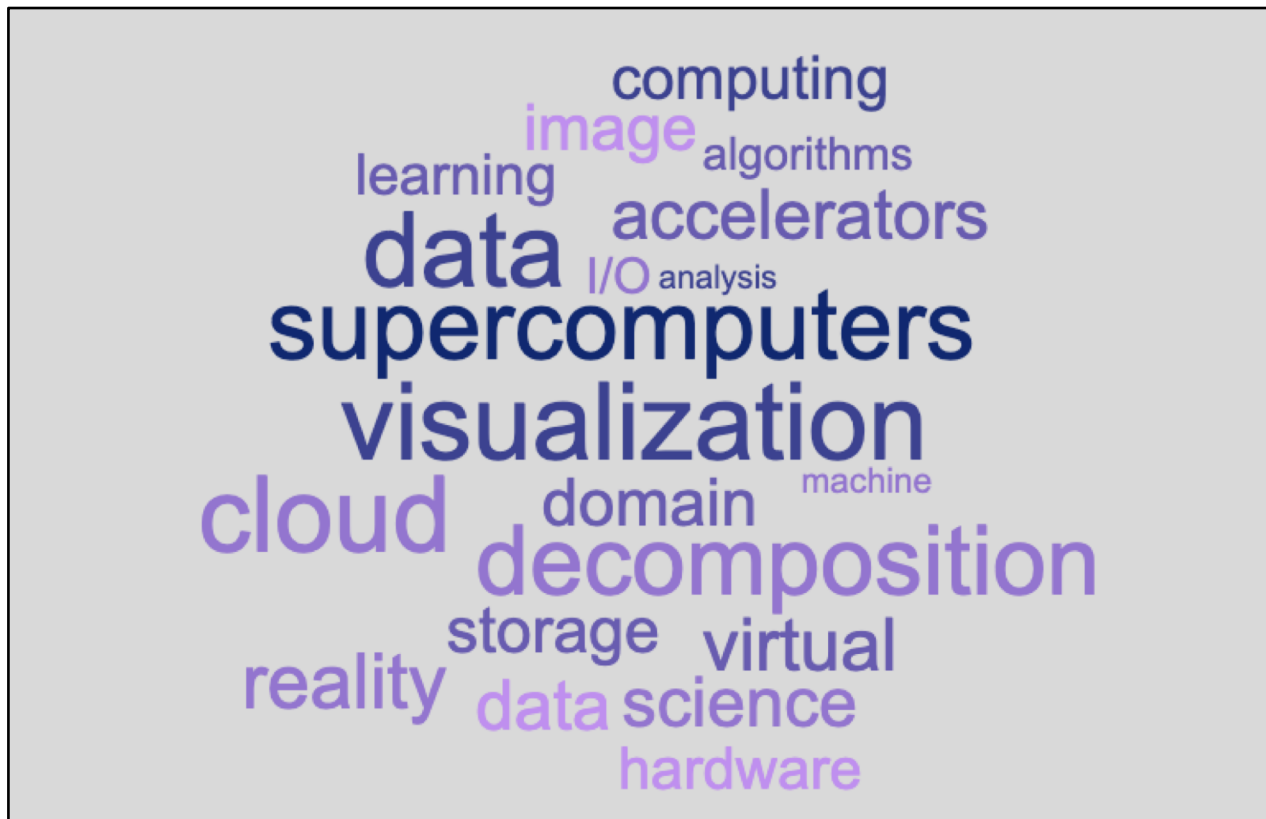




# FULL ARTERIAL NETWORK

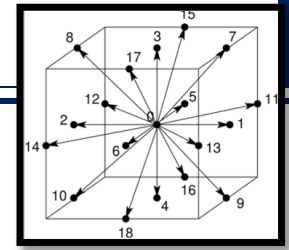


# COMPUTER SCIENCE CHALLENGES





# Computational Fluid Dynamics



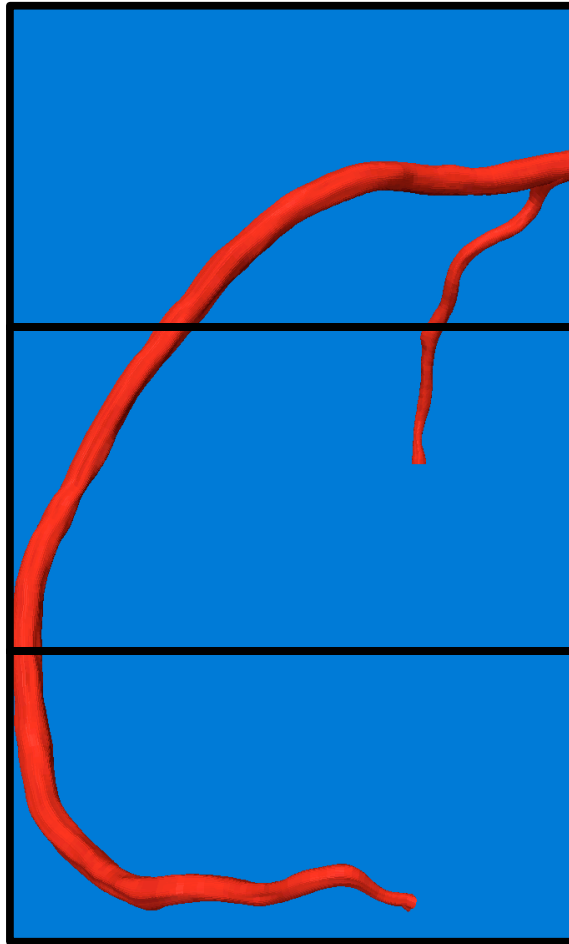
- Solves the (weakly compressible) Navier-Stokes equations
- Minimal communication between lattice points during update
- Macroscopic quantities computed at lattice points

$$\rho = \sum_i f_i \quad \vec{u} = \frac{1}{\rho} \sum_i \vec{c}_i f_i \quad P = c_s^2 \rho$$

- Straight forward treatment of complex geometry

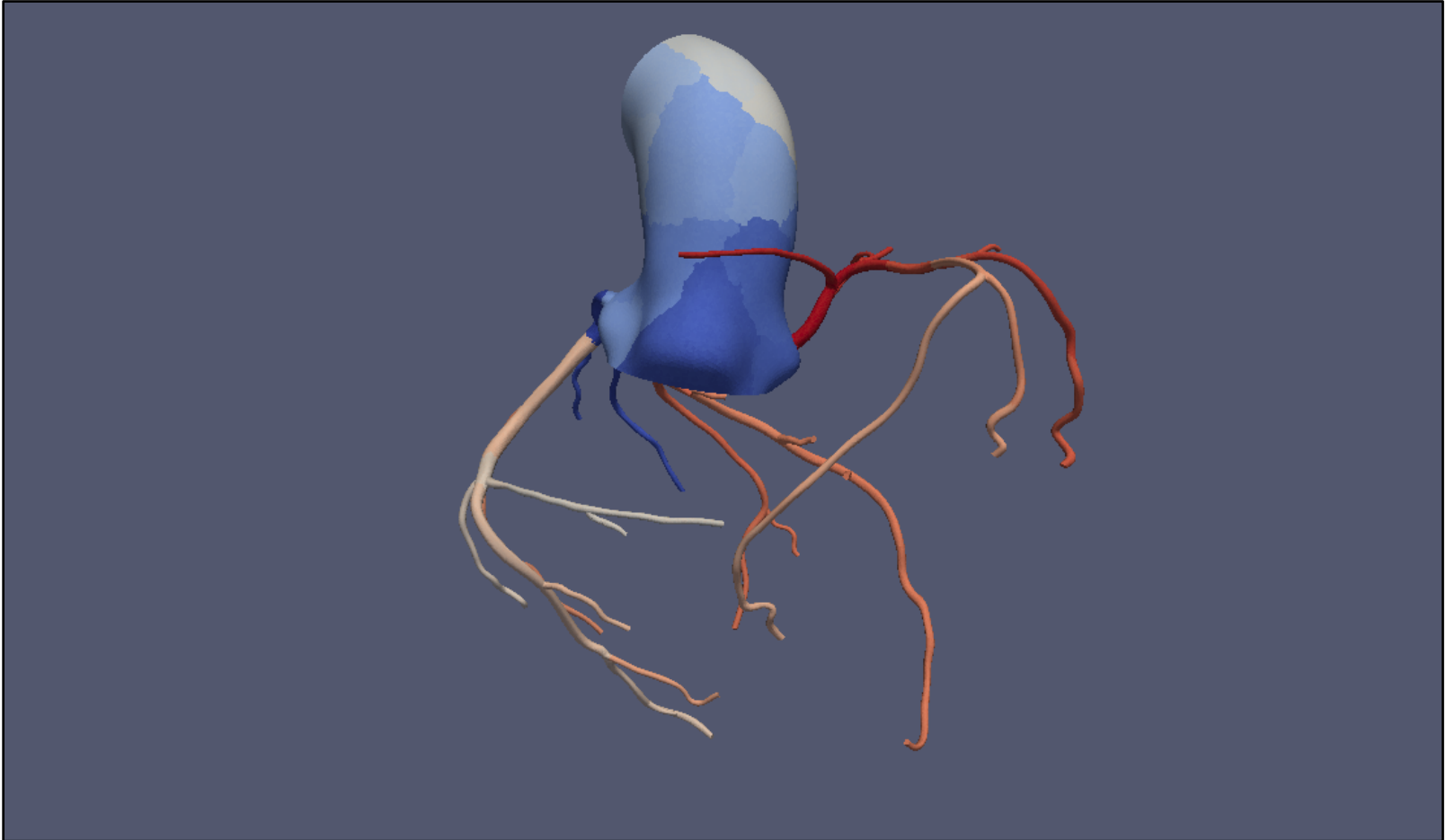
**How do we make these models  
tractable?**

