



Transforming FDA Approaches: The Role of In-silico Data, Multiscale Modeling, and Generative AI in Medical Device Product Development

Session Speakers



Darrell Swenson, PhD

Director of Numerical and
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Senior Managing Engineer
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Afrah Shafquat, PhD

Senior Data Scientist
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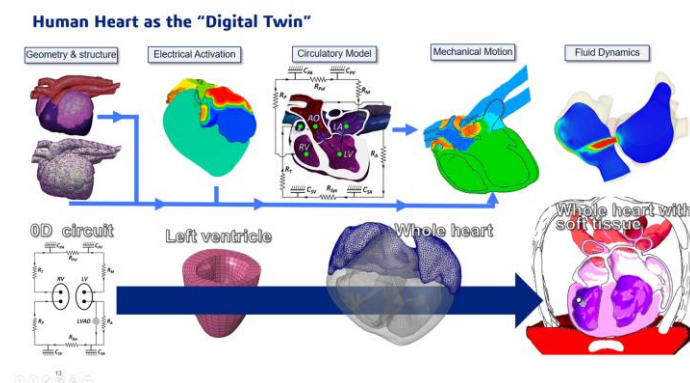
Heidi Sernoff, MD

Director
Medidata

Session Format

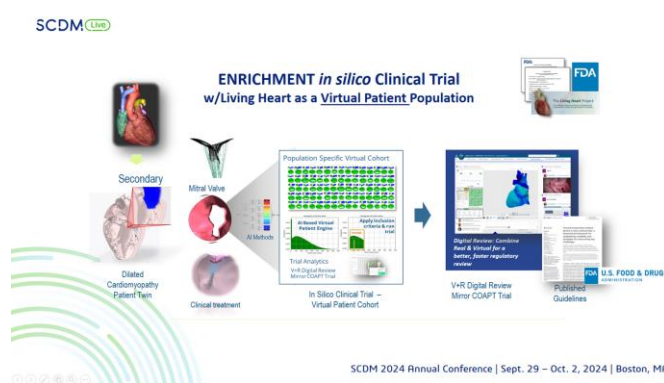
Focus: The rapidly evolving role of In-Silico Data in Medical Device Product Development

Lessons Learned on the Virtual Patient & Digital Twin Journey



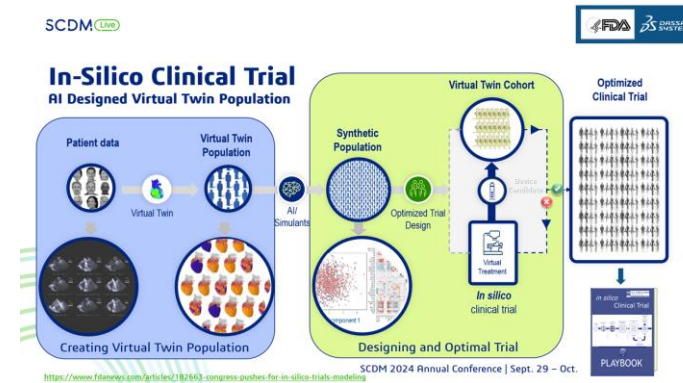
Darrell Swenson
Medtronic

In Silico Clinical Trial Data in Regulatory Decisions



Steven Kreuzer
Exponent

Generative Virtual Twins for Optimized Clinical Trial Design



Afrah Shafquat
Medidata



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Lessons Learned on the Virtual Patient and Digital Twin Journey



Darrell Swenson, PhD

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Kevin Sack, PhD

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Technical Lead
Physiology Modeling



Sofia Monaci, PhD

Medtronic

Physiology Modeling

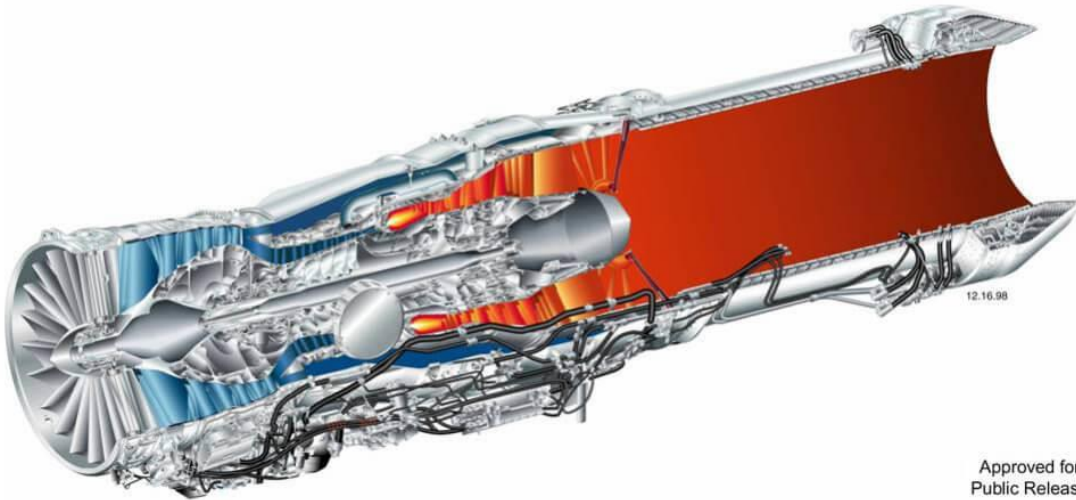


Nya Perry

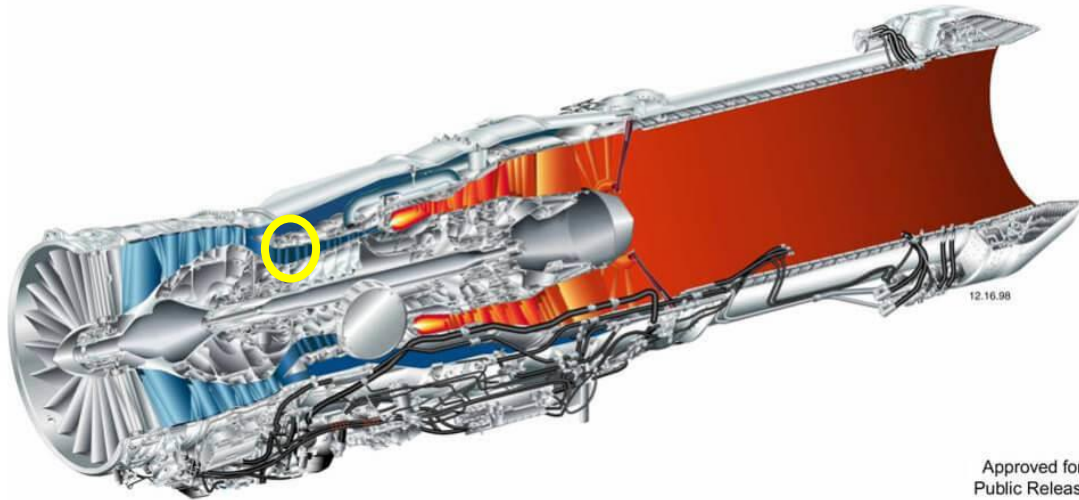
Medtronic

Physiology Modeling

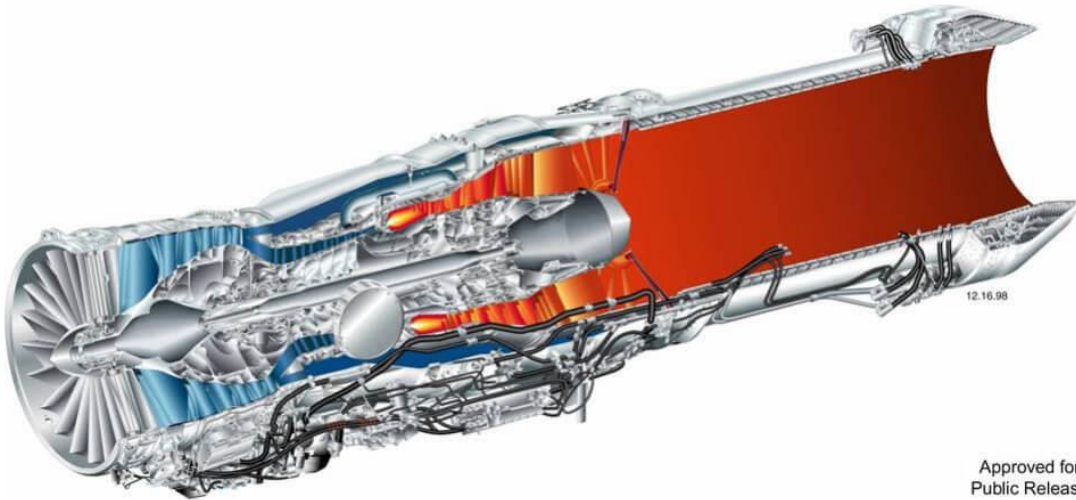
Joint Strike Fighter
F-35 Lightning II Propulsion
F135 Conventional Take-Off Landing

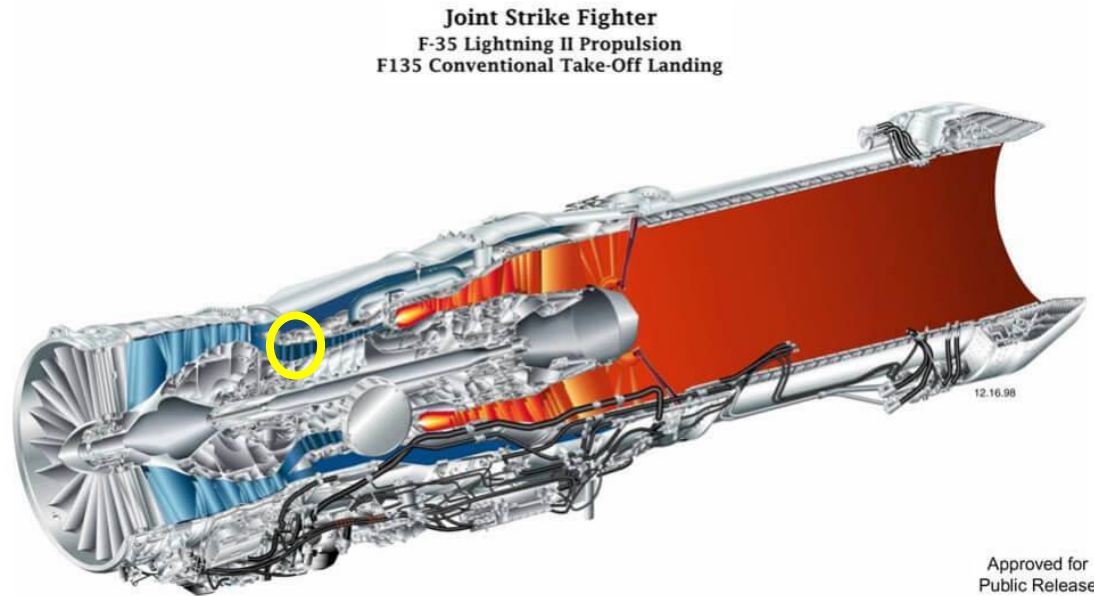


Joint Strike Fighter
F-35 Lightning II Propulsion
F135 Conventional Take-Off Landing

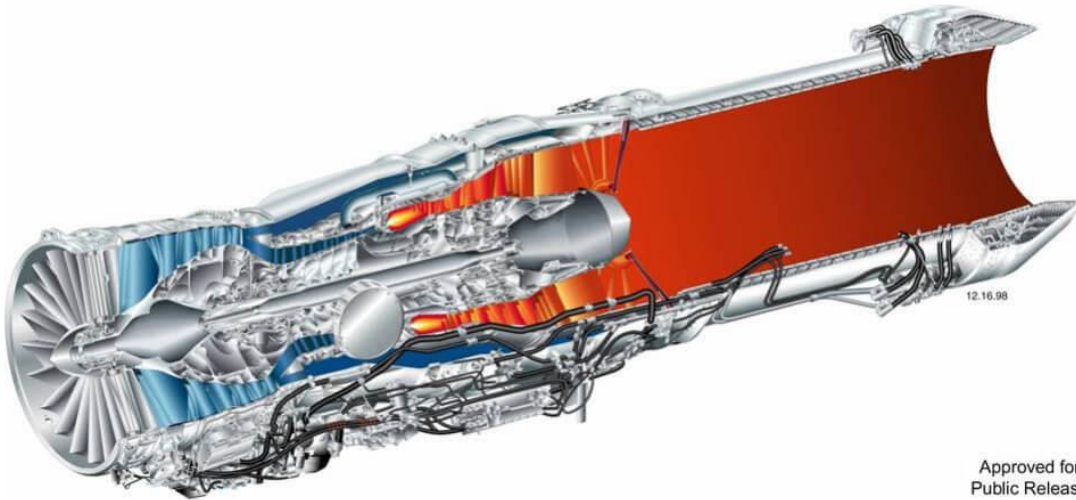


Joint Strike Fighter
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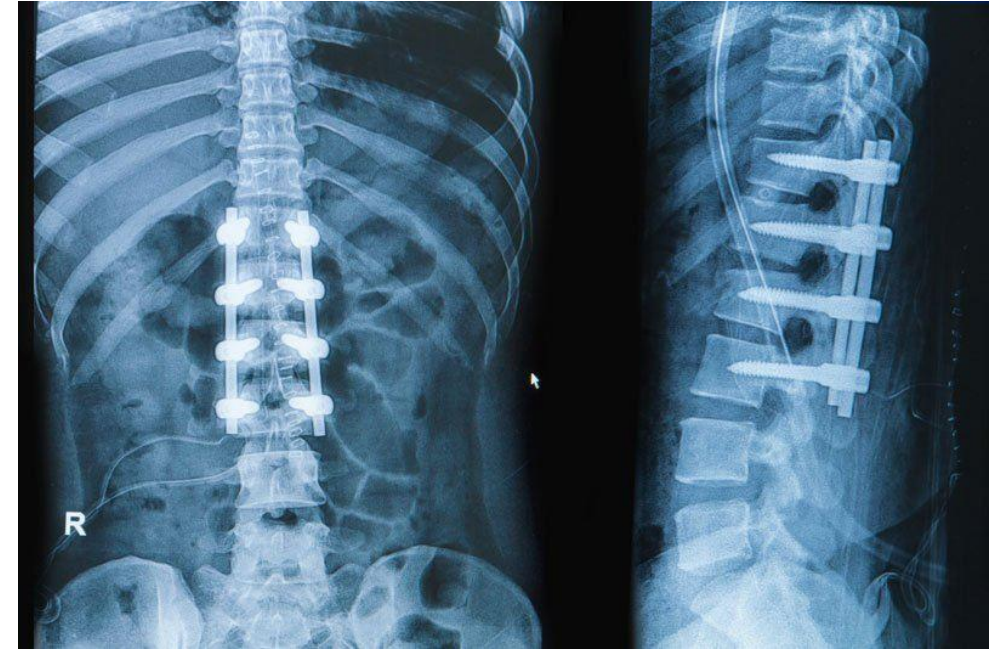




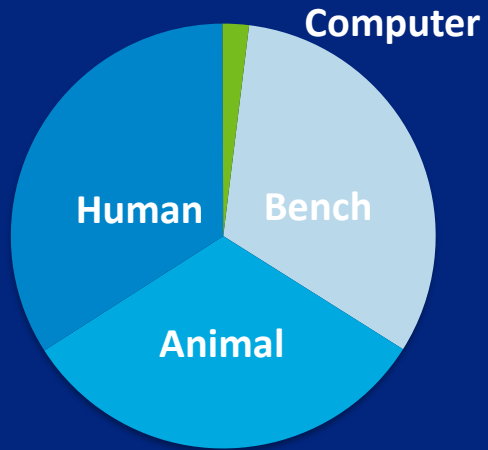
Joint Strike Fighter
F-35 Lightning II Propulsion
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Approved for
Public Release



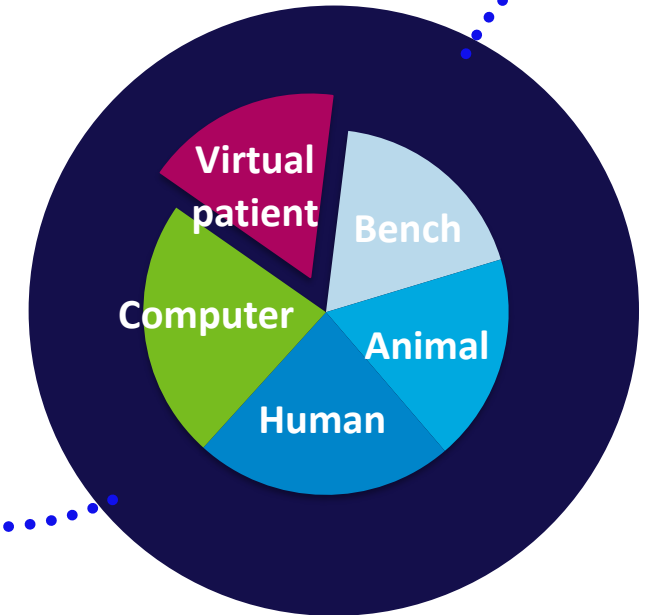
Current state



Regulatory Evidence

* Adapted from Bill Murray (CEO, MDIC), "21st Century Cores: Modernizing Clinical Trials, Testimony to Congress 7/2014

