PERSONALIZED MEDICATION DEPRESCRIBING FOR OLDER ADULTS:

Leveraging AI and Building Trust in AI-Driven Clinical Guidance

US DEPRESCRIBING NETWORK WEBINAR

March 4, 2025

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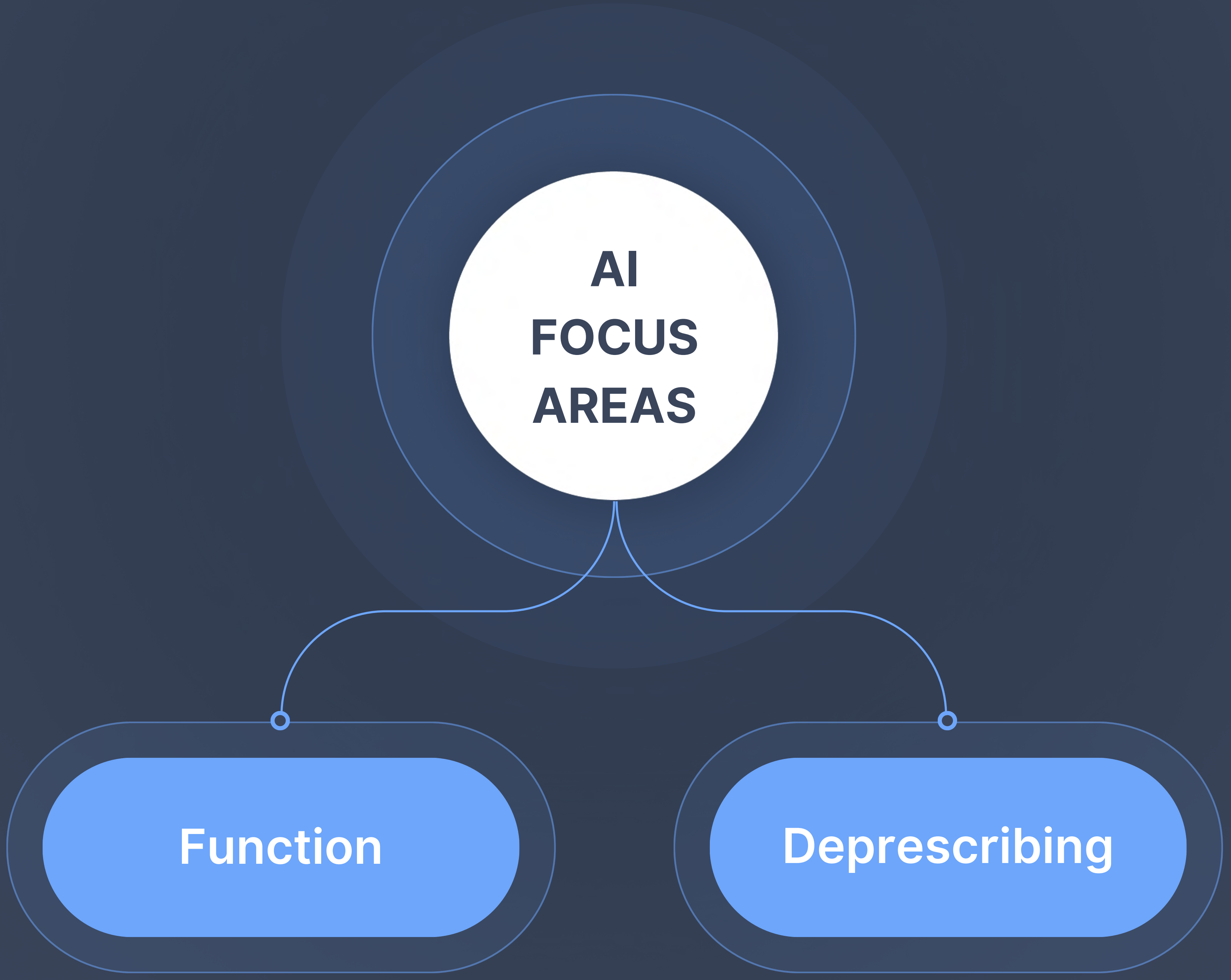


Disclosures

01

No financial disclosures or conflicts of interest

02

NIH National Institutes of Health
Turning Discovery Into Health

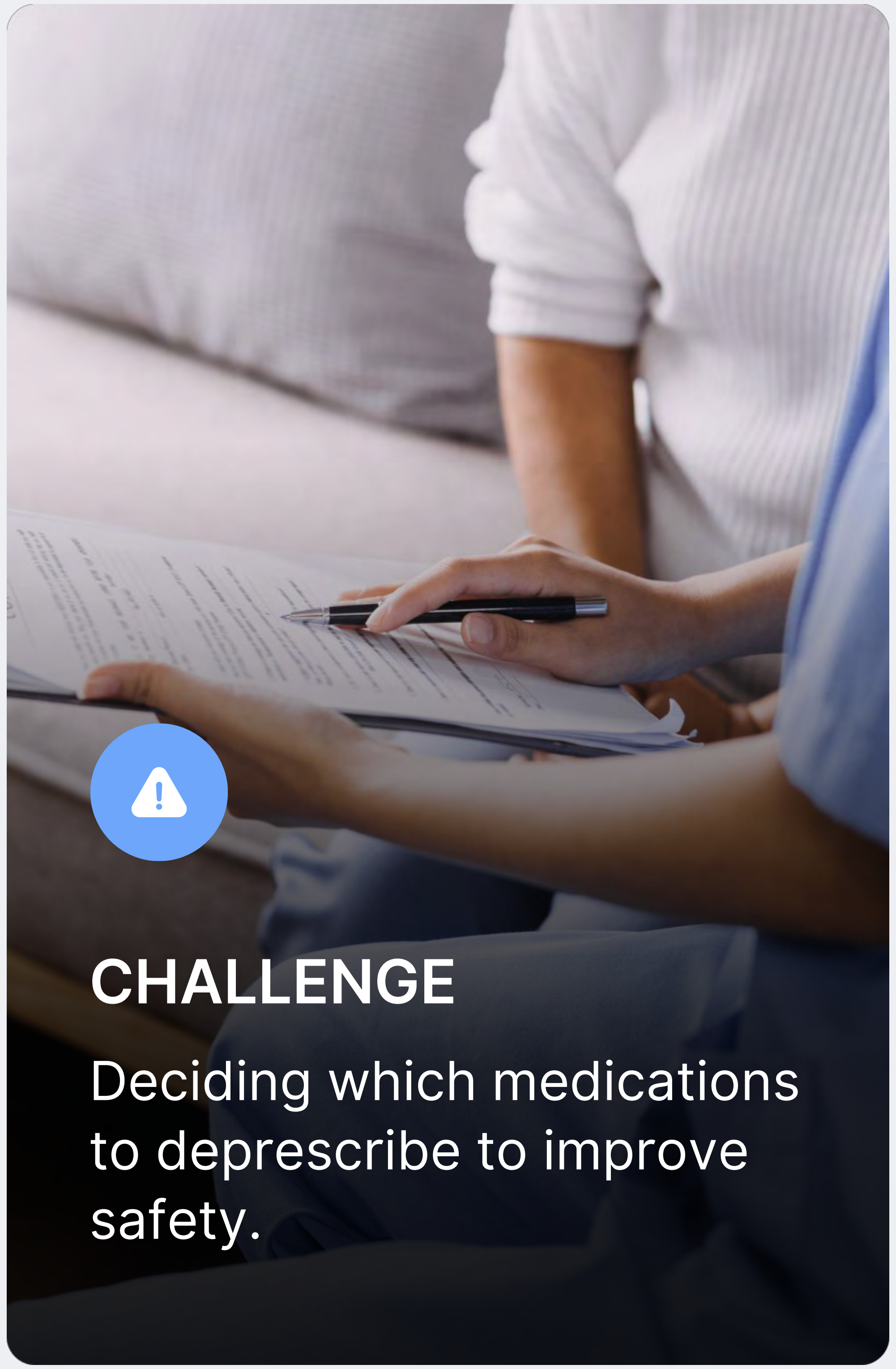
NIA 1R01-AG088214-01

03

I love data science, but I am not a data scientist

The Challenge of Polypharmacy in Older Adults

Nearly 4 million older adults take three or more central nervous system (CNS)-acting medications.



CHALLENGE

Deciding which medications to deprescribe to improve safety.

Mrs. P

AGE: 78 YEARS OLD

MEDICAL HISTORY

Chronic pain, anxiety, and insomnia

MEDICATIONS

Gabapentin, baclofen, citalopram, lorazepam, trazodone

SYMPTOMS

Drowsiness, balance issues, memory lapses, fall risk

IMAGINE A BETTER APPROACH

An AI-driven tool that:

- Analyzes medical history, symptoms, and drug interactions.
- Provides personalized recommendations for deprescribing medications.

IMPACT

- Lower falls risk and cognitive side effects.
- Greater independence and improved quality of life.
- Data-driven recommendations for safer outcomes.

What is Depreciating?

“

Deprescribing is the process of withdrawal of an inappropriate medication, supervised by a health care professional with the goal of managing polypharmacy and improving outcomes.

Reeve 2015, Br J Clin Pharmacol

Deprescribing Outcomes

Consider patient's priorities and goals

BENEFITS

Fewer

- Falls
- Adverse drug reactions
- Depression
- Frailty
- Costs
- Pill burden
- Acute care referrals
- Mortality

Better

- Self-rated health
- Quality of life
- Functional status
- Medication adherence

HARM

Condition Relapse

- Depression
- Anxiety
- Pain
- Agitation

Medication Restarts

References: Gnjidic, Clin Geriatr Med 2012 | Linsky, JAMA Intern Med 2013 | Maust, JAMA Intern Med 2017 | Page, Br J Clin Pharmacol 2016

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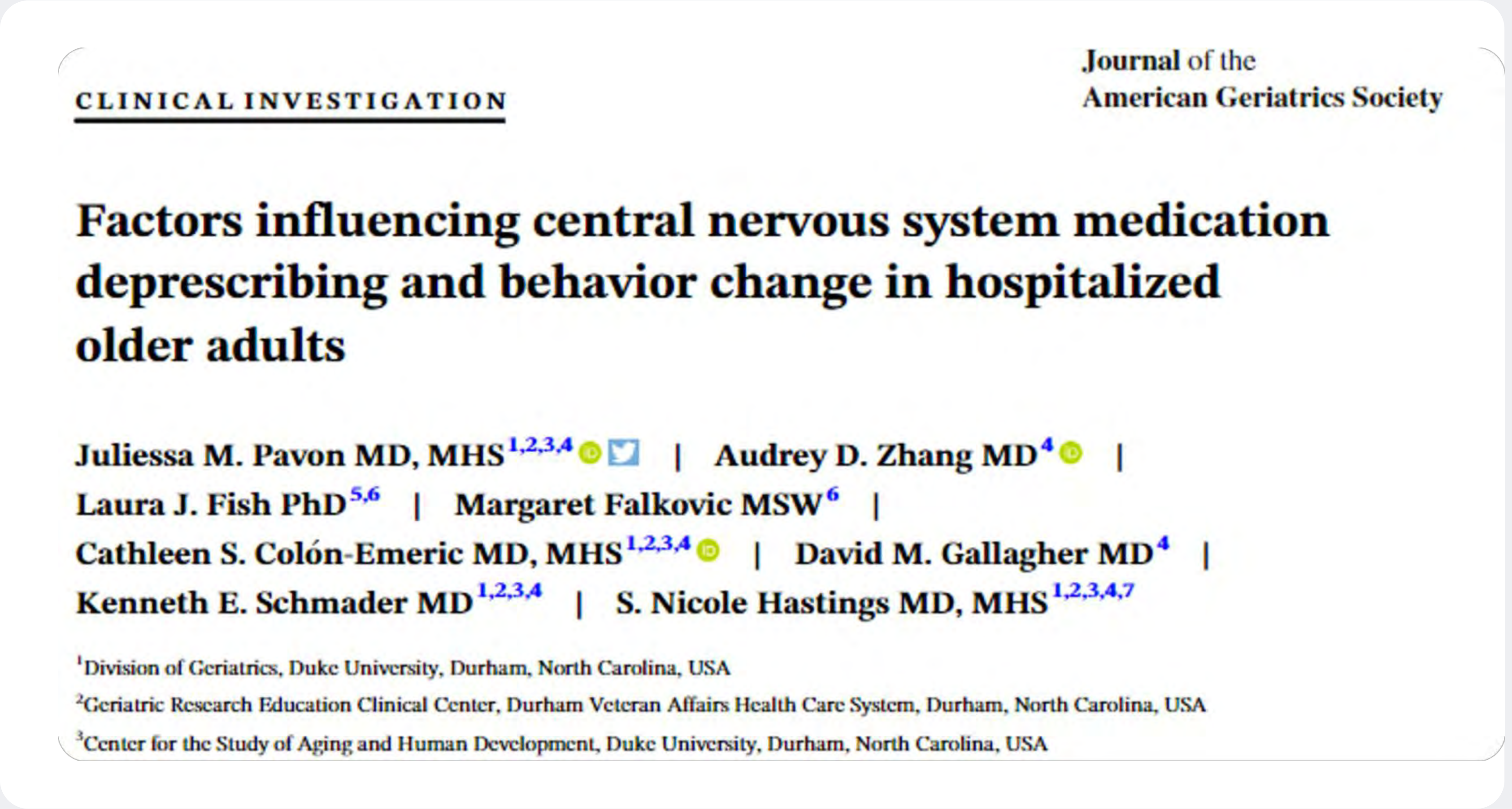
Desire for Deprescribing Tools



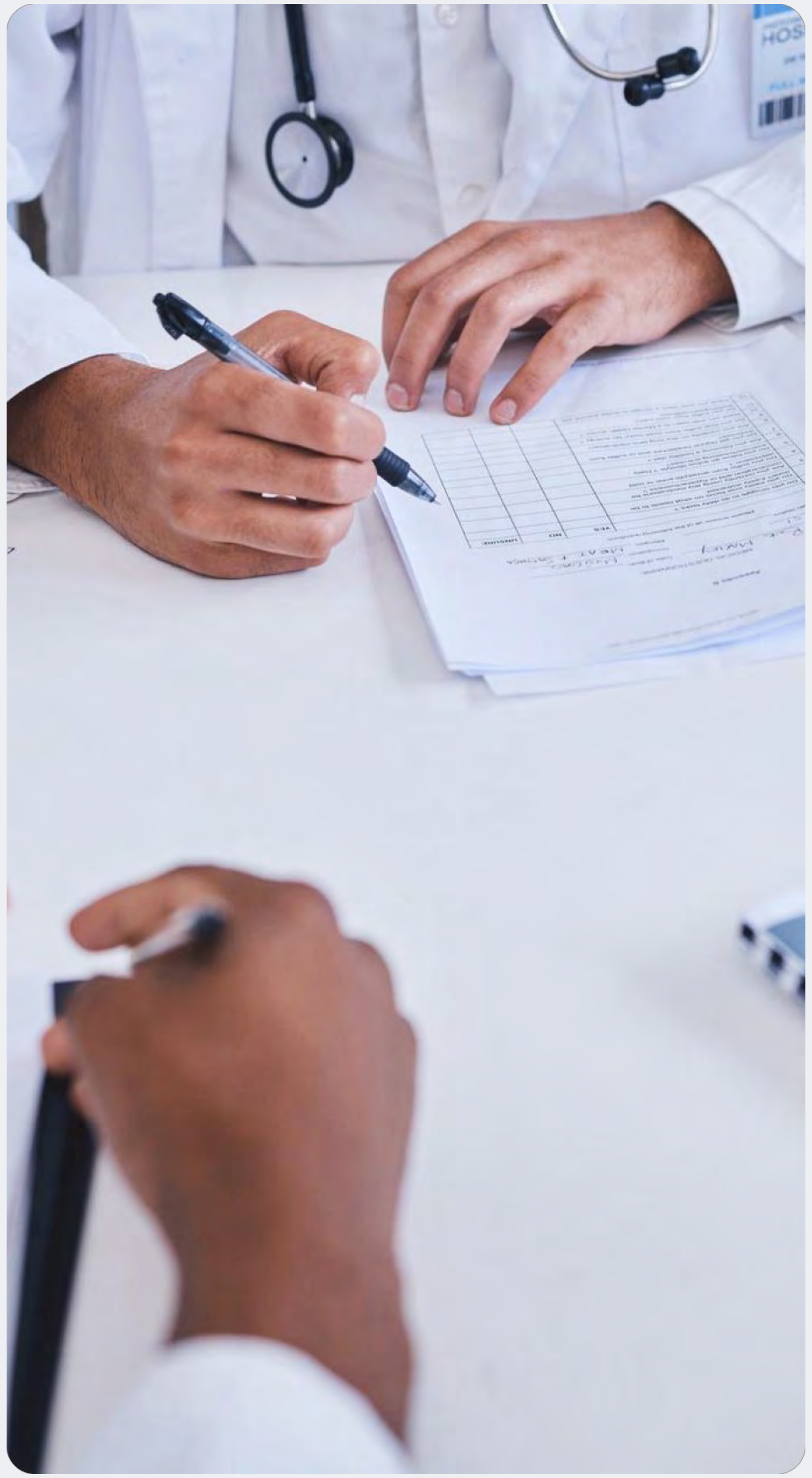
CLINICAL INVESTIGATION

Journal of the American Geriatrics Society

Factors influencing central nervous system medication deprescribing and behavior change in hospitalized older adults

Juliessa M. Pavon MD, MHS[1,2,3,4] | Audrey D. Zhang MD[4] | Laura J. Fish PhD[5,6] | Margaret Falkovic MSW[6] | Cathleen S. Colón-Emeric MD, MHS[1,2,3,4] | David M. Gallagher MD[4] | Kenneth E. Schmader MD[1,2,3,4] | S. Nicole Hastings MD, MHS[1,2,3,4,7]

