



National Institute of
Biomedical Imaging
and Bioengineering

Creating trustworthy open data for scientific discovery

New York Scientific Data Summit 2024: Addressing Data Challenges in Digital Twins

New York City, New York

September 16, 2024

Grace C.Y. Peng, PhD

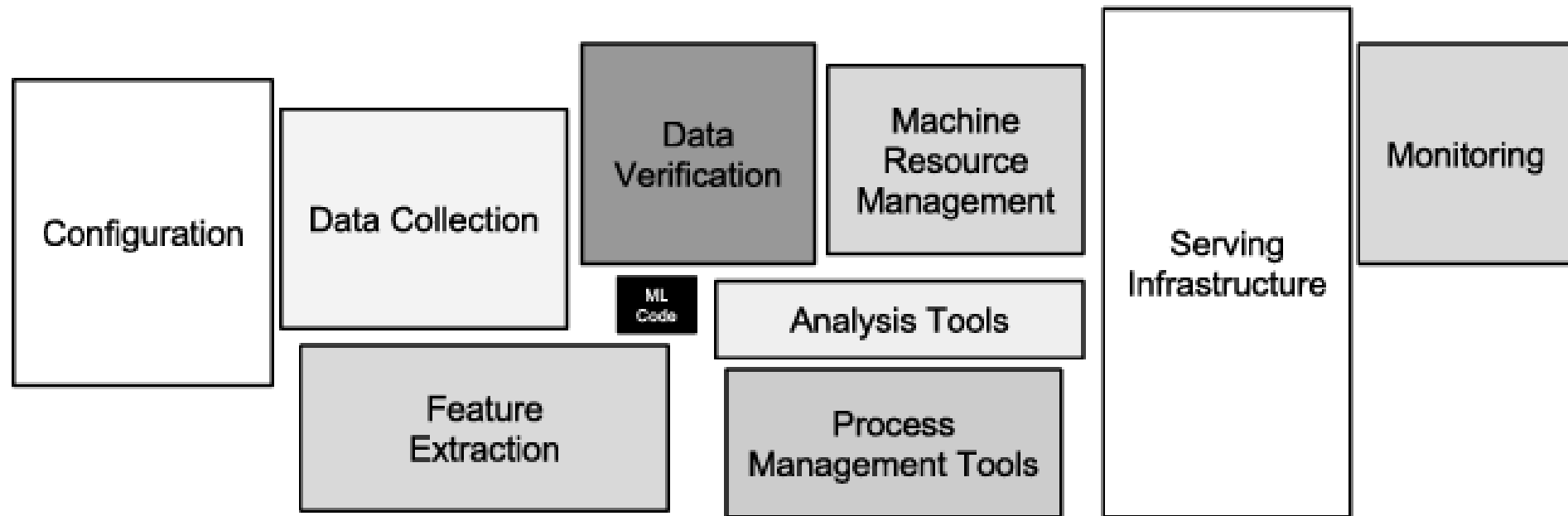


Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.

Scully et al. (2015): Hidden technical debt in Machine learning systems [doi: 10.5555/2969442.2969519]

Artificial Intelligence Working Group Update

119th Meeting of the Advisory Committee to the Director (ACD)
December 13, 2019



David Glazer
Engineering Director, Verily

Lawrence A. Tabak, DDS, PhD
Principal Deputy Director, NIH
Department of Health and Human Services



- **December 6, 2019 ACD AI WG Report**
- https://acd.od.nih.gov/documents/presentations/12132019AI_FinalReport.pdf
- **December 13, 2019 ACD presentation**
- <https://acd.od.nih.gov/documents/presentations/12132019AI.pdf>

Report of the ACD AI WG

December 6, 2019

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The NIH Bridge2AI Program

Supported by the NIH Common Fund

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NIAMS, NIGMS, NIMHD, NINDS, NLM

Other Federal Agencies:

DARPA, DOE, FDA, NIST, NSF



Bridge to Artificial Intelligence

Vision: to propel biomedical and behavioral research forward by setting the stage for widespread use of artificial intelligence (AI) technologies

Goals:

- Use biomedical and behavioral research grand challenges to generate **flagship datasets**
- **Prepare** AI/ML-friendly data
- Prioritize **ethical** best practices
- Promote **diverse perspectives**