Future state



Phase 2

Infrastructure & excellence

Replace animal trials
& optimize human
clinical trials

Widescale impact

Improve clinical
trial success
rates

Phase 3

Credibility & Methods

Therapy feasibility &
refinement
Reduce animal trial
size

Phase 1

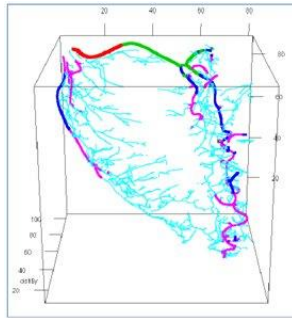


Obstacles

- Understanding clinical study complexity
- Asking the right questions

Modeling and Simulation to Generate Regulatory Evidence

Reduce Clinical
Endpoints



Leadless Pacemaker
Fixation



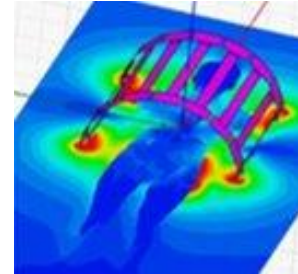
Augment
Clinical Trials



LEADER Study – Lead
Fracture Model



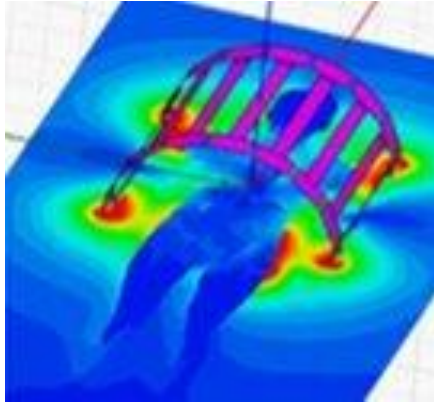
Avoid Clinical
Trials



MRI Safety Labeling



How are we impacting clinical studies

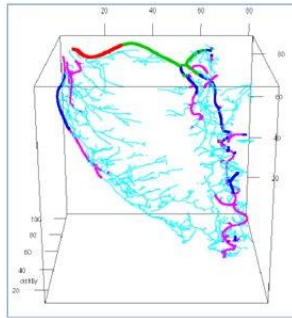


MRI modeling as Safety Evidence
Standard across most Regulatory Bodies

- Provide Evidence where Clinical studies are not practical
 - Very rare events
 - Underrepresented Populations
 - Too dangerous
 - Branching decision trees

Modeling and Simulation to Generate Regulatory Evidence

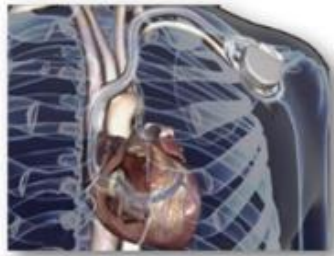
Reduce Clinical
Endpoints



Leadless Pacemaker
Fixation



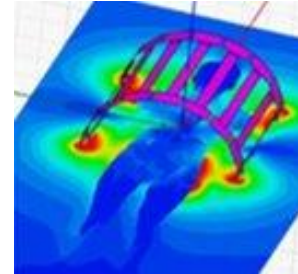
Augment
Clinical Trials



LEADER Study – Lead
Fracture Model



Avoid Clinical
Trials



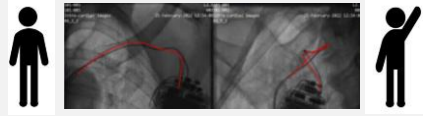
MRI Safety Labeling



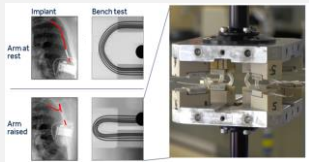
Predictive Engineering Augments Clinical Findings

LEADER STUDY

Predictive Engineering Model of Lead Fracture



Use Conditions



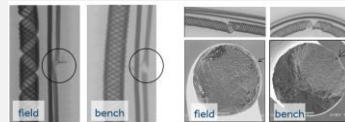
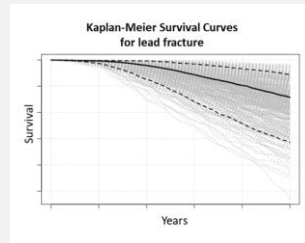
Bench Tests



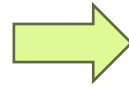
FEA Stress/Strain
Analysis



Bayesian Statistics



Materials



Secondary Safety Objective

Combined Clinical and simulated patient fracture-free rate



Results of the reliability model were incorporated as simulated patient outcomes

Clinical Patients

Implant Attempted
Cohort
657 patients

Zero observed
fractures



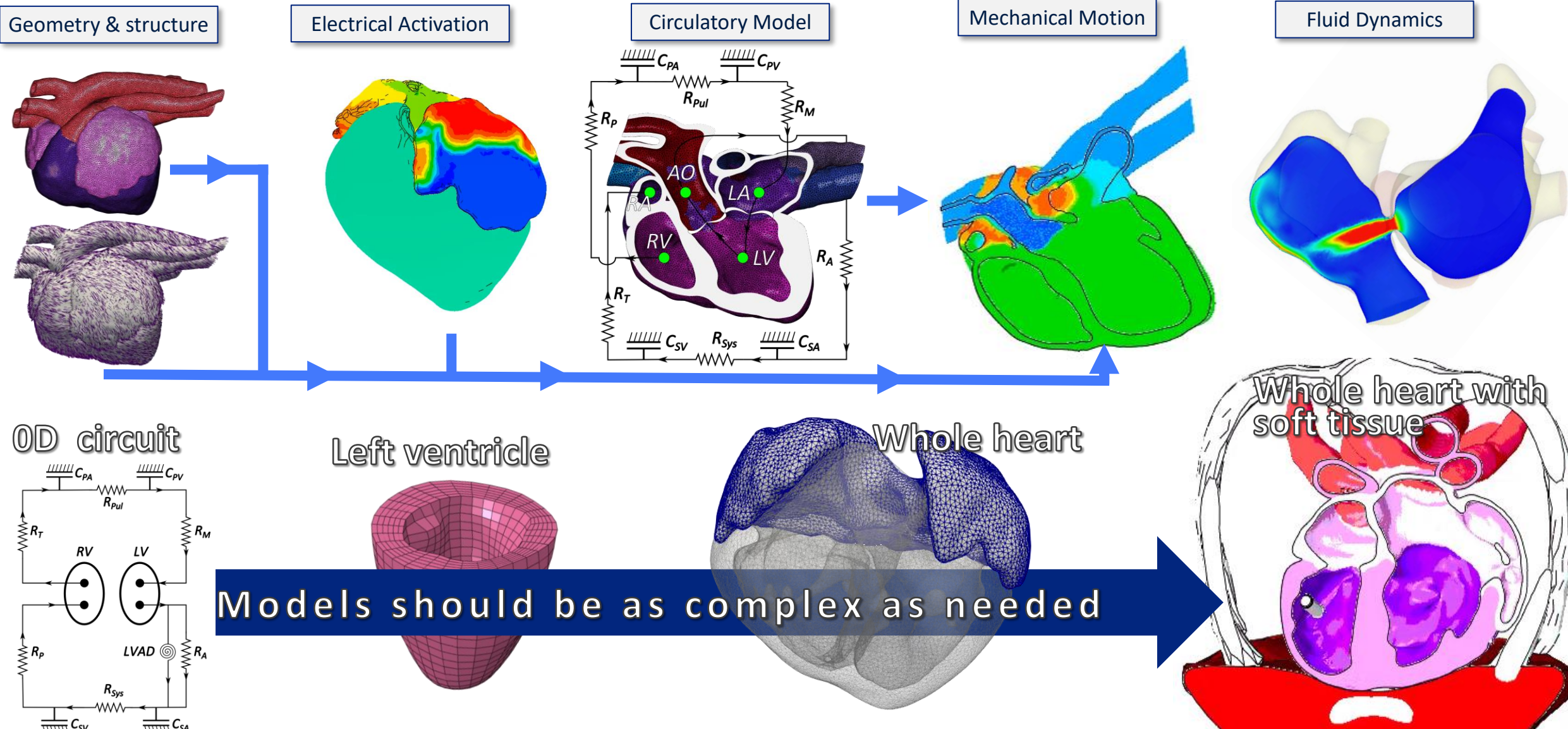
Simulated Patients

242 simulated
patients

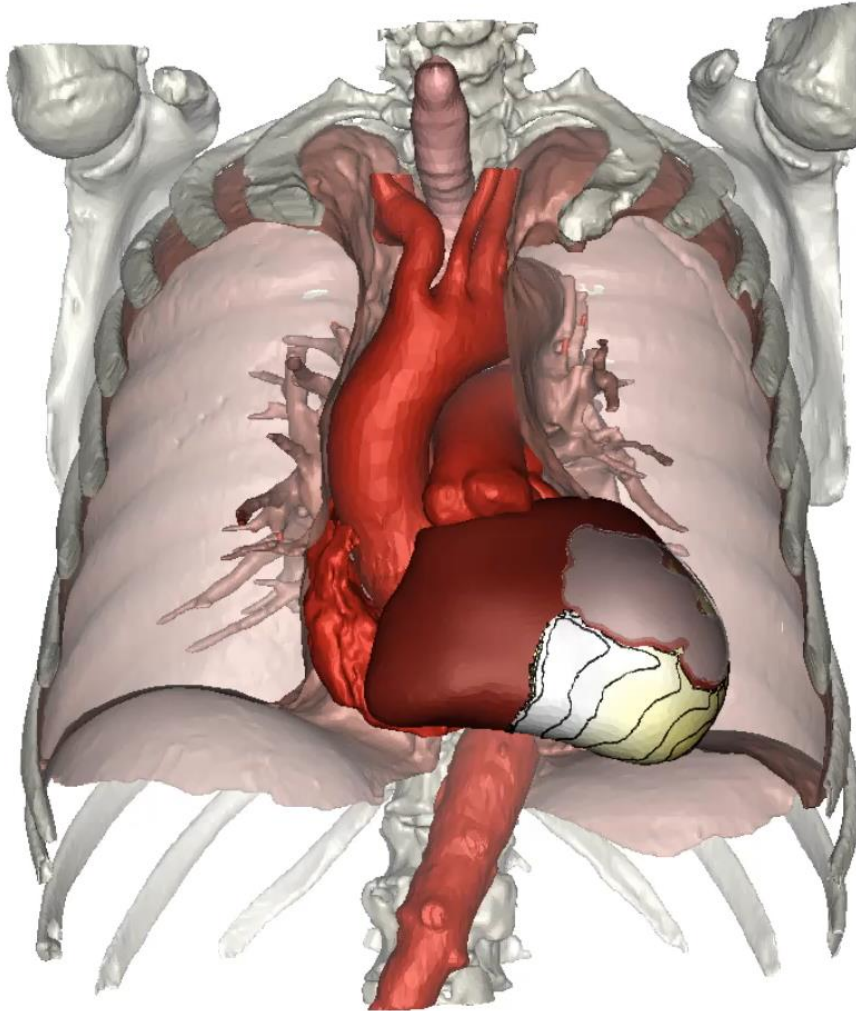


Secondary Safety Objective:
99.97% 12-month fracture-
free rate

Human Heart as the “Digital Twin”

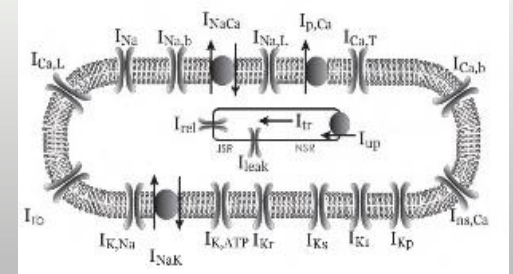


Multi-Scale Computational Electrophysiology

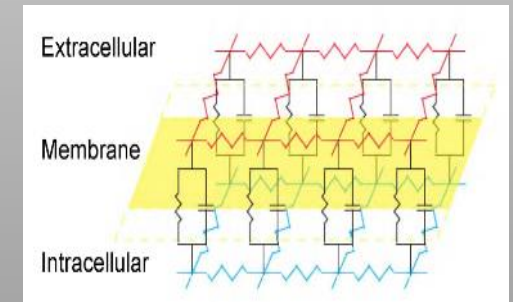


Reaction Diffusion Bidomain Ten Tusscher Cell model

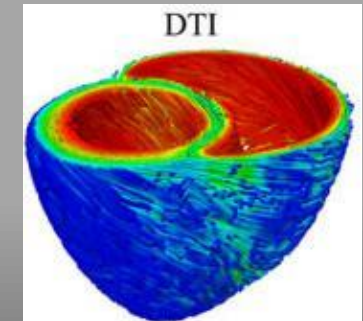
Cellular



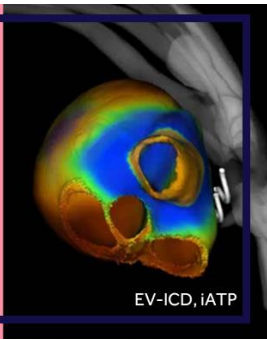
Tissue



Organ



Replicate **clinical protocols** to compare and **demonstrate efficacy** of anti-tachycardia (ATP) pacing algorithms



Case Study 1: Investigation into intrinsic-ATP efficacy

Problem:

Low ATP success rates.

Expense and difficulty in conducting clinical trials to compare ATP algorithms

Proposal:

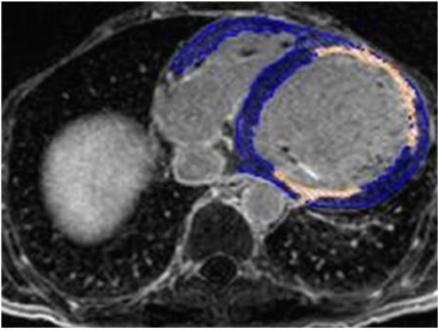
Utilize **patient-derived models** to compare burst ATP and novel iATP algorithms under real-world scenarios, **and understanding why ATP fails**

Antitachycardia Pacing Simulations
by Darrell Swenson

Patient Derived Models

Clinical Data

LGE MRI



EP Data

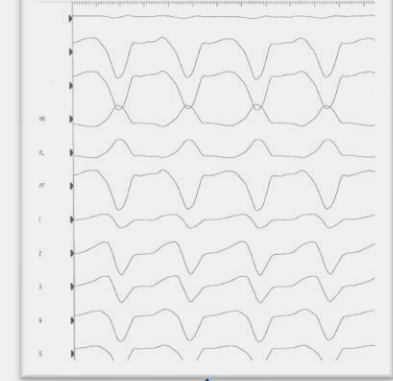
	ERP 1	ERP 2
Med 1	600/290	400/260
Med 2	500/270	350/240
Med 3	600/270	350/220
Med 4	600/260	400/230
Med 5	600/290	350/240
Med 6	600/300	300/240
Med 7	600/270	350/240
Med 8	600/290	350/250
Med 9	600/280	350/240
Med 10	600/280	NA
Med 11	600/280	350/240
Med 12	600/280	350/250

Induction Protocol

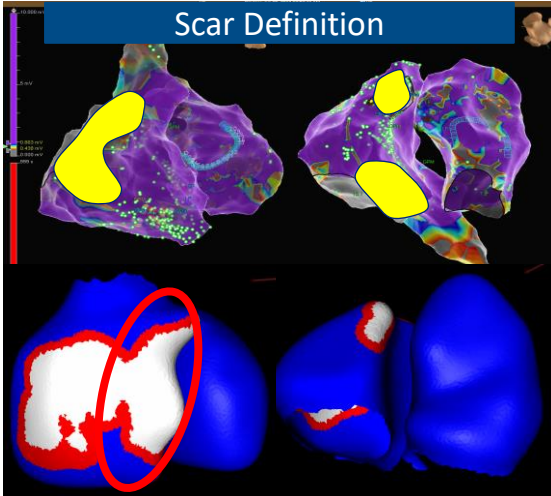
VT1	VT2
600/310/220/200	400/290/220
500/280/210	350/250/200
350/210/200/200	NA
600/250/250	400/240/210
NA	NA
NA	NA
NA	NA
600/320/240/210	350/280/220/200
600/290/220/200	350/280/200/200
600/300/230	NA
600/250/200/200	350/240/200/200
600/280/200/200	350/280/230