# DOMAIN DECOMPOSITON



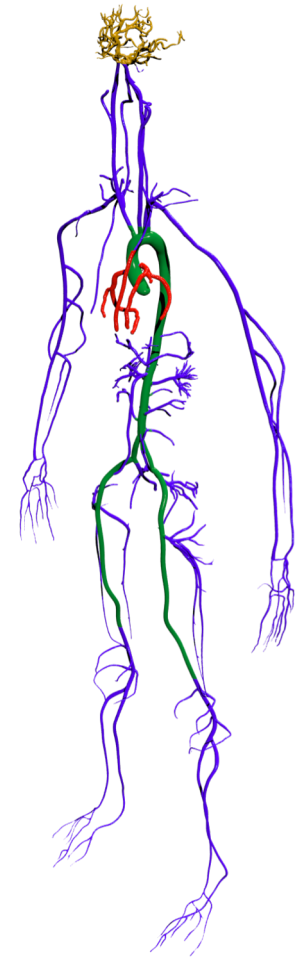


# IRREGULAR DOMAIN DECOMPOSITION



# MINIMIZING MEMORY FOOTPRINT

Full body arterial	20 micron	9 micron
Data Grid	68909 x 25107 x 188584	
Data memory	90.2 PB	
Fluid nodes	509 billion	
Fluid memory	140.7 TB	
Fluid Fraction	0.15%	



- Sequoia Blue Gene/Q total system memory: 1.6 PB
- Indirect addressing is mandatory, and only the first step
- Initialization and load balance now significantly more challenging

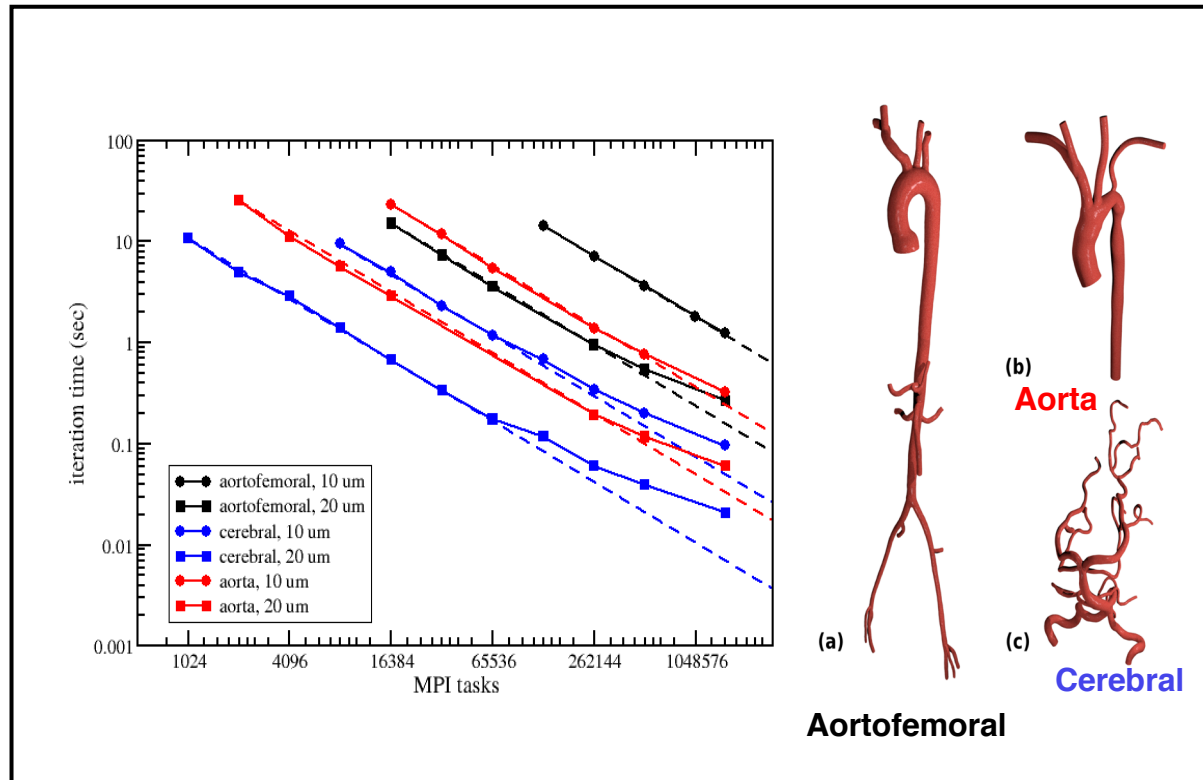
# MEMORY LAYOUT SCHEMES

A system of 4 lattice points to be addressed in memory:



Layout	How addressed in memory
AoS	
SoA	
CSoA (stride 2)	
Bundling (stride 2)	

# Efficient Use of Large-Scale Supercomputers



Randles *et al.* Journal of Computational Science, 2015



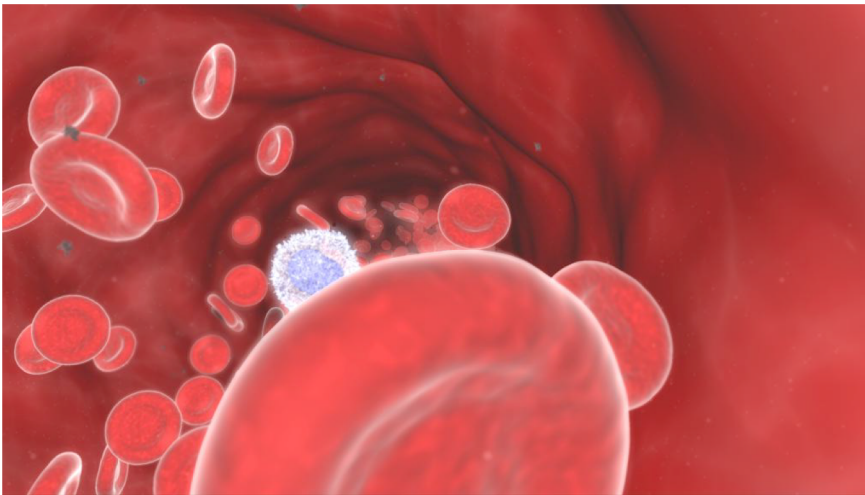


# **APPLICATIONS OF MASSIVELY PARALLEL FLUID MODELS**

# Cardiovascular Disease

CADs share **highest burden of heart diseases** with 370,000 death per year in the United States.

Personalized simulations can provide lesion-specific data to determine the functional severity of a stenosis and guide therapeutic action.

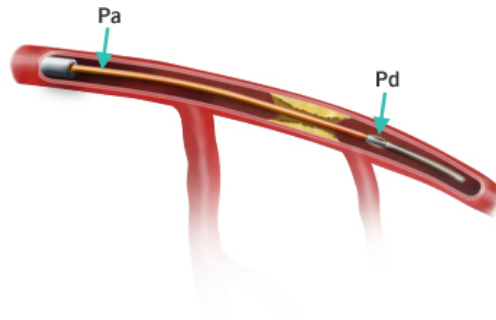


**50% of men** and **64% of women** who die of cardiovascular disease have no previously detected symptoms

# Diagnostics

# Determining lesion ischemia: to stent or not?

$$FFR = \frac{\text{Distal Coronary Pressure (Pd)}}{\text{Proximal Coronary Pressure (Pa)}} \\ \text{(During Maximum Hyperemia)}$$



1. COURAGE NEJM 2007
2. DEFER Study JACC 2007
3. FAME NEJM 2009
4. FAME II NEJM 2012
5. FAME III AHJ 2015
6. Clinical outcomes FAME II, Circ. 2019