DATA

Diverse

FAIR

AI-ready



ETHICS

Accurate

Reliable

Ethically-sourced

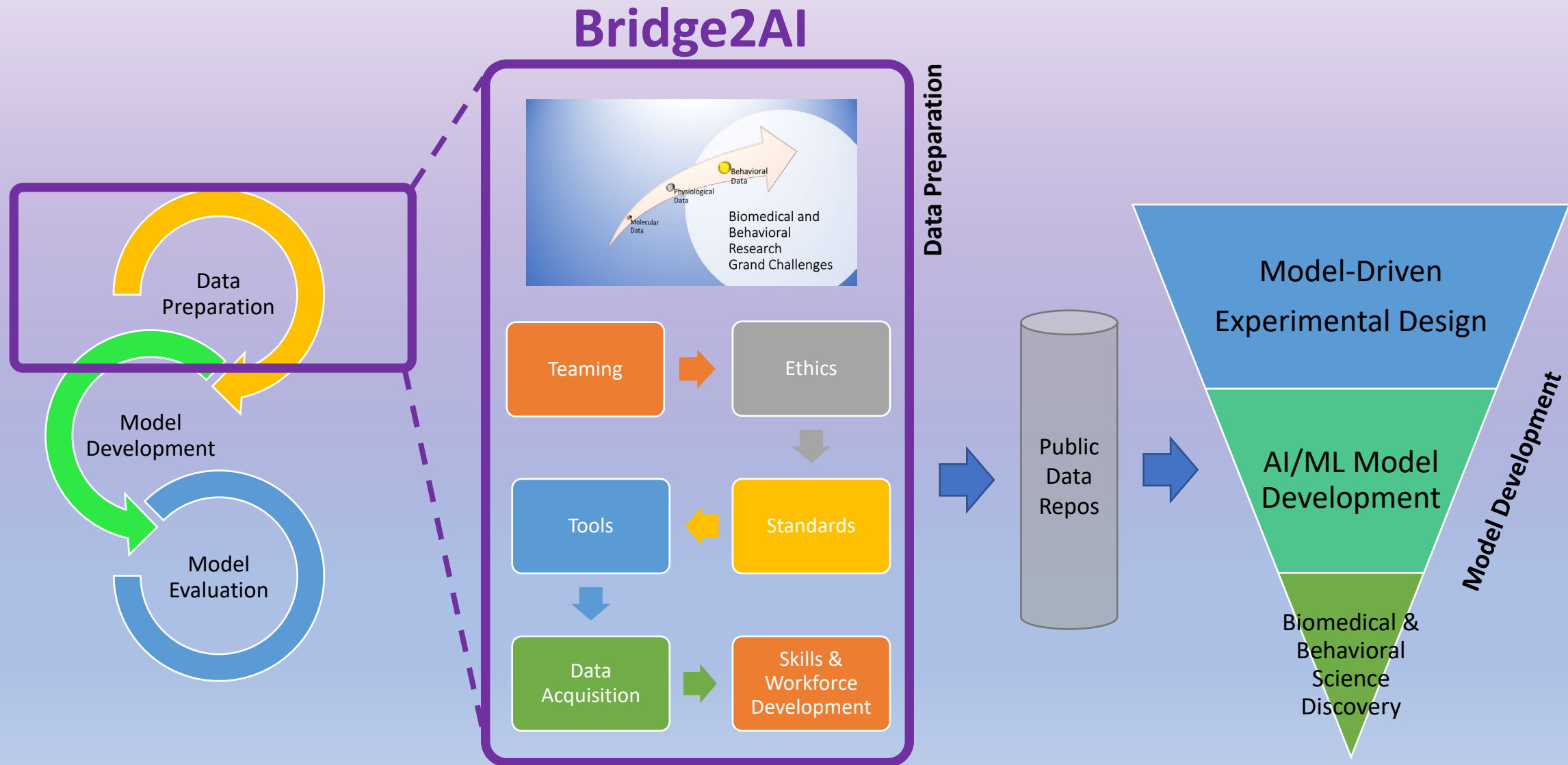


PEOPLE

Diverse teams
&
research cohorts

Training

Scientific Discovery Pipeline



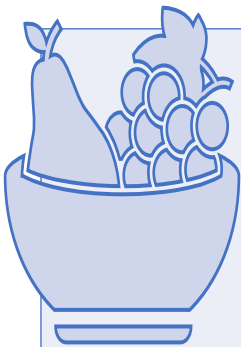
Grand Challenges -- Data Generation Projects



Clinical Care - Using imaging, clinical, and other data collected in an **ICU setting** for diagnosis and risk prediction



Precision Public Health - Using **voice as a biomarker** for human health, revealing how genomic variation, human development, behavioral, and environmental factors affect individual and population health

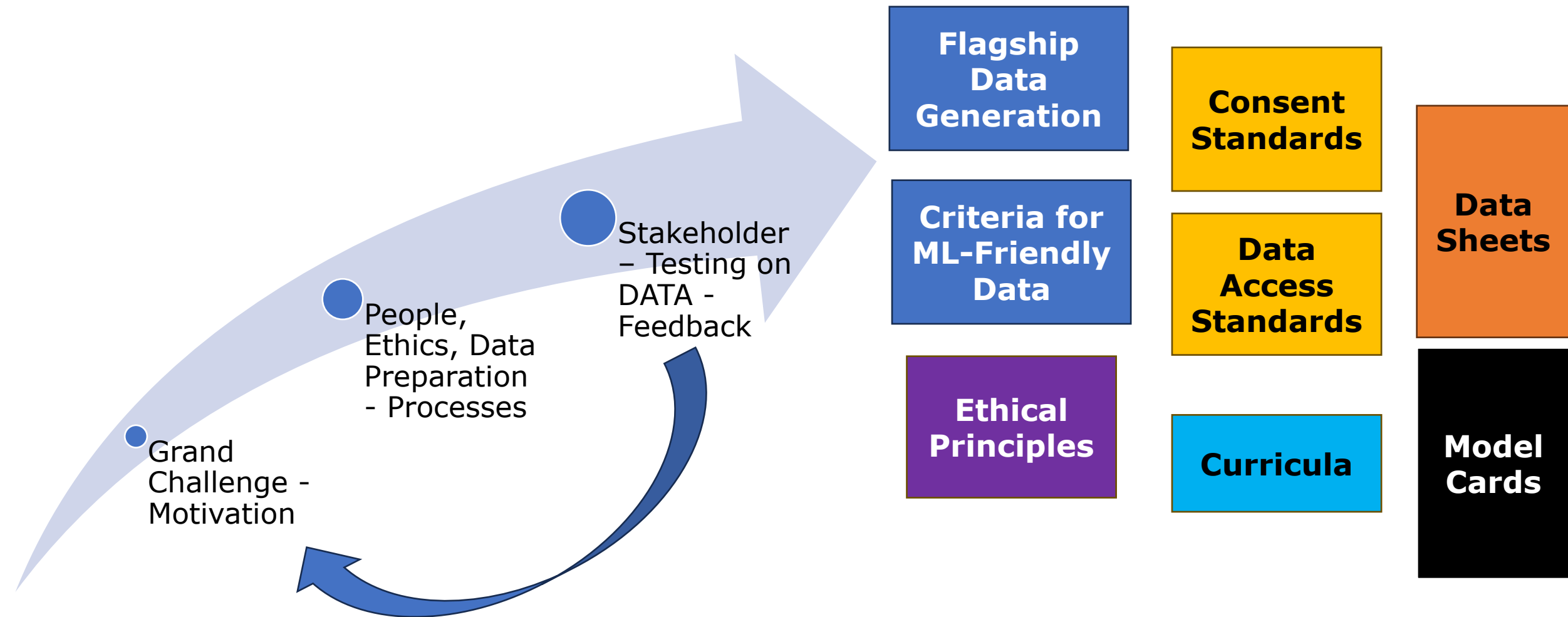


Salutogenesis (Return to Health) - Uncovering the details of how human health is restored after disease, using **type 2 diabetes** as a model



Functional Genomics - Mapping spatiotemporal architecture of human cells to interpret cell structure/function in health and disease