Physician Adjudication

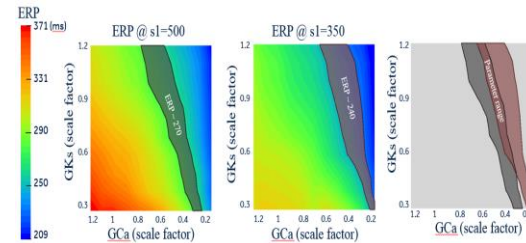
ECG



Scar Definition

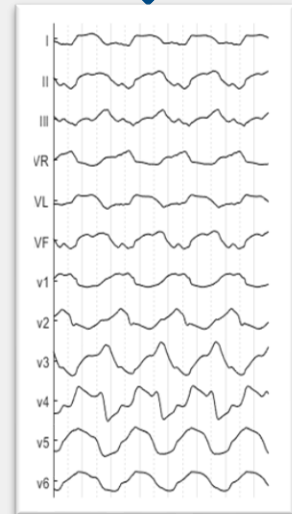


Machine Learning

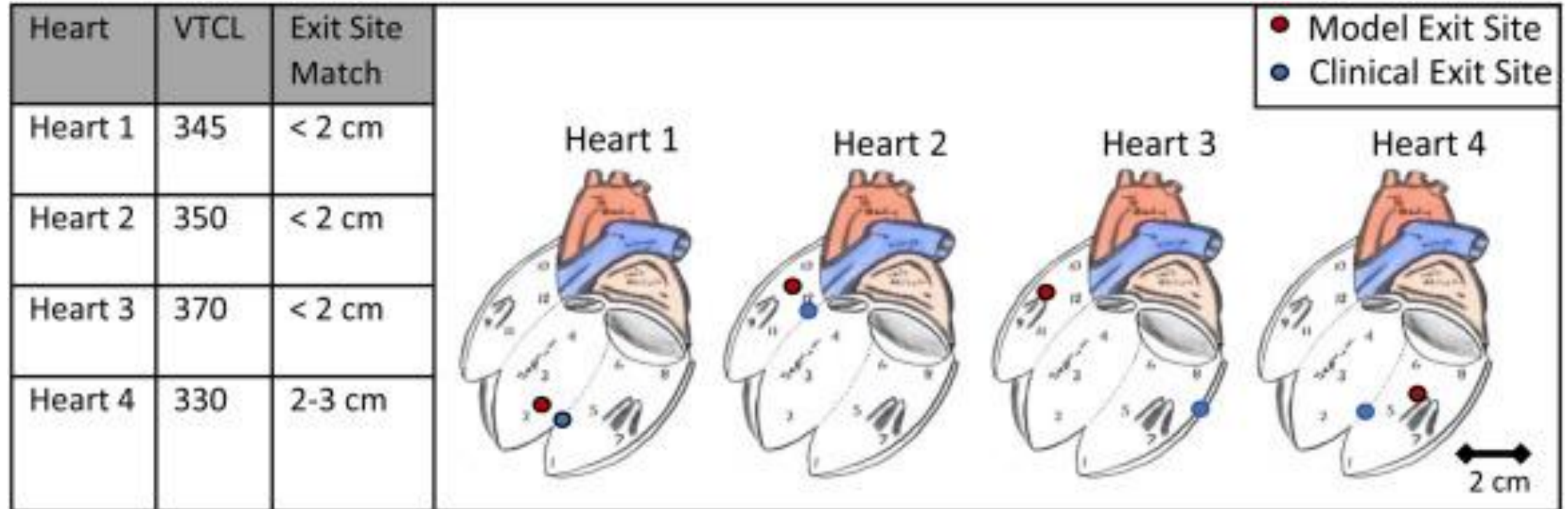


Cell Model Parameter Fitting

Induced VT

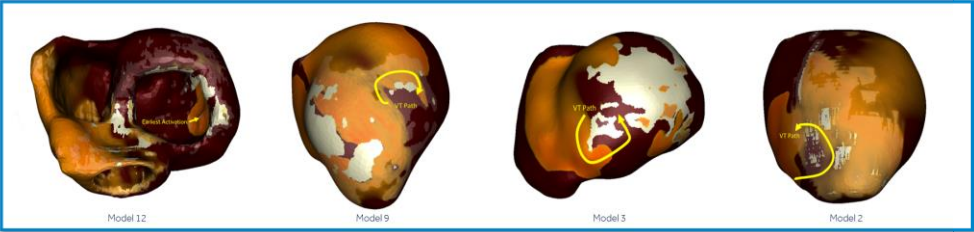


Adjudication

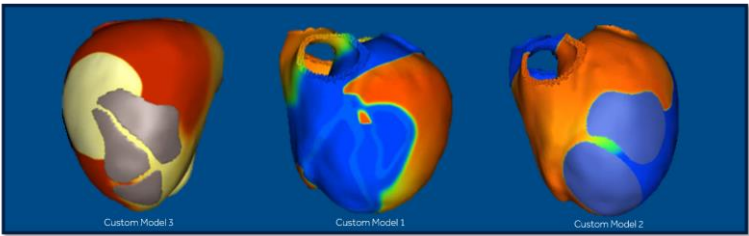


Virtual Human VT Modeling Cohort

Patient Derived Datasets

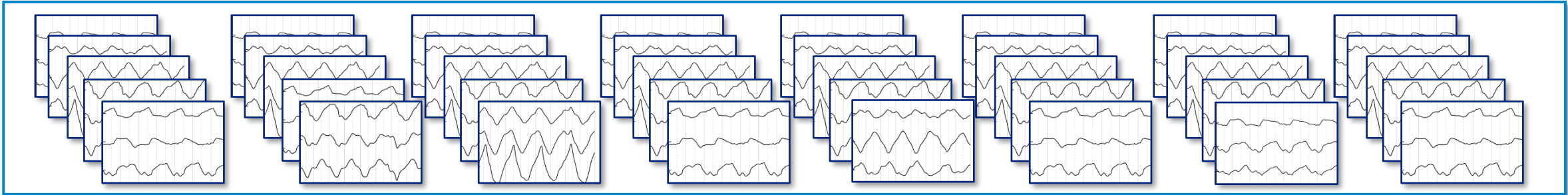


Custom Scar Datasets



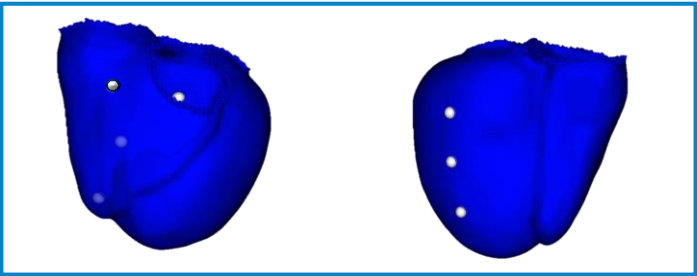
X **5 EP STATES**

Measured in Clinic + Small changes to EP parameters
E.g. Ischemia, Medication, Dehydration, ...



X **8-10 PACING LOCATIONS**

Each location has a unique interaction with the VT



=

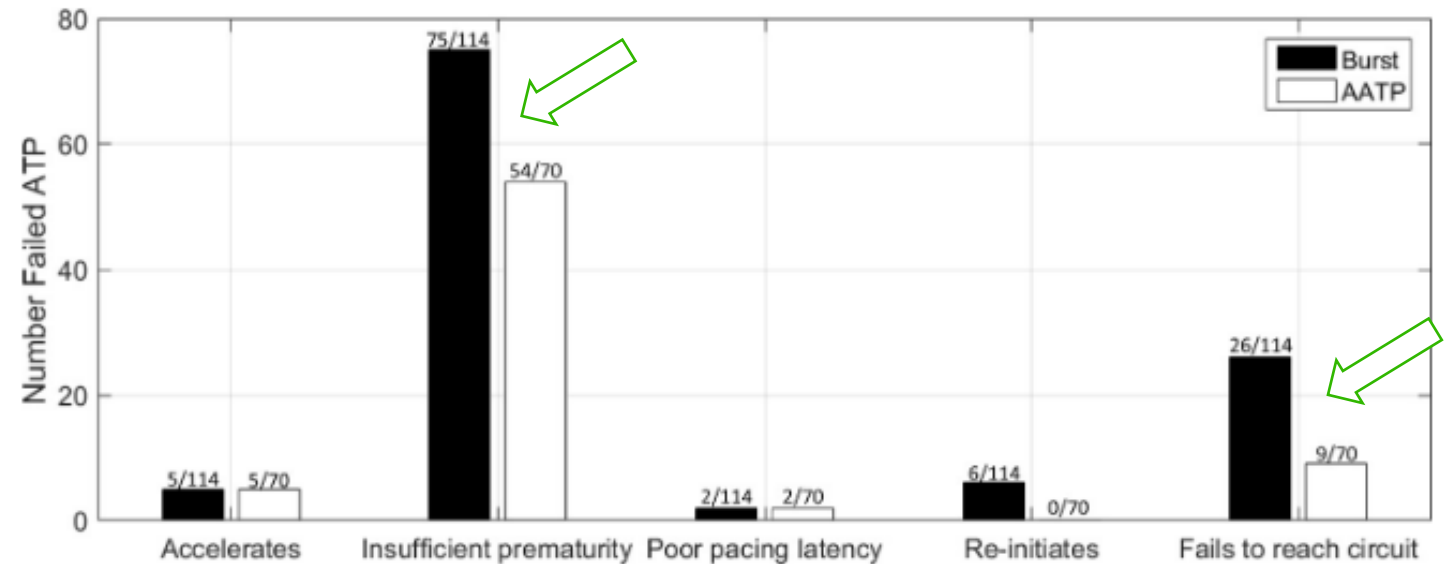
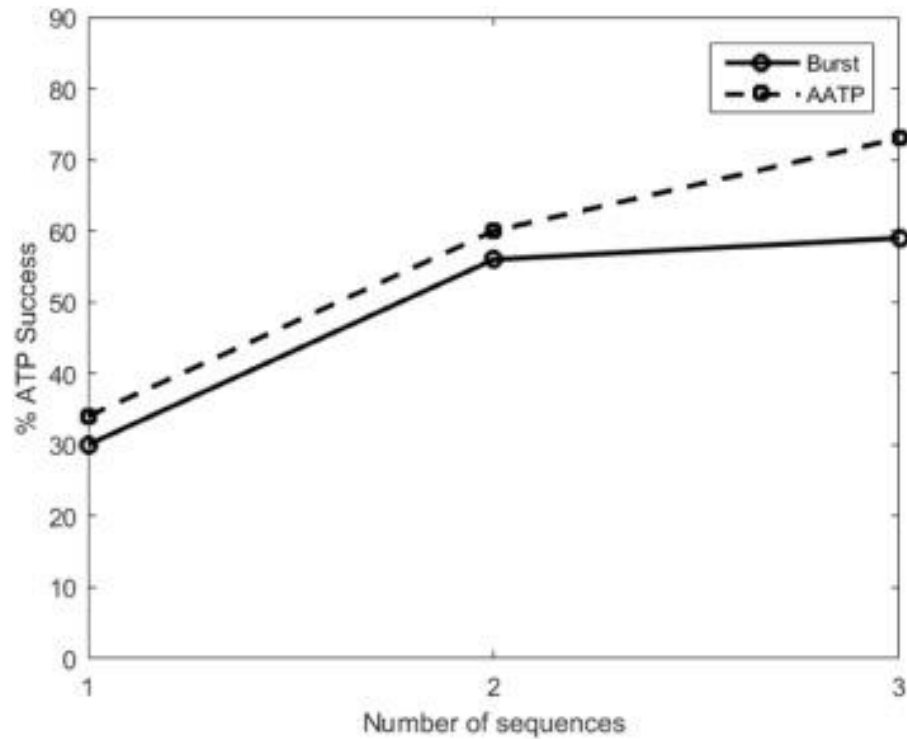
259 VIRTUAL PATIENTS



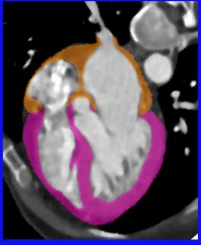
iATP efficacy is 17% greater than conventional ATP

iATP continues to learn

- iATP adapts to common mechanisms of failures without increase in accelerations



Use **virtual model** to **investigate effects of high-rate pacing** for the design of a clinical trial



FIRE - HFpEF

Case Study 2: Effects of high-rate pacing in HF-pEF patients

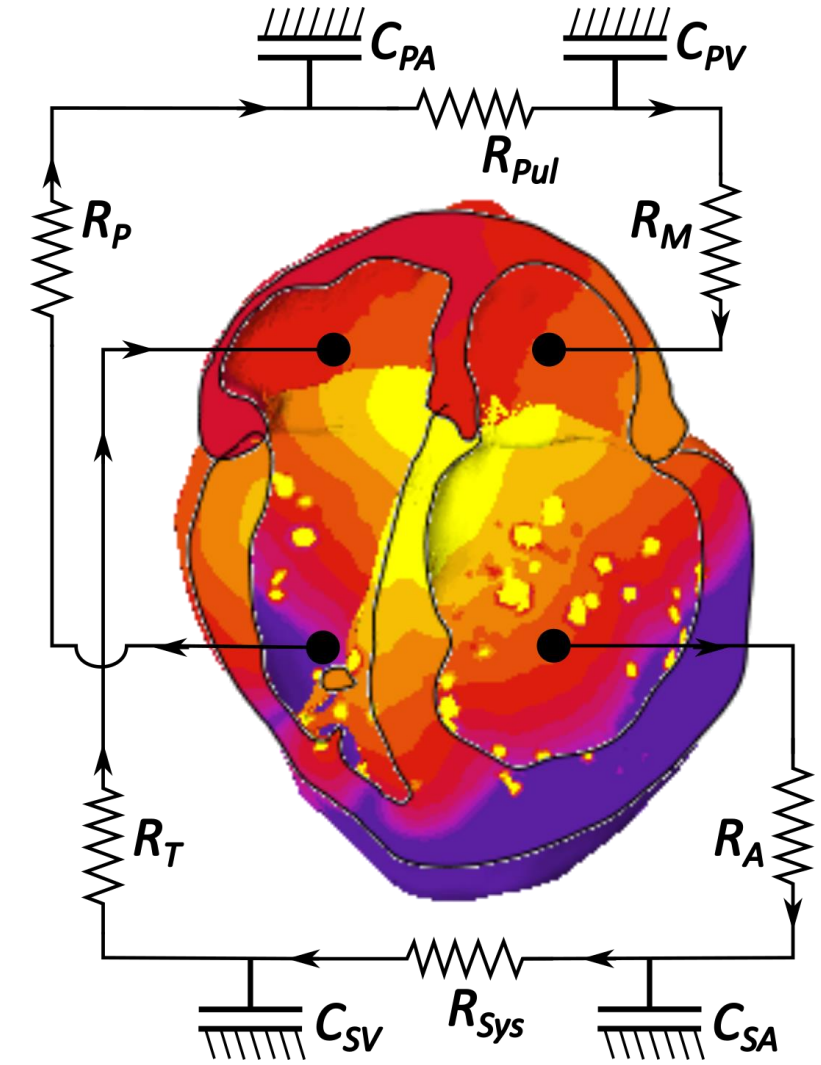
Problem:

Limited effective therapy for patients with HF-pEF

Necessity of designing a clinical trial to probe tachycardia remodeling as HF-pEF therapy

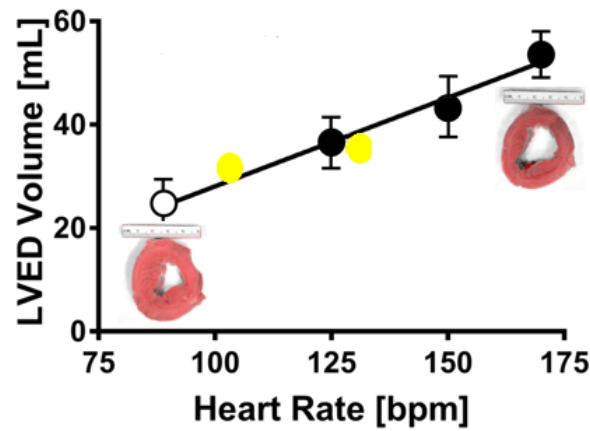
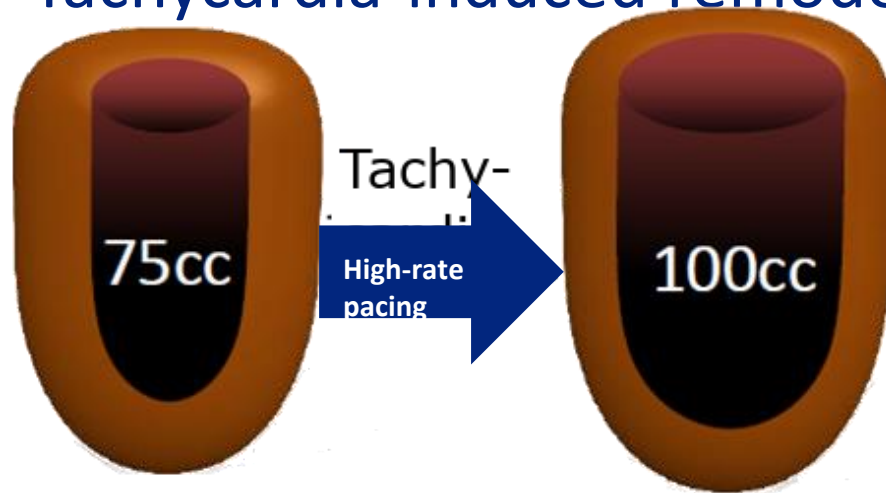
Proposal:

Utilize **whole-heart model** to investigate impact of **higher rate pacing** and help improve **safety and success of clinical study design**



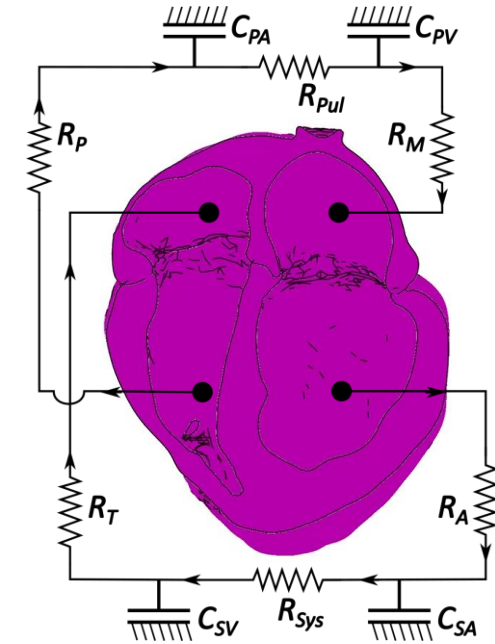
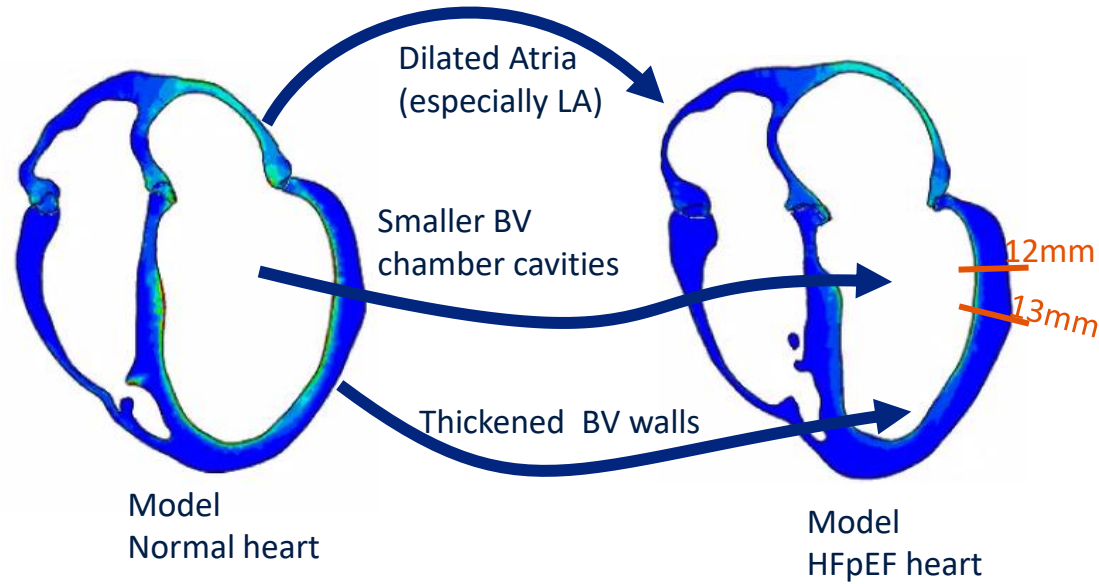
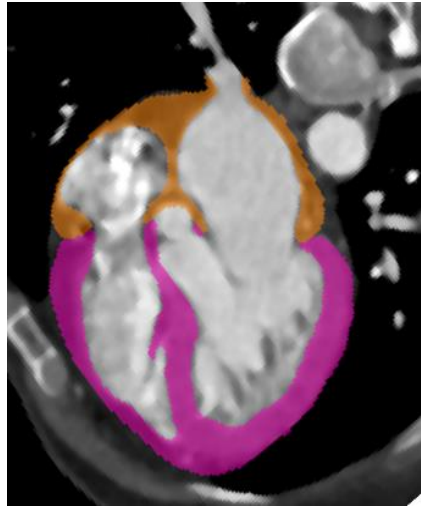
Modeling New Therapies for HFpEF

- Tachycardia-induced remodeling



- This is a new concept that utilizes a standard pacemaker to elevate heart rates (100+ bpm) for sustained periods of time.
- After two small human studies, **key questions remained:**
 1. What pacing sites to use?
 2. What is necessary for remodeling to occur?
 3. what is a safe rate range?
 4. should AV-intervals be set?

Overview of the 4chamber HFpEF model



	Normal	HF25	HF50	HF75	HF100
Myocardial stiffness [1-4]	baseline	150%	200%	250%	300%
Peak tension capacity (kPa) [7]	baseline	80%	80%	80%	80%
Lusitropic capacity [1-3,5,6]	baseline	79%	53%	26%	0%
Contractility reserve [7,8]	baseline	75%	50%	25%	0%
LV EDP (mmHg) [2-4]	9.3	17.3	21.7	27.5	30.7
mLAP (mmHg) [4,12]	6	12	16	22	27
MAP (mmHg) [1,4,9,10]	93	93	96	99	103

[1] R. Wachter *et al.*, "Blunted frequency-dependent upregulation of cardiac output is related to impaired relaxation in diastolic heart failure," *Eur. Heart J.*, vol. 30, no. 24, pp. 3027–3036, 2009.

[2] M. Kawaguchi, I. Hay, B. Fetics, and D. A. Kass, "Combined ventricular systolic and arterial stiffening in patients with heart failure and preserved ejection fraction: Implications for systolic and diastolic reserve limitations," *Circulation*, vol. 107, no. 5, pp. 714–720, 2003.

[3] D. Westermann *et al.*, "Role of left ventricular stiffness in heart failure with normal ejection fraction," *Circulation*, vol. 117, no. 16, pp. 2051–2060, 2008.

[4] M. R. Zile *et al.*, "Myocardial stiffness in patients with heart failure and a preserved ejection fraction contributions of collagen and titin," *Circulation*, vol. 131, no. 14, pp. 1247–1259, 2015.

[5] M. R. Zile, C. F. Baicu, and W. H. Gaasch, "Diastolic Heart Failure - Abnormalities in Active Relaxation and Passive Stiffness of the Left Ventricle," *N. Engl. J. Med.*, vol. 350, no. 19, pp. 1953–1959, 2004.

[6] K. E. Runte *et al.*, "Relaxation and the Role of Calcium in Isolated Contracting Myocardium from Patients with Hypertensive Heart Disease and Heart Failure with Preserved Ejection Fraction," *Circ. Hear. Fail.*, vol. 10, no. 8, pp. 1–15, 2017.

[7] B. A. Borlaug, C. S. P. Lam, V. L. Roger, R. J. Rodeheffer, and M. M. Redfield, "Contractility and Ventricular Systolic Stiffening in Hypertensive Heart Disease. Insights Into the Pathogenesis of Heart Failure With Preserved Ejection Fraction," *J. Am. Coll. Cardiol.*, vol. 54, no. 5, pp. 410–418, 2009.

[8] B. A. Borlaug *et al.*, "Global cardiovascular reserve dysfunction in heart failure with preserved ejection fraction," *J. Am. Coll. Cardiol.*, vol. 56, no. 11, pp. 845–854, 2010.

[9] A. M. Shah *et al.*, "Cardiac structure and function and prognosis in heart failure with preserved ejection fraction," *Circ. Hear. Fail.*, vol. 7, no. 5, pp. 740–751, 2014.

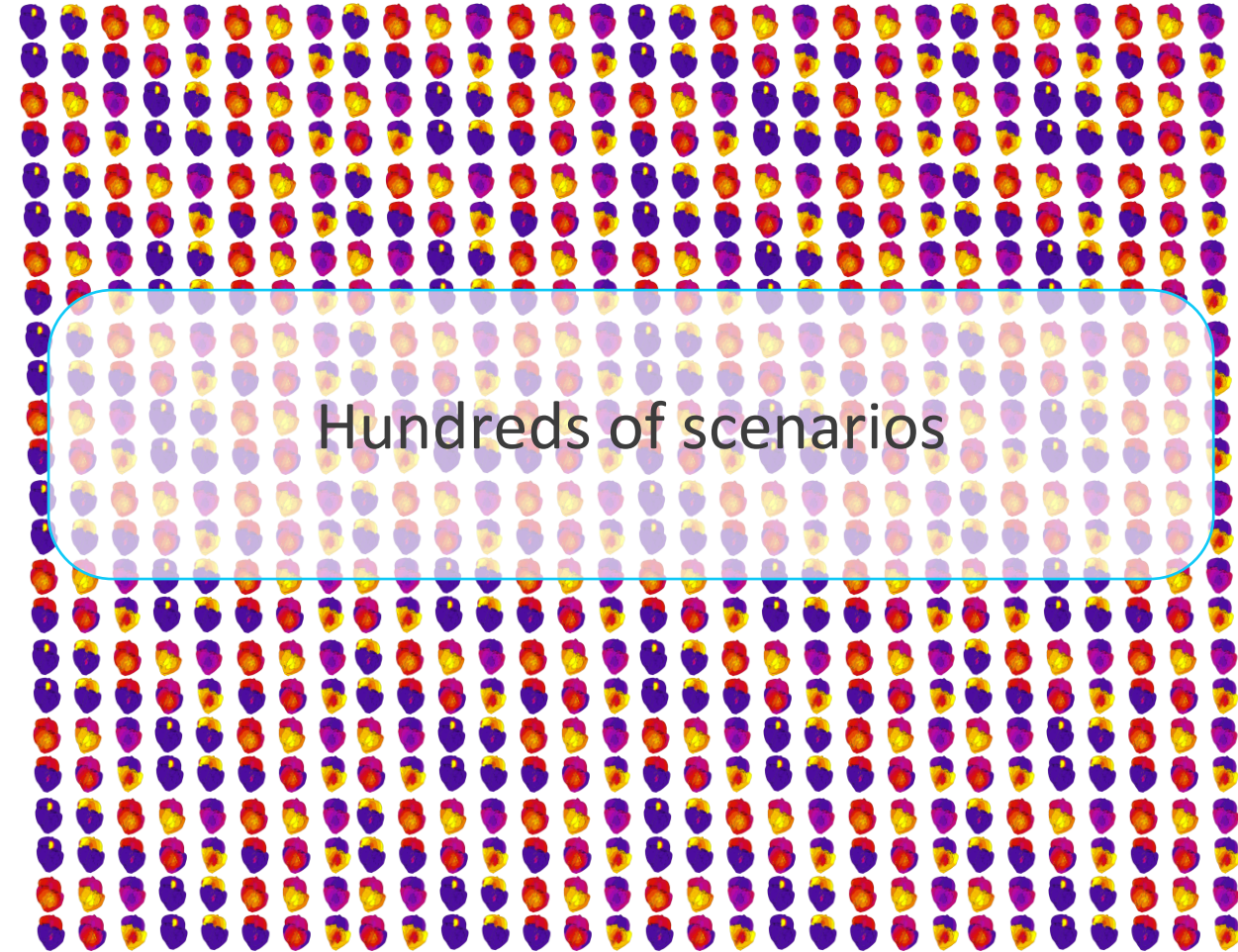
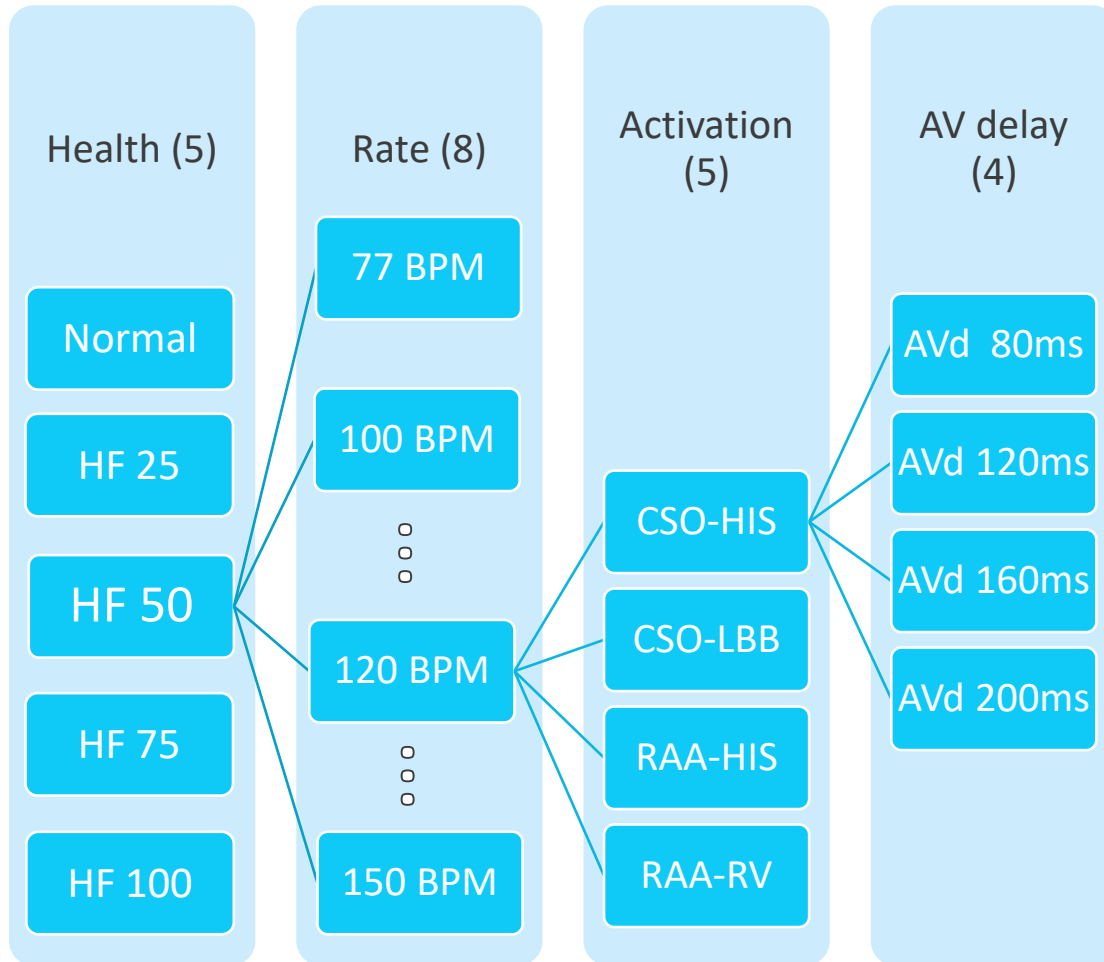
[10] M. R. Zile *et al.*, "Prevalence and significance of alterations in cardiac structure and function in patients with heart failure and a preserved ejection fraction," *Circulation*, vol. 124, no. 23, pp. 2491–2501, 2011.

[11] A. M. Shah *et al.*, "Prognostic importance of impaired systolic function in heart failure with preserved ejection fraction and the impact of spironolactone," *Circulation*, vol. 132, no. 5, pp. 402–414, 2015.

[12] E. Wolsk *et al.*, "Central and Peripheral Determinants of Exercise Capacity in Heart Failure Patients With Preserved Ejection Fraction," *JACC Hear. Fail.*, vol. 7, no. 4, pp. 321–332, 2019.

