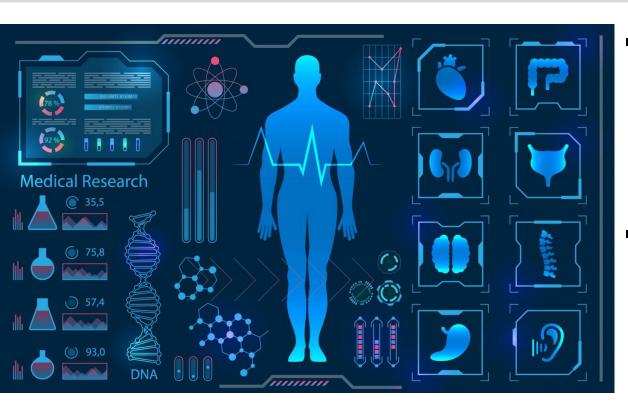
DT and AI for Precision Medicine

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Precision Medicine



- Uses one's genes, proteins, environment, and lifestyle information to prevent, diagnose, or treat disease
- Target the right patients with the right treatments at the right time



How is AI Changing the Future of

Precision Medicine?



Real-Time Monitoring of Patient Health

AI-Powered
Early Detection
of Diseases



Identifying Causal Genes

Phenotypic & Genetic Heterogeneity

Changing Role of Physicians

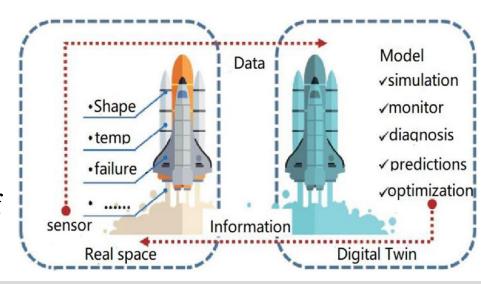
AI Applications in Medicine

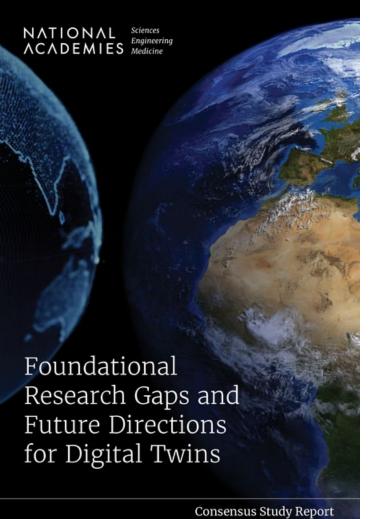
- Disease diagnosis, screening, monitoring, and treatment
- Large language models (LLMs)
- Clinical decision support
- Virtual reality and augmented reality
- New drug discovery
- Virtual clinical trials
- Telemedicine
- Human machine interface
- · Digital twins for health
-

Modern medicine is increasingly becoming a science of information

What is a Digital Twin?

- A digital representation of a real-world physical system or process that serves as the effectively indistinguishable digital counterpart of the original for practical purposes such as simulation, integration, testing, monitoring and maintenance
- Used in real time and regularly synchronized with the physical system
- Originated from NASA in 2010 to improve physical model simulation of spacecraft





REAL WORLD PATIENT

The patient and the tumor from which data is gathered using various clinical assessments to inform the digital twin.

VVUO --→

Verification, validation, and uncertainty quantification

As the patient and tumor are constantly evolving and the data collection can also change over time, VVUQ must occur continually for digital twins

Uncertainty quantification needs to be addressed for all aspects of the digital twin. including the patient's data, modeling and simulation, and decision making.

DIGITAL TWIN

using data from the real world patient.

The virtual representation comprised of models describing temporal and spatial characteristics of the patient and turnor with dynamic updates

Clinical assessments

Data are collected in many ways:







Clinical assessments





Patient reported outcomes

Human and digital twin interaction

Utilizing the simulated predictions and related uncertainties, the clinician and patient can make informed clinical-decisions around treatment and also the clinical assessments, which affect the data informing the digital twin.



Modeling

Models spanning a range of fidelities and resolutions may be utilized and potentially integrated together.