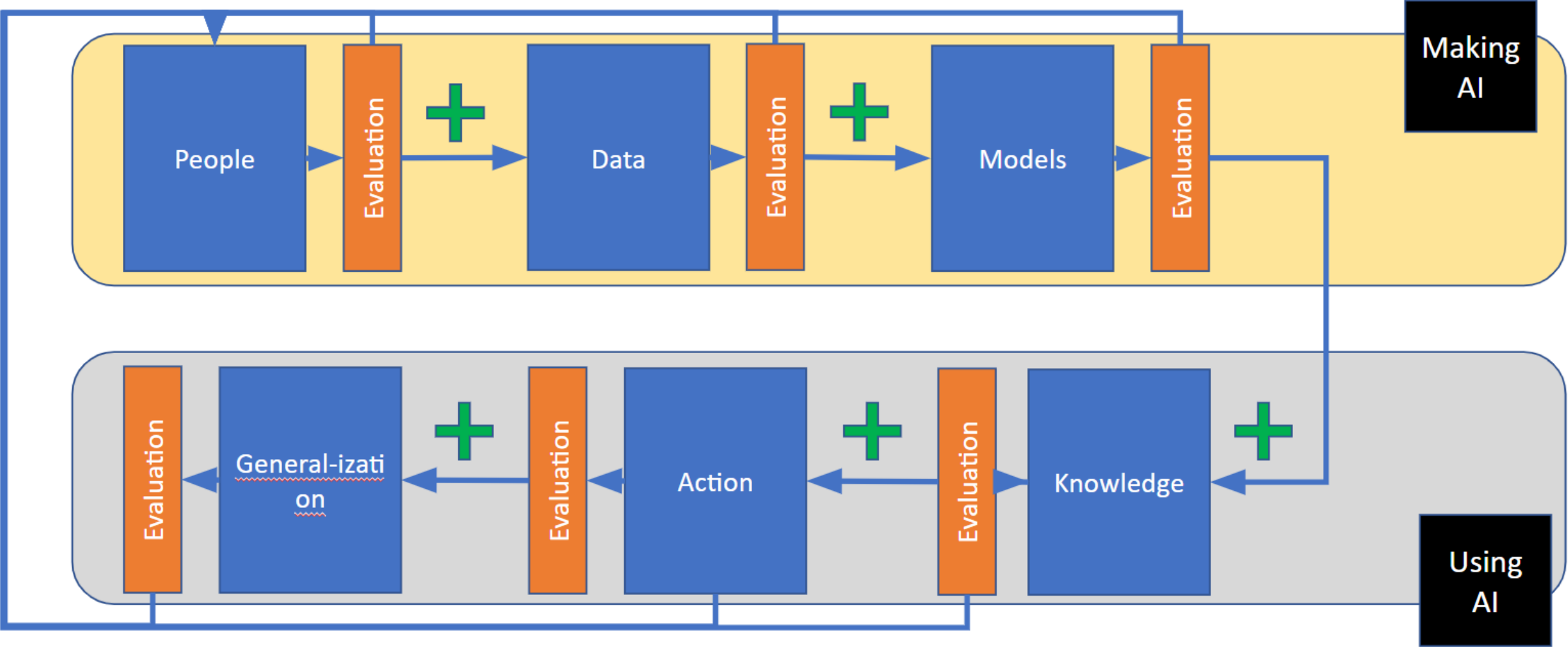
From Vision to Deliverables

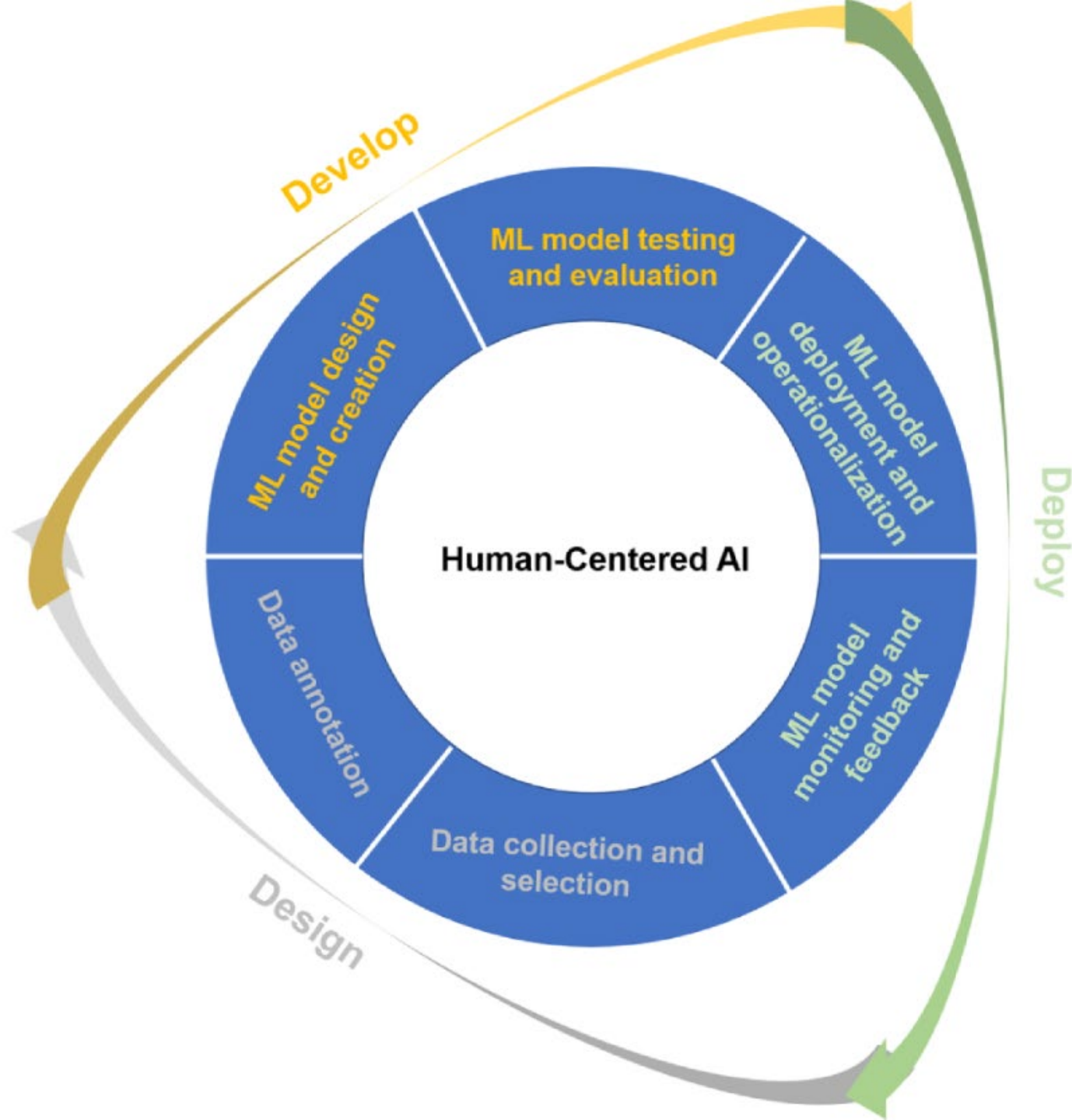


Bridge2AI

Generating ethically sourced data and best practices

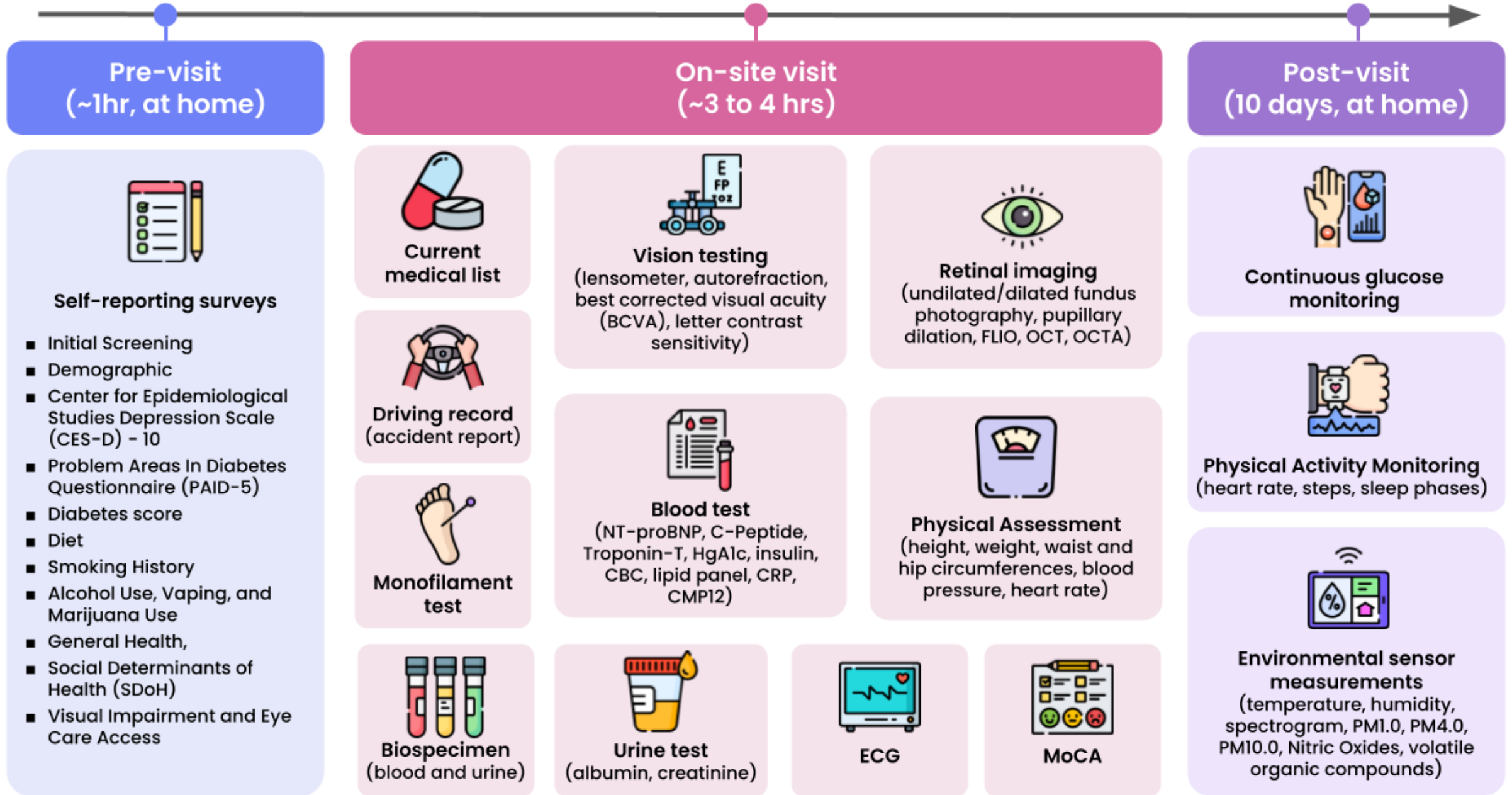
Ethics Must be Embedded from the Outset





Chen, Clayton, Novak, Anders, Malin. Human-Centered Design to Address Biases in Artificial Intelligence. JMIR. 2022.

Multimodal Data collection for AI



FLIO = Fluorescence Lifetime Imaging, OCT = Optical Coherence Tomography, OCTA = Optical Coherence Tomography Angiography, ECG = Electrocardiogram, MoCA = Montreal Cognitive Assessment, PM1.0, 4.0, and 10.0 = Particulate matter less than 1, 4, and 10 microns, respectively

Ethics beyond compliance

BRIDGE2AI

Consent example:

- **By signing this consent, you agree that all the medical data that is collected, apart from your direct HIPAA will be released in a public repository.**
- **Although low, there is a risk that someone will attempt to re-identify you through the data release and it there is a residual risk that development of new technologies will allow people to re-identify you in the future**
- **Companies who download your data are not allowed to sell it but may use your data to develop models for commercial intent**