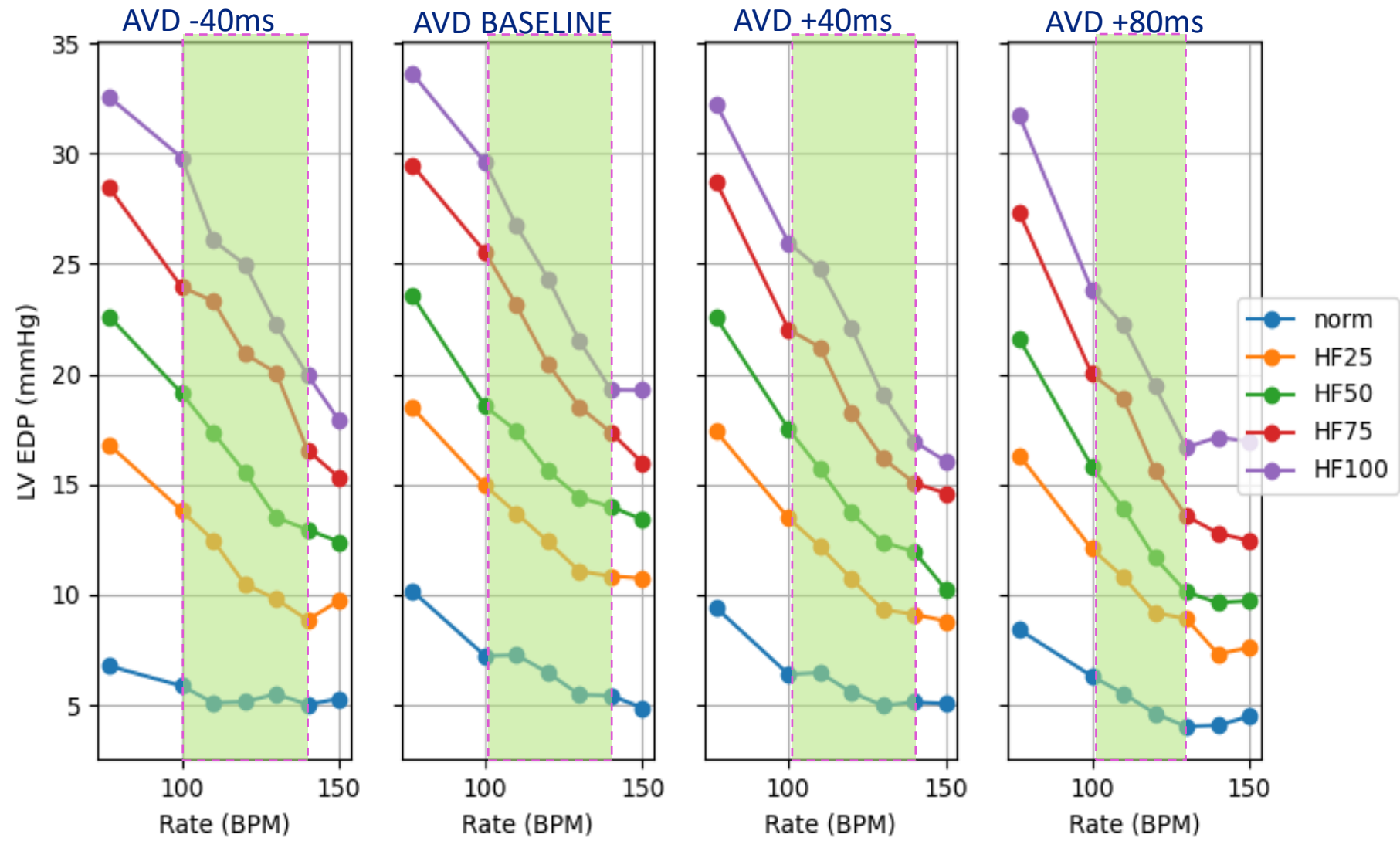
FINITE ELEMENT MODELING – STUDY DESIGN

EFFICIENT AND MECHANICALLY MEANINGFUL



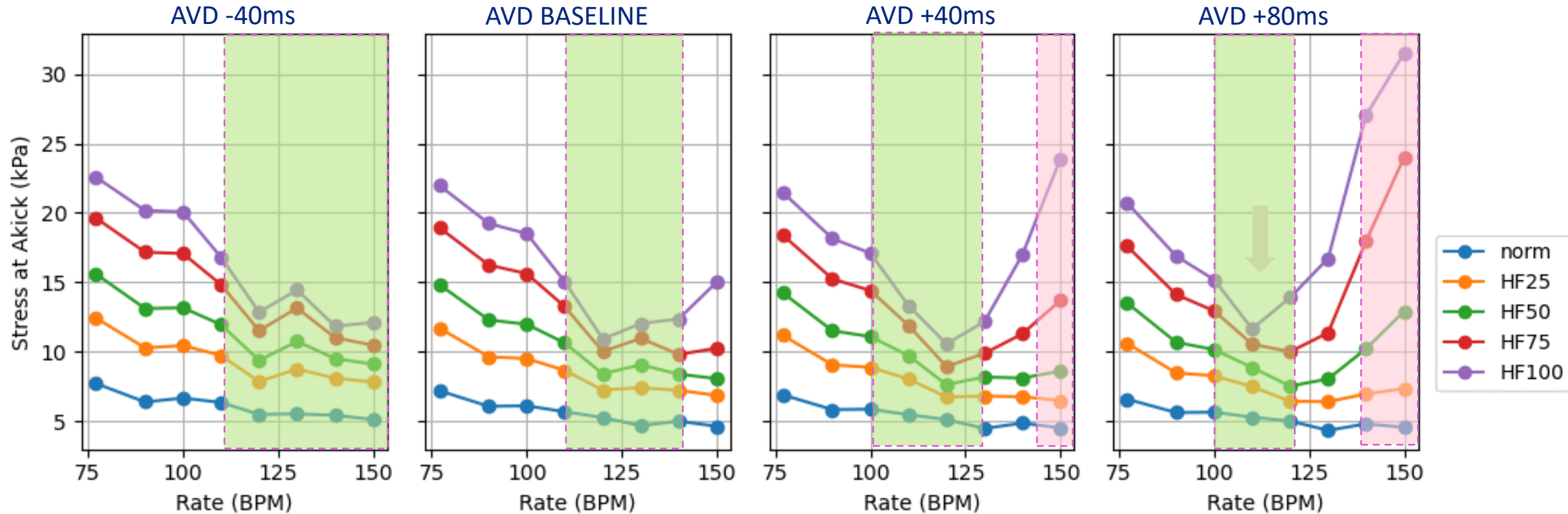
Potential Efficacy: LV EDP reduces with rate, could drive favorable remodeling

IMPROVEMENTS AT ALMOST EVERY RATE AND AVD



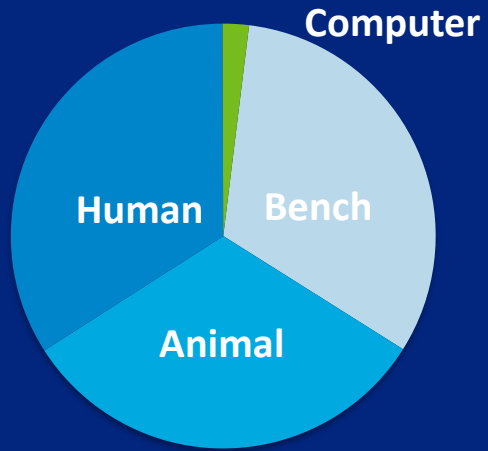
Modeling allows new insights: Left atrial stress even more effected by AVD

LONG AV DELAYS INTRODUCE ADVERSE STRESS EARLIER



- Increased wall stress means increased tissue damage, working against therapy
- This was also observed in the hypertrophic ventricular endocardium when non-CSP pacing sites were simulated

Current state



Regulatory Evidence

* Adapted from Bill Murray (CEO, MDIC), "21st Century Cores: Modernizing Clinical Trials, Testimony to Congress 7/2014

Phase 2

Infrastructure & excellence

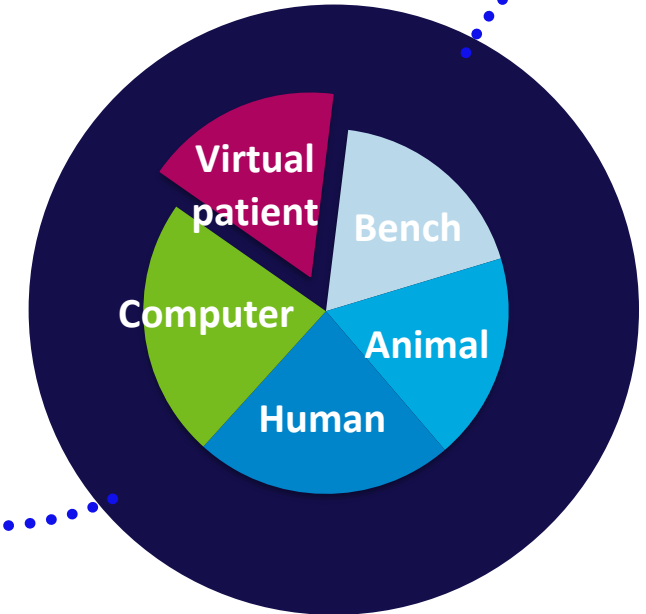
Replace animal trials
& optimize human
clinical trials

Widescale impact

Improve clinical
trial success
rates

Phase 3

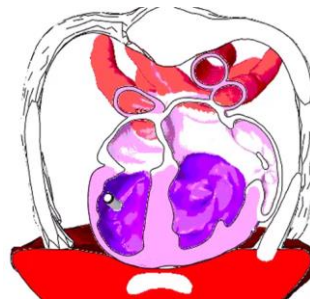
Future state



Credibility & Methods

Therapy feasibility & refinement
Reduce animal trial size

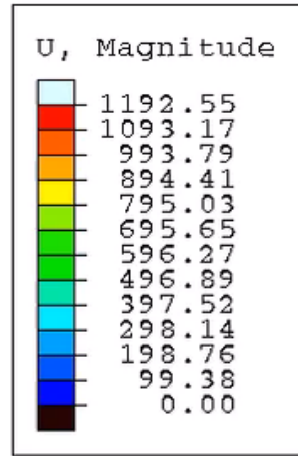
Phase 1



Opportunity

- Sustentative Progress... in the right way
- Continue to partner to ask the right questions

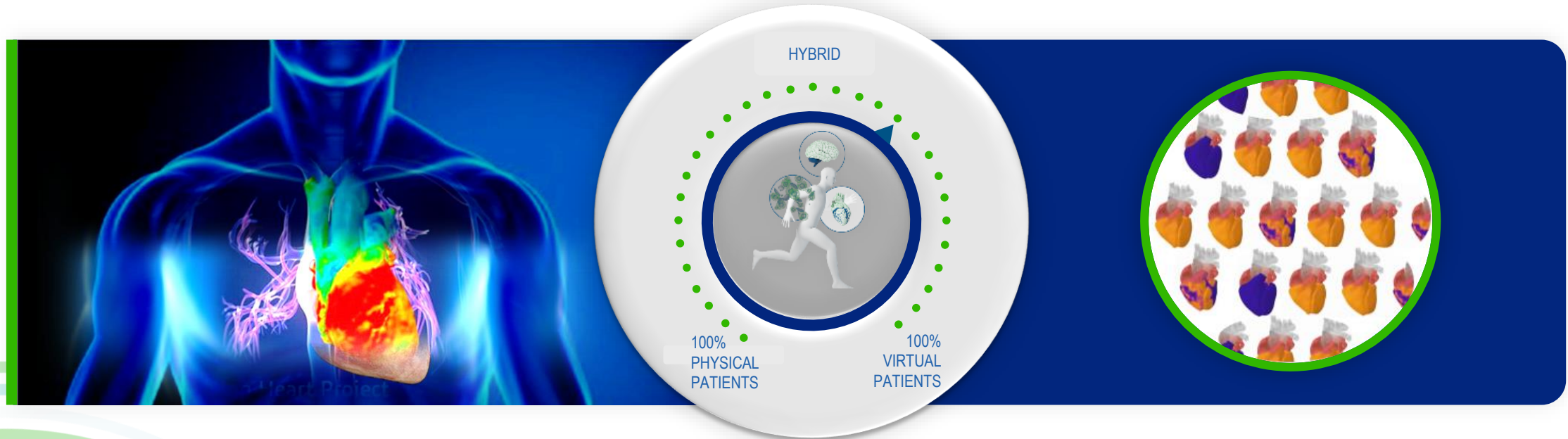
Thanks!





Transforming FDA Approaches: The Role of In-silico Data, Multiscale Modeling, and Generative AI in Medical Device Product Development

In Silico Clinical Trial Data in Regulatory Decisions



Steve Kreuzer, Ph.D., P.E.
Senior Managing Engineer
Exponent Inc.

It takes too long...



The way we do business today, how we go about designing, testing, developing, evaluating manufacturing, distributing, and ultimately thereafter accessing technology is not really fit for purpose*.

It's kind of is out of date. It's time to change."

"It's time to change the world."

Dr. Jeff Shuren | FDA Director | Center for Devices and Radiological Health
ENRICHMENT Project Kickoff – Feb 2020

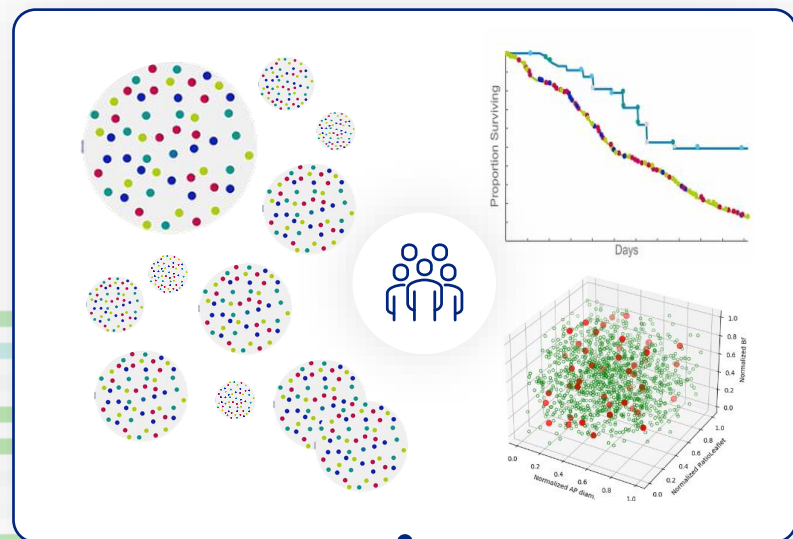


*Less than ½ new Class I Medical Devices every make it to market—Patients suffer & cost gets passed onto those that do.

Virtual Patients: A New Era of Digital Evidence

Merging *in vitro*, *in vivo* + *in silico*

Synthesized **Control Arm**
based on *Real* Patient Data

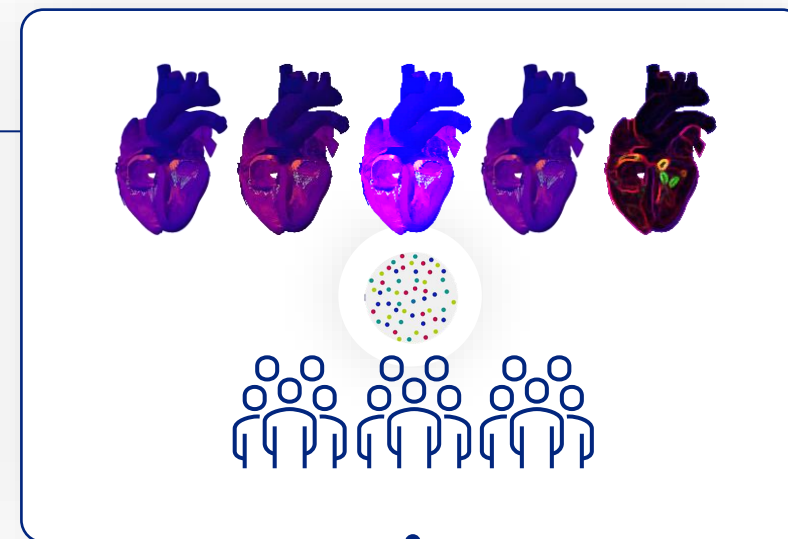


Simulant Generative AI



Smaller, Safer, Predictable
Clinical Trials

Synthesized **Treatment Arm**
based on *Virtual* Patient Data

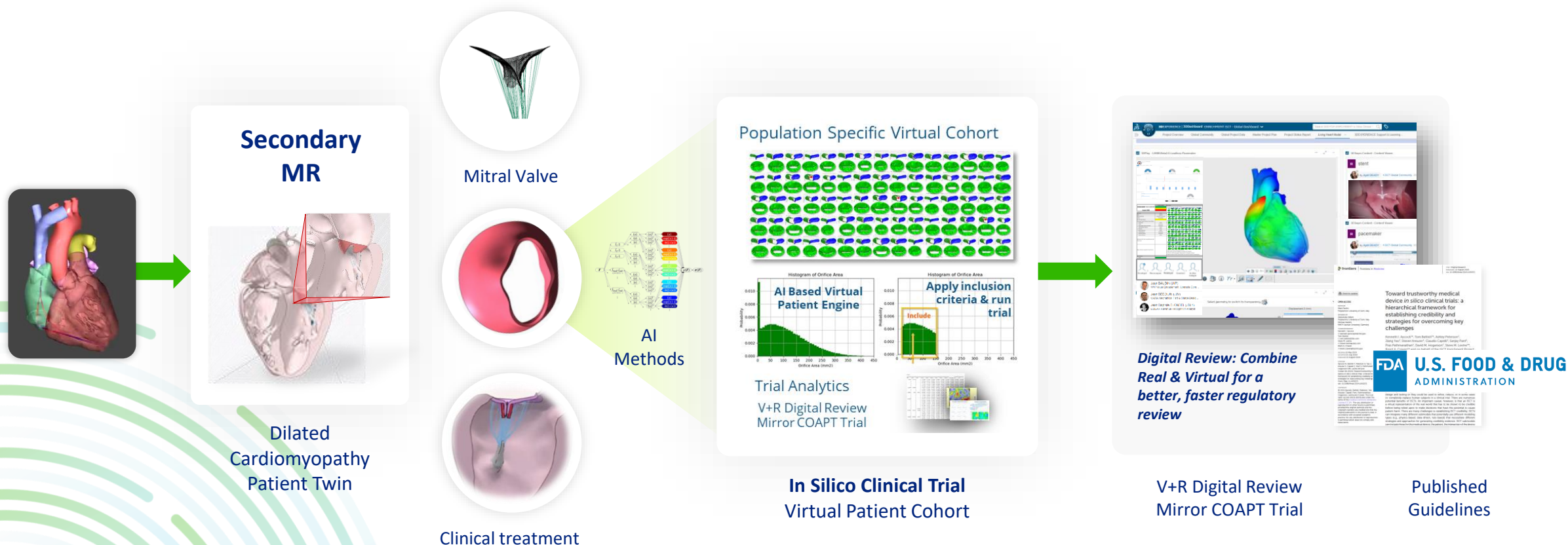


The Living Heart Project

Virtual Twin of a Human Heart

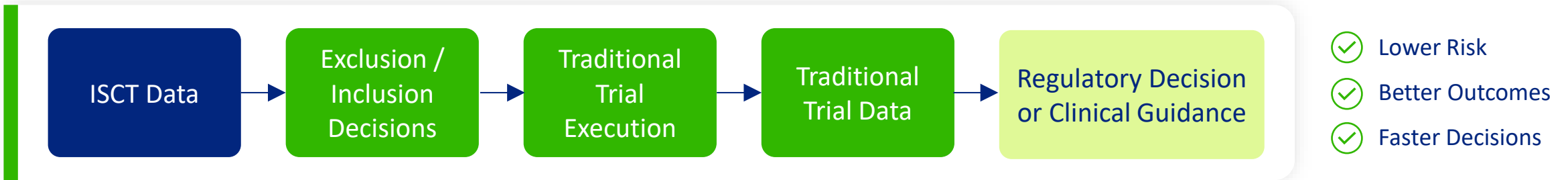


ENRICHMENT *in silico* Clinical Trial with Living Heart as a Virtual Patient Population