As new observed data are acquired. the data are assimilated and the models are cali brated, updated, and estimated.















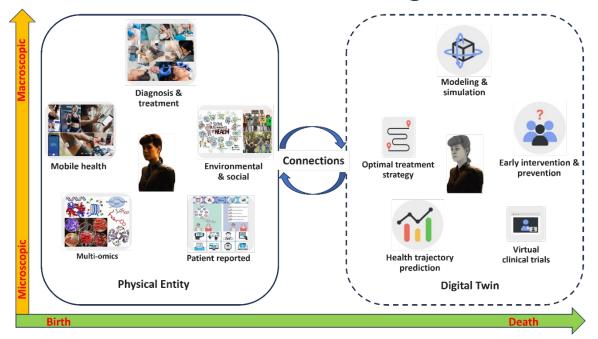




Simulations of potential treatments can generate predictions of outcome and in turn can be optimized to determine the most favorable treatment options.

A Human Digital Twin

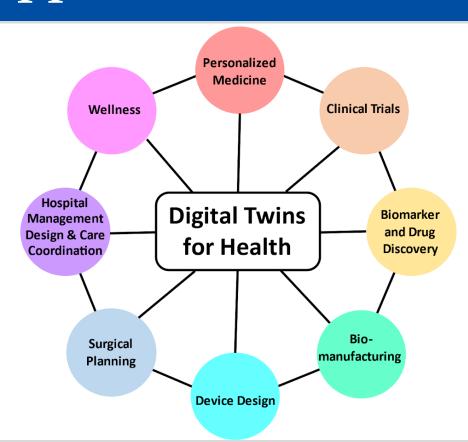
• A dynamic virtual representation of an individual, an organ, or an organ system based on multiscale modeling of multimodal data



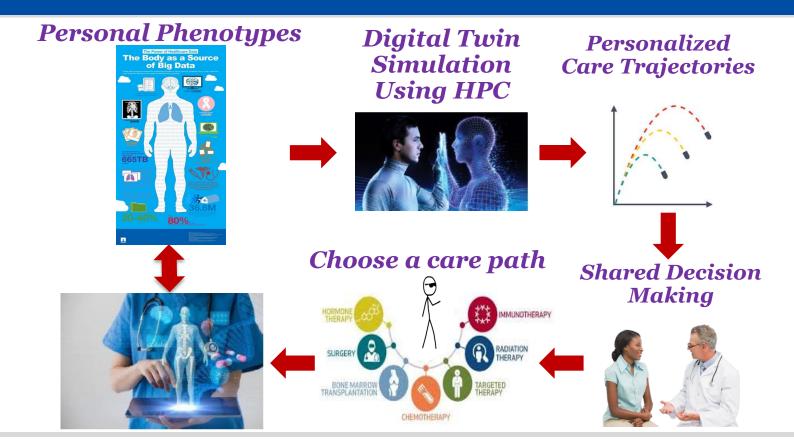
DT vs AI/ML vs Computational Models

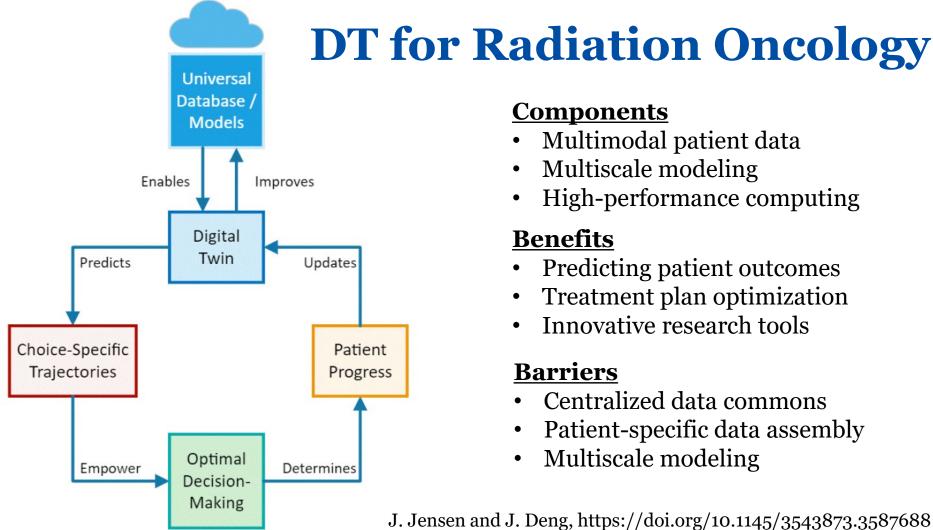
- While they form an important approach toward virtual replica of a physical entity, neither computational modeling nor AI/ML algorithm is the totality of DT
- A DT must have the three components: <u>a physical entity</u>, <u>a virtual replica</u>, and <u>a connection between the two</u>
- A DT should be individualized, interconnected, interactive, informative, and impactful (5Is)