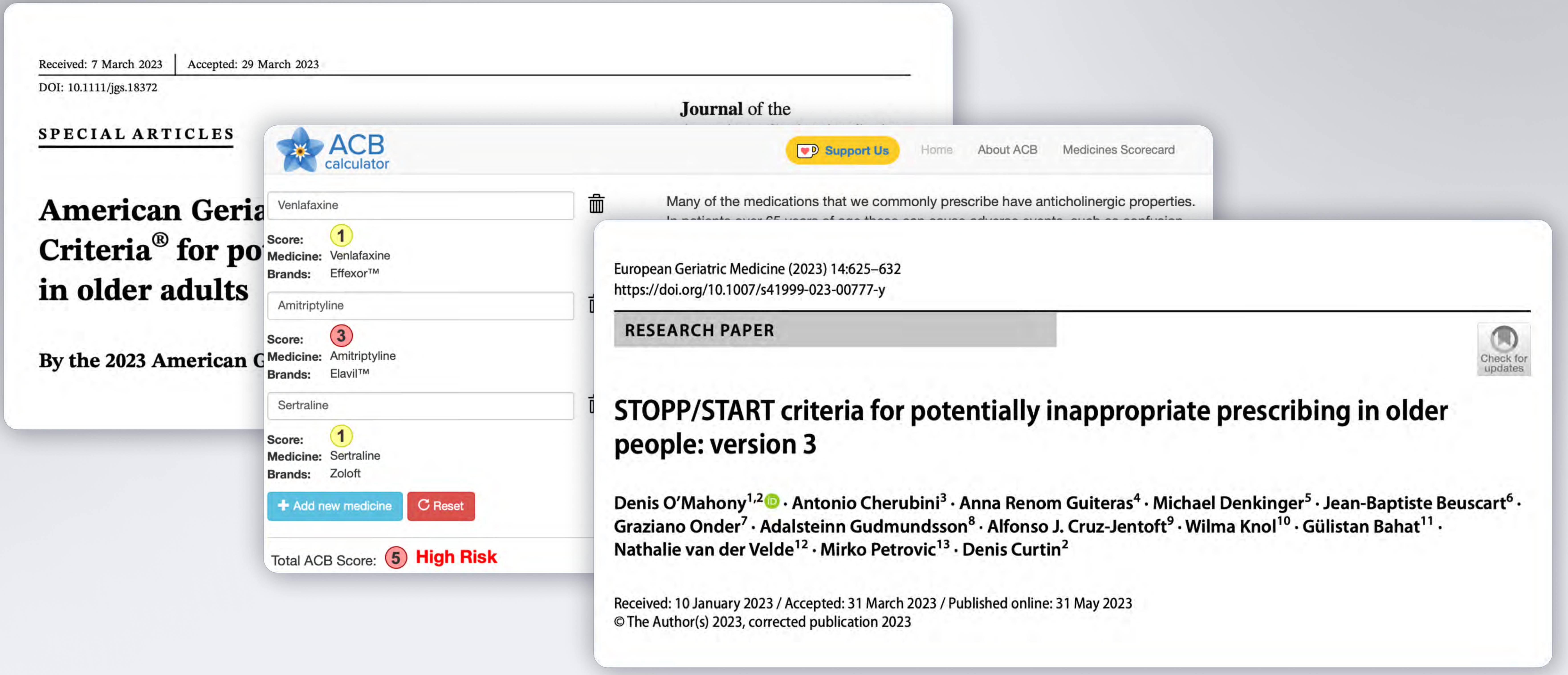
[1]Division of Geriatrics, Duke University, Durham, North Carolina, USA
[2]Geriatric Research Education Clinical Center, Durham Veteran Affairs Health Care System, Durham, North Carolina, USA
[3]Center for the Study of Aging and Human Development, Duke University, Durham, North Carolina, USA



A qualitative study with patients and providers identified barriers and facilitators to hospital deprescribing.

Clinicians expressed a strong desire for EHR-embedded algorithms or automated tools to guide deprescribing decisions.

Current Tools

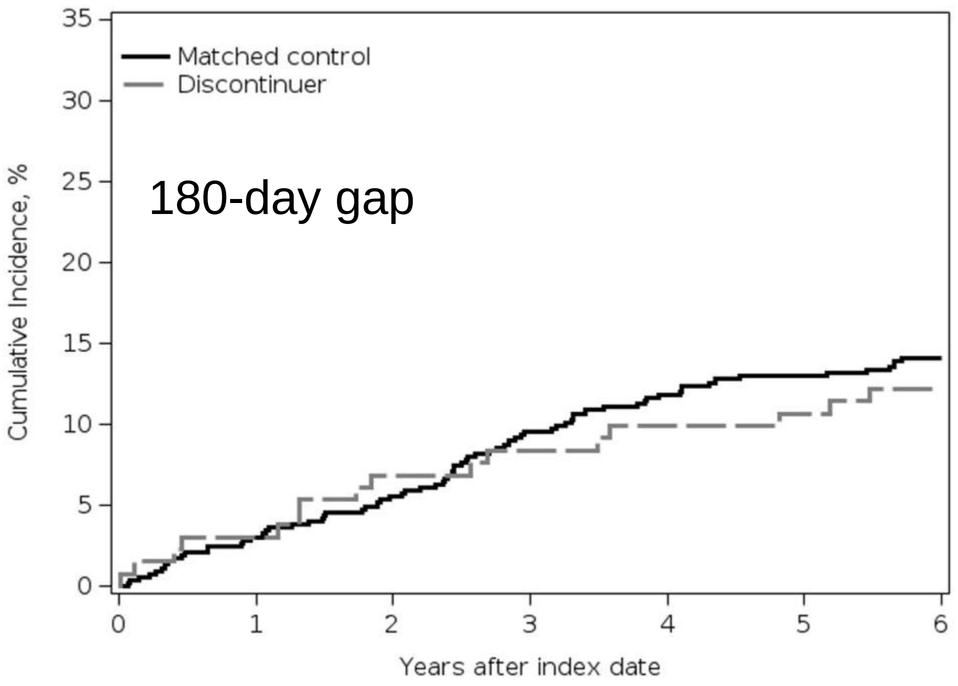


References: AGS Beers Criteria Update Expert Panel, J Am Geriatr Soc 2023 | Kiesel BMC Geriatr, 2018 | O'Mahony Eur Geriatr Med, 2023

Deprescribing and Clinical Outcomes

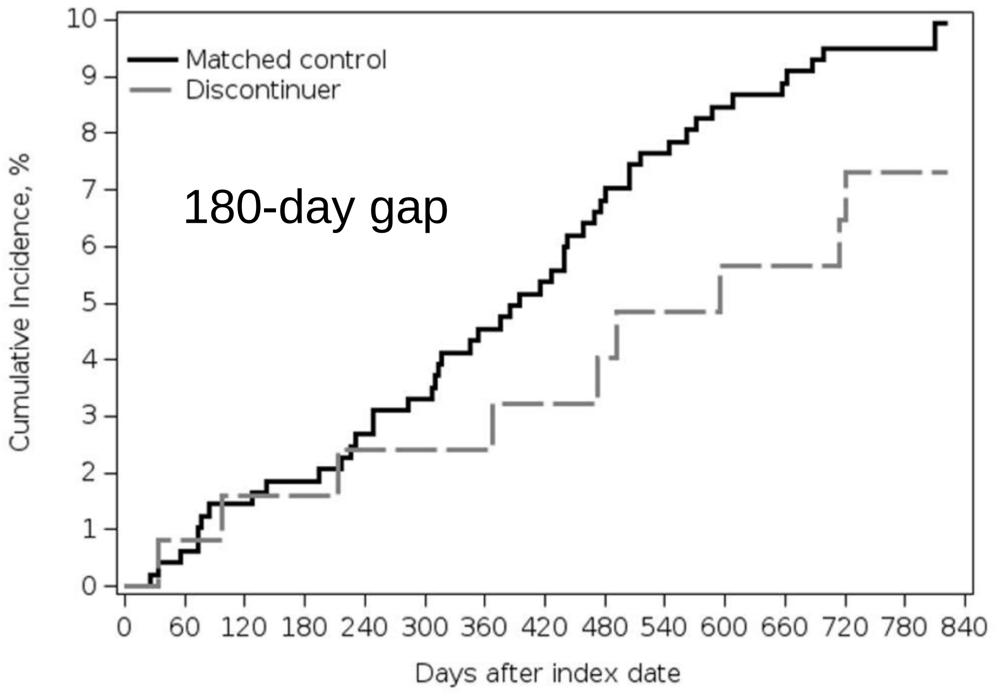
DEMENTIA

Observed 6-year cumulative incidence of recognized dementia, 180-day cohort

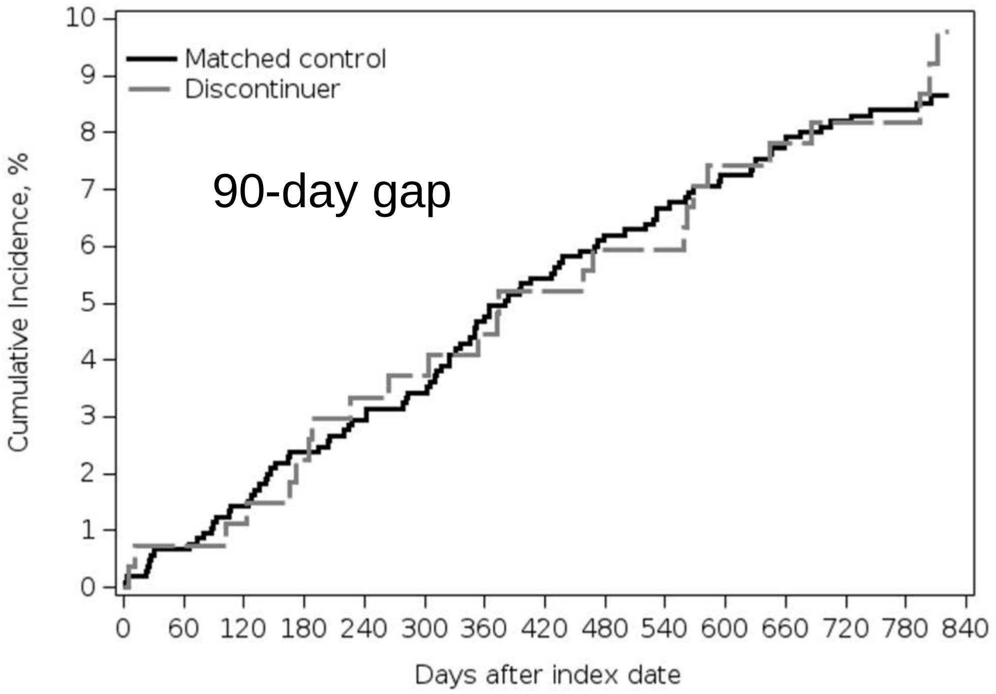


FALLS

Older adults with chronic benzodiazepine/z-drug use (N=2200)



FALLS



Fall Outcomes in Older Adults Following Benzodiazepine/Z-Drug Discontinuation: A Retrospective Cohort Study in an Academic Health System

Nicole J Schindler [1], Lindsay Zepel [2], Matthew L Maciejewski [3, 2, 4, 5, 6], Susan N Hastings [3, 2, 4, 7, 8, 9], Amy Clark [2], Sascha Dublin [10, 11, 12], Ladia Albertson
Juliessa M Pavon [13, 14, 15, 16]

	180-DAY DEFINITION		90-DAY DEFINITION	
	Non-discontinuers (n=484)	Discontinuers (n=124)	Non-discontinuers (n=1,049)	Discontinuers (n=269)
Total Falls (cumulative incidence %)	47 (9.9)	9 (7.3)	87 (8.4)	25 (9.8)

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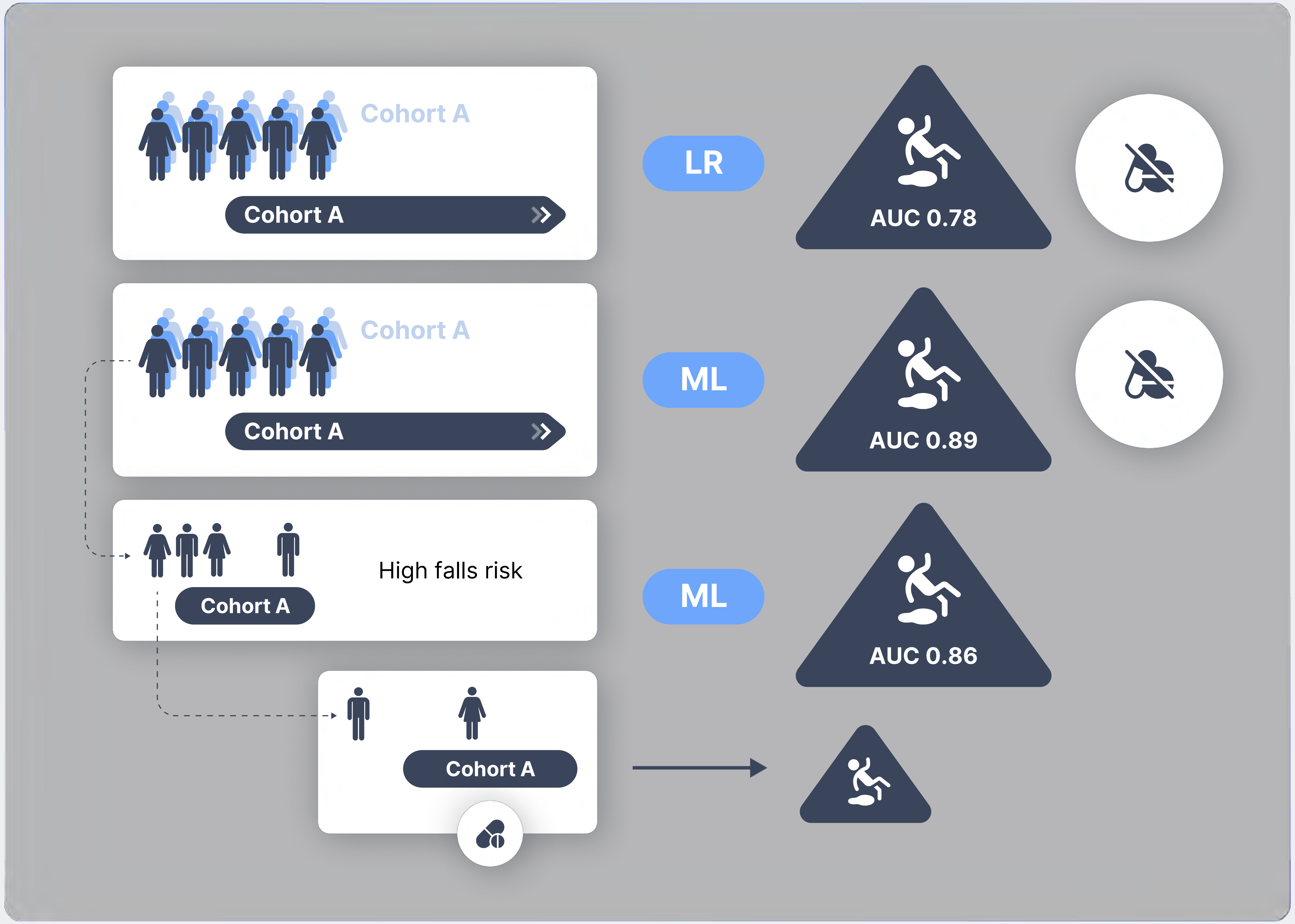
Toward Individualized Deprescribing: Integrating AI

Preliminary work

Older adults with chronic benzodiazepine/z-drug use (N=2200)



DEPRESCRIBING A FACTOR IN PREDICTING FALLS RISK:

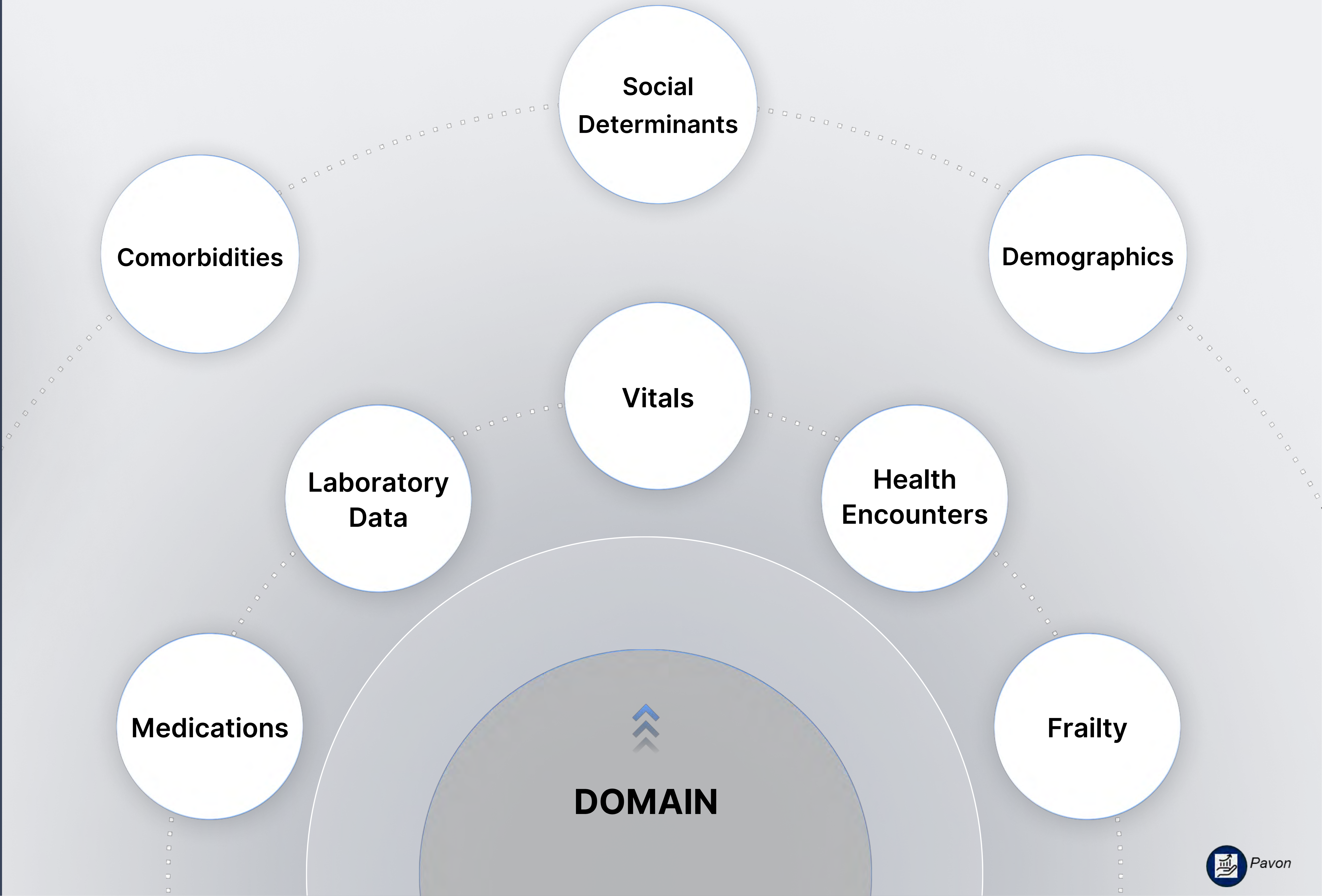
- Younger
- Fewer chronic conditions
- Diabetes