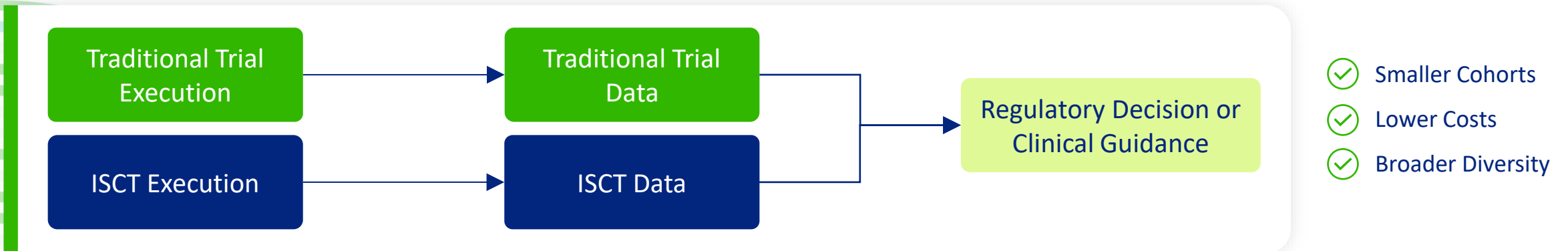


Use of ISCT Data in Clinical Trial Decision Making

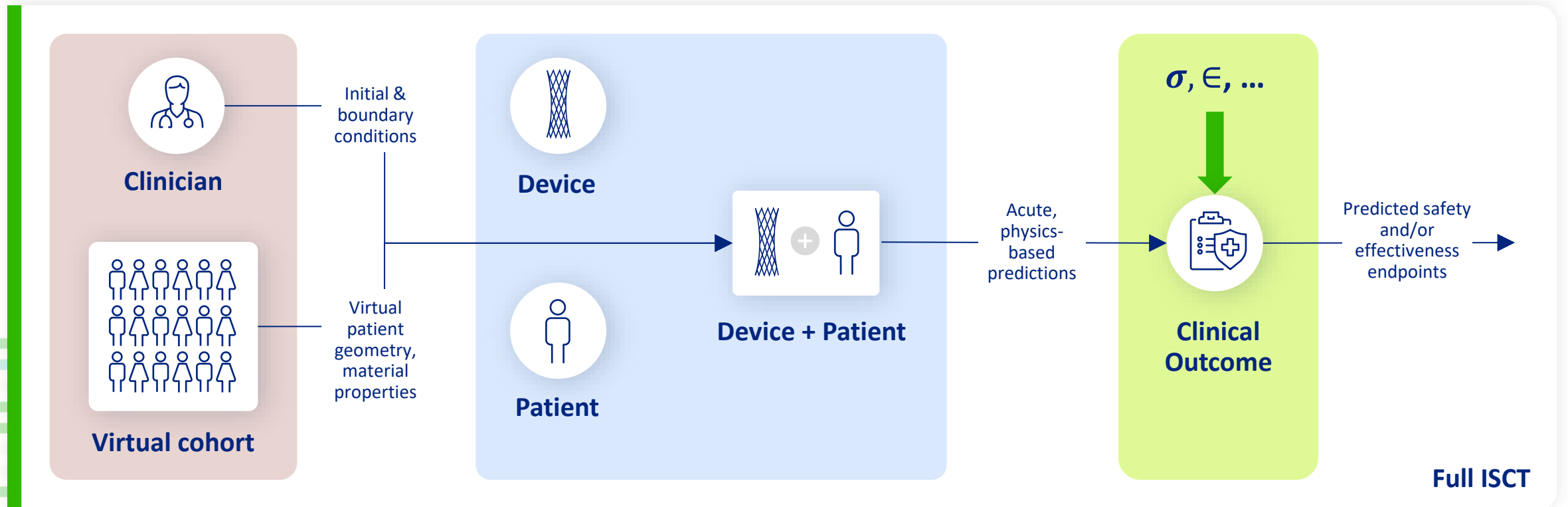
Enrichment via Prospective Trial Design & Execution






Enrichment via Data Incorporation

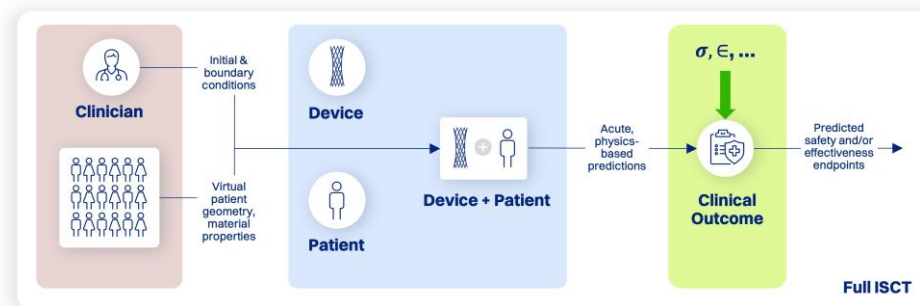


In Silico Clinical Trials



-  Clinical experience + data → target population
-  Computer model of new medical treatment
-  Clinical outcome predictions

In Silico Clinical Trials – Data Types



Statistics of Patient Populations

- Anatomy
- Tissue Characteristics
- Systemic Physiology
- Activity Levels

Device + Individual Patients

- Anatomy
- Tissue Characteristics
- Systemic Physiology
- Activity Levels
- Device Interaction

Clinical Outcome

- Traditional clinical endpoints
- Measurable digital health
- Inferred / non-measurable

Data required for ISCT

Data used for trial analysis

Needed: Improved Diagnostic & Interventional Data



**More complete
procedural data to
calibrate ISCTs**

CT, echo, robotic procedure data, etc.



**Higher fidelity
understanding of
procedure success**

Useful for high fidelity predictions of interventions.



**Pharma & biotech
applications (absence of
a device)**

Clinical Delivery

Infusion rates, physiological data,
etc.

Patient Delivered

Compliance rates, longitudinal physiological data,
including at times of injections, etc.

U.S. Government Accountability Office (GAO)

Feb, 2023

GAO

U.S. Government Accountability Office

For Congress | Press Center | Careers | Blog

REPORTS & TESTIMONIES

VIEW TOPICS

VIEW AGENCIES

BID PROTESTS & APPROPRIATIONS LAW

ABOUT

Home > Reports & Testimonies > Science & Tech Spotlight: Digital Twins—Virtual Models of People and Objects

Science & Tech Spotlight:

Digital Twins—Virtual Models of People and Objects

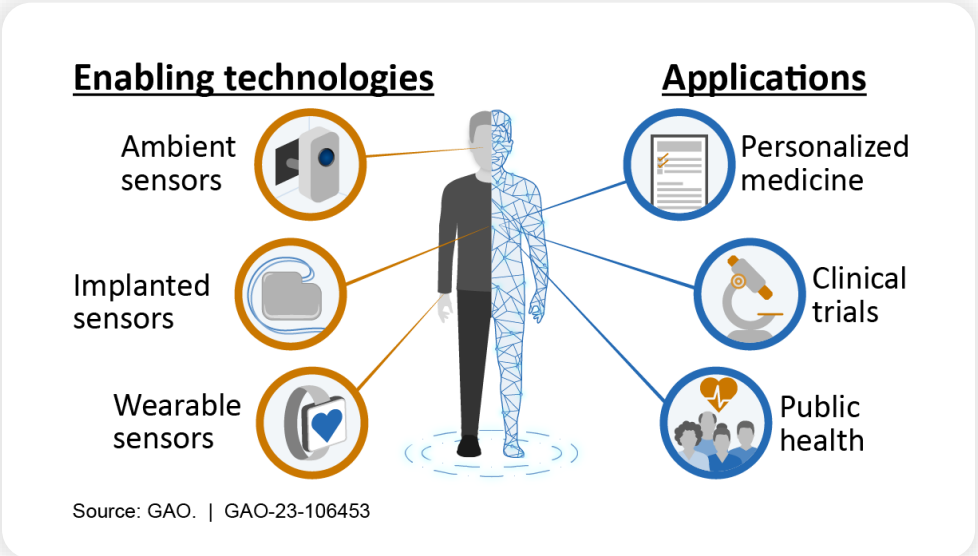
GAO-23-106453

Published: Feb 14, 2023. Publicly Released: Feb 14, 2023.

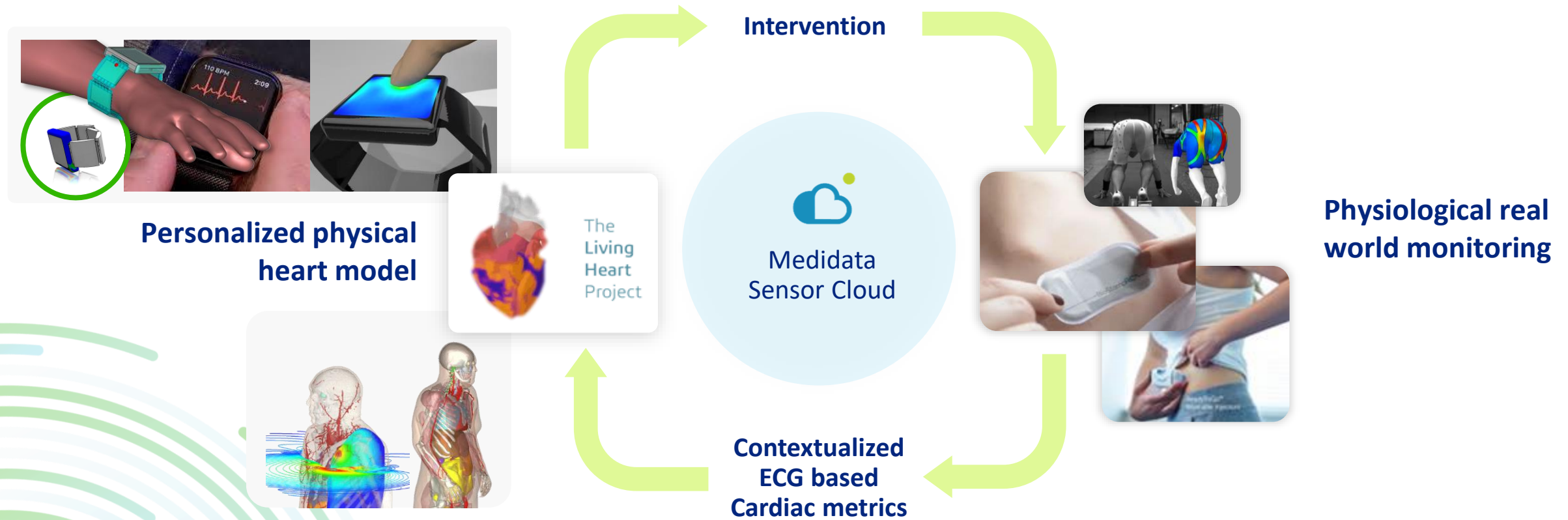
f

in

Jump To



The Vision Applied



ISCTs and Opportunities for You

What capabilities can this unlock for your company & value delivery?

How can you be on the forefront of applying these concepts to design better trial processes that will differentiate you with sponsors?

New role of “ISCT Data Manager”: bridging the gap between analysts and consumers of simulation data



It's time to
change the
world.”

**Be part of
the change!**





Transforming FDA Approaches: The Role of In-silico Data, Multiscale Modeling, and Generative AI in Medical Device Product Development

Generative Virtual Twins for Optimizing Clinical Trial Design



Afrah Shafquat, PhD

Sr. Staff Data Scientist
Medidata Solutions



Steven Levine, PhD

Sr. Director Virtual Human
Modelling, Life Sciences and
Healthcare
Dassault Systèmes



Jiang Yao, PhD

Biomechanics
Application Specialist
Dassault Systèmes

Chaired by



Heidi Sernoff, MD, MBA

Marketing Executive
Dassault Systèmes



12%

of new therapies
entering **Phase I**
make it to market

*Congressional Budget Office, Research & Development in the
Pharmaceutical Industry, April 2021

Key Considerations

For Designing a Trial



Using Historical Clinical Trial Data to design better trials

Selecting the right patients

- ✓ Unmet medical need
- ✓ Response and tolerance to the drug

Identifying the best treatments

- ✓ Con-meds
- ✓ Treating the AEs



Optimal measures

- ✓ Endpoints
- ✓ Rationale behind the endpoints

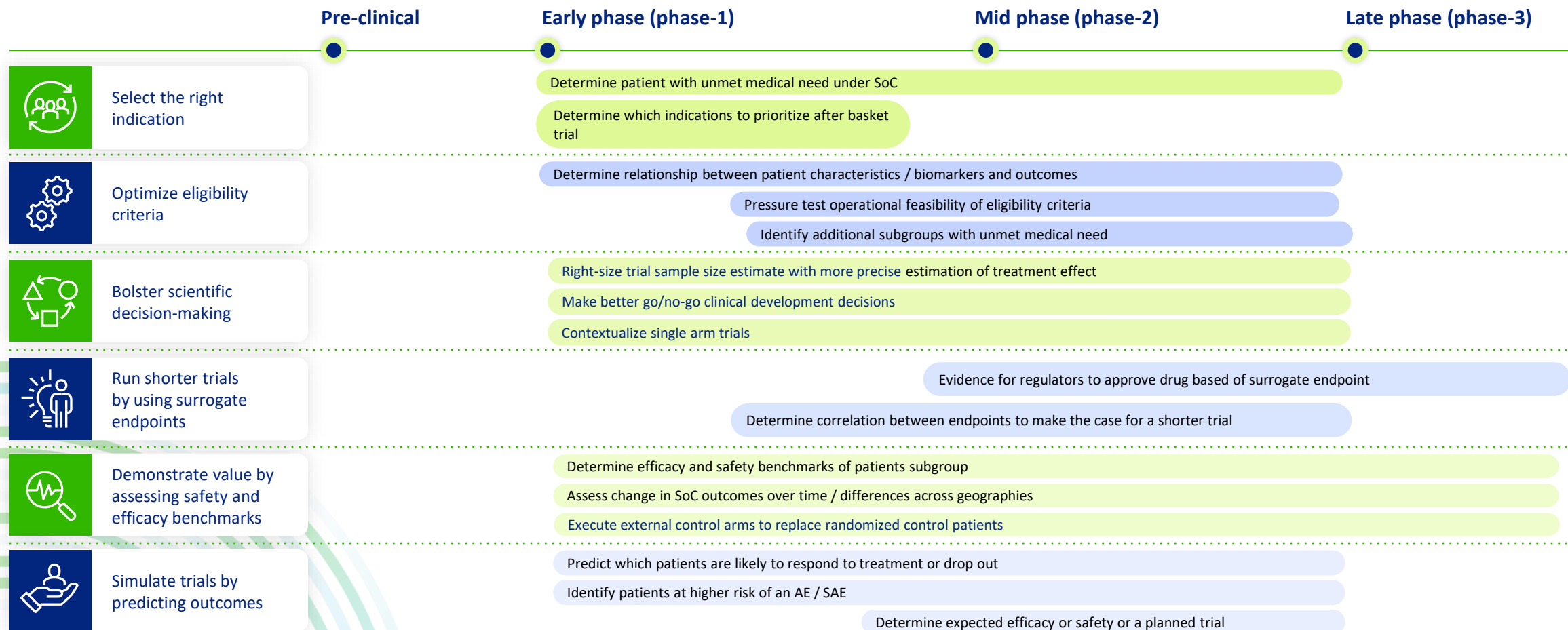
Right-size your trials

- ✓ Statistical power
- ✓ Scientific certainty

Value of Historical Clinical Trial Data



How can Historical Clinical Trial Data Support R&D?