PRECISION
PUBLIC
HEALTH

BRIDGE2AI



Bridge2AI Voice

Cloud environment
Microsoft Azure

SALUTOGENESIS



Cloud environment
Microsoft Azure

CLINICAL
CARE



Cloud environment
Microsoft Azure

FUNCTIONAL
GENOMICS



CM4AI

Cell Maps for AI

Cloud environment
Google Cloud

	EHR/CLINICAL	SURVEYS	IMAGING	SENSOR-BASED	OMICS	WAVEFORM
<p>A database of 10,000 diverse bioacoustic waveforms is being established to establish voice biomarkers in mental health, respiratory, neurological, and other areas.</p>	<ul style="list-style-type: none"> Demographics Diagnosis (ICD) Severity of disease Treatment information Social history (smoking, alcohol) 	<ul style="list-style-type: none"> 12 validated questionnaires (e.g., MOCA, GAD-7, VHI-10, PANAS, DI, etc.) 	<ul style="list-style-type: none"> Brain MRI/CTs Chest/neck CTs Laryngoscopy 		<ul style="list-style-type: none"> Whole genome sequencing 	<ul style="list-style-type: none"> Bioacoustic data tasks of voice and non-voice sounds, shared as waveforms, Mel spectrograms, features
	OMOP	OMOP	Brain imaging: DICOM; laryngoscopy: MP4		CRAM & VCFs with metadata	Waveform database (WFDB); creating new standard for bioacoustics
<p>Creating a temporal atlas from 3,000 individuals around pathogenesis and salutogenesis to expand applications of AI in clinical care, focusing on Type 2 diabetes</p>	<ul style="list-style-type: none"> Demographics, SDoH Diet Social history Lab tests (blood, urine) Monofilament test Physical assessment Medications Vision testing 	<ul style="list-style-type: none"> Multiple validated self-reporting surveys (CES-D, PAID-5, etc.) 	<ul style="list-style-type: none"> Retinal imaging (undilated/dilated fundus photography, pupillary dilation, FLIO, optical coherence tomography (OCT), OCT angiography) 	<ul style="list-style-type: none"> Continuous glucose monitoring (CGM) Physical activity monitoring (heart rate, steps, sleep phases) Environmental sensors (air quality and particulate measures, temperature) 	<ul style="list-style-type: none"> Whole genome sequencing 	<ul style="list-style-type: none"> Electrocardiogram (ECG)
	OMOP, LOINC	OMOP, LOINC	DICOM	CGM, physical activity: open mHealth; Air: Earth Science Data Spec	CRAM & VCFs with metadata	Waveform database (WFDB)
<p>Establishing a set of >100,000 patients from 14 ICU sites across the United States to improve recovery from acute illnesses</p>	<ul style="list-style-type: none"> Demographics, SDoH Clinical notes Lab tests Medications Encounters Procedures 		<ul style="list-style-type: none"> All imaging acquired during ICU setting and captured in PACS (MR, CT, US, x-ray) 			<ul style="list-style-type: none"> Physiological data (ECG; electroencephalogram, EEG)
	OMOP, LOINC		DICOM			Waveform database (WFDB)
<p>Creating a library of large-scale maps of cellular structure, function, and disease contexts using cell lines. 200 genes/proteins are the subject of coordinated experiments in three modalities</p>			<ul style="list-style-type: none"> Immunofluorescence imaging data for cell imaging 		<ul style="list-style-type: none"> Proteomic mass spectrometry CRISPR perturbation scRNA-Seq Datasets Cell maps 	
			Cell imaging: RO-Crate with JPEG 4-channel (red, green blue, yellow) and metadata		Mass spec: RO-Crate w/TSV & metadata; CRISPR: RO-Crate with h5ad file & metadata; Cell maps: RO-Crate with Cytoscape CX & metadata	

Towards Best Practices

What type of Data are you collecting?

Identifier under HIPAA

Non-Identifier under HIPAA

High/low Risk of Re-identification under Common Rule

Do you need consent and what should it contain?

Consent exempt

Consent

Assent

Blanket Consent, Opt-in/Opt Out, Menu?

Who will be using your data and how?

Only Pis from Academia

Only academic researchers

Public population

Companies

What kind of regulatory contracts do you need?

Codes of Conducts

DUA

License

What are the risk vs benefits of your data being released?

Technology available

Type of similar data online

Public health context

Urgency

Can technology be used to diminish risk?

Blockchain technology

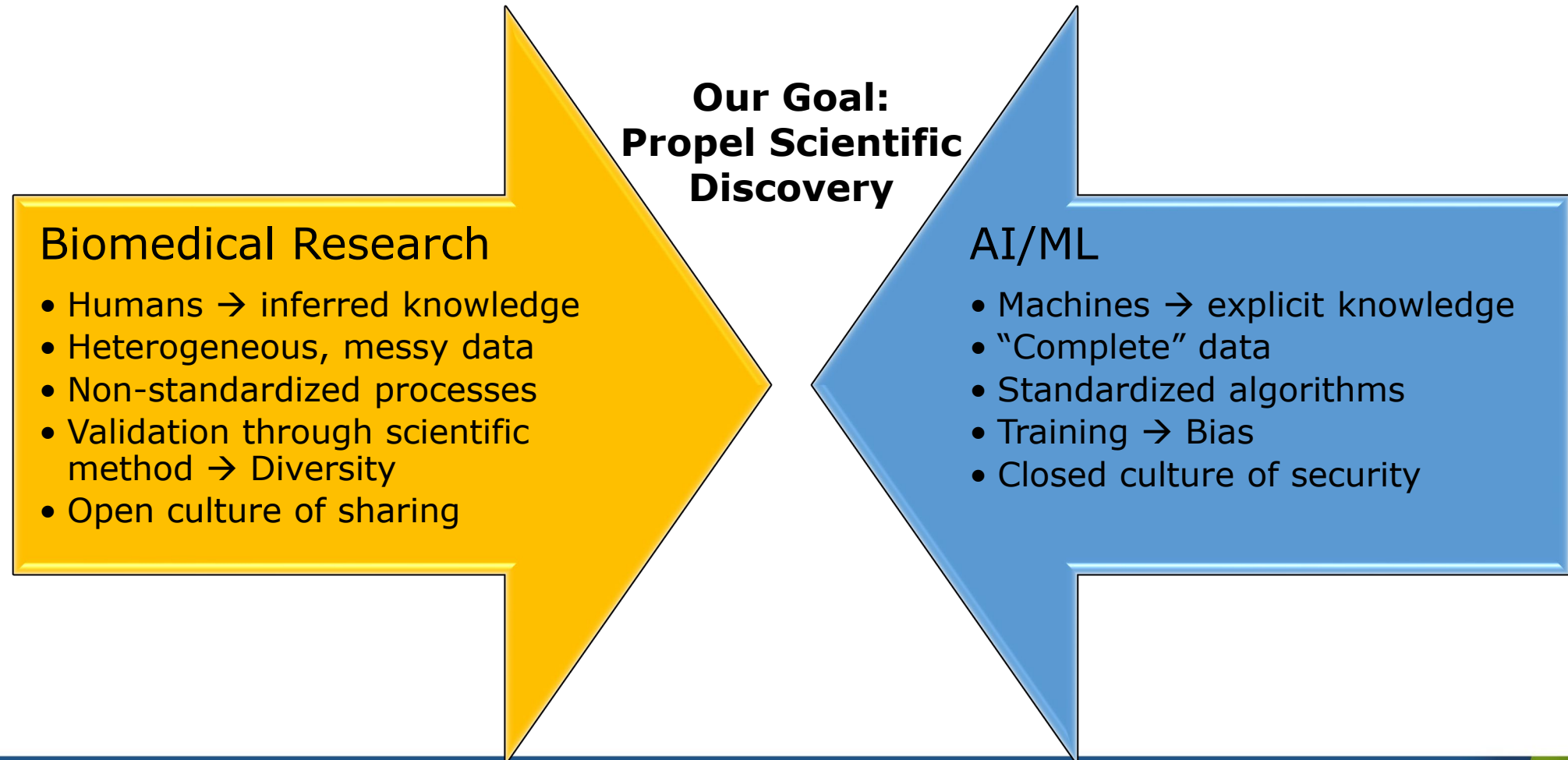
Watermarking

Others!