Toward Individualized Deprescribing: Integrating AI

GOALS

Develop AI tools that tailor deprescribing recommendations based on individual clinical characteristics

Patient Factors Influencing Deprescribing



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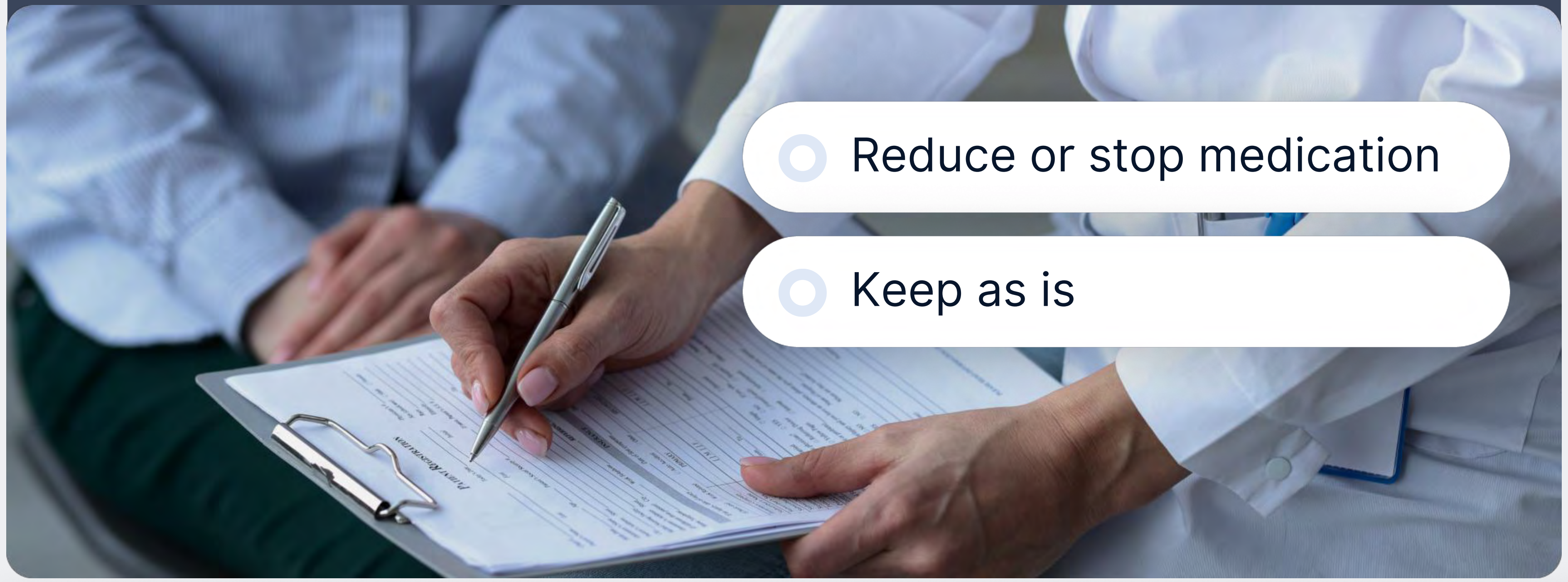
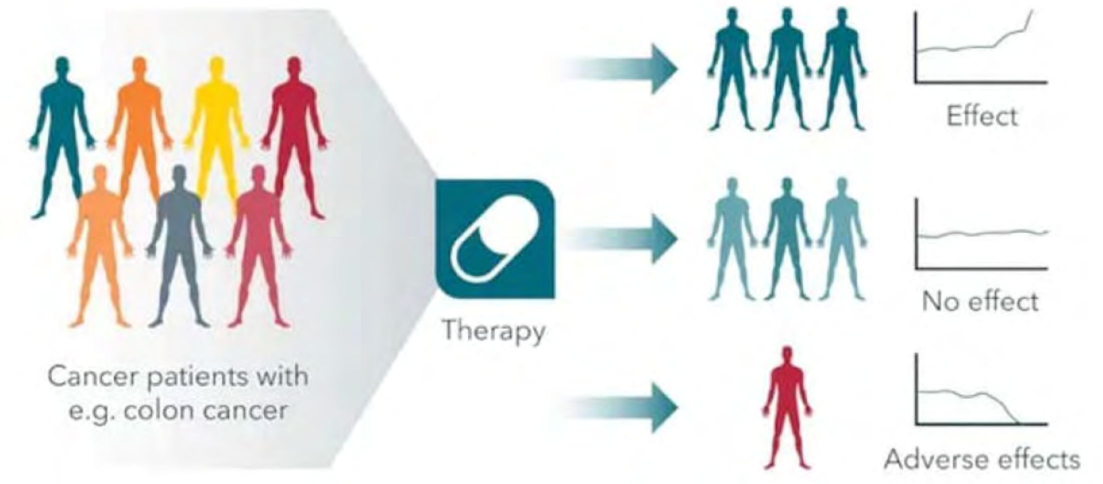
What Are Individualized Treatment Rules?

- Individualized Treatment Rules (ITRs) guide doctors in making the best treatment decisions for each patient by considering individual characteristics
- Models that recommend optimal treatment based on a patient's **unique characteristics.**



- Reduce or stop medication
- Keep as is

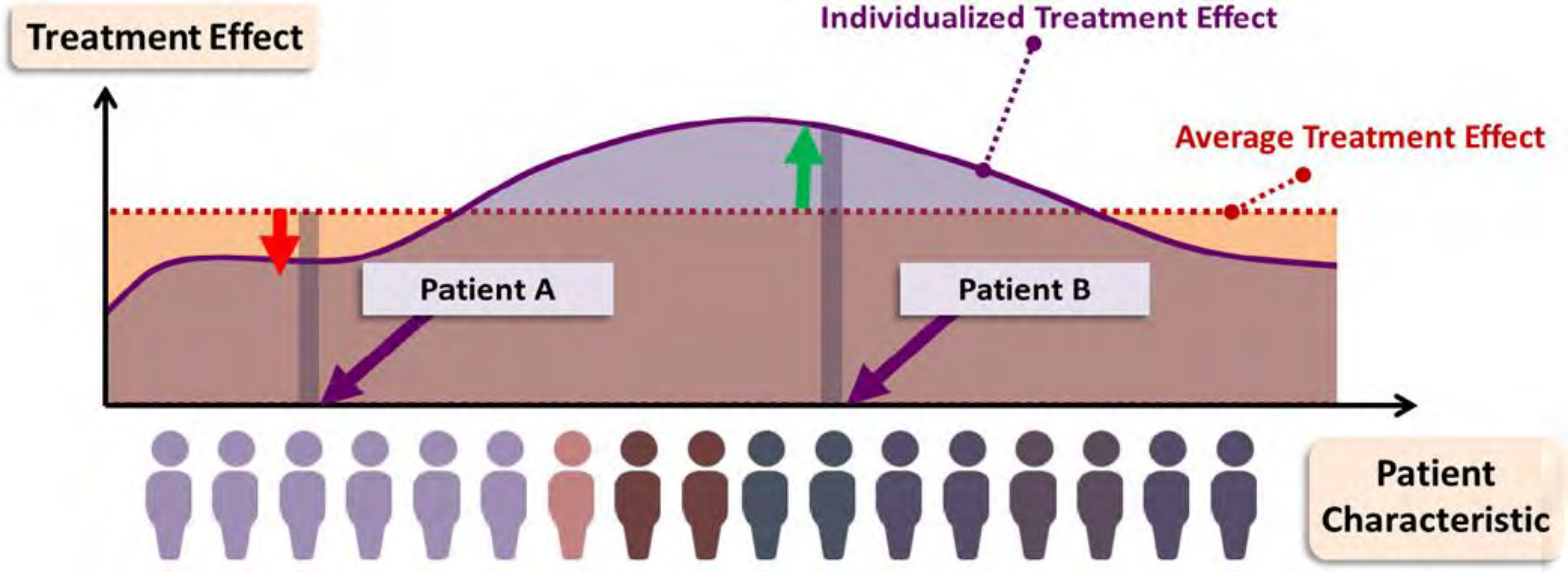
Current Medicine
One Treatment Fits All



Future Medicine
More Personalized Diagnostics

Personalized medicine, supported by ITRs, moves away from a one-size-fits-all approach **to achieve better outcomes**

What Are Individualized Treatment Rules?



Individualized Treatment Rules in Medicine

Hypertension

AI-based ITRs reduced systolic blood pressure by 14 mmHg, outperforming standard care.[1]

Depression

AI-based ITRs improved remission rates and reduced adverse events [2,3]

Schizophrenia

AI-based ITRs increased treatment success rates for first-episode schizophrenia from 45% to 52%.[4]

Diabetes

AI-based ITRs outperformed non-personalized rules in reducing HbA1c% by as much as 1.4.[5]

Oncology

AI-based ITRs achieved diagnostic accuracy exceeding specialists, supporting individualized oncology strategies.[6]

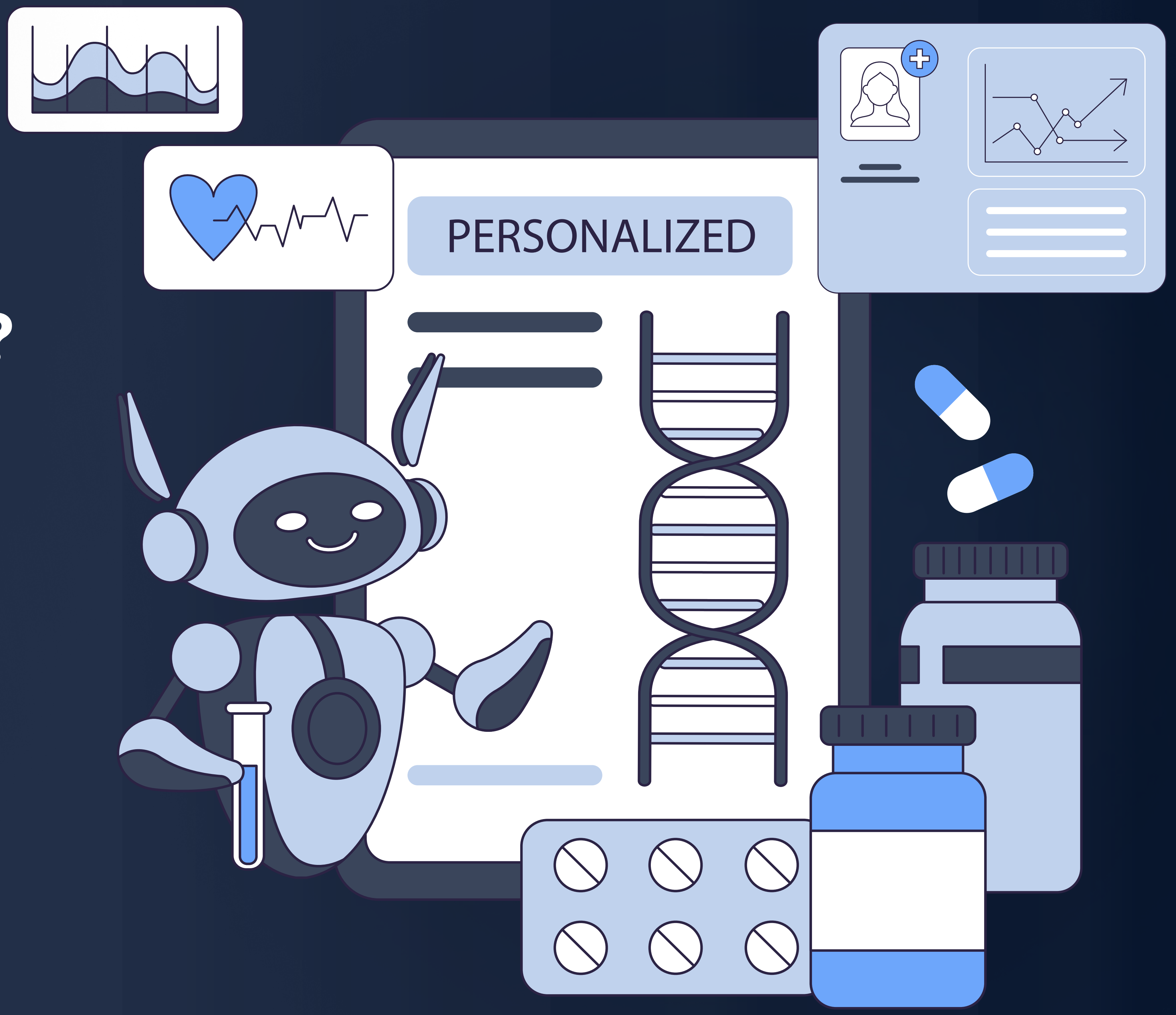
Critical Illness

AI-based ITR for individualized oxygen targets reduced ICU mortality by 6%.[7]

References: 1. Hu, BMC Med Inform Decis Mak 2023 | 2. Kessler, Psychol Med 2021 | 3. Zainal, Mol Psychiatry 2024 | 4. Wu, JAMA Netw Open 2020 | 5. Wu, J Am Stat Assoc 2020 | 6. The Lancet, Lancet 2017 | 7. Buell, JAMA 2024

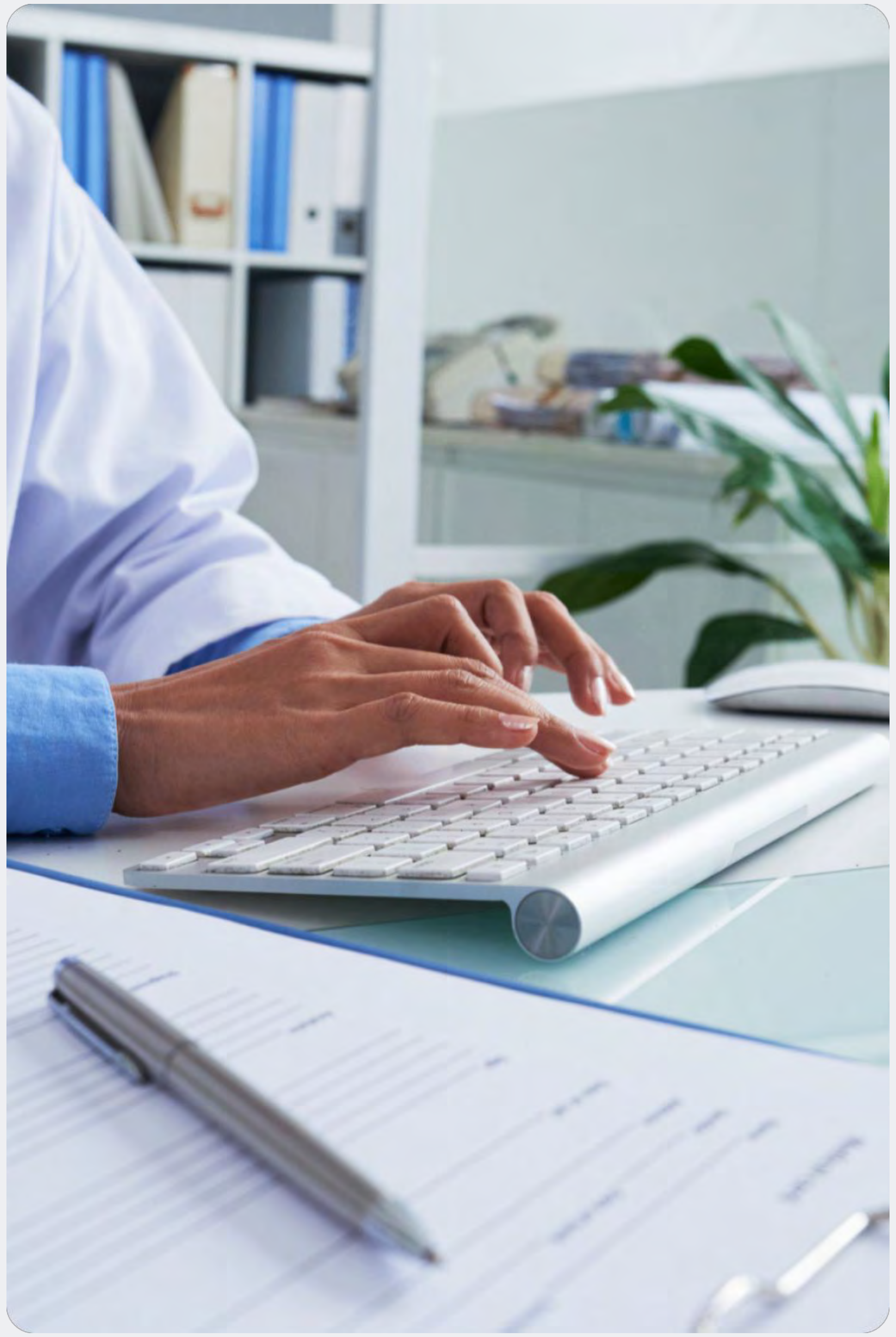
How Do We Build These Individualized Treatment Rules?

We use advanced artificial intelligence models to analyze patient data and predict the best treatment for each person.