Main Applications of DT in Health



Digital Twins for Precision Medicine





Components

- Multimodal patient data
- Multiscale modeling
- High-performance computing

Benefits

- Predicting patient outcomes
- Treatment plan optimization
- Innovative research tools

Barriers

- Centralized data commons
- Patient-specific data assembly
- Multiscale modeling

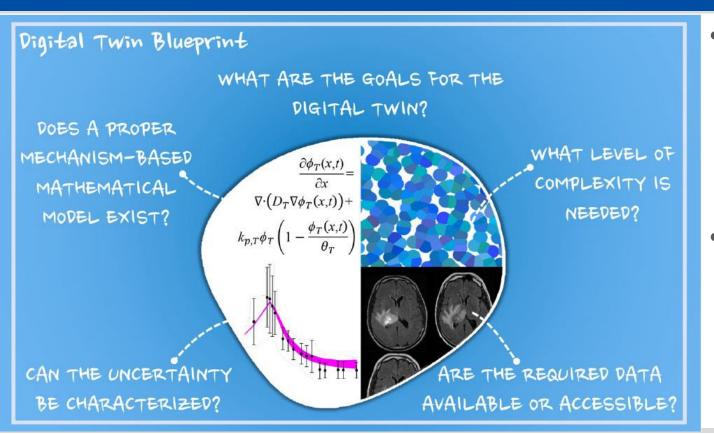
J. Jensen and J. Deng, https://doi.org/10.1145/3543873.3587688

Potential DT Applications in RT

- Real-time monitoring and comprehensive analysis of cancer patient health status undergoing RT
- DT-enabled optimal treatment pathway
- Treatment plan optimization and adaptation based on DT simulations of individual cancer patient, considering their anatomy, treatment history, RT toxicity, treatment goal, and personal preferences
- Virtual clinical trials with DT-enabled patient control
- A linac DT assisted with an agile robot for proactive maintenance and automated QA

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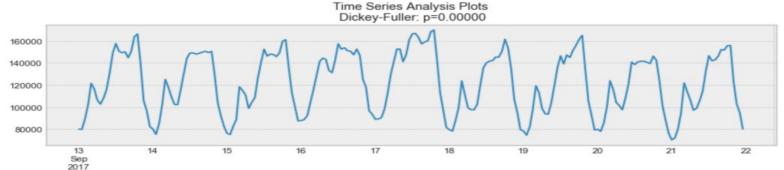
Digital Twin Blueprint



- "All models are wrong but some are useful", George Box
- "Everything should be made as simple as possible, but not simpler", Albert Einstein