Bridge2AI

Lessons Learned so far

What make Bridge2AI challenging?



Ethical Challenges → for Open Science

- **Biases:** Issues related to inherent biases of the data
- **Informed Consent:** Going beyond a legal consent form
 - How do we ensure consent given the evolving landscape of AI/ML?
- **Re-identification:** Navigating the risk of re-identification with multi-modal data
- **Unauthorized Use:** How do we prevent unauthorized secondary use?

People Challenges



▪ Teaming & Collaboration

- Multidisciplinary teams
- Cross-Consortium collaboration
- Community engagement committees

▪ Diverse cohorts for data collection

- Consent & privacy
- Legal issues
- Sovereignty issues

▪ AI/ML Training Needs

- Computational science training on the ethical, legal, and social implications
- New material with use cases
- Training for non-computational scientists (e.g., clinicians, physician scientists)
- Hands-on training

Lessons Learned

- **Program vision & goals:** Promote repeatedly and continuously and consistently
- **Governance:** Create iterative governance structure to adapt to the changing needs
- **Iterative AI model build and evaluation:** As data and best practices are being created
- **Synchronized stakeholders:** Partner with each team from the outset, equitably
- **Sustainability plan:** For data storage, access, distribution, sovereignty from the outset

Other NIH Programs

Supporting trustworthy data for open science

DATA COLLECTION

- Data Acquisition & Aggregation Bias
- Biased Synthetic Data

- Population Bias
- Popularity/Patient-based Bias
- Temporal Bias
- Sampling/Representation/Selection Bias
- Detection Bias
- Amplification Bias
- Training Data Bias
- Cognitive Bias

MODEL DEVELOPMENT

- Inherited/Error Propagation Bias

MODEL EVALUATION

- Statistical Bias

- Institutional/Systemic Bias
- Activity Bias

DATA PREPARATION

- Content Production Bias

- Exclusion Bias

- Automation Complacency/Loss of Situational Awareness Bias

- Annotator Bias

MODEL DEPLOYMENT

- Deployment Bias
- Concept Drift/Emergent Bias
- User Interaction Bias

- Uncertainty Bias/Epistemic Uncertainty

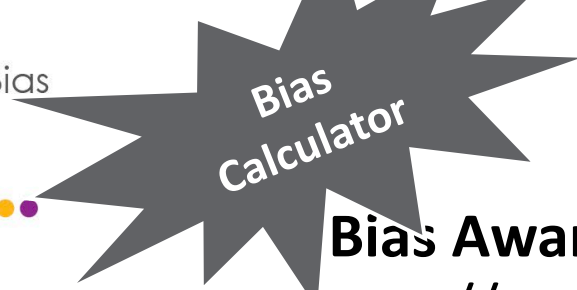
- Evaluation Bias

- Funding/Publication Bias

-Membership Bias
-Historical Bias
-Behavioral Bias

Major Bias Sources

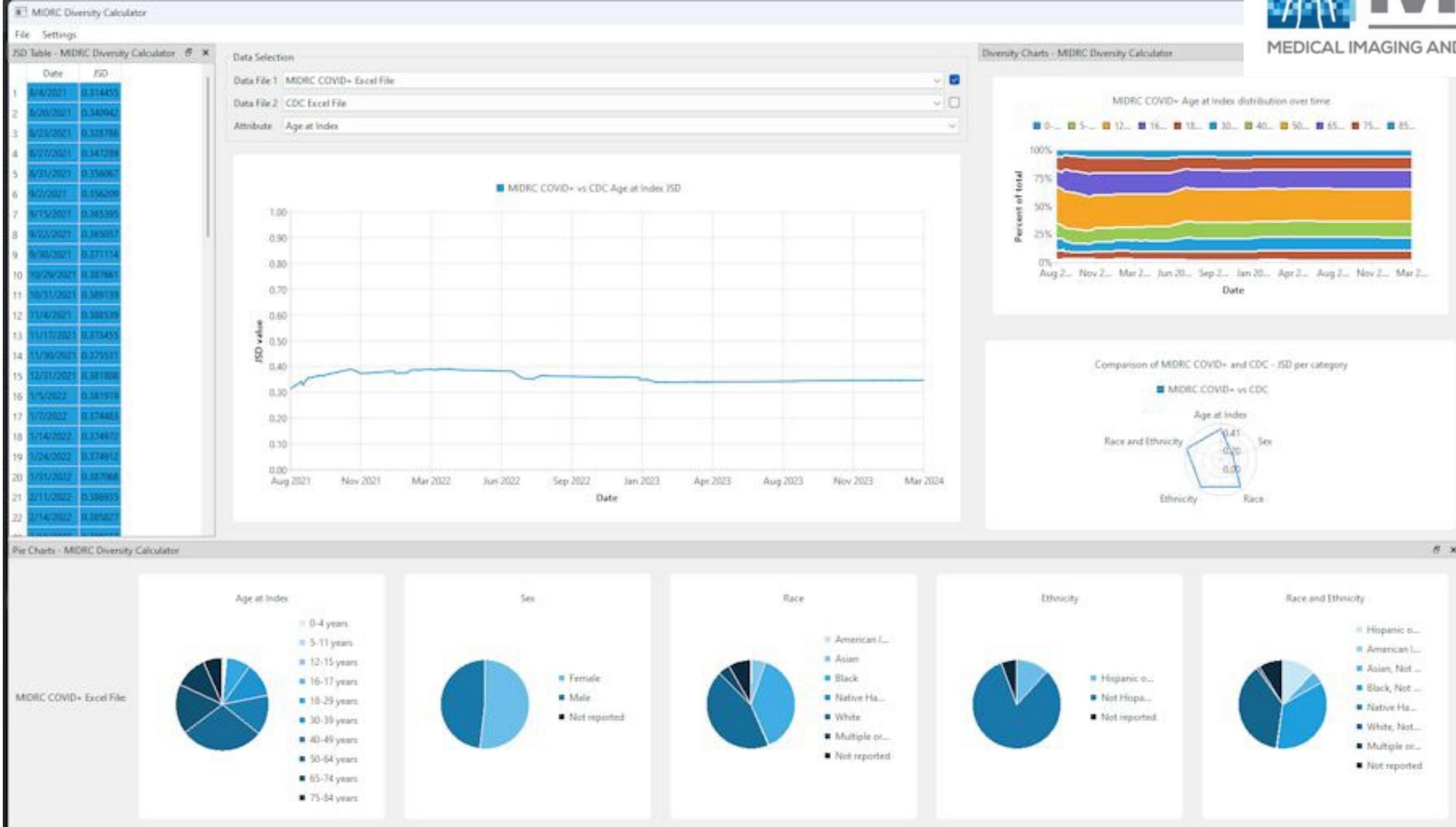
- Data Collection
- Data Preparation
- Model Development
- Model Evaluation
- Model Deployment