Developing Individualized Treatment Rules (ITRs) Using AI

Create a Dataset	01
Estimate Treatment Probabilities	02
Train and Test Outcome Prediction Models	03
Model Refinement	04
Combine Methods into ITRs	05
Mitigate Health Disparity Bias	06



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Step 1: Dataset

pcornet
The National Patient-Centered Clinical Research Network
Clinical Research Networks

STAR Science, Technology, And Research partnership

EHR DATA SOURCES

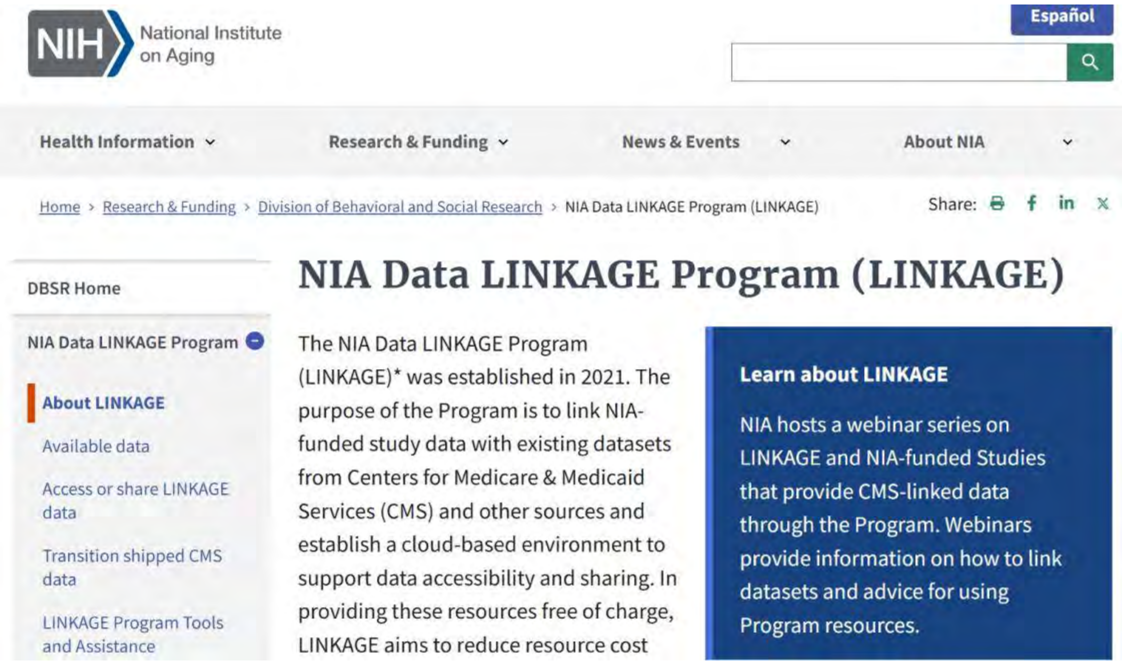
- Data from PCORnet Clinical Research Network and STAR Network Sites.
- Partners: Duke, Vanderbilt, MUSC.

PATIENT DATA

278,590

Patients continuously enrolled (2020-2023)

We will also link to Medicare Claims data to obtain medication dispensing data, using **the NIA Data LINKAGE Program.**


NIH National Institute on Aging

Español

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DBSR Home

NIA Data LINKAGE Program

About LINKAGE

Available data

Access or share LINKAGE data

Transition shipped CMS data

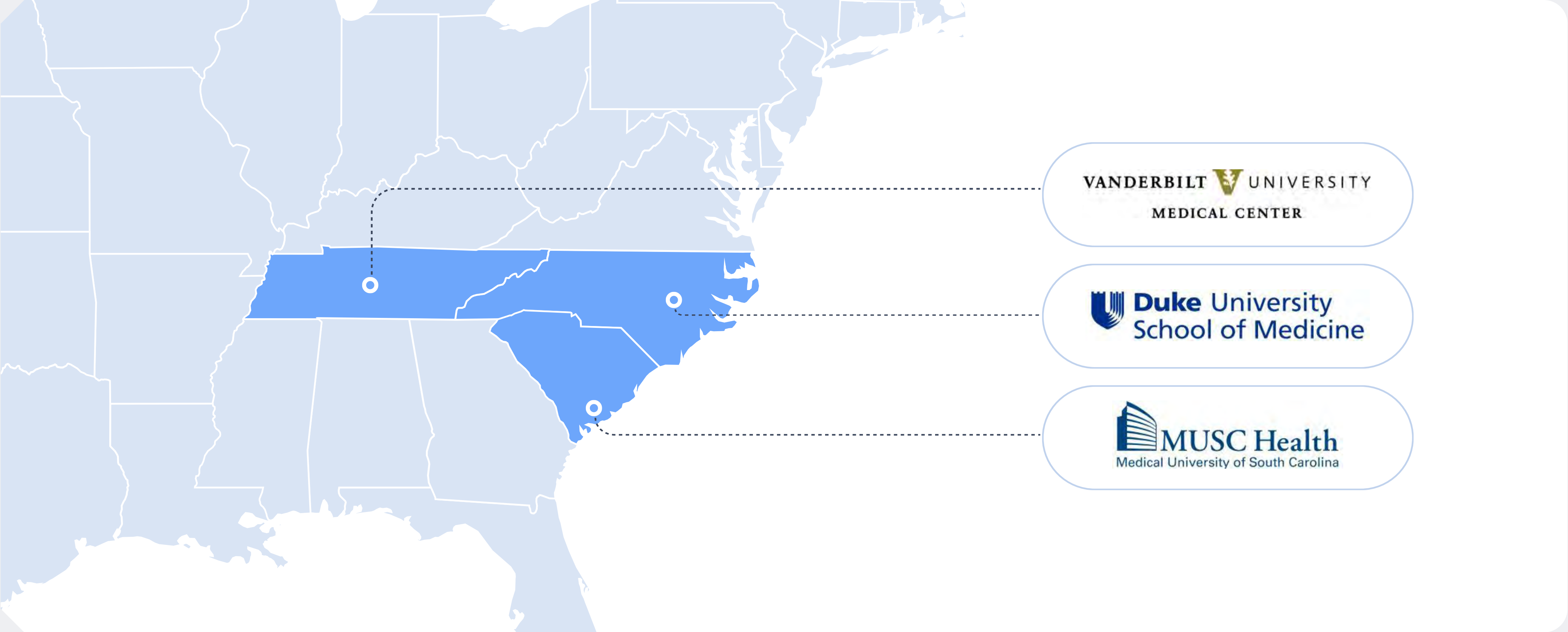
LINKAGE Program Tools and Assistance

NIA Data LINKAGE Program (LINKAGE)

The NIA Data LINKAGE Program (LINKAGE)* was established in 2021. The purpose of the Program is to link NIA-funded study data with existing datasets from Centers for Medicare & Medicaid Services (CMS) and other sources and establish a cloud-based environment to support data accessibility and sharing. In providing these resources free of charge, LINKAGE aims to reduce resource cost

Learn about LINKAGE

NIA hosts a webinar series on LINKAGE and NIA-funded Studies that provide CMS-linked data through the Program. Webinars provide information on how to link datasets and advice for using Program resources.



Measures: Medications and Outcomes

MEDICATION CLASSES

- Anticholinergics
- Antidepressants
- Antipsychotics
- Benzodiazepines
- Gabapentinoids
- Hypnotics
- Muscle Relaxants
- Opioids

Falls (Primary)

Cognitive Disorder

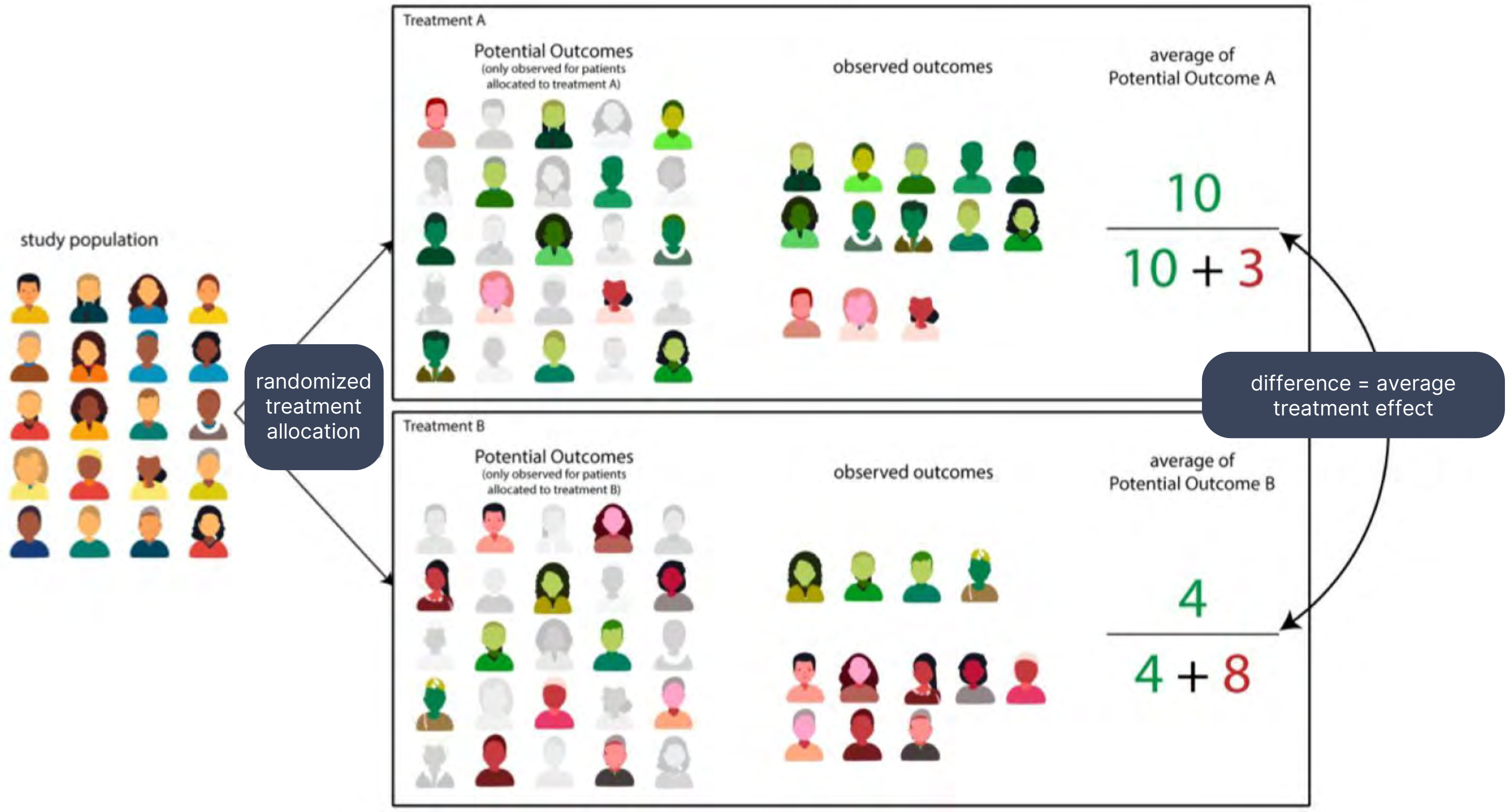
Hospitalization

Adverse Drug Withdrawal Events

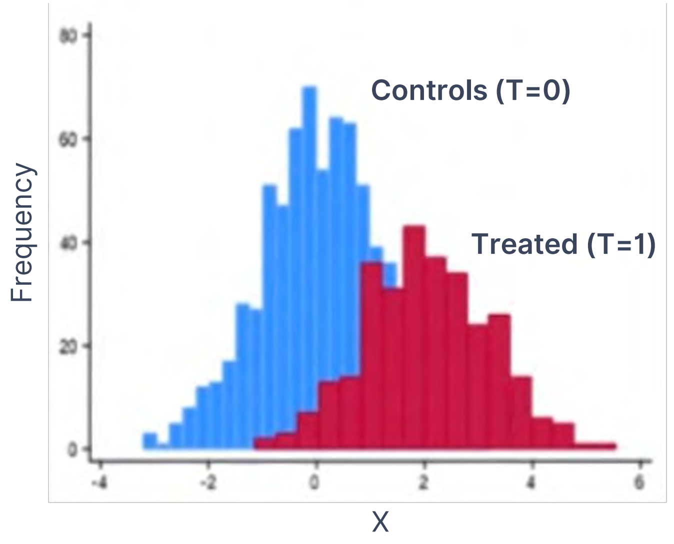
Outcome

Time **Over 2 years**

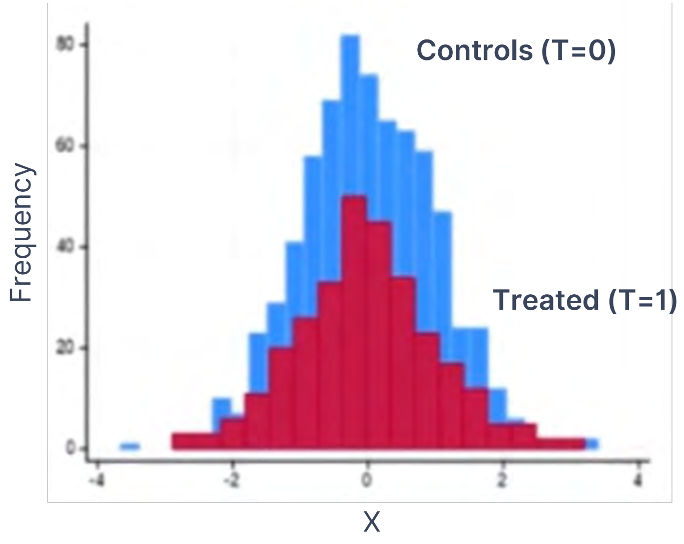
Step 2: Address Bias in Observational Data