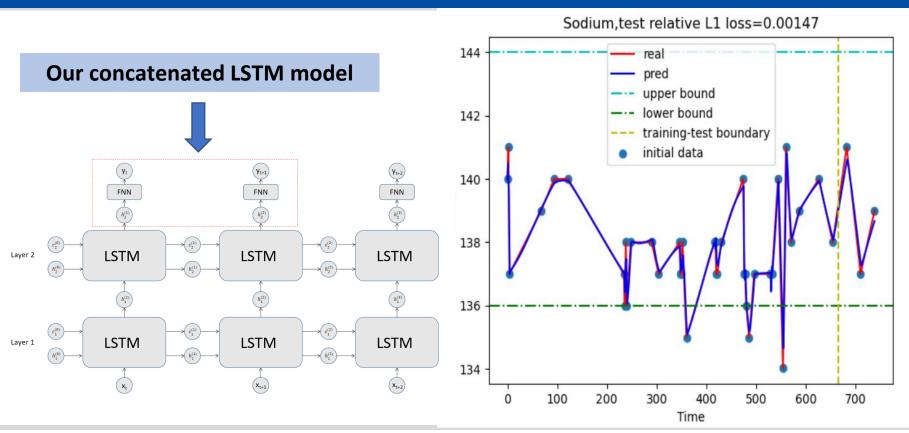
Modeling of Time-Series Patient Data

- Collected at multiple time points before, during, and after cancer treatments
- Δ time-series data correlate with treatment outcomes, QoL
- More precise and effective treatments and interventions and faster responses to mitigate adverse effects



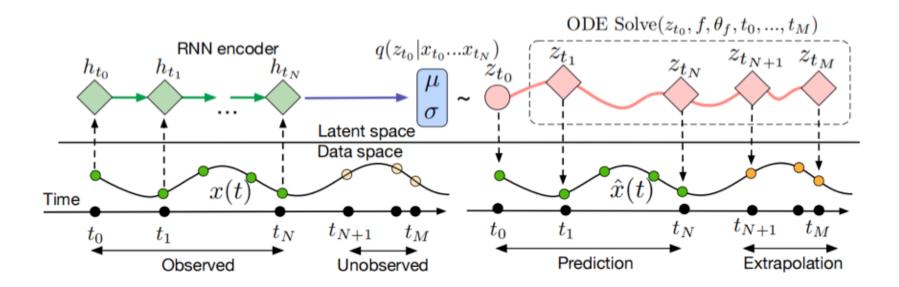
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Forecasting Metabolic Indices Using LSTM

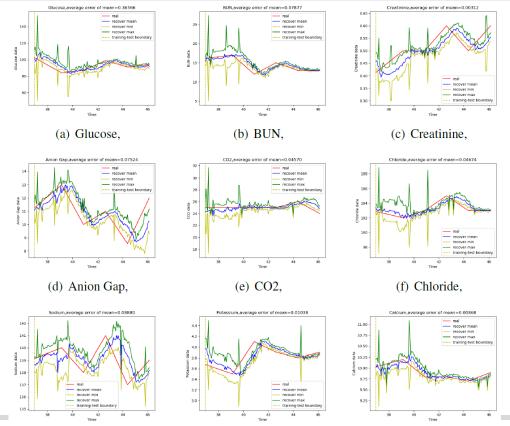


Latent Ordinary Differential Equations

• Reduced-order methods can be used to "smooth" noisy data and produce more robust Neural Ordinary Differential Equations in the latent variable space



Forecasting Metabolic Indices Using LODE



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(g) Sodium,

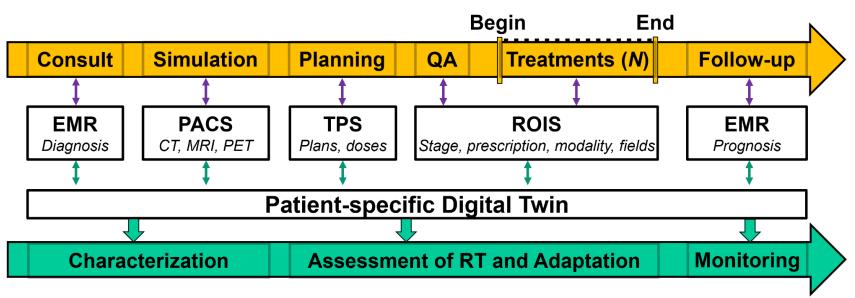
(h) Potassium.