Bias Awareness Tool:

<https://www.midrc.org>

Diversity Calculator



Community Partnerships to Advance Science for Society (ComPASS)

To advance the science of health disparities and health equity research, the National Institutes of Health (NIH) Common Fund launched the ComPASS Program.

The goals of ComPASS are to:

1. Study ways to reduce health disparities by addressing underlying structural factors within communities.
2. Develop a new research model for NIH where the projects are led by community organizations in collaboration with research partners.

ComPASS has three initiatives:



Community-Led, Health Equity Structural Interventions (CHESIs)



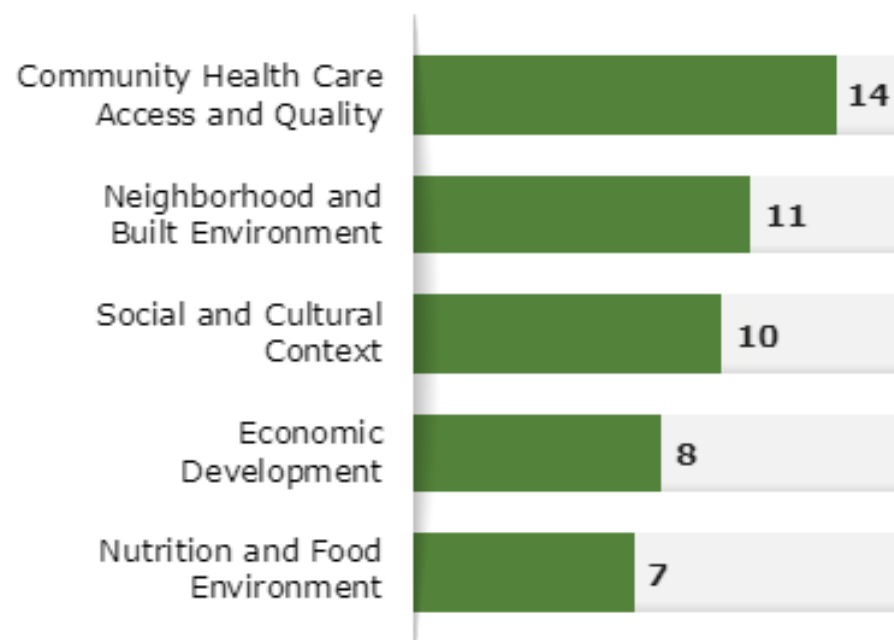
ComPASS Coordination Center (CCC)



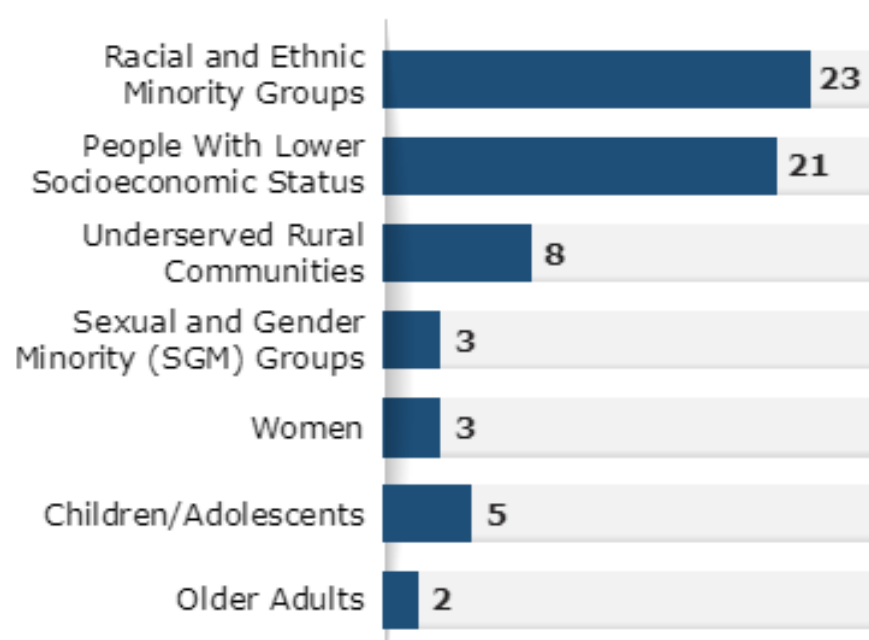
Health Equity Research Hubs (Hubs)

The 25 CHESI Structural Factors and Participant Populations

Social Determinants of Health and Structural Factors of the Projects



Populations That Experience Health Disparities and Other Participant Populations*



*Note that CHESI projects that focus on more than one social determinants of health and/or population experiencing health disparities are counted more than once.

Connect With Us!



For more information, visit the NIH Common Fund ComPASS website at commonfund.nih.gov/compass.