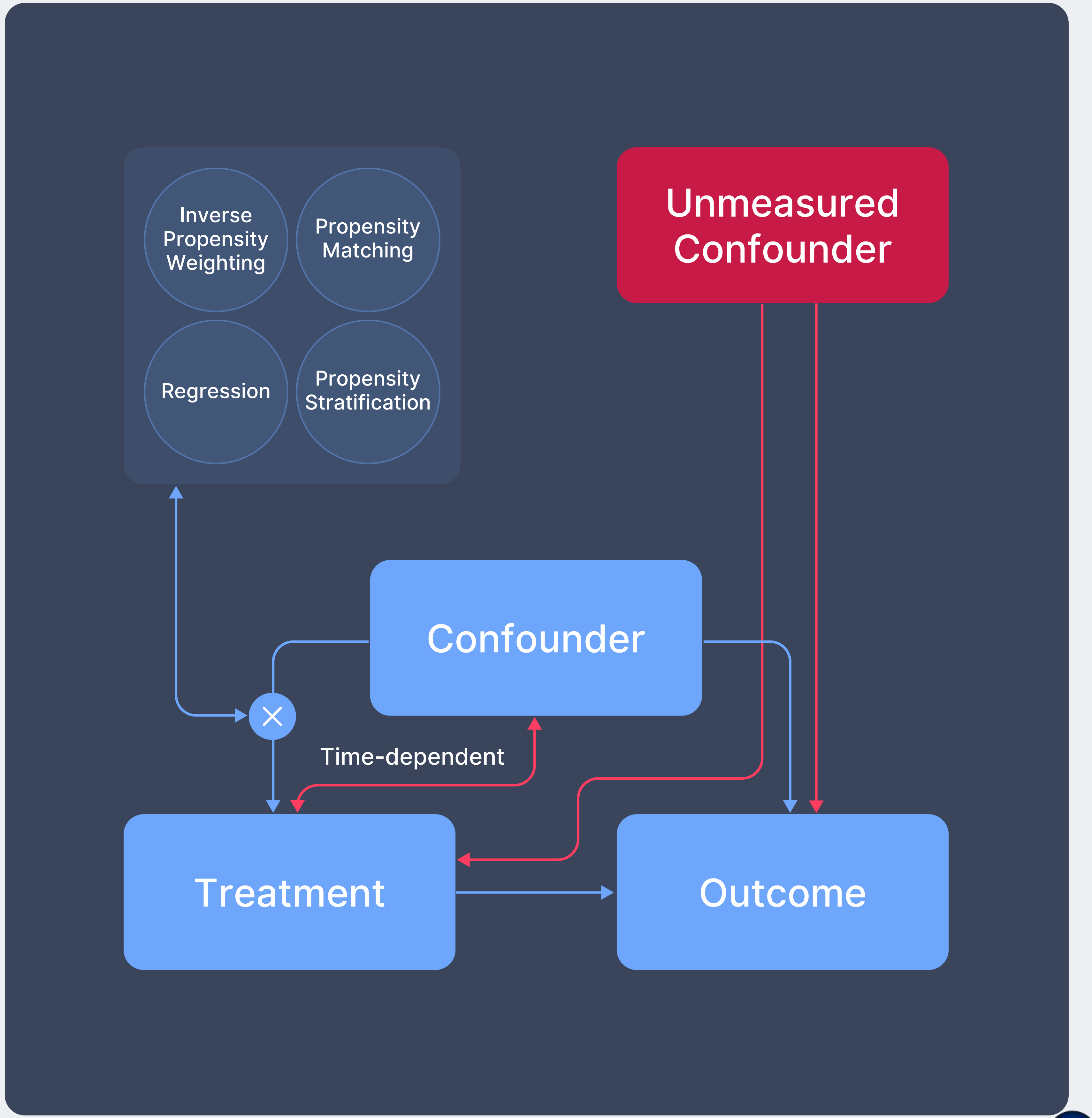


OBSERVATIONAL STUDY



RANDOMIZED EXPERIMENT





Step 2: Address Bias in Observational Data

PROPENSITY SCORE

Probability of treatment

Actually took pill

Didn't take pill

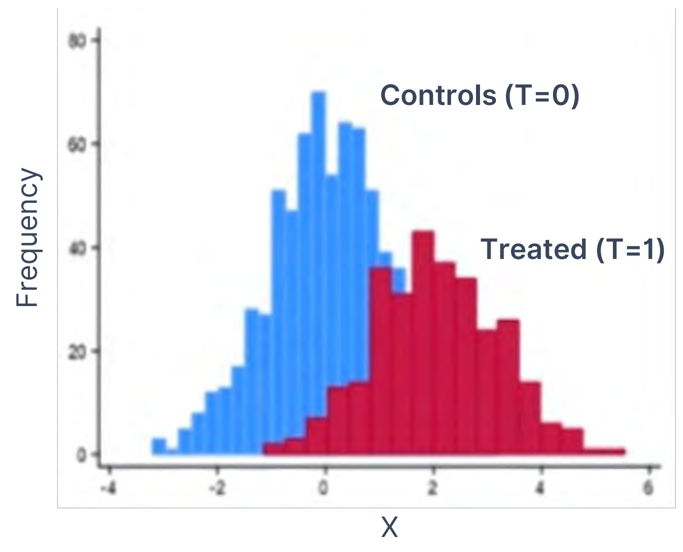
Propensity Matching

Propensity Stratification

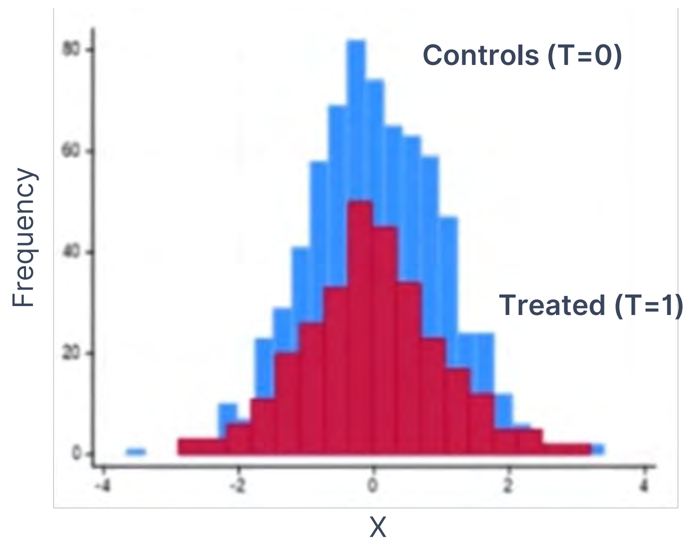
Inverse Propensity Weighting

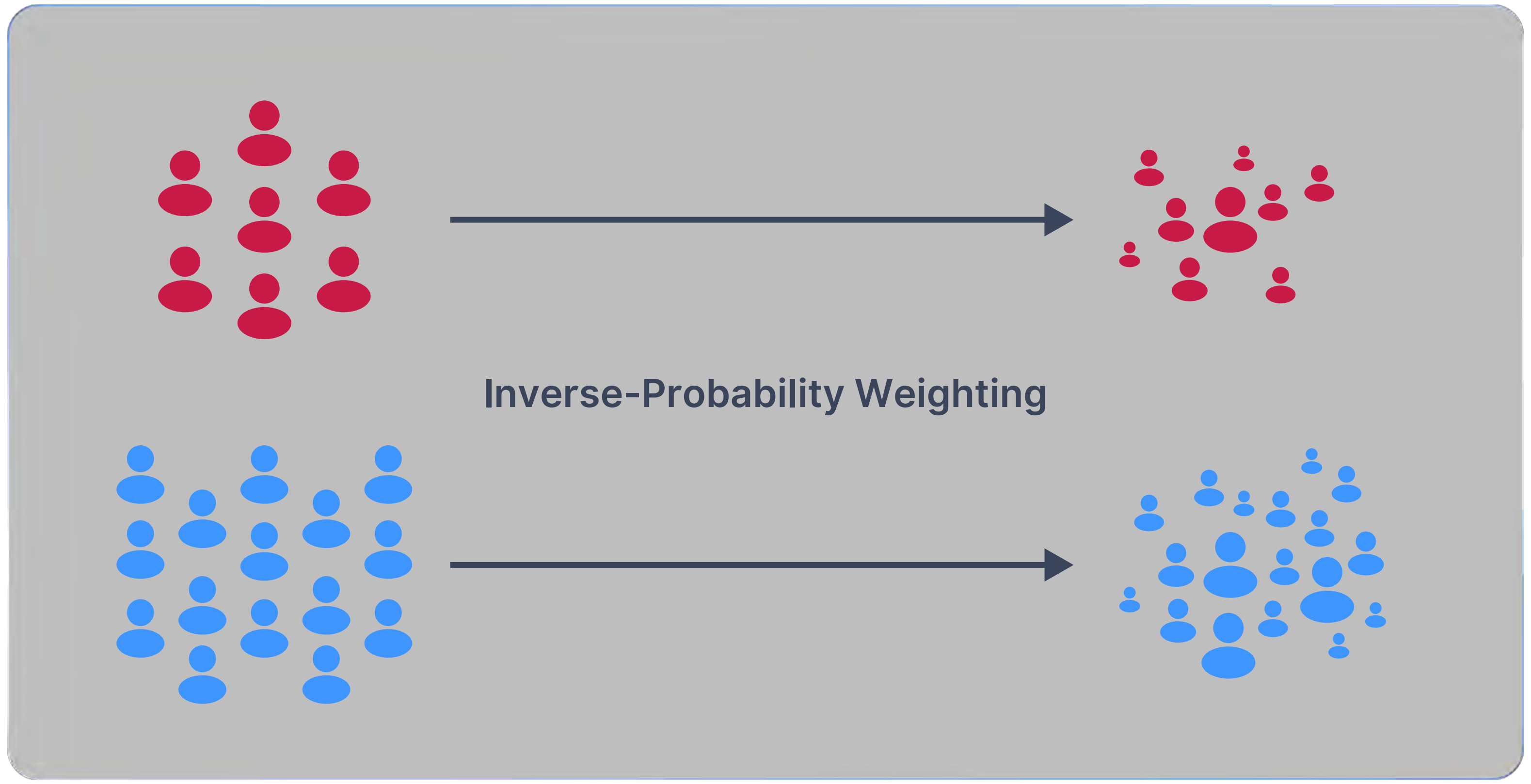
HOW = CAUSAL INFERENCE METHODS

OBSERVATIONAL STUDY



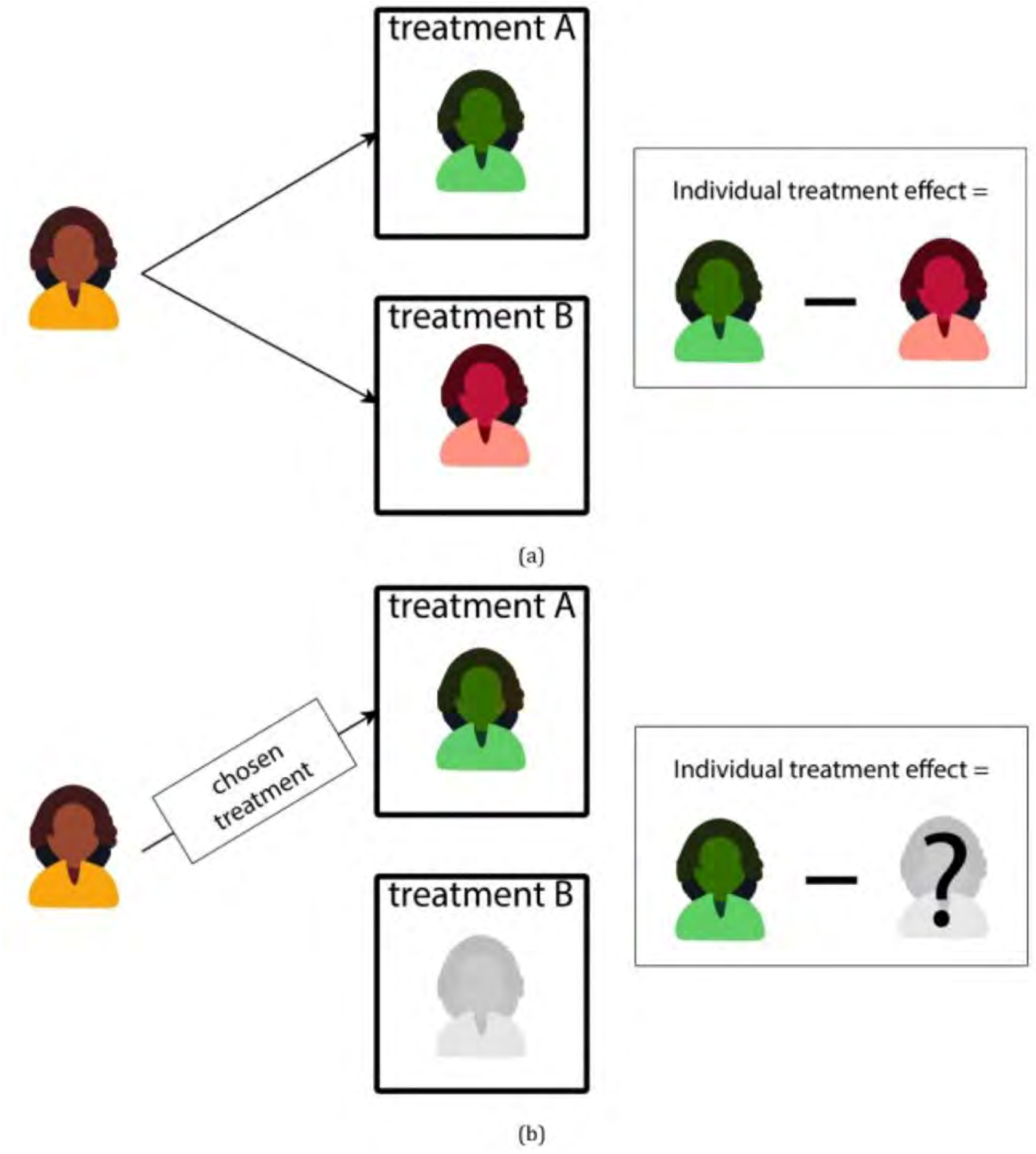
RANDOMIZED EXPERIMENT

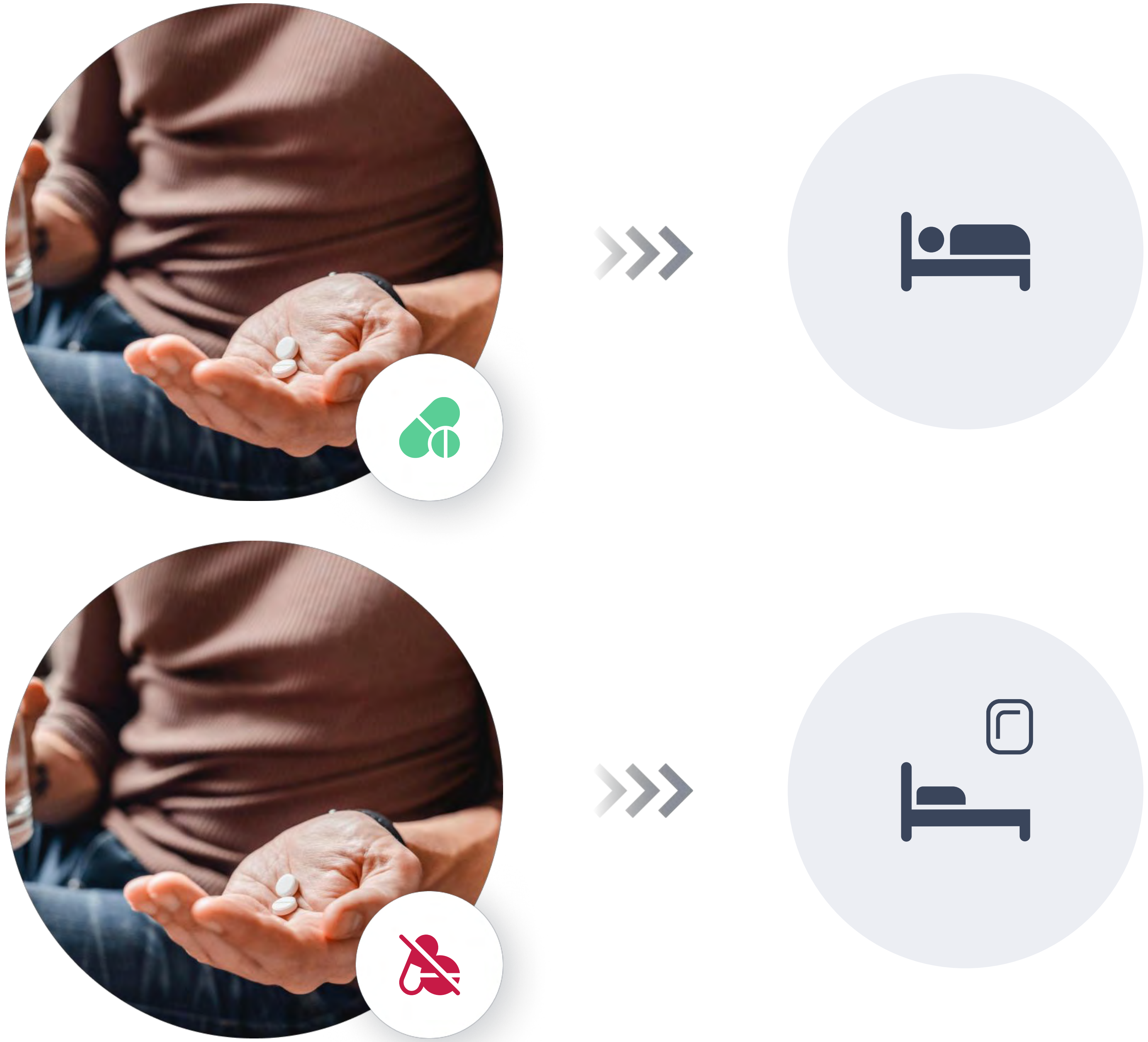




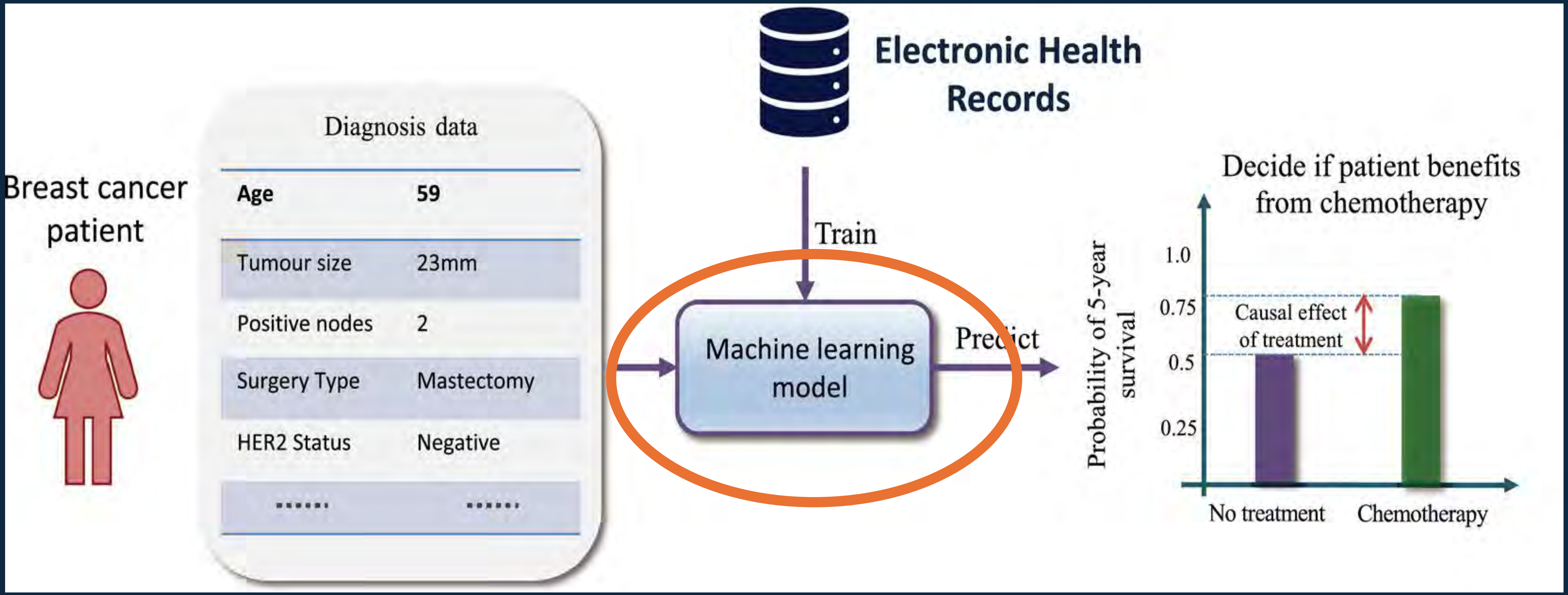
Step 2: Problem of Counterfactuals?... What if?

It helps us answer "what if" questions, like **"What would happen if this patient stopped a medication?"**





Step 3: Train and Test Outcome Prediction Models



Step 3: Learning Predictions

DATA-DRIVEN INSIGHTS FOR BETTER DECISIONS

AI Model Development

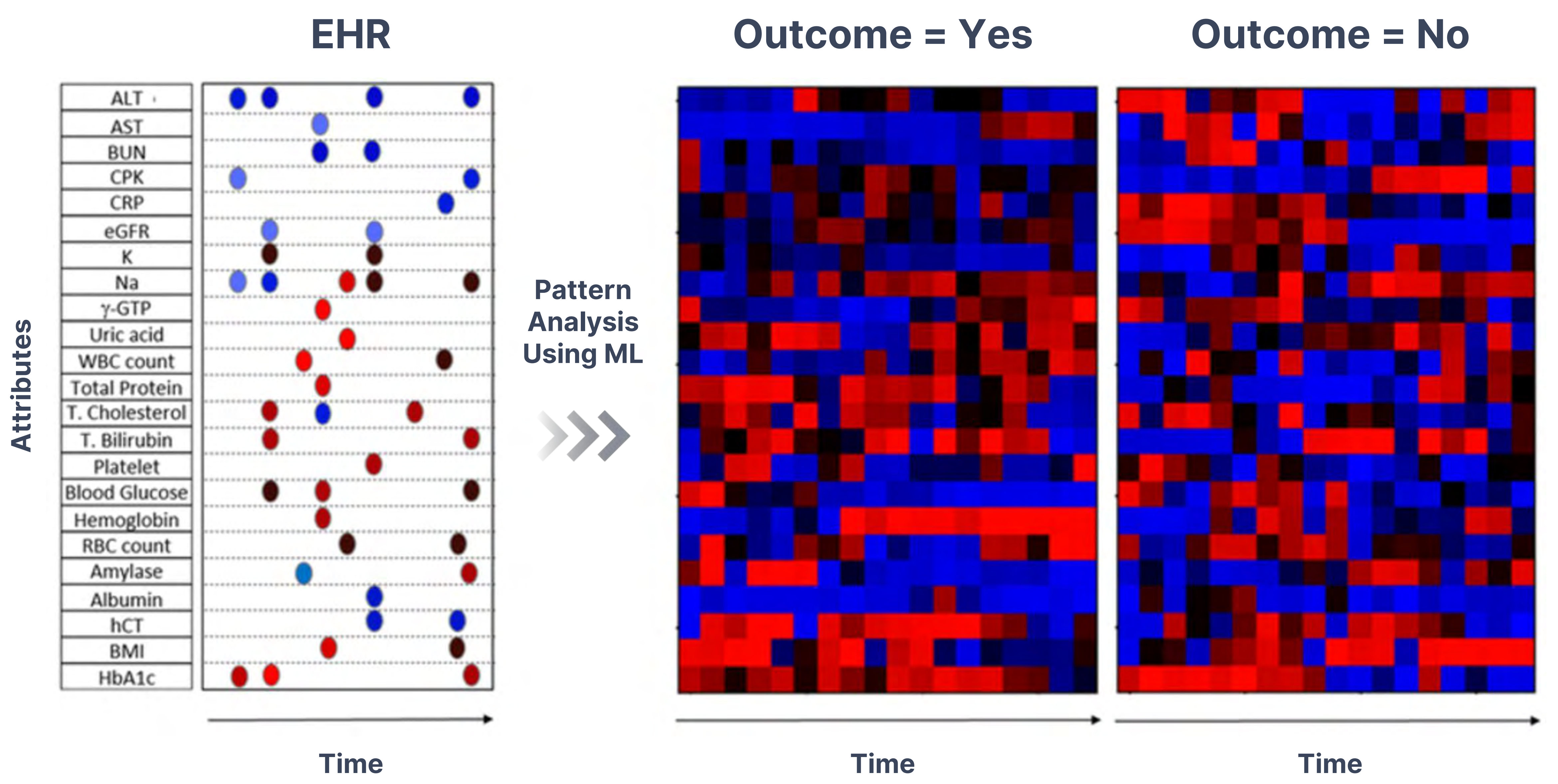
01 Patient Information (Inputs include age, health conditions, and medication history)