(i) Calcium,

SLIDE 16

Radiotherapy Workflow

Radiation Therapy Clinical Workflow

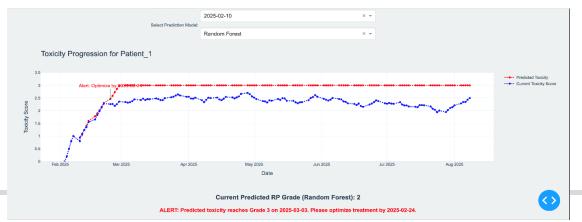


Patient Outcome Trajectory

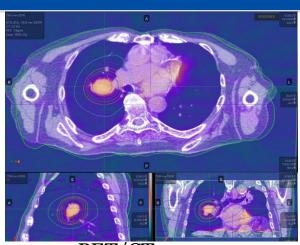
Cancer Patient Digital Twin

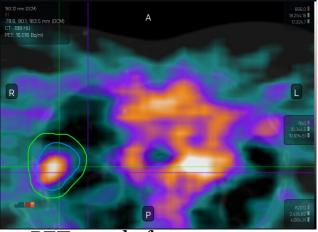


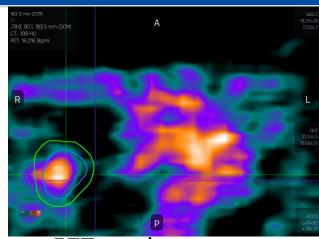
- Patient health prediction
- Treatment outcome trajectory
- Shared decision making with patient engagement
- An early warning system for whole body all organ monitoring of toxicity induced by RT



Biology-Guided Radiotherapy







PET/CT merge

PET scan before treatment

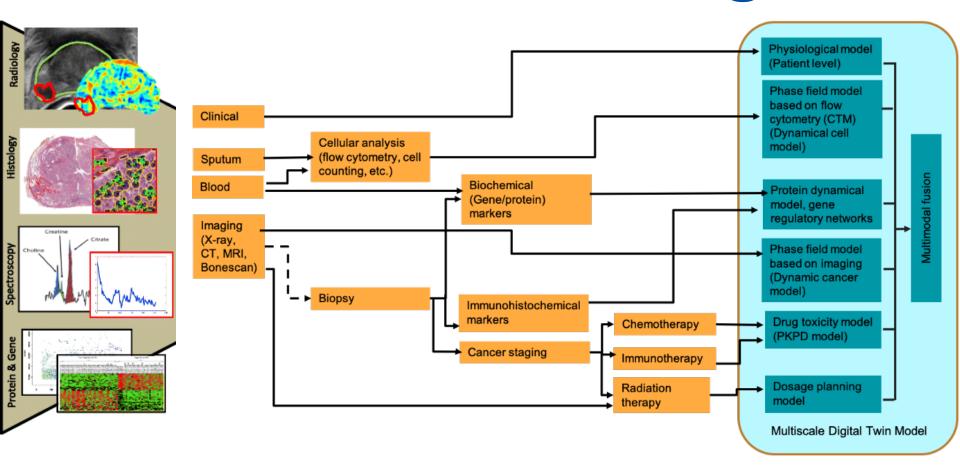
PET scan in treatment

A reaction diffusion model including RT-induced cell death

$$\frac{\partial c}{\partial t} = \nabla \cdot (D\nabla c) + \rho c \left(1 - \frac{c}{k}\right) - R(x, t, Dose) c \left(1 - \frac{c}{k}\right)$$

Develop digital twins to predict NSCLC response to RT *via* integrating *mechanistic modeling* with *patient-specific longitudinal PET scans*

Multiscale Modeling



Challenges

Data Acquisition, Integration, Standard, and Quality

- Multimodal data acquisition, integration and curation
- Data standards, quality and accuracy

Multiscale Modeling and Simulations

- Complex human behaviors with vast dynamic impacting factors and sophisticated causal relations
- Dynamic biological phenomena at multiscale in space-time

Responsible AI

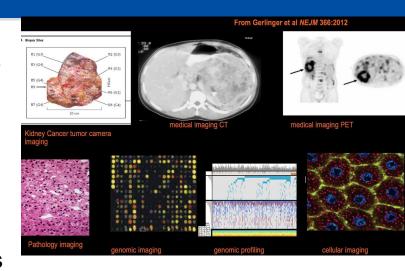
- Fairness, transparency (explainability), accountability, robustness, safety, privacy, and security