**A**



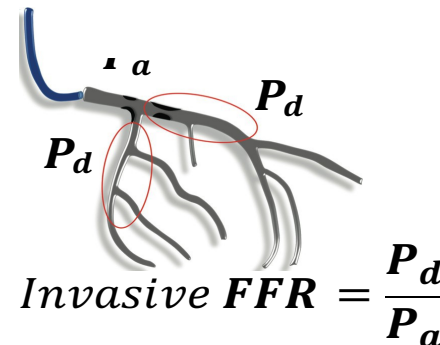
**B**

Pressure  
guide-wire

+



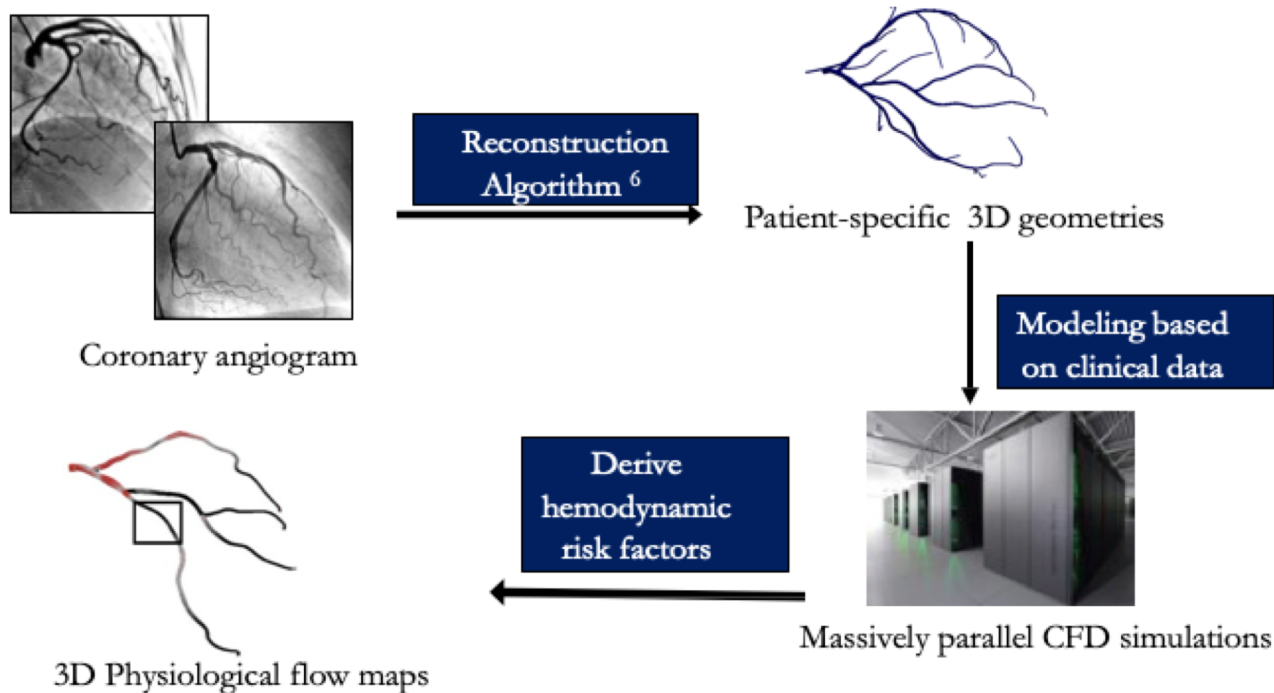
=



FFR is the current gold standard for the assessment of coronary artery disease

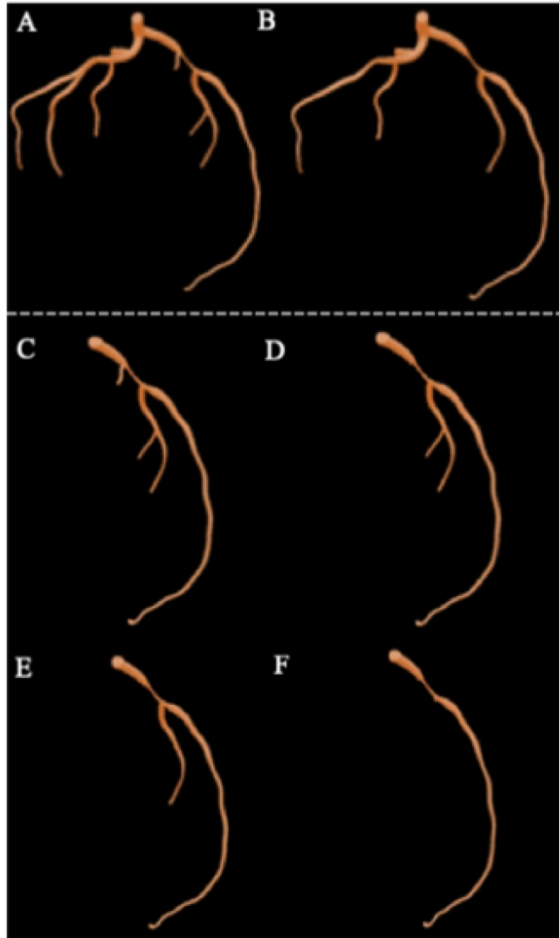


# Deriving flow from angiography data

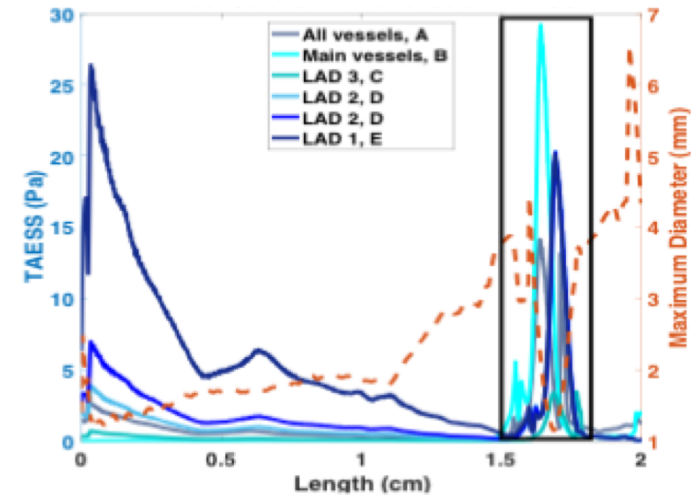


**Significant physiology can be resolved using CA applied to CFD, which can help determine intracoronary hemodynamics more accurately and augment FFR**

# Importance of including side branches



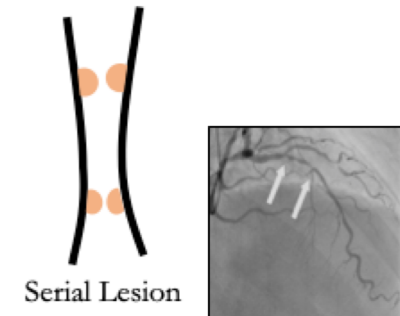
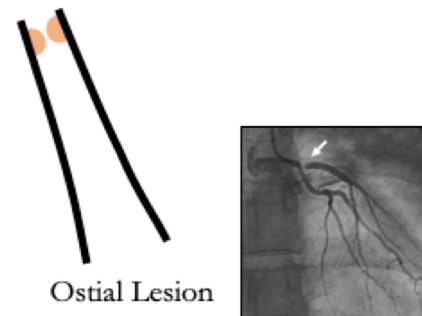
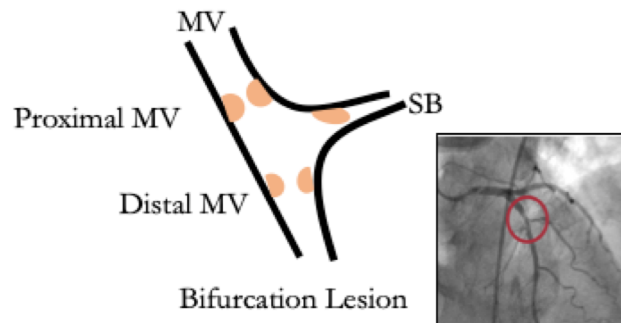
Vardhan et al. Nature Scientific Reports 2019



Capturing the full arterial tree including side branches is critical to accurately assessing flow characteristics.

# Capturing complex lesions

- Complex lesions found in more than 20% of patients
- High risk of developing secondary adverse cardiac events
- Commonly excluded from most non-invasive clinical trials



**Determining hemodynamic precarity in complex lesions can help understand disease progression and guide future treatment decisions**

# Matching CA-CFD to *in vivo* data

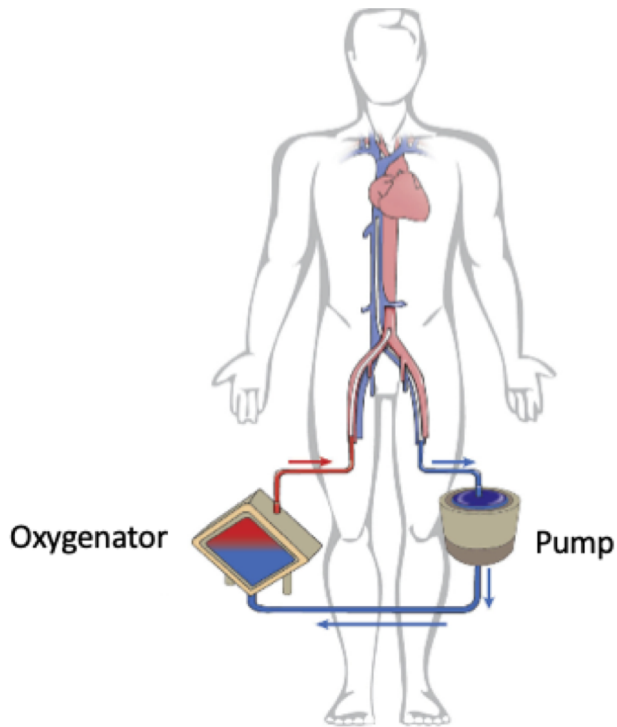
Case	Vessel	Clinical Resting Pressure	CFD Resting Pressure	Percent Error
Case 1	LAD	0.93	0.94	0.6%
Case 2	RCA	0.97	0.98	1.0%
Case 3	LCx	0.96	0.97	1.0%
Case 4	RCA	0.88	0.88	0.0%
Case 5	LAD	0.95	0.95	0.0%
Case 6	RCA	0.91	0.90	0.7%
Case 7	Left Main	0.96	0.99	3.1%
Case 8	LCx	1	0.98	2.0%
Case 9	RCA	0.98	0.92	6.0%
Case 10	LAD	0.82	0.72	12.2%
Case 11	LAD	0.92	0.95	3.3%
Case 12	RCA	0.98	0.93	5.1%
Case 13	LAD	0.93	0.97	4.3%
Case 14	RCA	1	0.95	5.0%
				3.16%

Invasive resting gradient and CA-CFD resting gradient are in close agreement with each other



# **Mixed order models: VA-ECMO**

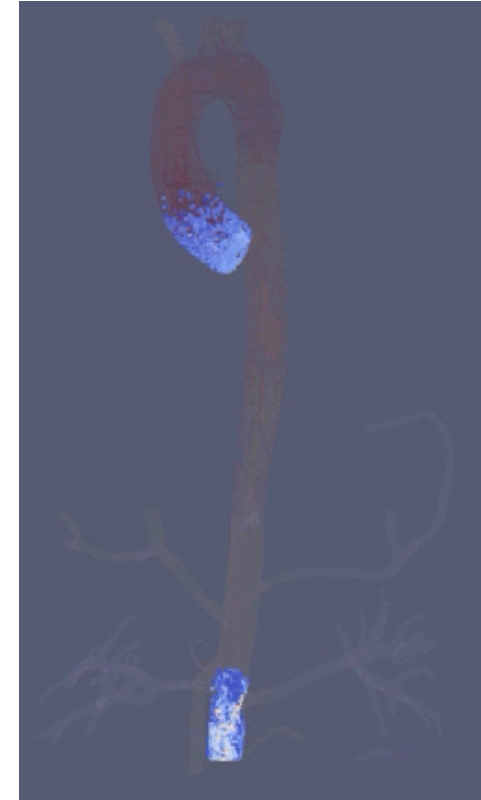
# VA-ECMO – mechanical support system



- External heart and/or lungs for patients with cardiopulmonary failure
- Process
  1. Drain deoxygenated blood from veins
  2. Pump
  3. Oxygenate
  4. Infuse blood through insertion cannula in femoral artery, axillary artery, or aorta