02 Model Training (AI identifies patterns in patient data)

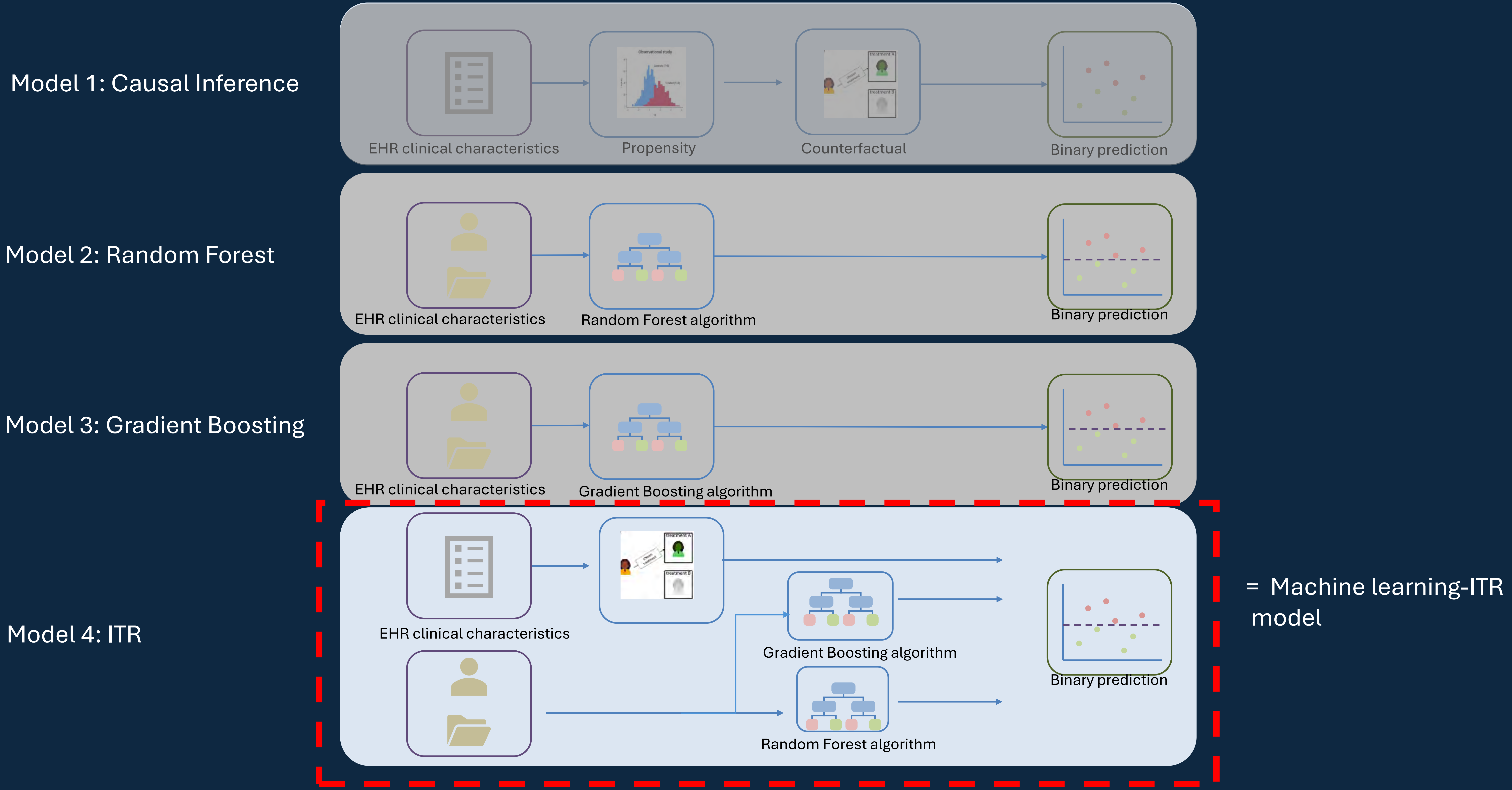
03 Predicted Outcomes:

- Falls (primary)
- Cognitive disorders
- Hospitalizations
- Adverse drug withdrawal events

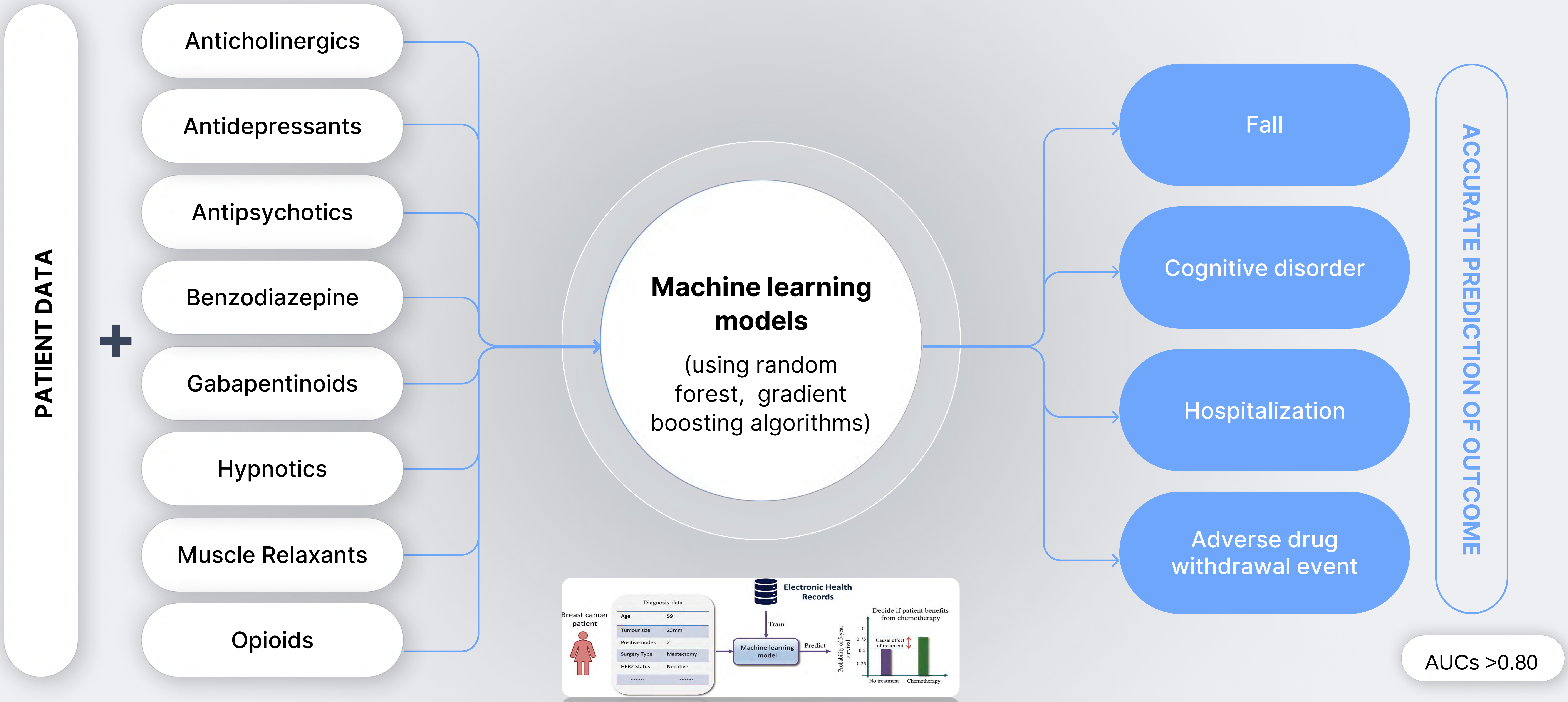
The heatmap shows AI's pattern recognition during model training, predicting outcomes



References: Makino, Sci Rep 2019


Model 1: Causal Inference
EHR clinical characteristics
Propensity
Counterfactual
Binary prediction
Model 2: Random Forest
EHR clinical characteristics
Random Forest algorithm
Binary prediction
Model 3: Gradient Boosting
EHR clinical characteristics
Gradient Boosting algorithm
Binary prediction
Model 4: ITR
EHR clinical characteristics
Gradient Boosting algorithm
Random Forest algorithm
Binary prediction
= Machine learning-ITR model

Outcome Prediction Models



8 MEDICATION CLASSES X 4 OUTCOMES = 32 SEPARATE MODELS ARE TRAINED AND TESTED

Combining Steps to for Individualized Treatment Rule Model

STEP 4: MODEL REFINEMENT

Patient Data

E.g. age, function, medications, SDOH, encounters

Branches of different conditions

Low risk

High risk

Outcome prediction

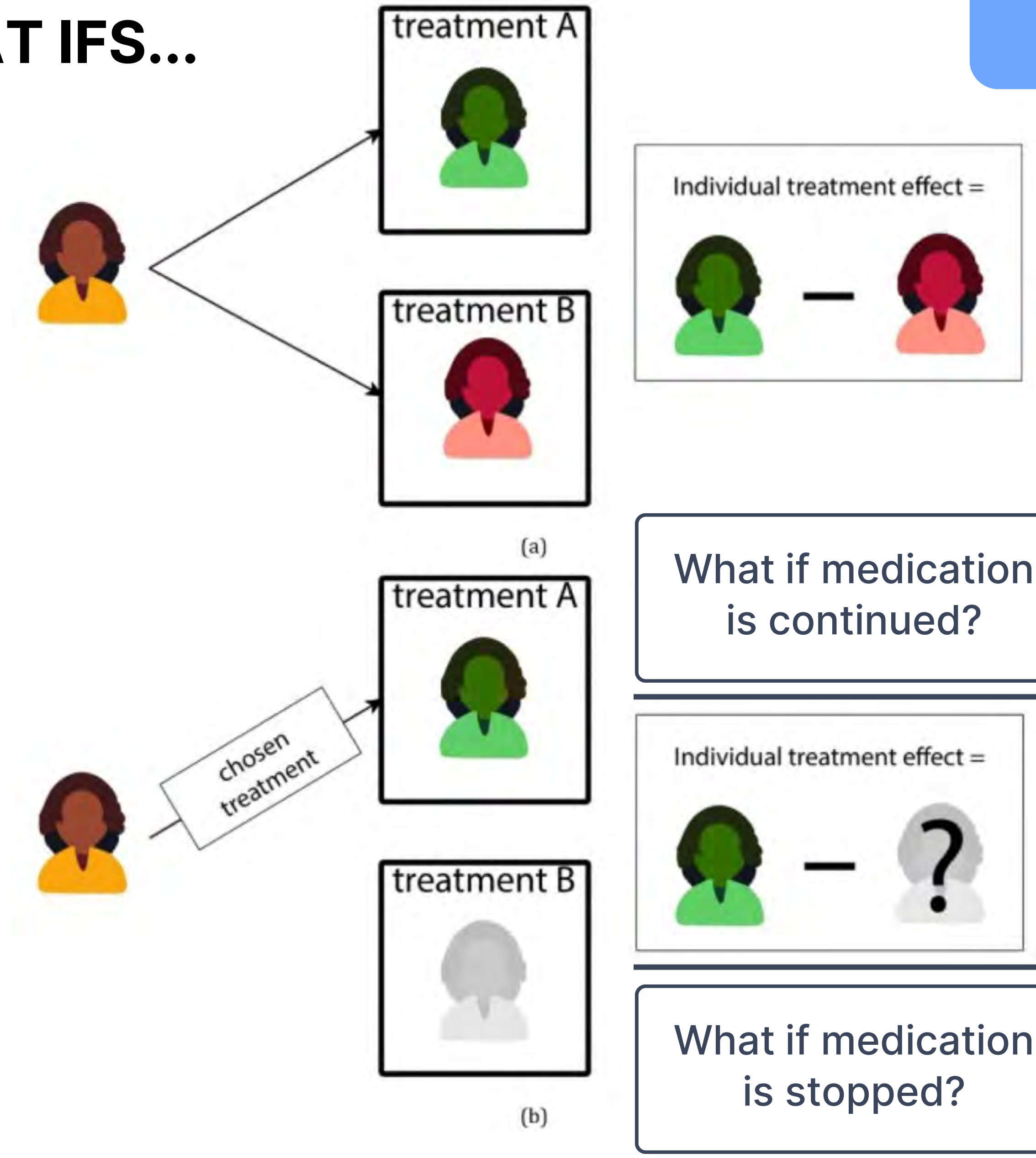
Fall No | Fall Yes | Fall No | Fall Yes

Each decision tree pathway reflects **the best decision** for that unique patient

STEP 5: COMBINATION OF METHODS INTO ITRS

AI predicts the best option for each patient

WHAT IFS...



What if medication is continued?

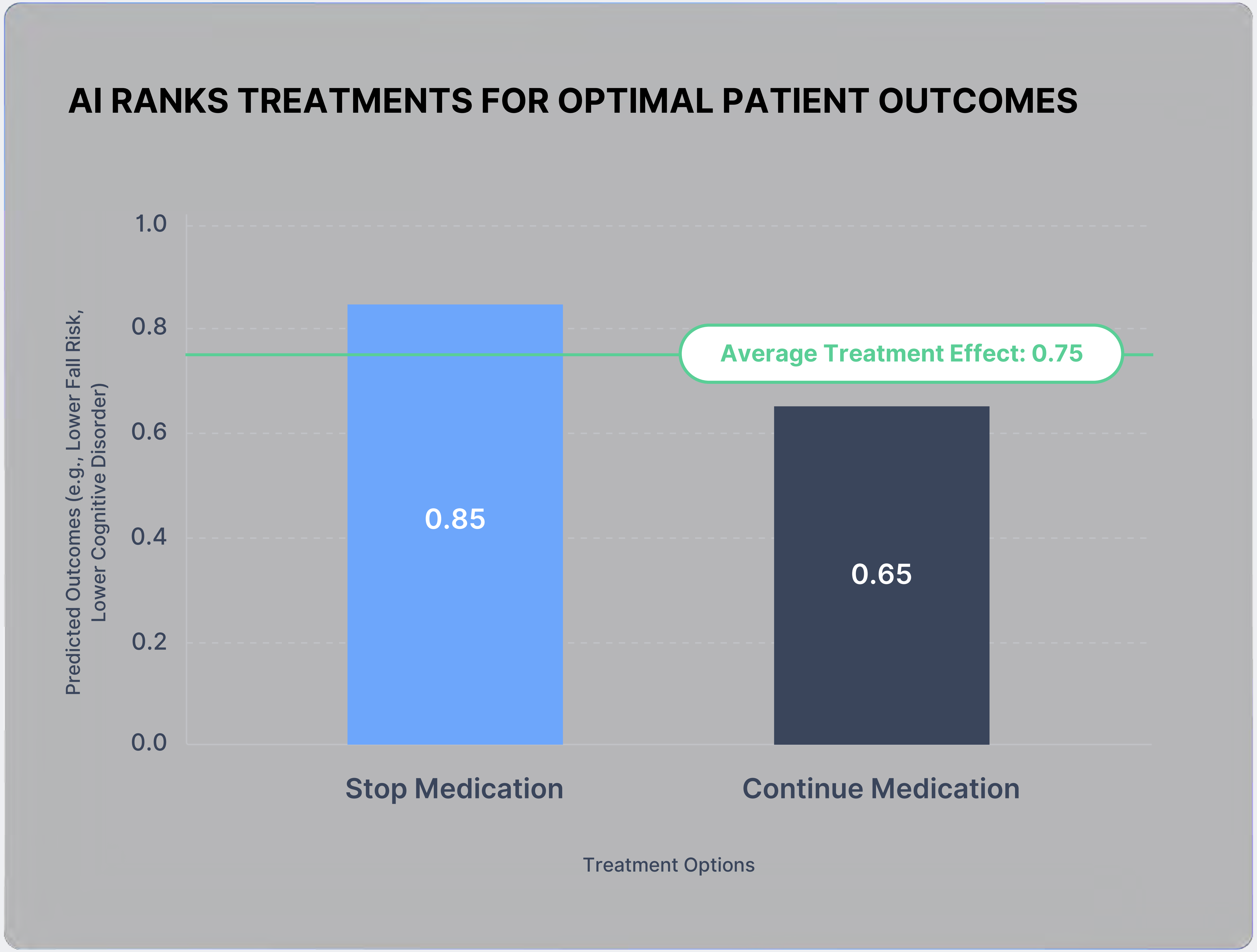
AI predicted outcome

What if medication is stopped?

AI predicted outcome

Step 5: Individualized Treatment Rule

AI ranks treatments to find the best match for each patient's needs.