Computing Infrastructure

- HPCs, quantum computing, and their access

Multimodal Data Fusion

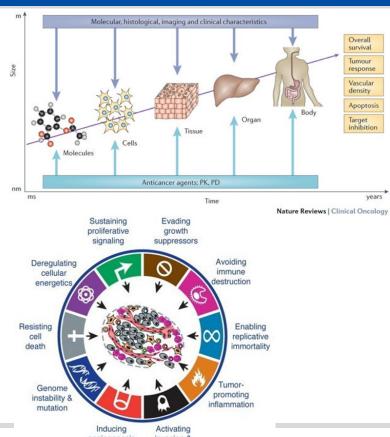
- Functional and molecular imaging
- Radiomics (deep learning-augmented analysis of radiology)
- Liquid biopsies (e.g., circulating tumor cells)
- Whole-slide, highly-multiplexed digital pathology
- Genomic profiling
- Single-cell profiling (e.g., scRNA-seq)
- Patient-derived cell cultures, organoids, & assays
- Intravital imaging (live microscopy within a patient)
- Fitness trackers & wearables
- Implantable sensors



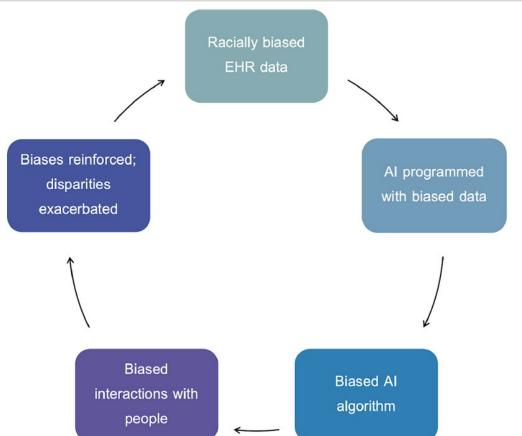
Each technology gives new light on a patient's health state, but it is challenging to coherently <u>fuse</u> these together

Complex Human Body

- Individual cell processes and dynamics
- Interactions between heterogeneous cells
- Physical constraints (e.g., oxygen diffusion, mechanical barriers)
- Procedures can cause toxicity, resistance, and long-term adverse effects
- Constant interactions with environment
- Social determinants influence one's health and wellbeing across life course
- Many factors involved (e.g., lifestyle, dietary, family history, medication)



Responsible AI



- Require right people, right processes, and right technologies
- Clinical practitioners need to be trained to understand what responsible AI means, what tools and metrics are available to quantify and evaluate responsible AI
- Appropriate technologies need to be used to enforce responsible AI from the beginning to the end for every model, every time

Outlook

- Human digital twins fully functional and autonomous as HDT agents
- True companions and safeguards of people's health
- Interact with humans in physical world, with other HDT agents in virtual world
- Human digital twin simulations from birth to death

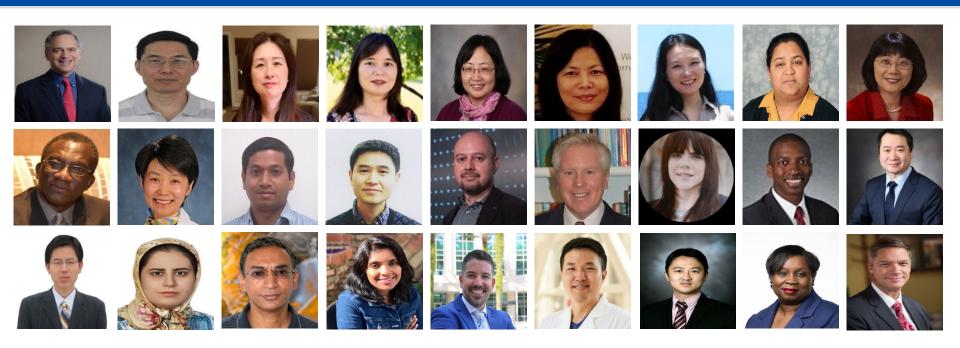


Ability to simulate the future has been a motive for human intelligence evolution