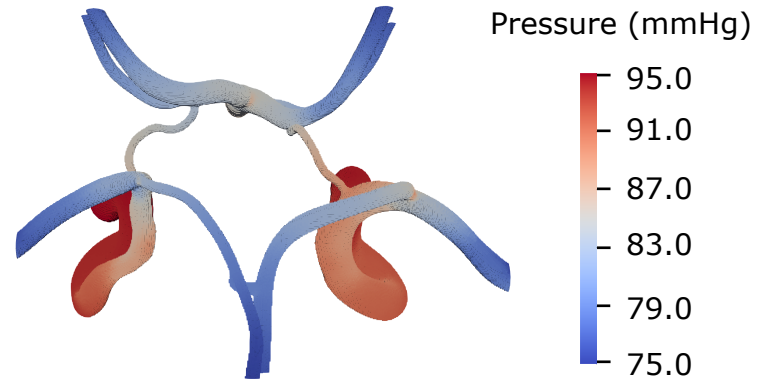
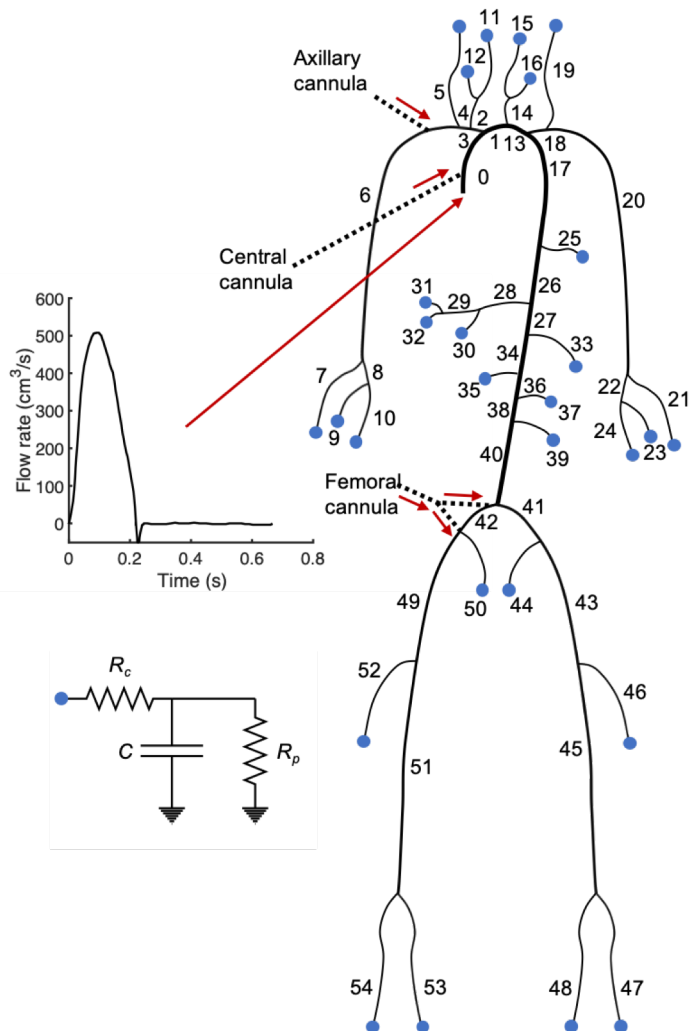
# Importance of the mixing zone

- ~15% patients develop neurological complications
- Cerebral hypoxia
  - Differential hypoxia - well oxygenated VA-ECMO flow meets poorly oxygenated cardiac output
  - Mixing zone – region of mixing in the aorta



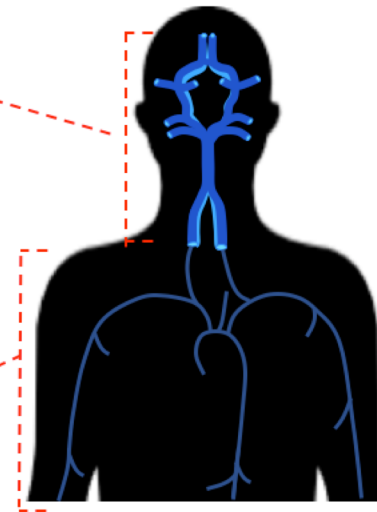
Important to determine how physician tunable parameters and cannulation location influence flow to the brain and location of mixing zone

# Building 1D-3D coupled models



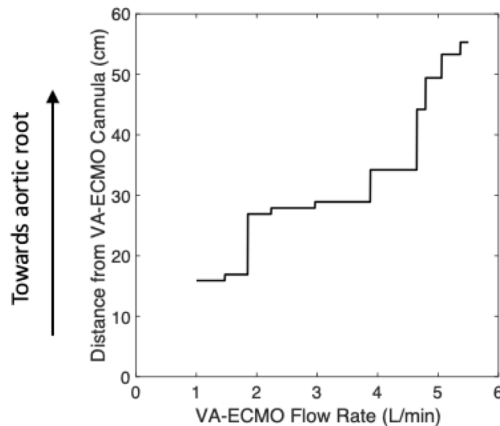
3D regions –  
higher fidelity,  
global and local  
hemodynamics,  
slower

1D regions –  
lower fidelity,  
global  
hemodynamics,  
faster

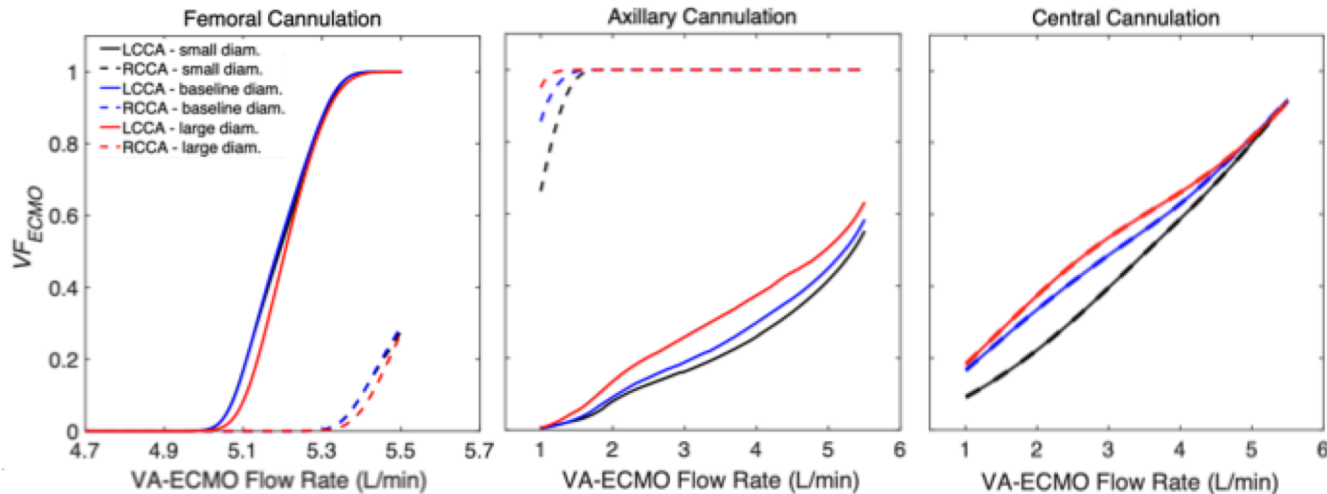


Feiger *et al.* J Biomech 2020  
Feiger *et al.* Comp in Bio and Med. 2020

# Building 1D-3D coupled models



- Coupled models provide accurate 3D hemodynamics and capture VA-ECMO properties
- VA-ECMO flow rate drives mixing zone
- High flow rates are needed to oxygenate the brain