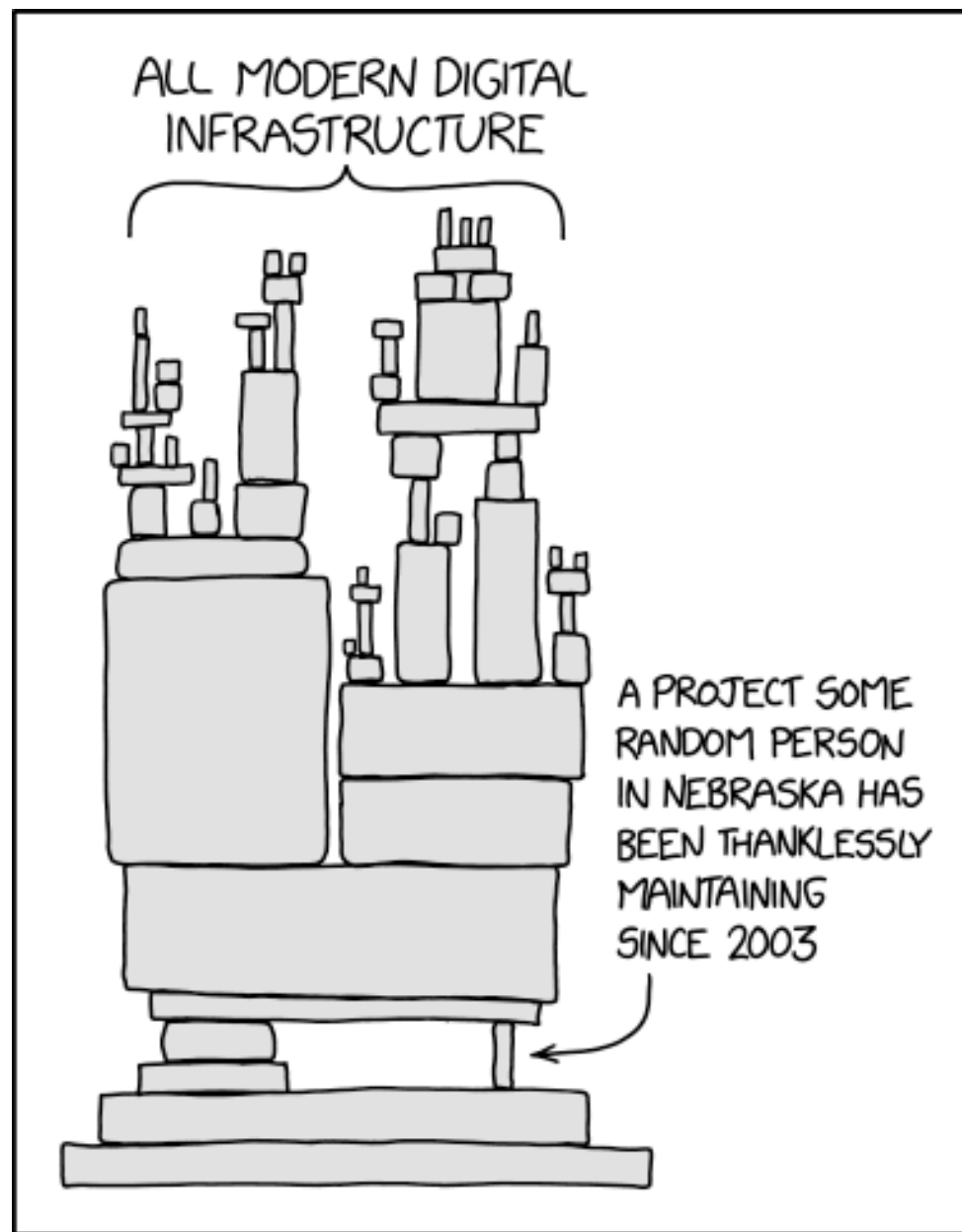


Learn more by viewing the [ComPASS Video Overview](#).



To receive ComPASS program announcements and information about funding opportunities, join the [ComPASS listserv](#).

Trustworthy open data
→ requires understanding
dependencies!
<https://xkcd.com/2347/>



2024 IMAG MSM Consortium Meeting

Setting up TEAMS for Biomedical Digital Twins (Teaming4BDT)

- September 30 - October 2, 2024
- Bethesda, Maryland
- Register on the [IMAG WIKI](#)
- In-person and online – open to all!


Special thanks to NSF for providing Travel Awards




Special thanks to the Society for Mathematical Biology for providing refreshments

IMAG MULTISCALE MODELING CONSORTIUM

Setting up TEAMS for Biomedical Digital Twins (Teaming4BDT)


$$f\left(\mathbf{r} + \frac{\mathbf{p}}{m} \Delta t, \mathbf{p} + \mathbf{F} \Delta t, t + \Delta t\right) d^3 \mathbf{r} d^3 \mathbf{p} = f(\mathbf{r}, \mathbf{p}, t) d^3 \mathbf{r} d^3 \mathbf{p}$$
$$dN = f(\mathbf{r}, \mathbf{p}, t) d^3 \mathbf{r} d^3 \mathbf{p}$$
$$\frac{\partial f_i}{\partial t} + \frac{\mathbf{p}_i}{m_i} \cdot \nabla f_i + \mathbf{F} \cdot \frac{\partial f_i}{\partial \mathbf{p}_i} = \left(\frac{\partial f_i}{\partial t} \right)_{\text{coll}}$$
$$\hat{\mathbf{L}}_{\text{NR}} = \frac{\partial}{\partial t} + \frac{\mathbf{p}}{m} \cdot \nabla + \mathbf{F} \cdot \frac{\partial}{\partial \mathbf{p}}$$
$$\frac{\partial}{\partial t} \left(u + \frac{1}{2} \rho V_i V_i \right) + \frac{\partial}{\partial x_j} \left(u V_j + \frac{1}{2} \rho V_i V_i V_j + J_{qj} + P_{ij} V_i \right) - n F_i V_i = 0,$$

September 30 - October 2, 2024 | NIH Bethesda, MD



Day 1 - Defining Biomedical Digital Twins (BDT)

- Goal 1: To understand the NASEM Digital Twin components
- Goal 2: To identify unique features for digital twins in the biomedical domain (BDT)

Create requirements template for BDT

Day 2 - Approaches to address BDT challenges

- Goal 1: To understand the challenges unique to developing BDT
- Goal 2: To discuss needs with experts and compile BDT component resources

Create review template for BDT

Day 3 - Operationalizing Team Science for BDT

- Goal 1: To form BDT idea teams guided by team science approaches
- Goal 2: To present and review realizable, fit for purpose BDT ideas

Utilize consensus requirements and review templates developed in Day 1 and Day 2