Power of Generative AI



Software engineering

Write better code with AI Pair programmer, explain code/documentation, code generation



Healthcare

Design better drugs, Build better AI models for disease classification



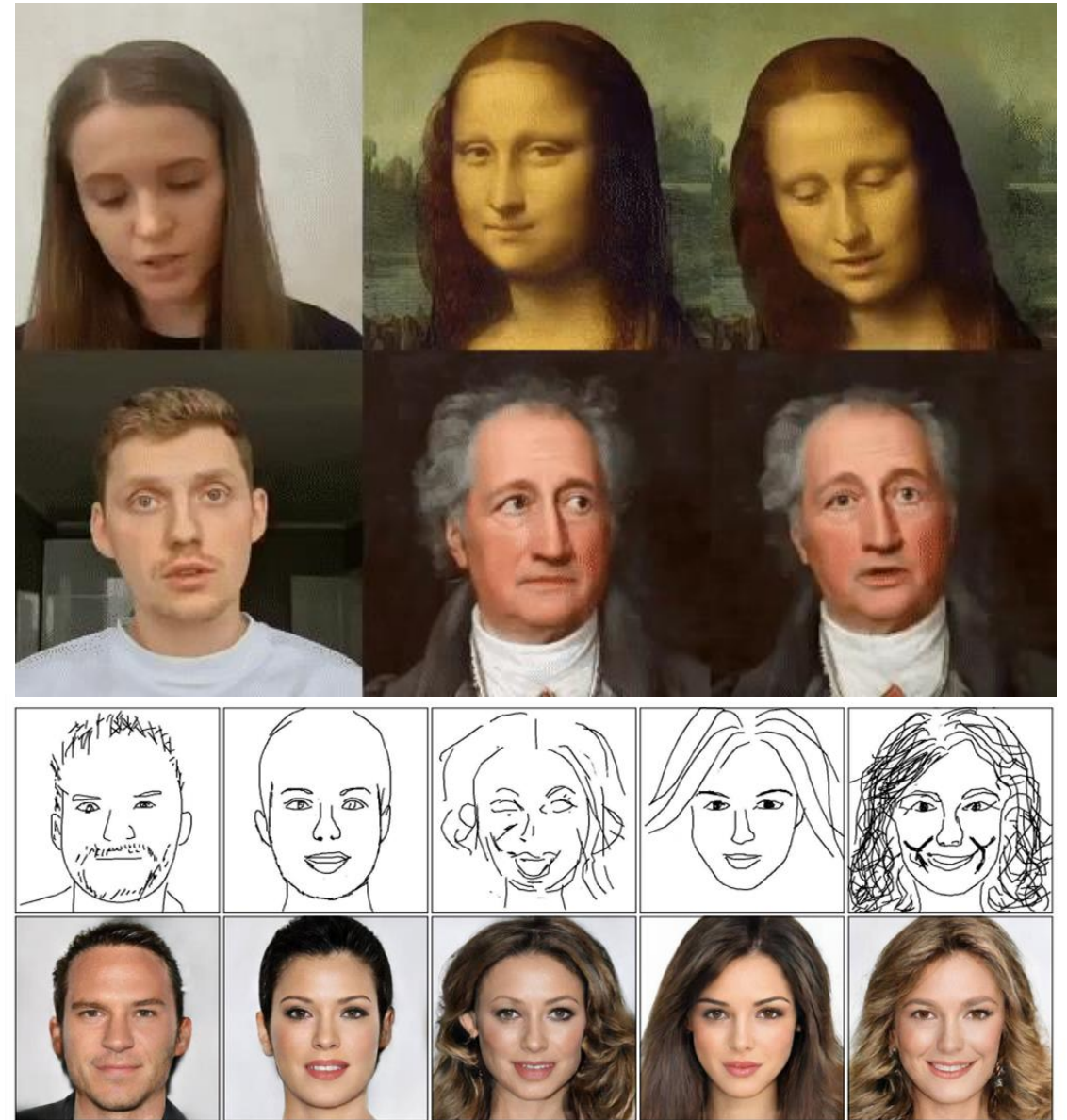
Media

Text summarization, content copywriting, market content generation

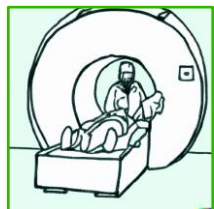


Art

Virtual photoshoots, 2D sketches to digital renderings and artwork



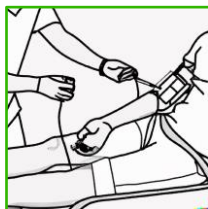
Virtual twins for patient journeys in clinical trials



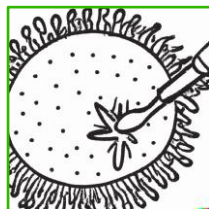
Relapse



Enrollment



Apheresis



Manufacturing



Treatment



Management



Response



Control



Home

Now, what if we
understood this
journey for 100
patients?

3000?

Medidata

Powerful, artificial intelligence ... making trial data available ... across all major indications



10M

Trial Participants



33,000

Clinical Trials



110+

Clinical variables

Oncology

Lung, breast, skin,
gastrointestinal,
genitourinary, brain

Cardiometabolic

Diabetes, hypertension, obesity,
hyperlipidemia, kidney disease,
cardiovascular

Autoimmune

Skin, connective tissue,
gastrointestinal,
musculoskeletal

CNS

Pain, movement,
auto-immune,
degenerative

Simulants

Gen AI based technology to create and share synthetic data



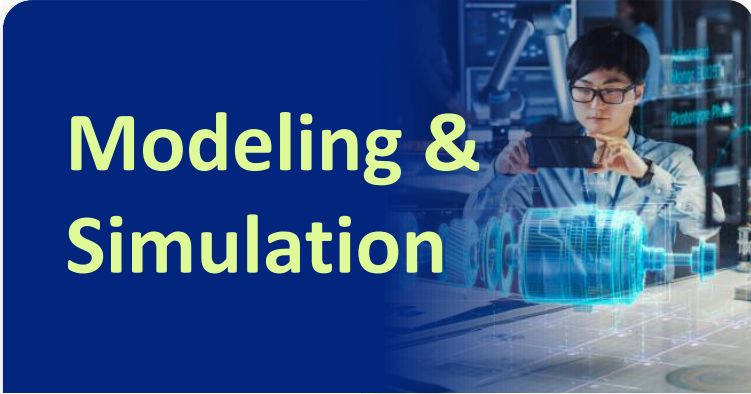
Data Sharing

Access high value datasets w/o
privacy/regulatory concerns



SW Testing & Demo

Generate high quality test, UAT
data for efficient SW engineering



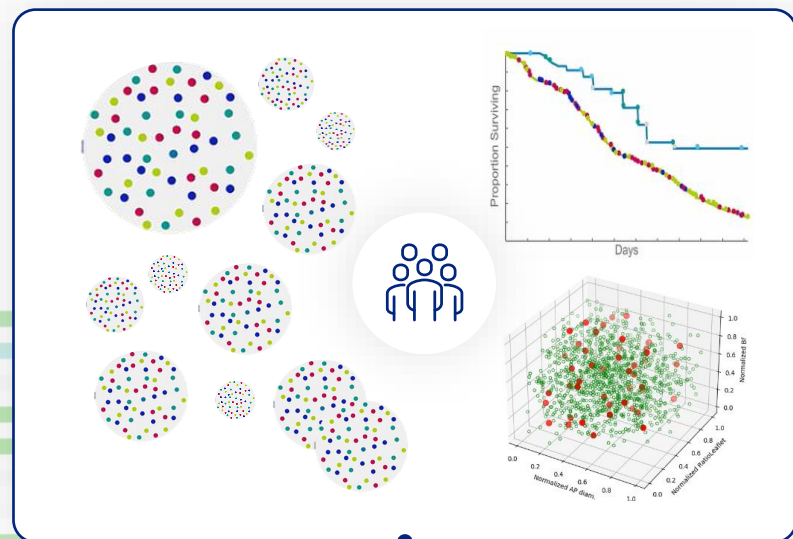
Modeling & Simulation

Augment model, generate
balanced data at low cost, address
bias

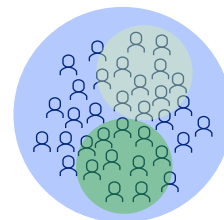
Virtual Patients: A New Era of Digital Evidence

Merging *in vitro*, *in vivo* + *in silico*

Synthesized **Control Arm**
based on *Real* Patient Data

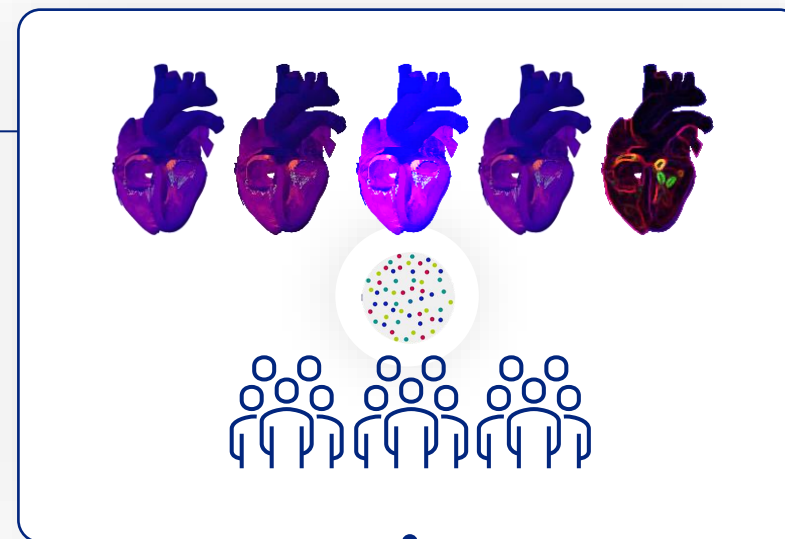


Simulant™ Generative AI



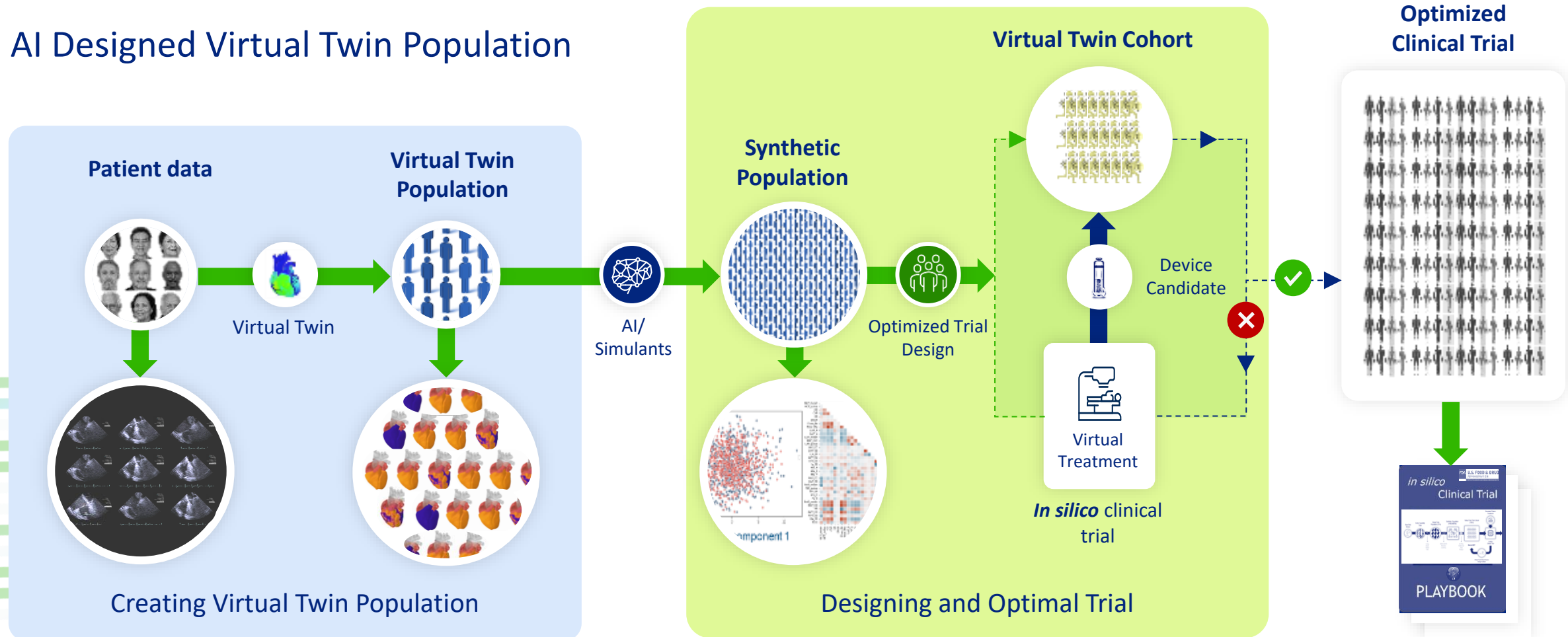
Smaller, Safer, Predictable
Clinical Trials

Synthesized **Treatment Arm**
based on *Virtual* Patient Data



In-Silico Clinical Trial

AI Designed Virtual Twin Population

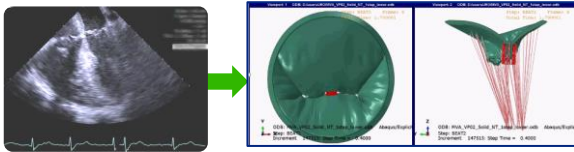


Virtual Patient Engine Schematic

Input

Virtual Twin of Real Patients

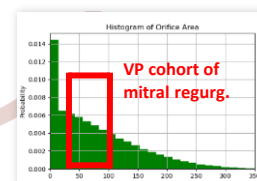
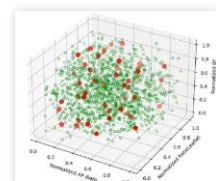
A collection of (physics-based) patient model definitions & pre-operative simulation results



AI Powered Virtual Patient Engine

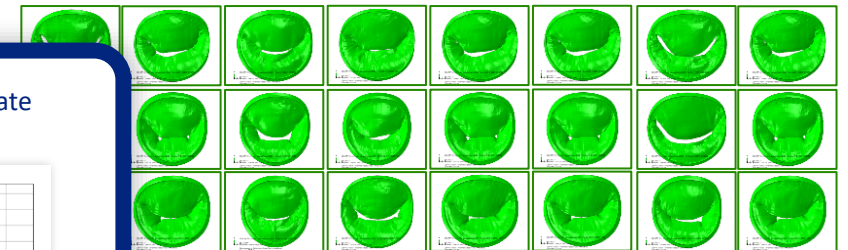
- The diagram illustrates a four-step process for generating a virtual population:

 - Create AI surrogate model**: A network diagram showing various input nodes connected to a central node labeled "MACHINE LEARNING". The logo for "Control Science" is visible in the top right corner.
 - Generate surrogate population**: A histogram titled "Histogram of Orifice Area" showing the distribution of orifice areas. The x-axis is labeled "ORIFICE AREA (mm²)" and ranges from 0 to 350. The y-axis is labeled "Probability" and ranges from 0.000 to 0.014.
 - Virtual Population for ISCT**: This step is represented by a large, light blue arrow pointing from the histogram to the next step.
 - Filter w/defined inclusions criteria**: This step is also represented by a large, light blue arrow pointing from the previous step to the final output.