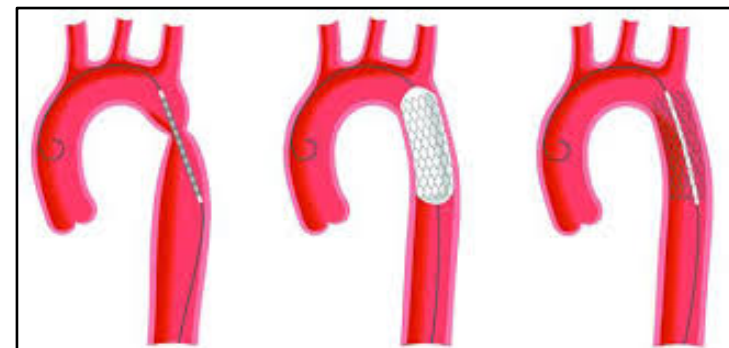
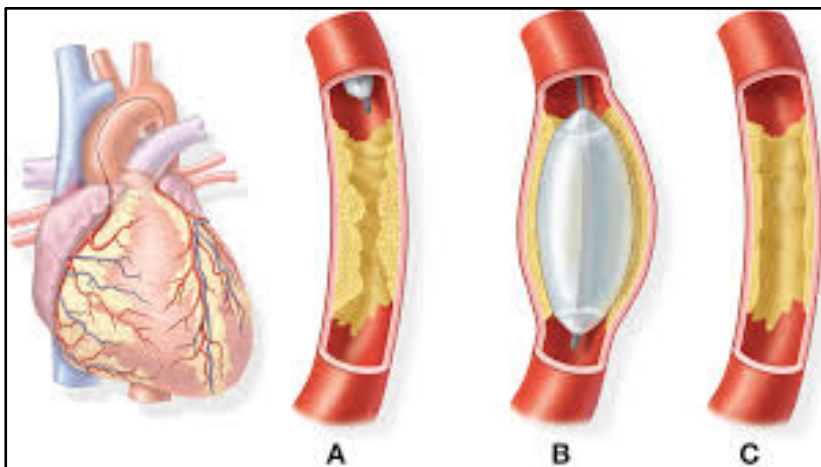
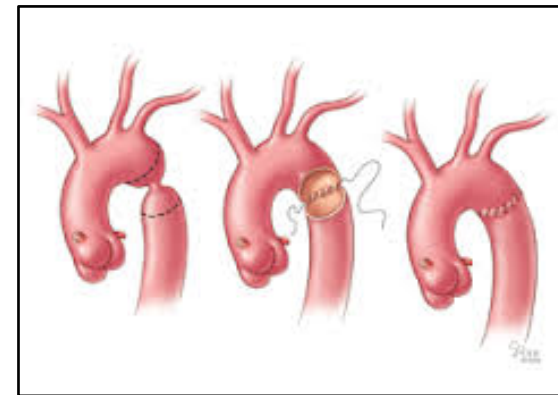
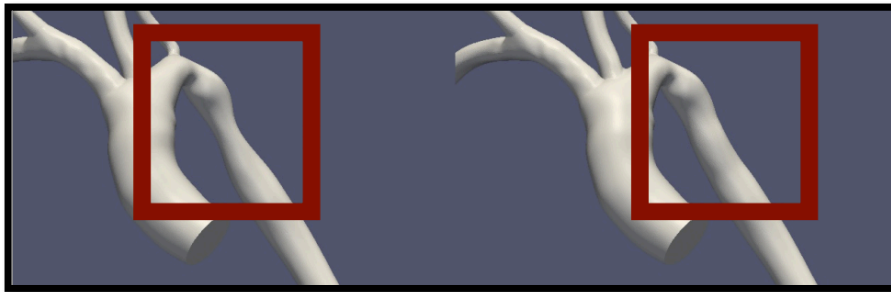
Feiger *et al.* J Biomech 2020  
Feiger *et al.* Comp in Bio and Med. 2020

# Treatment Planning

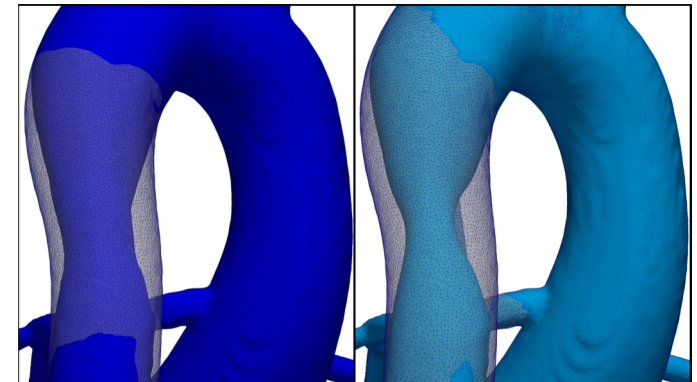
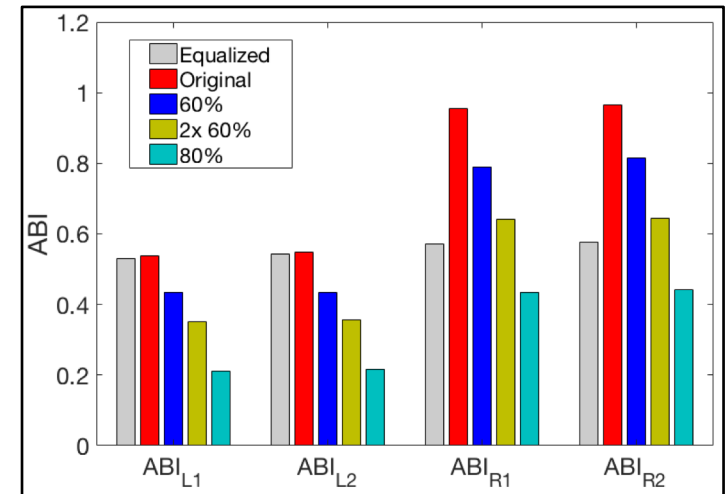
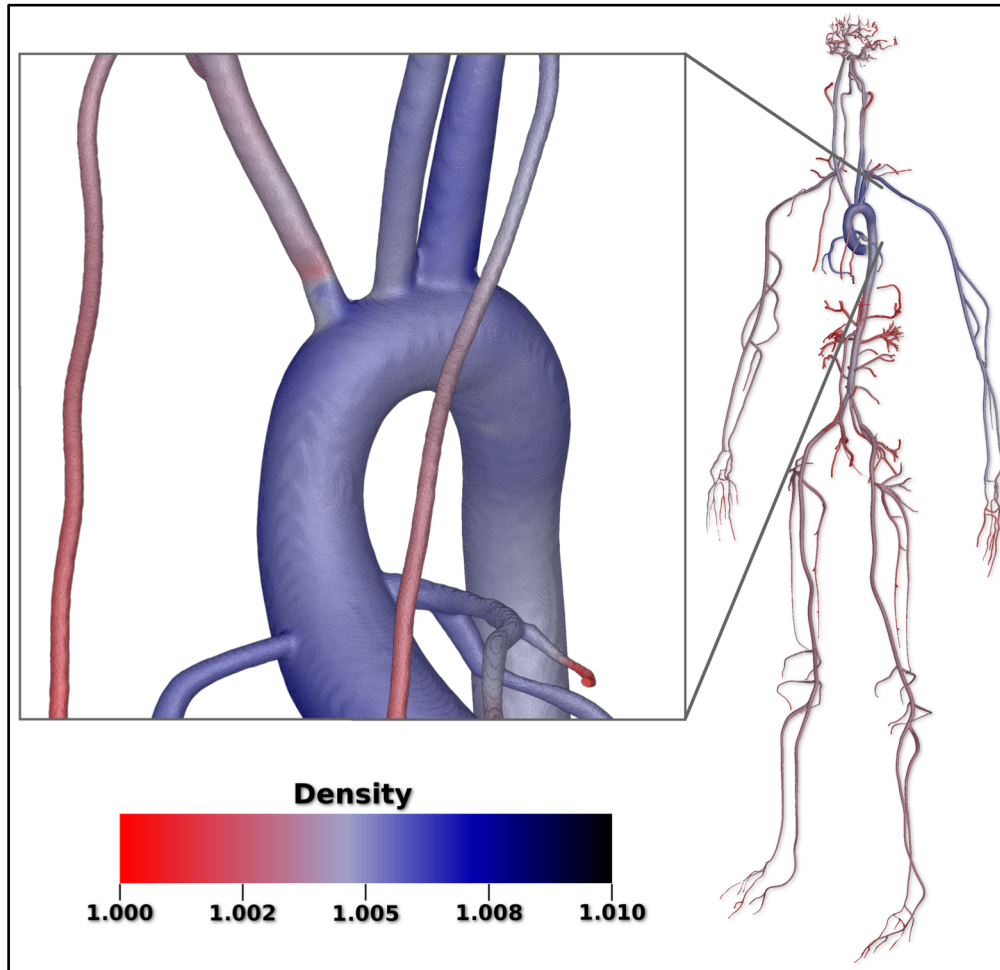


# Treatment planning

**Results from CFD simulations can guide clinical treatment.**



# Simulations can capture local effects on ABI



Gounley et al. Journal of Biomechanics 2019

# HarVis: XR interaction

- Using devices like the Oculus Rift, HTC Vive, and zSpace to investigate different modes of interaction



2D

Traditional  
Desktop or Laptop



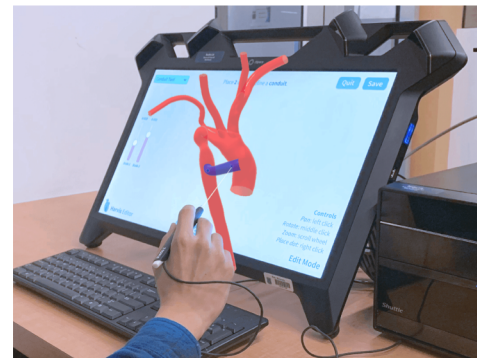
MR

zSpace



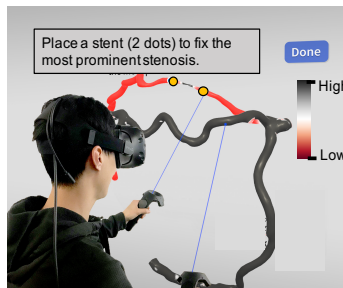
VR

HTC Vive

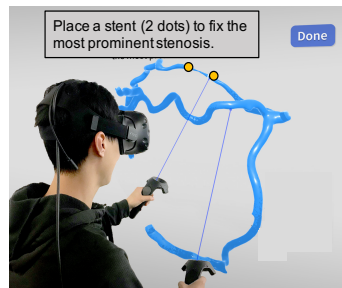


# Assessing user interaction

- Full immersive devices can provide reduced error for completing defined tasks like conduit placement or virtual revascularization
- Fully immersive devices prove most effective for PCI planning
- Access to shear stress maps reduces differences in participant accuracy across devices