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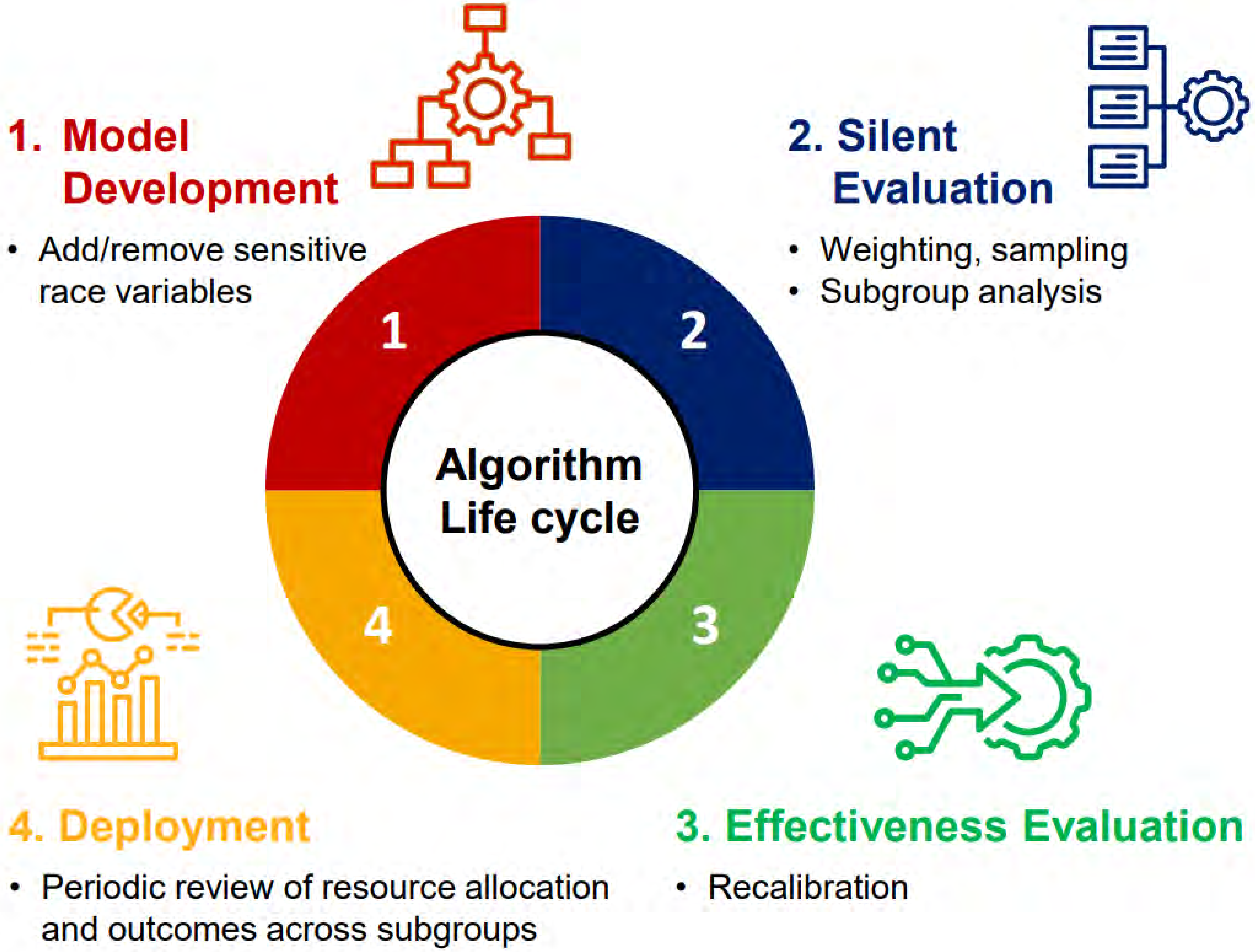
Step 6:

Bias Mitigation Strategies

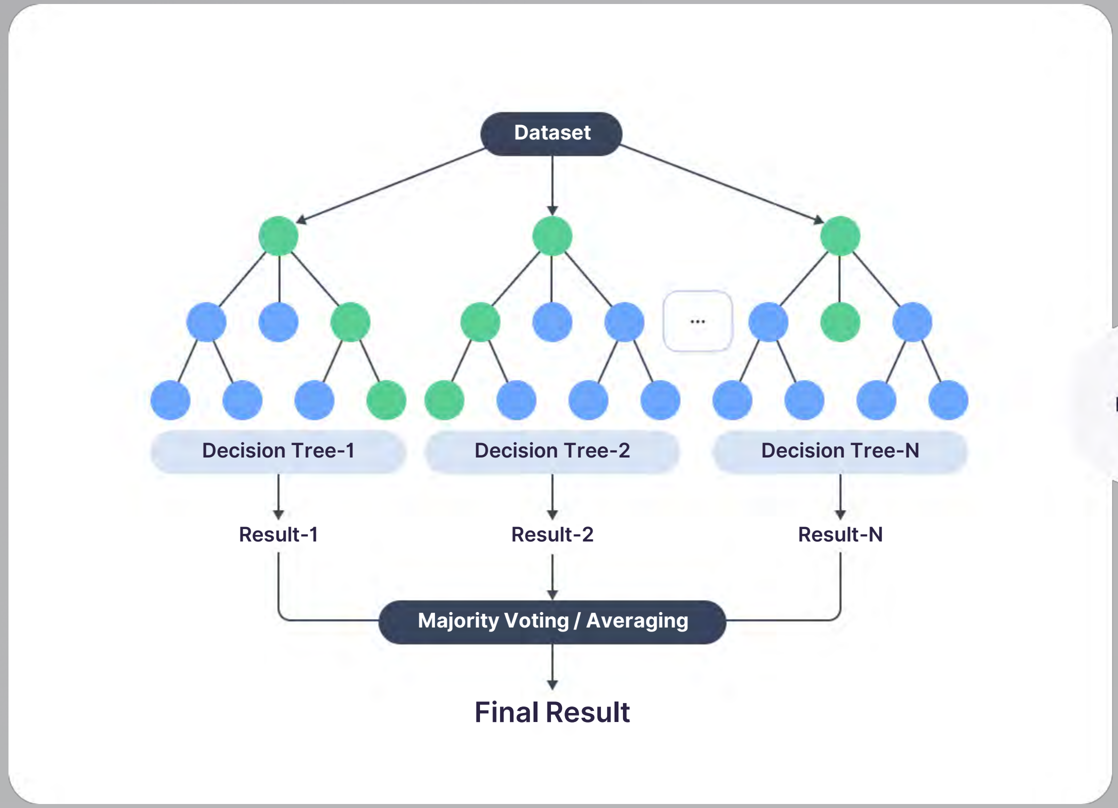


Reference: Cary, Health Affairs 2023

Innovation

01

Super Learner Ensemble Methods



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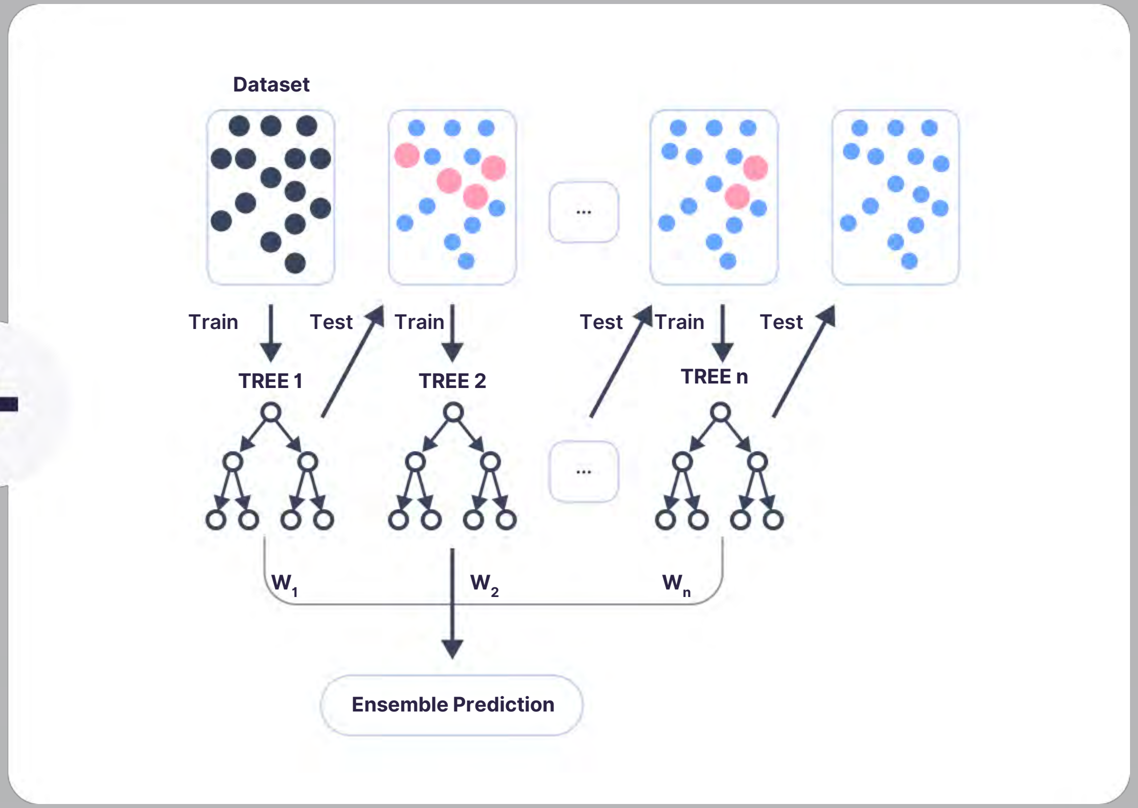


02

Doubly Robust Methods

Causal Inference + Machine Learning

03

Early end-user engagement throughout model development through scientific advisory team

Explainable AI (XAI) Components & Methods

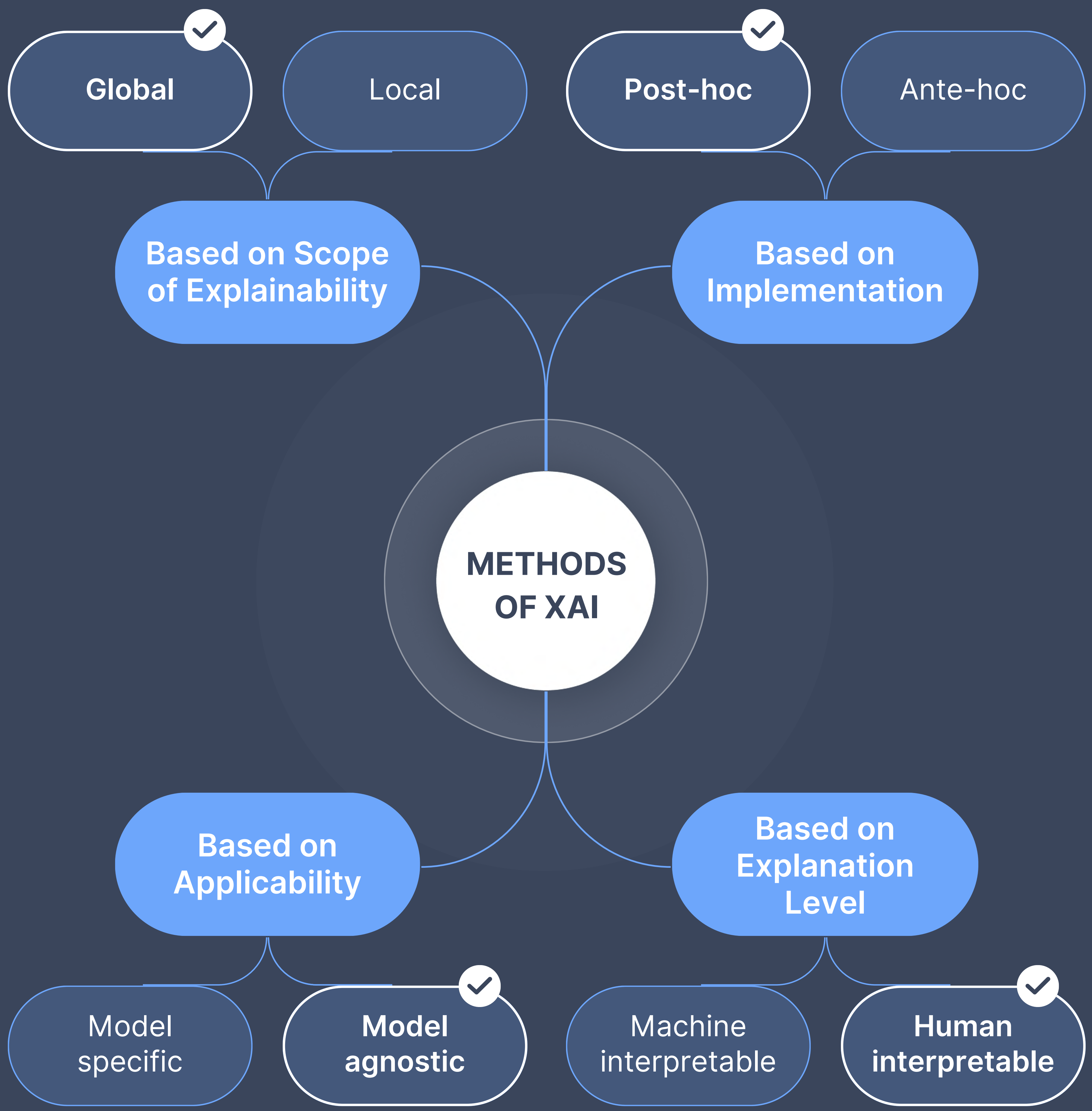
KEY COMPONENTS OF XAI

01 **Why:** Explains an AI model's predictions to clarify reasoning behind decision-making.

02 **Who:** Stakeholders (developers, users, regulators) interpreting the explanations.

03 **What:** Features or factors considered by the model.

04 **Where:** Context or scenario where the AI is applied.



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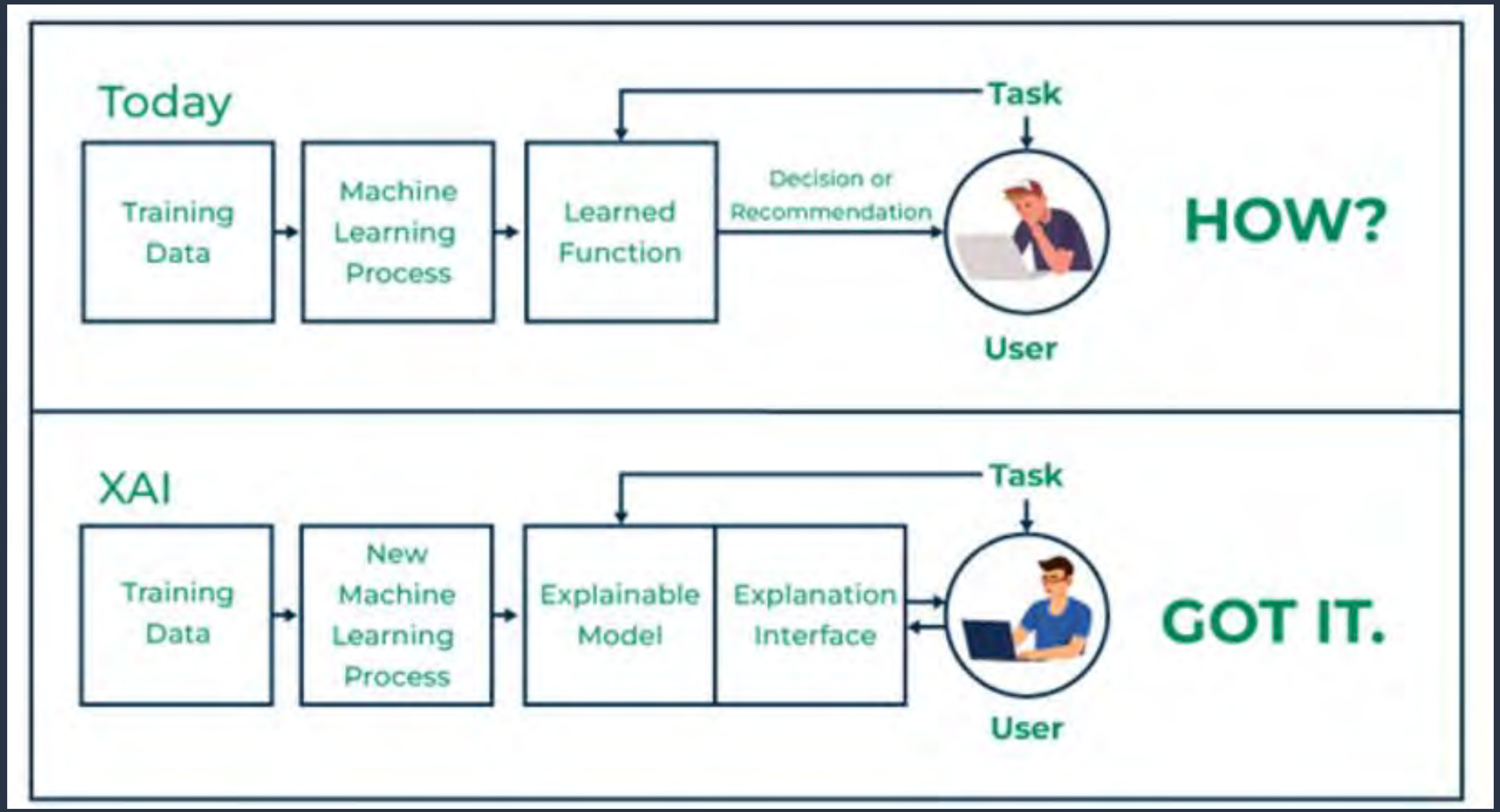
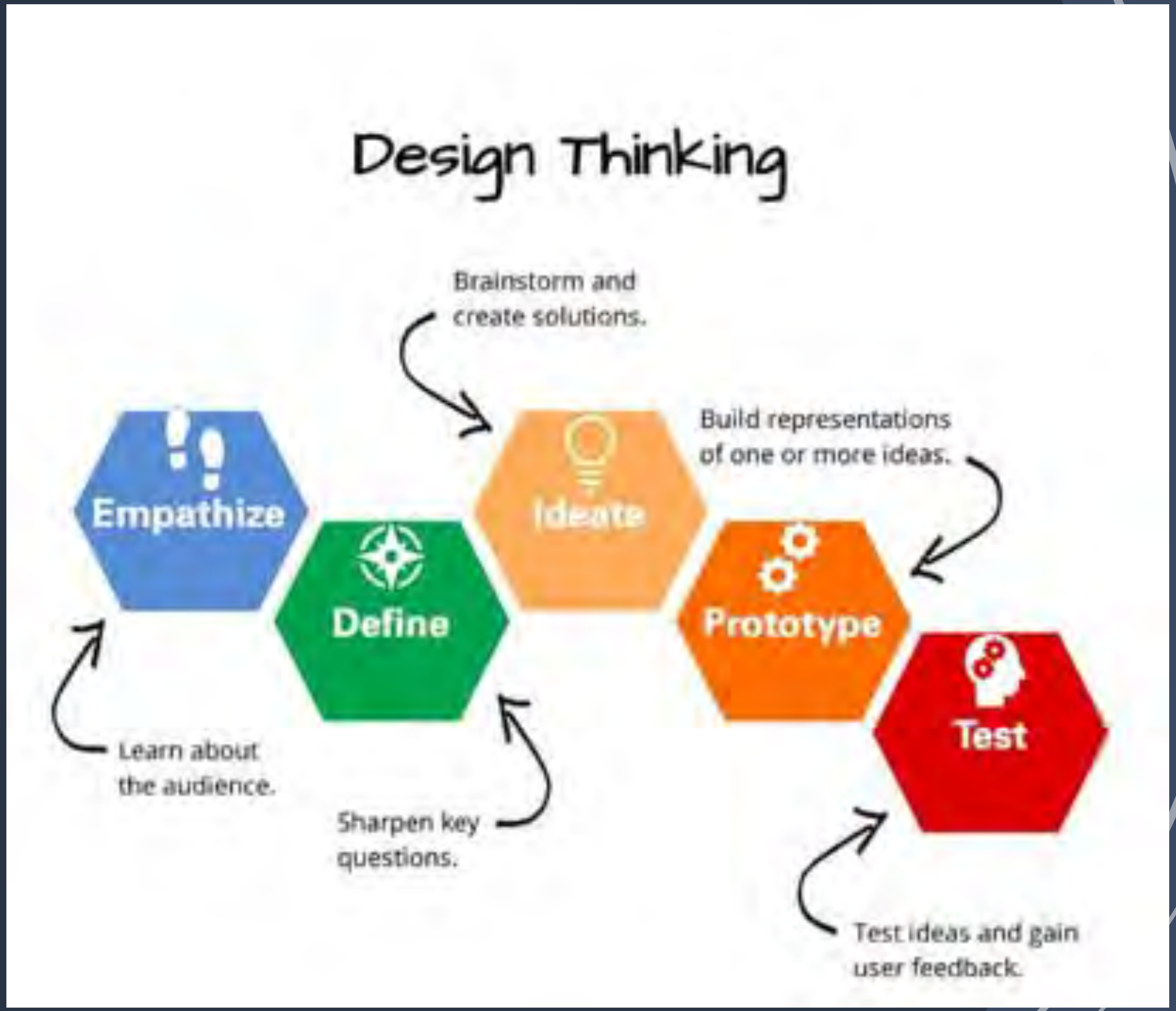
Understandable and Trustworthy AI