Conclusions

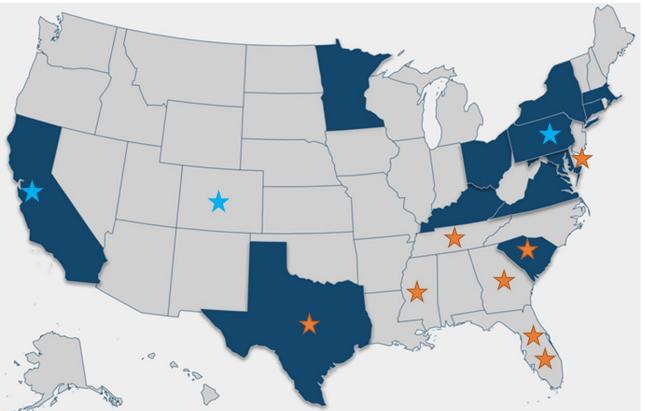
- Human digital twins have great potential in precision medicine
- Deep understanding of human biology is the key
- Multimodal data integration and multiscale modeling are challenging
- We must tame AI before the arrival of AGI
- Cross-disciplinary collaborations are essential

Acknowledgement



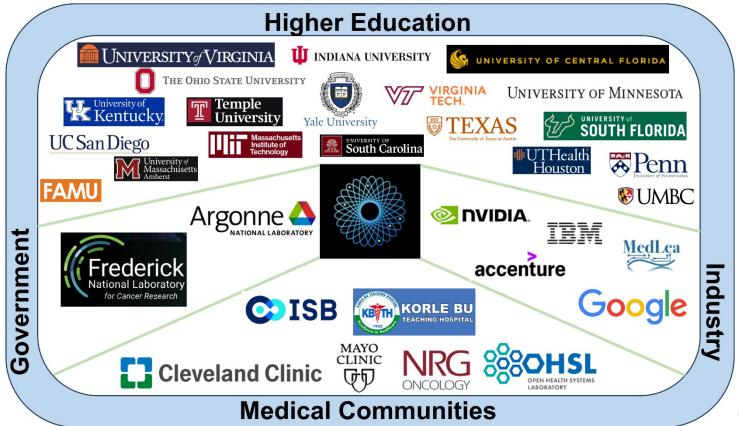
Digital Twins for Health Consortium

Digital Twins for Health Consortium



- **Yale**
- Florida A&M University
- George Washington University
- Indiana University
- MIT
- Ohio State University
- Temple University
- University of Virginia
- University of Kentucky
- University of Texas Austin
- University of Texas Health
- U of California San Diego
- U of Maryland Baltimore County
- UMass Amherst
- University of South Carolina
- University of Pennsylvania
- University of Central Florida
- University of South Florida
- University of Minnesota
- Virginia Tech
- Mayo Clinic
 - **IBM**

DT4H Ecosystem



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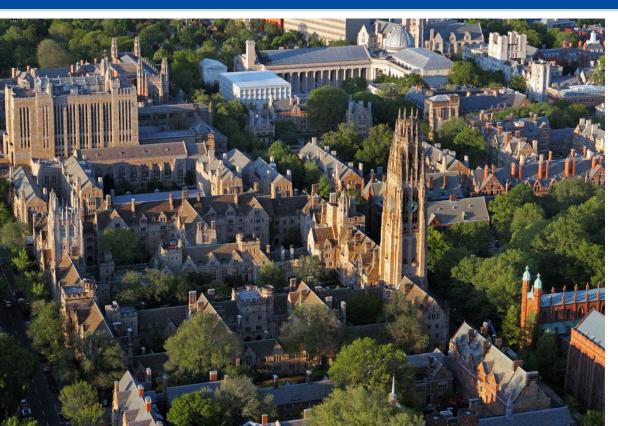


Digital Twins for Health Consortium

Forging a leading international network in developing and applying digital twins for better health and well-being in collaboration with all the stakeholders in the healthcare spectrum.

https://dt4h.org

Thank You



Yale Smart Medicine Lab

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