Fully Immersive  
With WSS



Fully Immersive  
No WSS



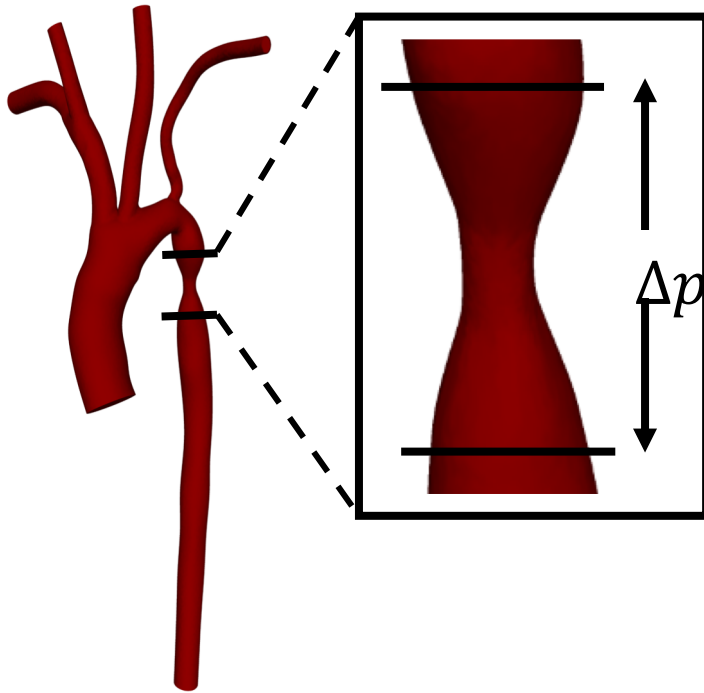
Semi Immersive  
With WSS



Semi Immersive  
No WSS

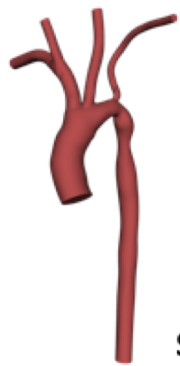
# **Holistic view of the patient**

# Coarctation of the aorta

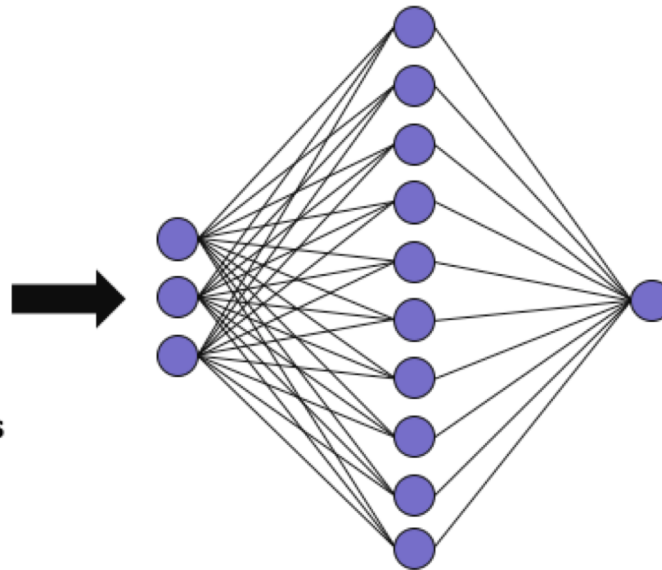


- Congenital heart defect
- Stenosis in descending aorta
- Affects 3,000 – 5,000 patients in U.S. each year
- Intervention if  $\Delta p > 20 \text{ mmHg}$
- TAWSS  $\rightarrow$  plaque progression

# Machine learning pipeline



**Step 1) Simulate hemodynamics**

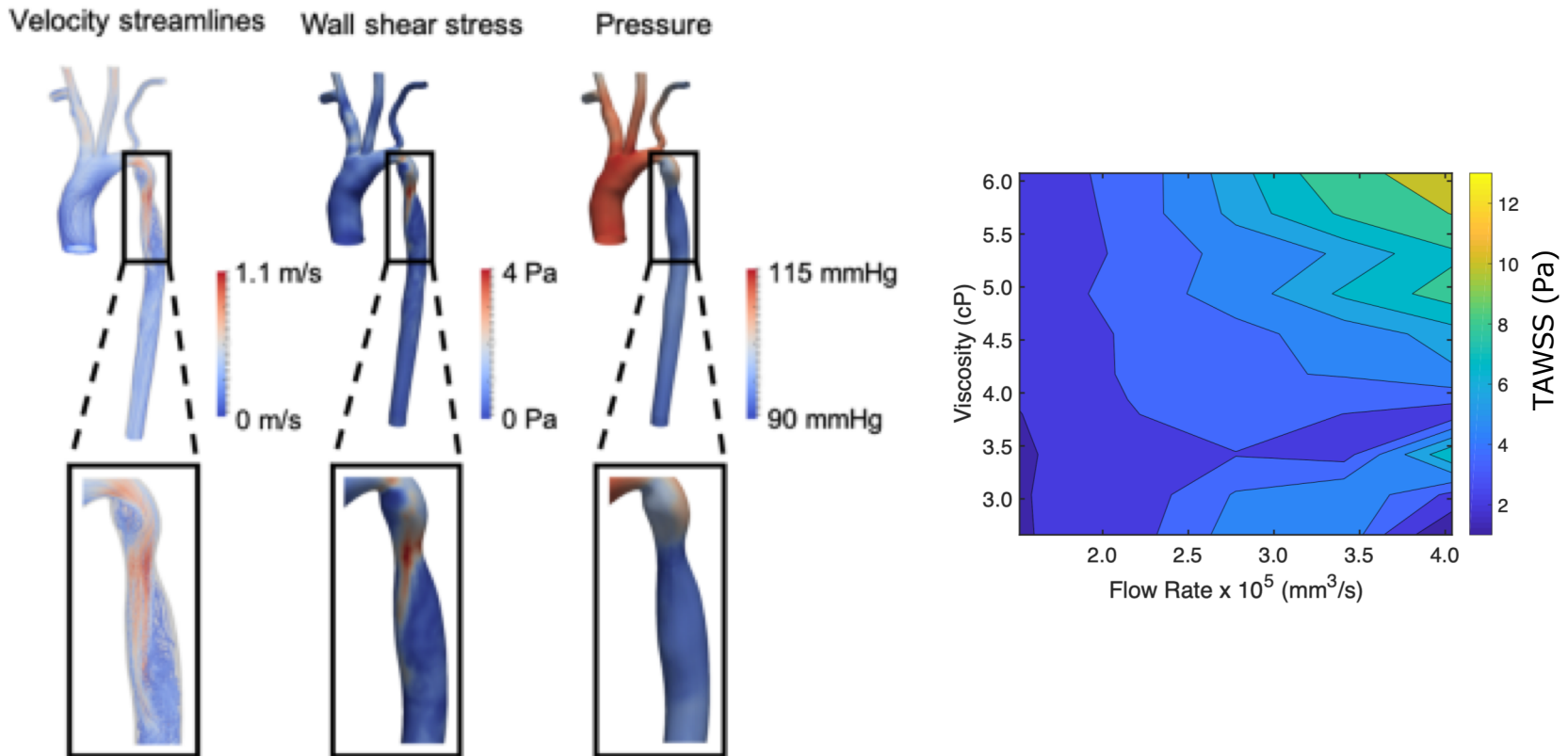


**Step 2) Train machine learning model**  
Inputs are viscosity, flow rate, stenosis degree, and period

**Step 3) Predict**  
 $\Delta P$ , TAWSS



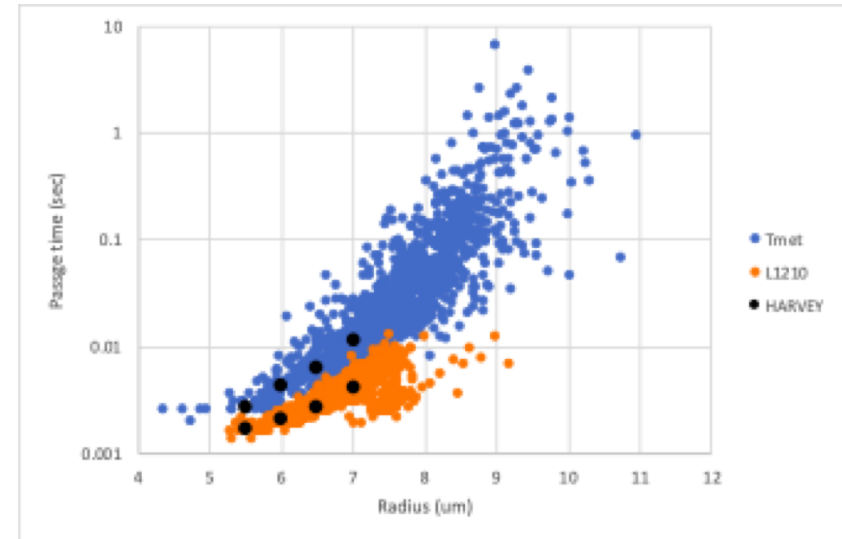
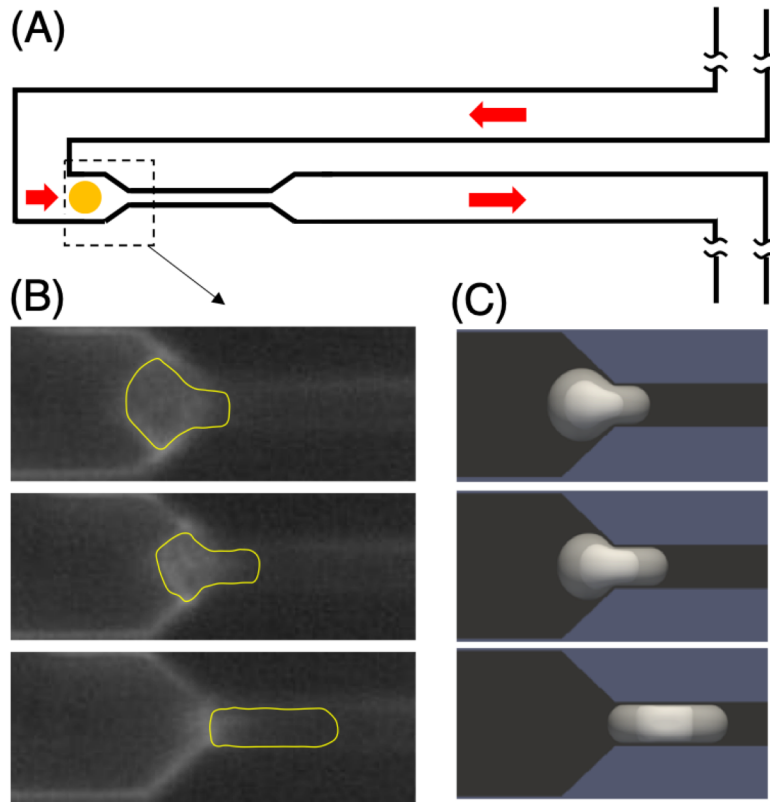
# AI-driven Simulations: Stratifying Patient Risk