Output

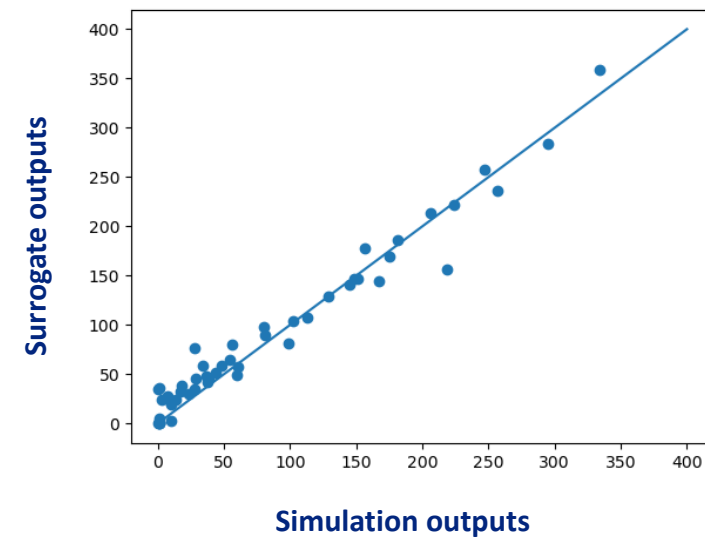
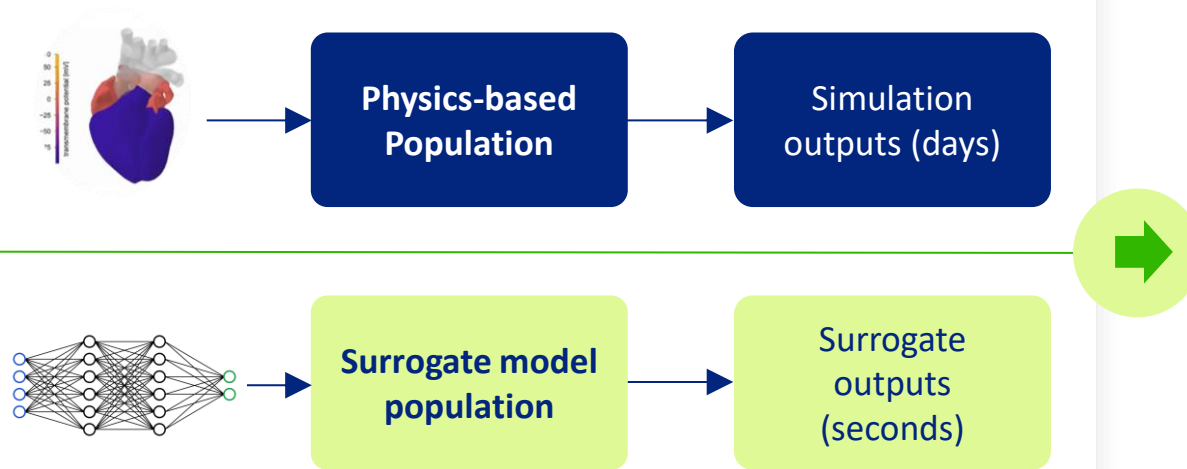
A Virtual Patient Cohort with precise pre-operative characteristics to be treated in an iSCT



Create Surrogate: Testing Results

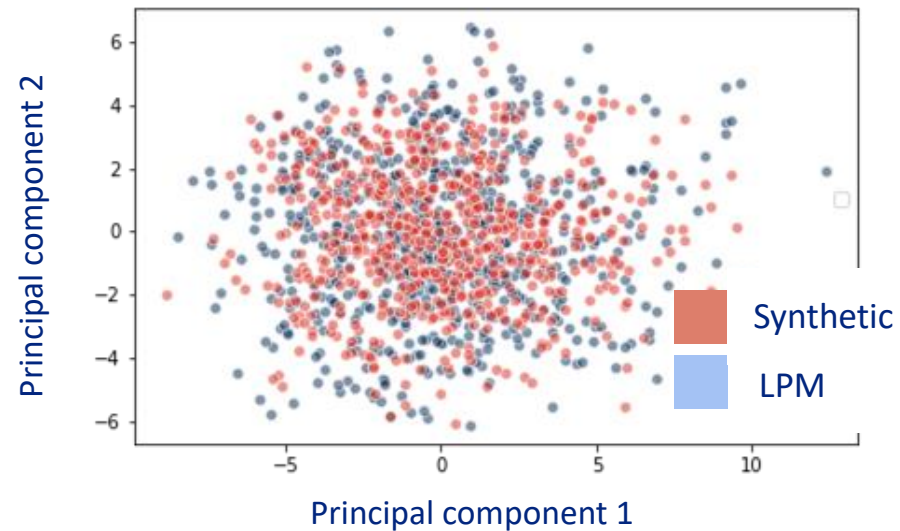
Input
parameters of
patient data

Surrogate Model Validation



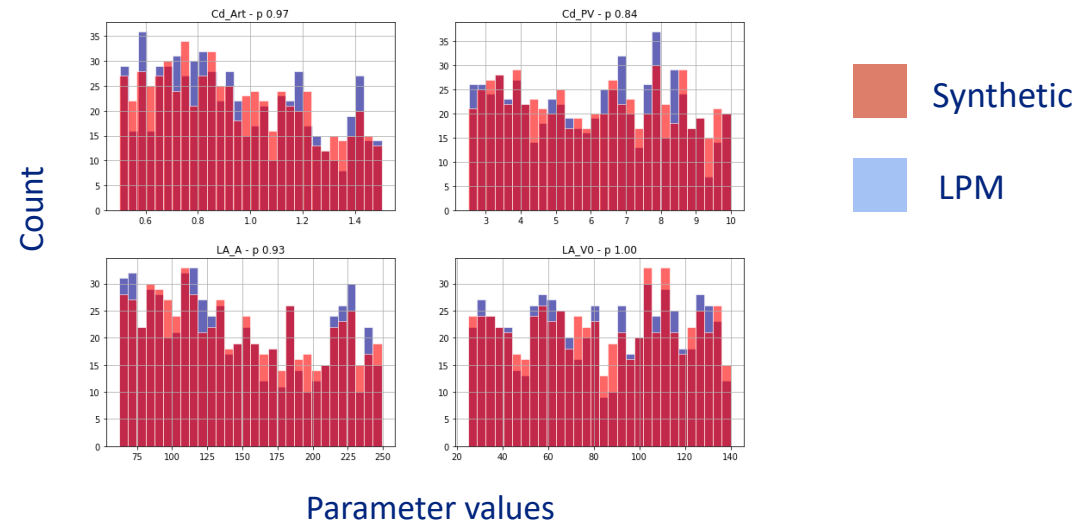
Synthetic (AI) POPULATION aligns with (physical) Virtual Twins

Synthetic vs. physics-based simulated data



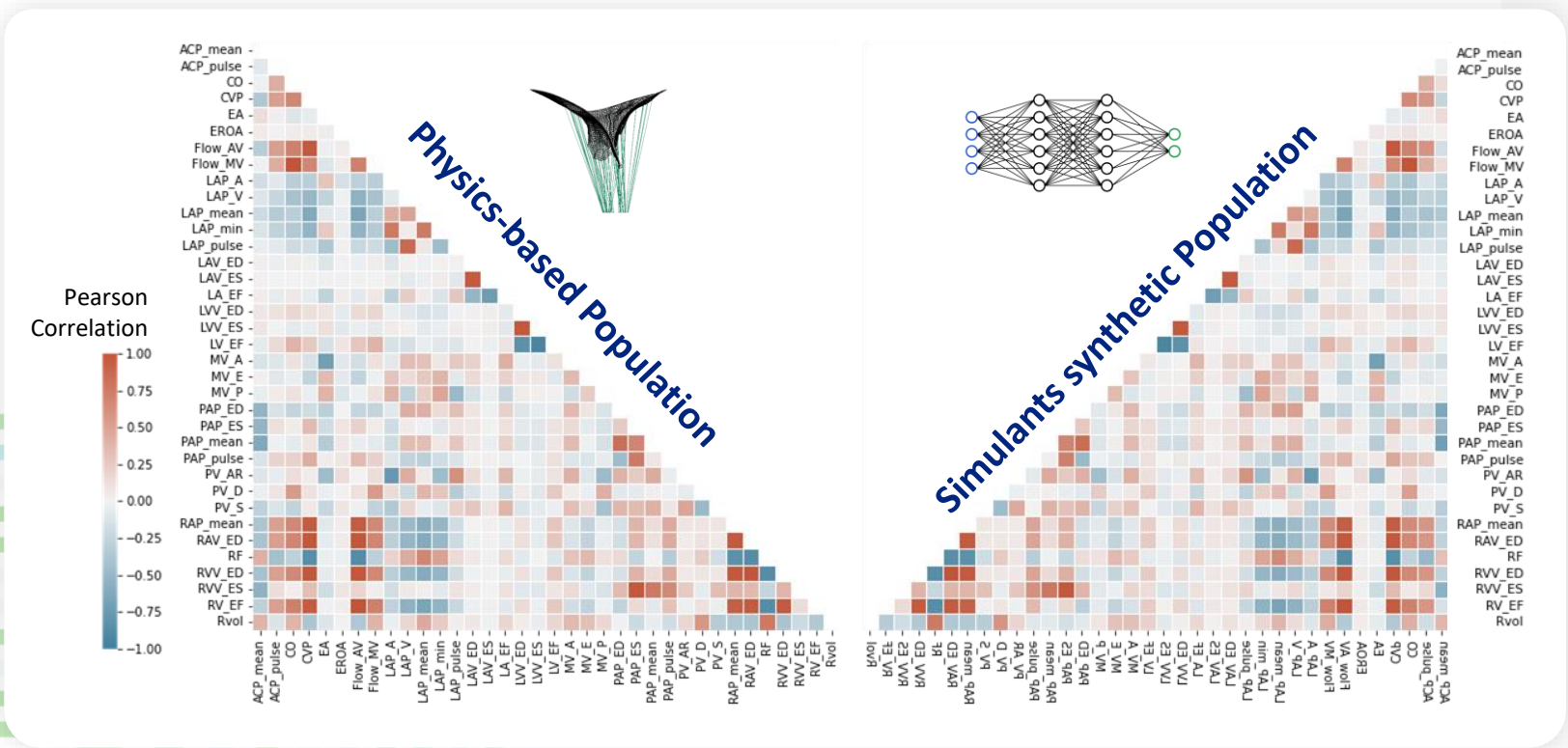
Alignment between source/template and Simulants generated synthetic dataset indicates synthesis reflects the source population well

100% alignment across input parameters between datasets

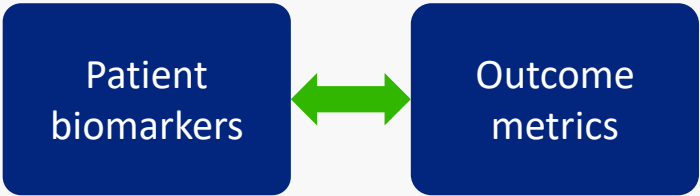


Alignment between input parameters is evaluated by performing the K-S test for input parameters produced by Simulants and the physics-based model. All 14 input parameters had non-statistically significant differences using the K-S test.

Preservation of bidirectional relationships in synthetic data



Heatmaps confirm the essential bidirectional relationships



are preserved in
SIMULANTS population

Correlations drive weighting
factors for ISCT population

Generative Virtual Twins: From Years to Seconds

Input
parameters of
patient data

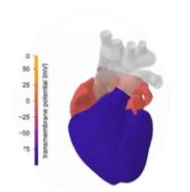


Model Validation



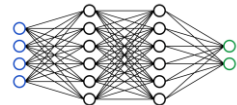
Clinical Trial
Population

Clinical outputs
(years)



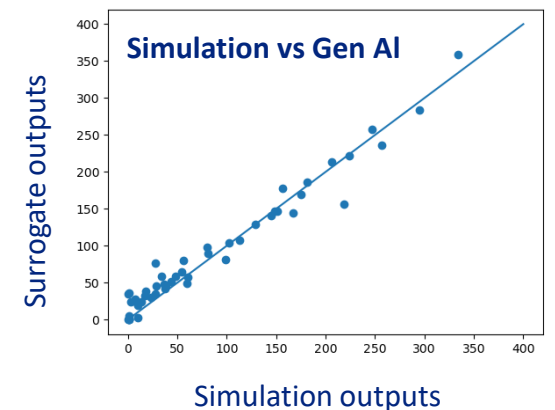
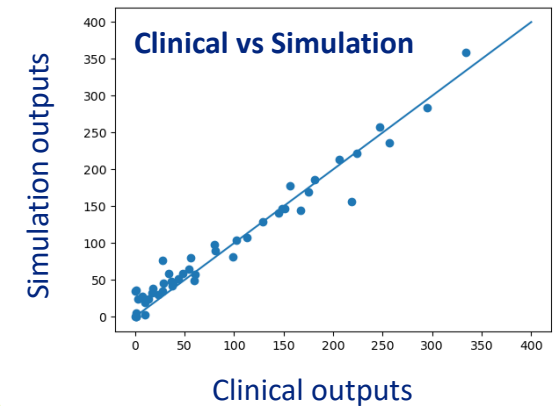
Physics-based
Population

Simulation
outputs
(days)



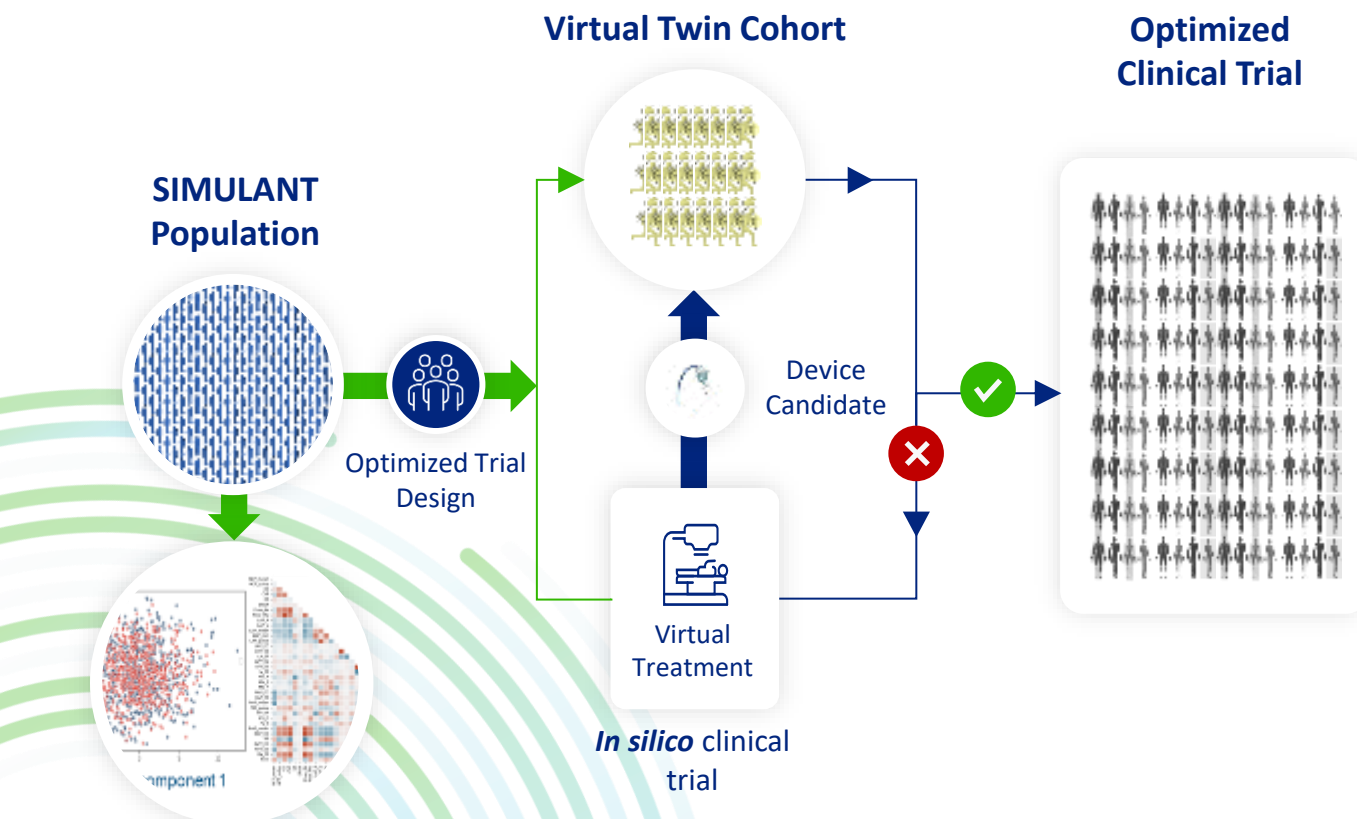
AI Surrogate
Population

Surrogate
outputs
(seconds)



In-Silico Clinical Trial

AI Designed Virtual Twin Population



Simulant Optimized Trials Offer



Selecting the right indication



Optimized eligibility criteria



Increased diversity



Smaller/shorter trials



Improved safety/efficacy analytics
& decisions making



Streamlined regulatory review