*Identified minimal number of simulations needed to stratify patient risk*

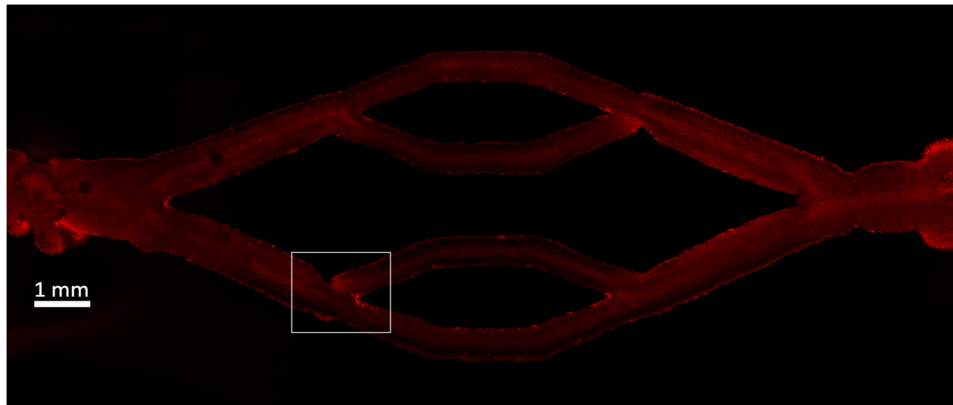
# **Fluid Structure Interaction Models**

# Cell-specific models

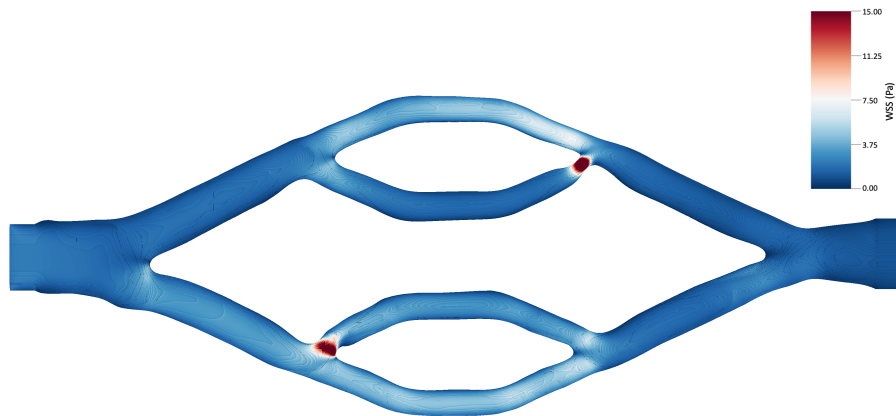


*We need a tunable model to capture cancer cell-specific parameters.*

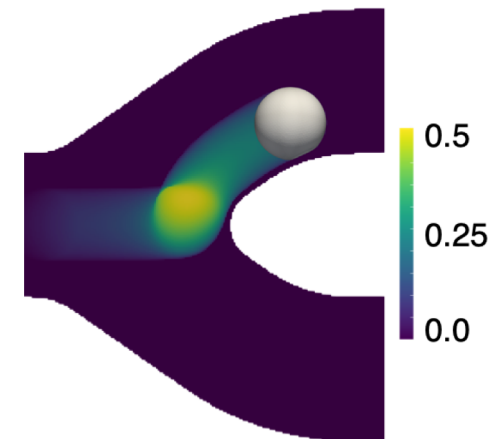
# Predicting cellular attachment



3D Bioprinted Bed



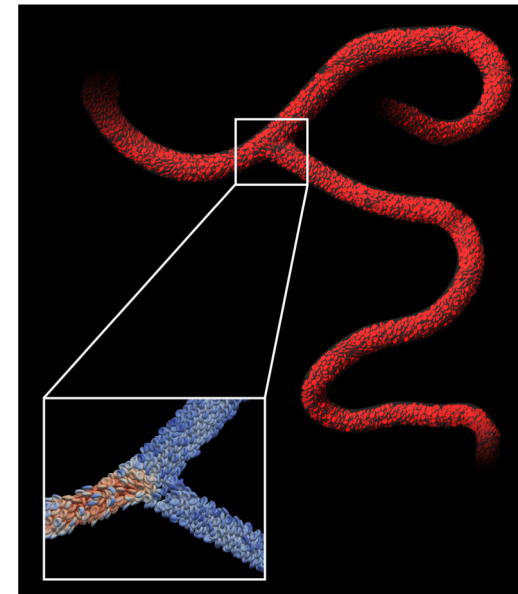
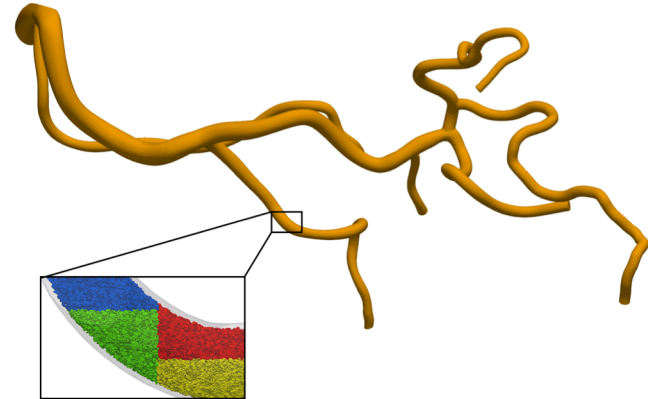
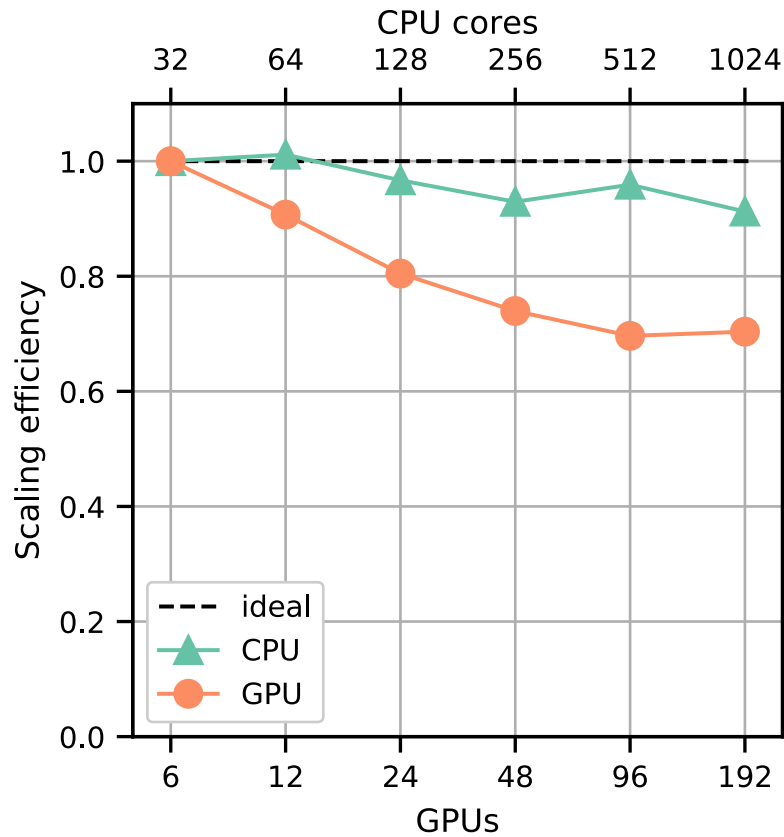
Bulk Fluid Simulation



FSI model

Hynes et al. Science Advances 2020  
Pepona et al. CMBE 2020

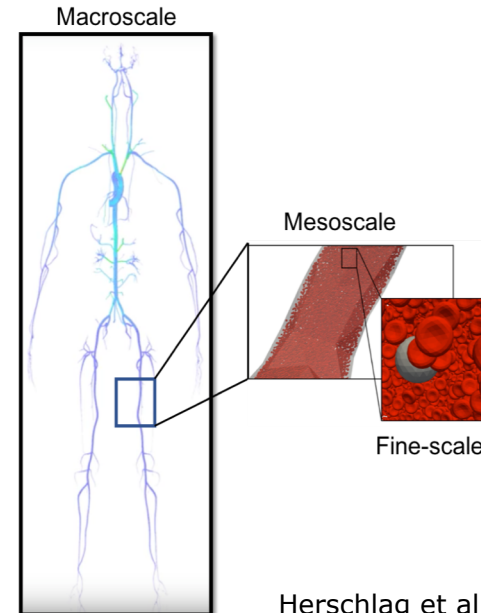
# Scaling the LBM-IB model



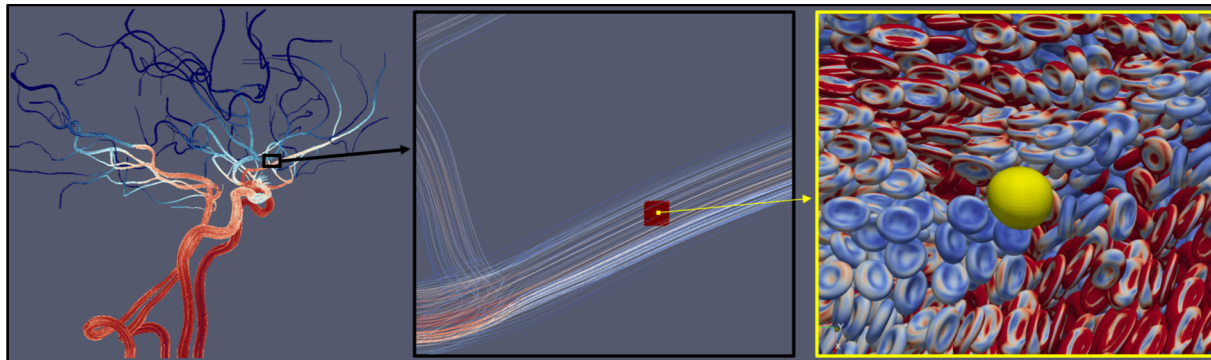
Gounley et al. ICCS 2019  
Ames et al. JCS 2020

# Adaptive Physics Refinement

- Generate an adaptive domain, multi-physics algorithm to resolve tumor cell trajectories
- Full or partial body simulations in which parts of the arterial system are purely fluid, whereas other parts resolve red blood cells.
- Utilize heterogeneous architectures efficiently.



Herschlag et al. IEEE Cluster 2019



# Next steps: preparing for exascale

- Large-scale simulations create petabytes of data **per timestep**.
- The gap between the speed of computation and speed of I/O is increasing with next generation systems.
- Developing methods to enable efficient, in situ and in transit visualization and analysis.
- Enabling communication free and re-wind capabilities.
- Supported under the Aurora Early Science Program for Data and Learning.



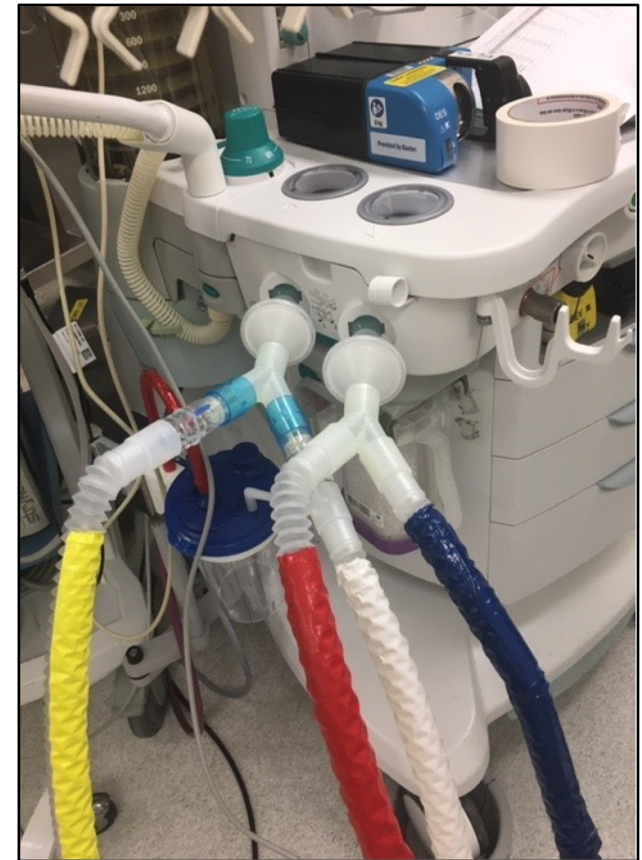
Planned first Exascale  
System in the US



## **Use Case 2: Ventilator Splitting**

# Case study: ventilator shortage

- Ventilators are vital equipment for assistance with respiration
- A shortfall of 45,000-160,000 ventilators with the U.S. was predicted for the ongoing pandemic
- Duke researchers paired up with restor3D to develop a safe, efficacious ventilator splitter and resistor system (VSRS)



Note: Ventilator splitting should **NOT** be standard-of-care and should only be used as a last recourse.

# What was needed?

- Tuning to select optimal restrictor for specific patients
- Computational fluid dynamics model to capture airflow
- Validation of fluid model
- Quick time-to-solution

### Calculator

Retrieve Previous Values

**Patient A**  
Weight:  kg  
Compliance:  ml/cmH<sub>2</sub>O  
Endotracheal Tube Diameter:  mm

**Patient B**  
Weight:  kg  
Compliance:  ml/cmH<sub>2</sub>O  
Endotracheal Tube Diameter:  mm

**Context**  
Peak Inspiratory Pressure (PIP):  cmH<sub>2</sub>O  
PEEP:  ml/cmH<sub>2</sub>O  
Respiratory Rate (RR):  breaths/minute  
Inspiratory/Expiratory Ratio:

Submit >

Calculator Setups Resources About

### Results

← Results

**Results**

Resistor Radius (mm):

None 2.5 3 3.5 **4** 4.5 5 5.5

**Patient A - No Resistor**  
Delivered Tidal Volume:  ml  
Delivered PIP:  cmH<sub>2</sub>O  
Delivered PEEP:  cmH<sub>2</sub>O

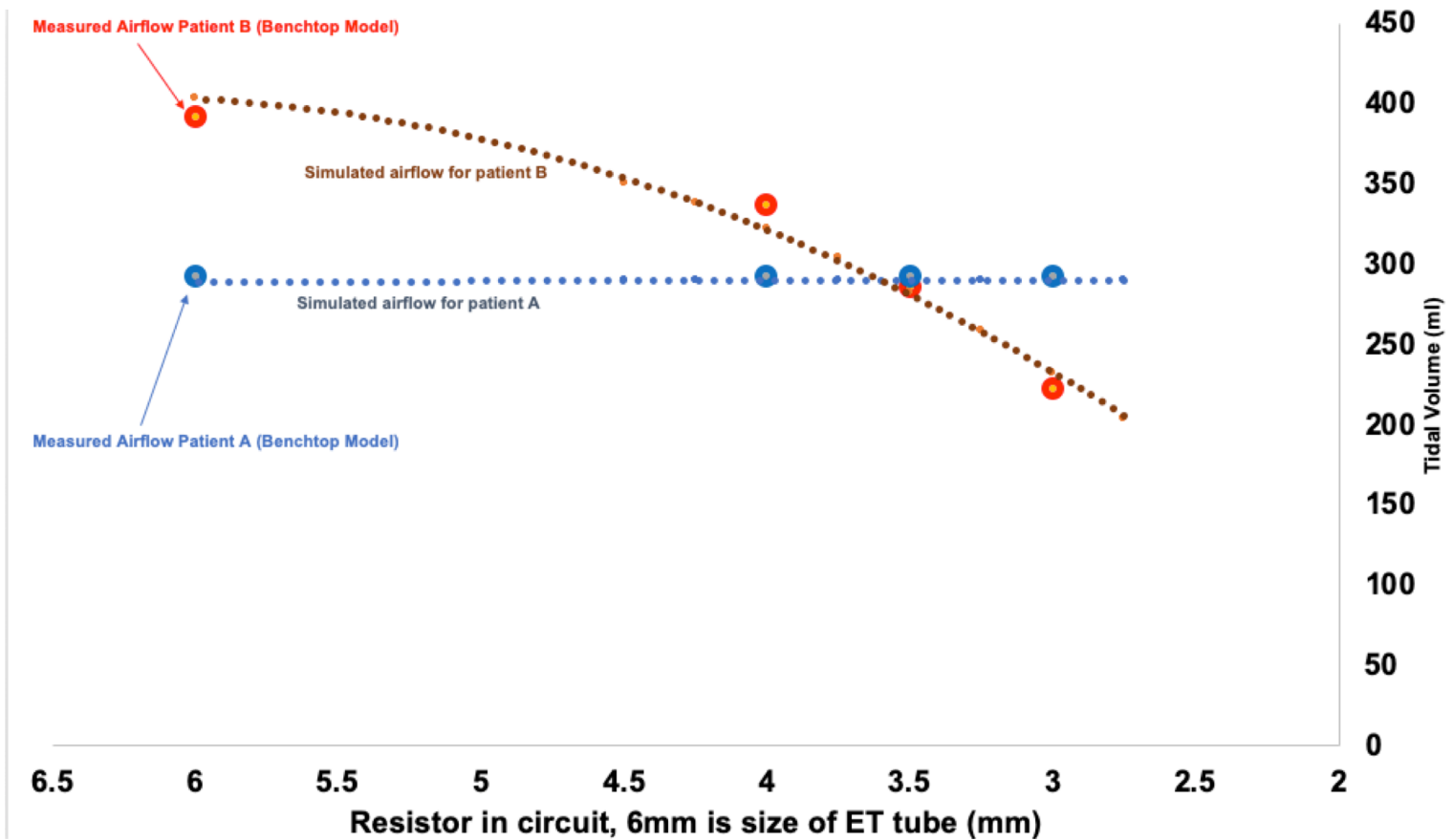
**Patient B - 4 mm**  
Delivered Tidal Volume:  ml  
Delivered PIP:  cmH<sub>2</sub>O  
Delivered PEEP:  cmH<sub>2</sub>O

Save Setup

Calculator Setups Resources About

Courtesy of CrossComm

# Validating Computational Model



# >200,000 Simulations Needed

	Minimum Value	Maximum Value	Step Size
Pulmonary Compliance (ml / cmH <sub>2</sub> O)	10	100	1-2
Endotracheal Tube Diameter (mm)	6	8.5	0.5
Peak Inspiratory Pressure (cmH <sub>2</sub> O)	20	50	1
Positive End-Expiratory Pressure (cmH <sub>2</sub> O)	5	20	1
Inspiratory to Expiratory Ratio	1:3	1:1	fractional
Respiratory Rate (breaths / minute)	10	30	1
Resistor Radii (mm)	2.5	5.5	0.5

# Science-Driven Solution

- COVID-19 HPC Consortium
- Coupled with Microsoft and Duke Office of Information Technology
- Worked with Microsoft Azure
- Need for minimal time-to-solution

Within days of submitting our request, we completed  
**800,000** compute hours in one weekend.

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