How we will explain



How we will build a
prototype clinical interface

Design Thinking Sessions and Playbook Activities

PARTICIPANTS

Providers

- Primary Care Providers
- Geriatricians
- Neurologists
- Psychiatrists

Patients and Caregivers

DESIGN THINKING SESSIONS

SESSION 1

Emphasize

Structured Interview Guide, Problem Prioritization

SESSION 1

Define

Gap Analysis, Identifying Barriers

SESSION 2

Ideation

Brainstorming, Storyboarding

SESSION 2

Prototype

Think Aloud Protocol, Feature Prioritization

SESSION 3

Testing

Task Scenarios, Usability Testing

SESSION STRUCTURE

Total Sessions: 18

Duke University School of Medicine

PARTICIPANT GROUPS: **Providers, Patients**

6 sessions

3 sessions x 2 groups

VANDERBILT UNIVERSITY MEDICAL CENTER

PARTICIPANT GROUPS: **Providers, Patients**

6 sessions

3 sessions x 2 groups

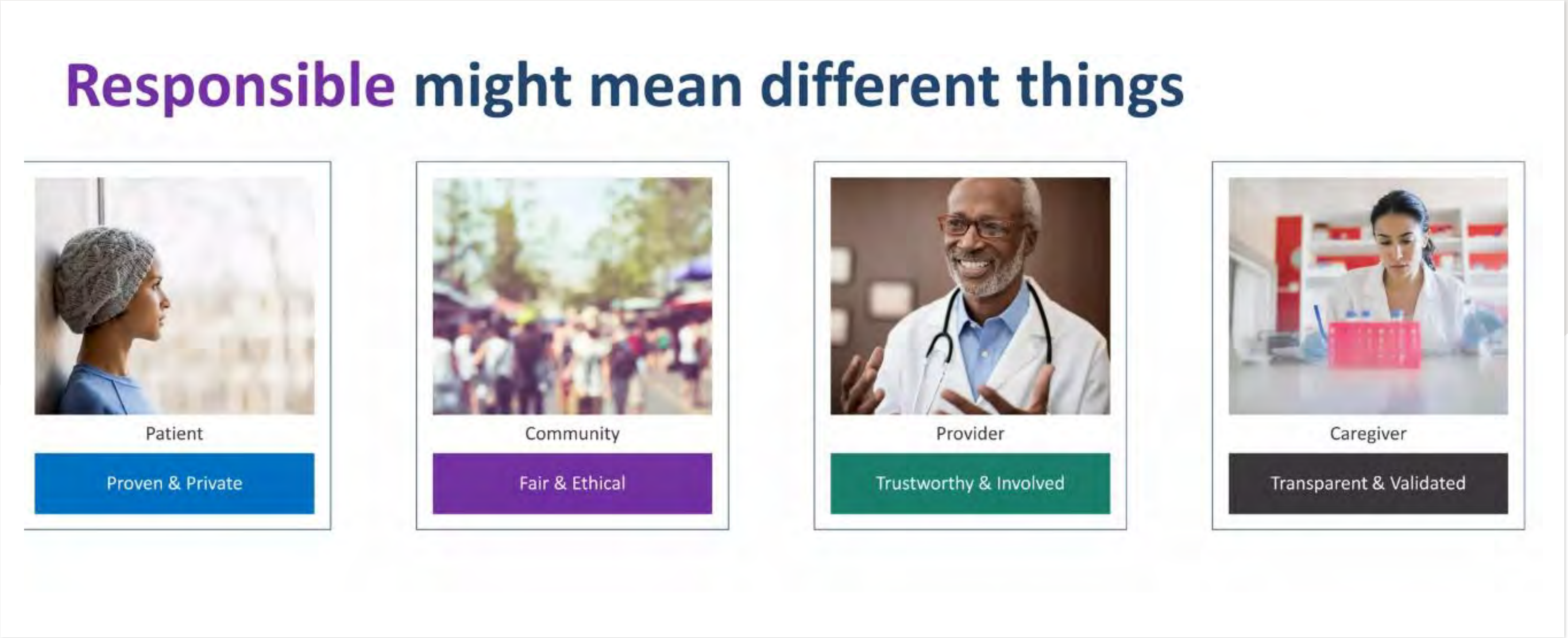
MUSC Health Medical University of South Carolina

PARTICIPANT GROUPS: **Providers, Patients**

6 sessions

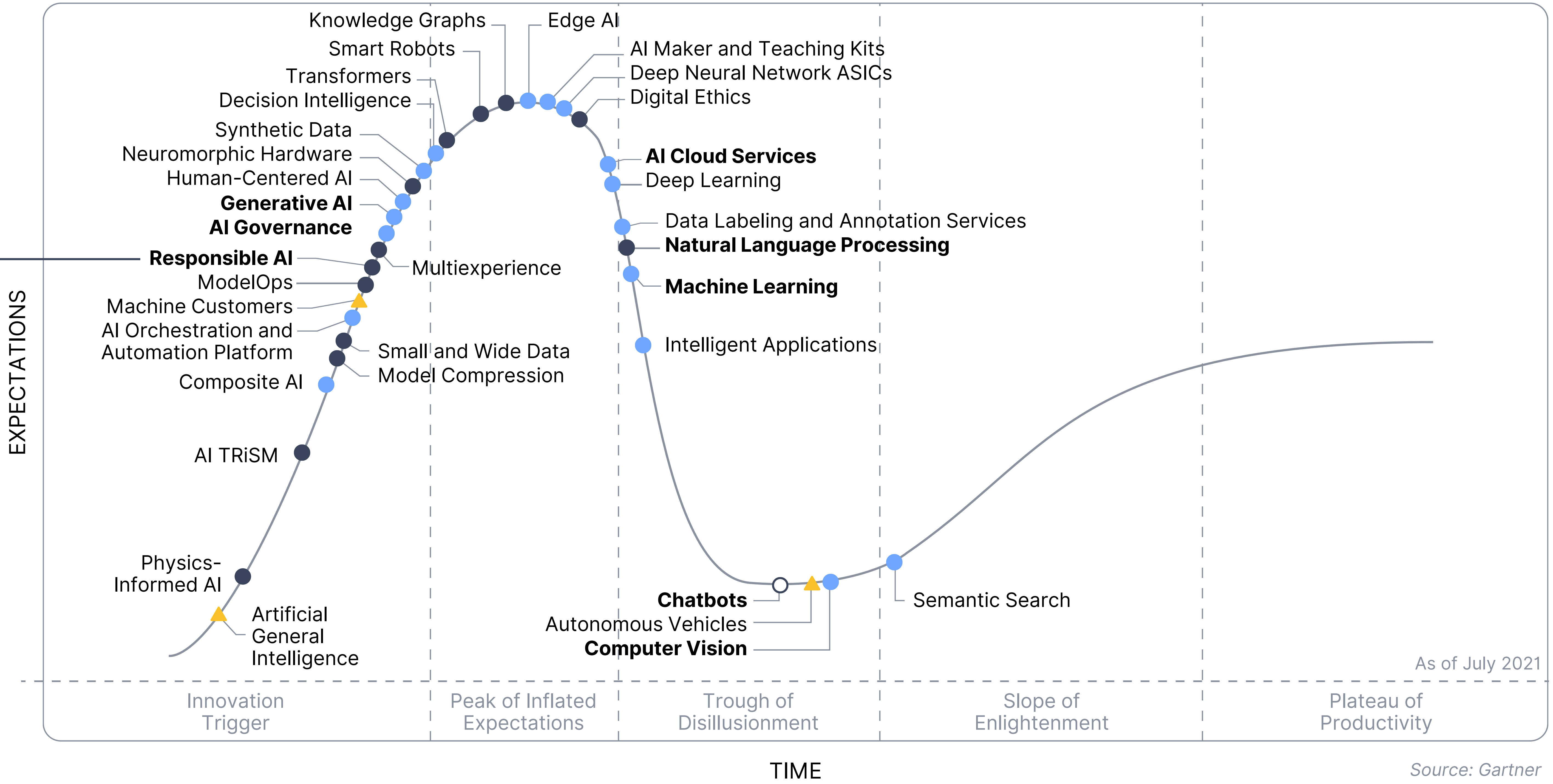
3 sessions x 2 groups

What does Responsible Use mean?



Responsible AI is not a static domain: the innovation landscape is evolving at a breakneck pace

Responsible AI still has **5-10 years** to reach plateau



Source: Gartner

Plateau will be reached:

- <2 yrs
- 2-5 yrs
- 5-10 yrs
- >10 yrs
- Obsolete before plateau

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Five things every geriatrician should know about responsible use of AI

AI in Geriatrics

UNDERSTAND HOW IT WORKS

Have basic knowledge of the technology underlying healthcare AI.

Gradient Boosting, Random Forest

BUILD PATIENT TRUST

Through transparent discussions about the use of healthcare AI.

Explainable AI and Human Centered Design

APPRAISE EVIDENCE

Assess the evidence for the safety and efficacy of healthcare AI.

TRIPOD AI and DECIDE AI Guidelines

ASSESS TRAINING DATA

Know the origin of AI training data, ensure it was ethically sourced, and understand its relevance to individual patients.

Internal and External Validation (PCORnet)

Bias mitigations methods from development to deployment

MITIGATE BIAS

Recognize and counteract potential biases in healthcare AI and oppose biased AI technologies.

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Appraise Evidence

TRIPOD AI

TRIPOD+AI

Purpose

Clear, complete reporting of AI **prediction** models.

Key Elements

22 items on AI observational design, methodology, and discussion.

APPLICATION

Improves study reporting for quality, transparency, bias assessment.

Collins, BMJ 2024

SPIRIT AI

Purpose

Guidelines for **AI clinical trial** protocols.

Key Elements

15 items on AI vs. standard of care clinical trials.

APPLICATION

Improves design and reporting for quality and transparency.

Ibrahim, BMC 2021

DECIDE AI

Purpose

Bridge the gap between algorithm development and clinical use.

Key Elements

Early-stage evaluation on human factors and usability.

APPLICATION

Ensures real-world testing before large trials.

Vesey, Nature Medicine 2021

Five things every geriatrician should know about responsible use of AI

AI in Geriatrics

UNDERSTAND HOW IT WORKS

Have basic knowledge of the technology underlying healthcare AI.

Gradient Boosting, Random Forest

BUILD PATIENT TRUST

Through transparent discussions about the use of healthcare AI.

Explainable AI and Human Centered Design

APPRAISE EVIDENCE

Assess the evidence for the safety and efficacy of healthcare AI.

TRIPOD AI and DECIDE AI Guidelines

ASSESS TRAINING DATA

Know the origin of AI training data, ensure it was ethically sourced, and understand its relevance to individual patients.

Internal and External Validation (PCORnet)

MITIGATE BIAS

Bias mitigations methods from development to deployment

Recognize and counteract potential biases in healthcare AI and oppose biased AI technologies.

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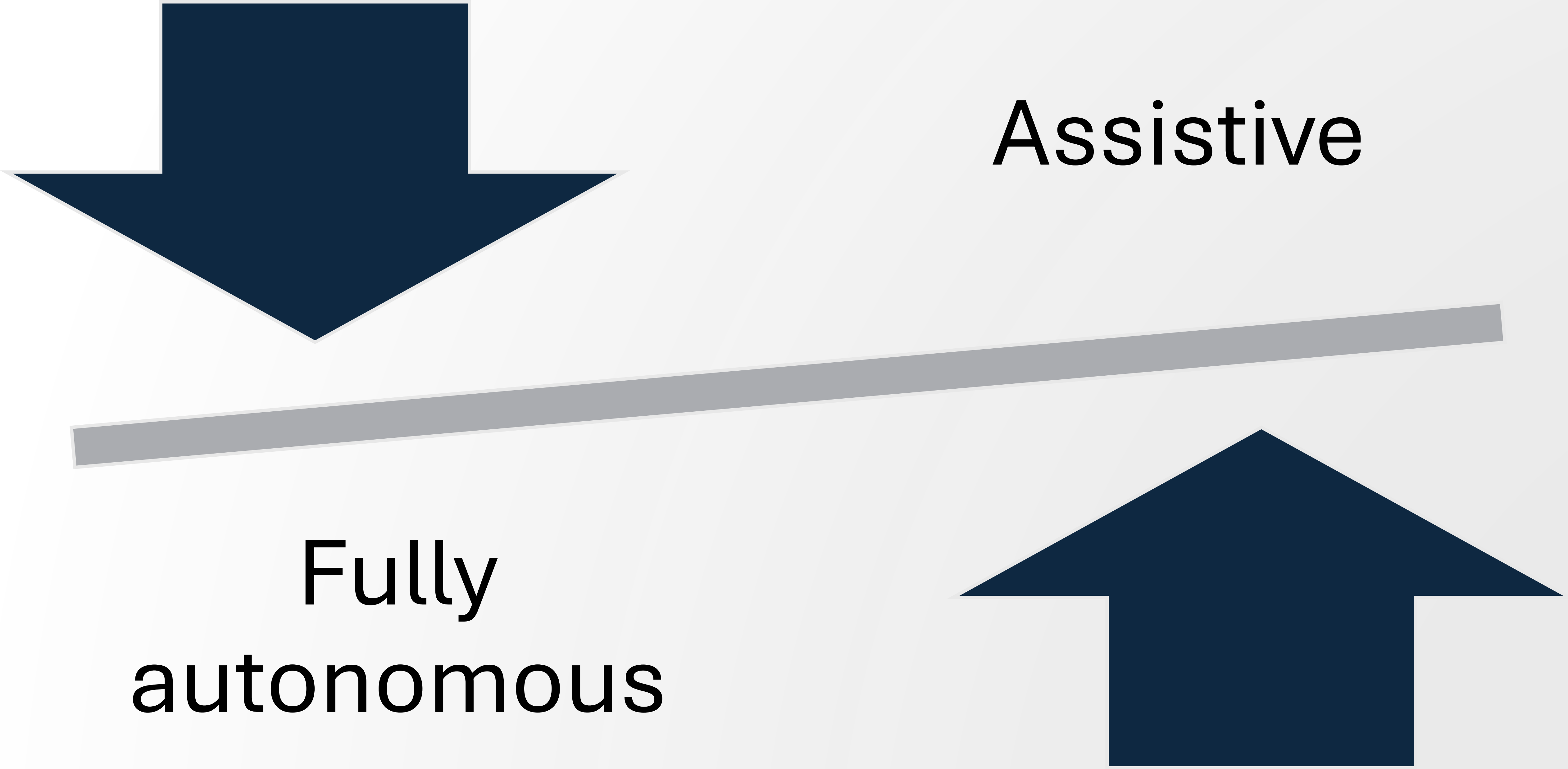
Medical AI Systems-Levels of Automation



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	Assistive AI algorithms		Autonomous AI algorithms		
	Level 1	Level 2	Level 3	Level 4	Level 5
	Data presentation	Clinical decision-support	Conditional automation	High automation	Full automation
Event monitoring	AI	AI	AI	AI	AI
Response execution	Clinician	Clinician and AI	AI	AI	AI
Fallback	Not applicable	Clinician	AI, with a backup clinician available at AI request	AI	AI
Domain, system, and population specificity	Low	Low	Low	Low	High
Liability	Clinician	Clinician	Case dependent	AI developer	AI developer
Example	AI analyses mammogram and highlights high-risk regions	AI analyses mammogram and provides risk score that is interpreted by clinician	AI analyses mammogram and makes recommendation for biopsy, with a clinician always available as backup	AI analyses mammogram and makes biopsy recommendation, without a clinician available as backup	Same as level 4, but intended for use in all populations and systems

THE LANCET
Digital Health

Levels of automation of medical AI systems

Reference: Bitterman, Lancet Digital Health 2020

Build Patient Trust

01

Clarify how AI assists in care to reduce fears and build trust

SCHIFF & BORENSTEIN, 2019

02

Present AI as a tool guided by skilled professionals to ease concerns

SCHIFF & BORENSTEIN, 2019

03

Share AI's advantages and limitations for realistic expectations

NAGY & SISK, 2020

04

Personalize AI information: 43% are unaware of AI's role in healthcare

HEATH, 2024

05

Explain AI in simple terms: 57% fear AI will harm patient-provider relationships

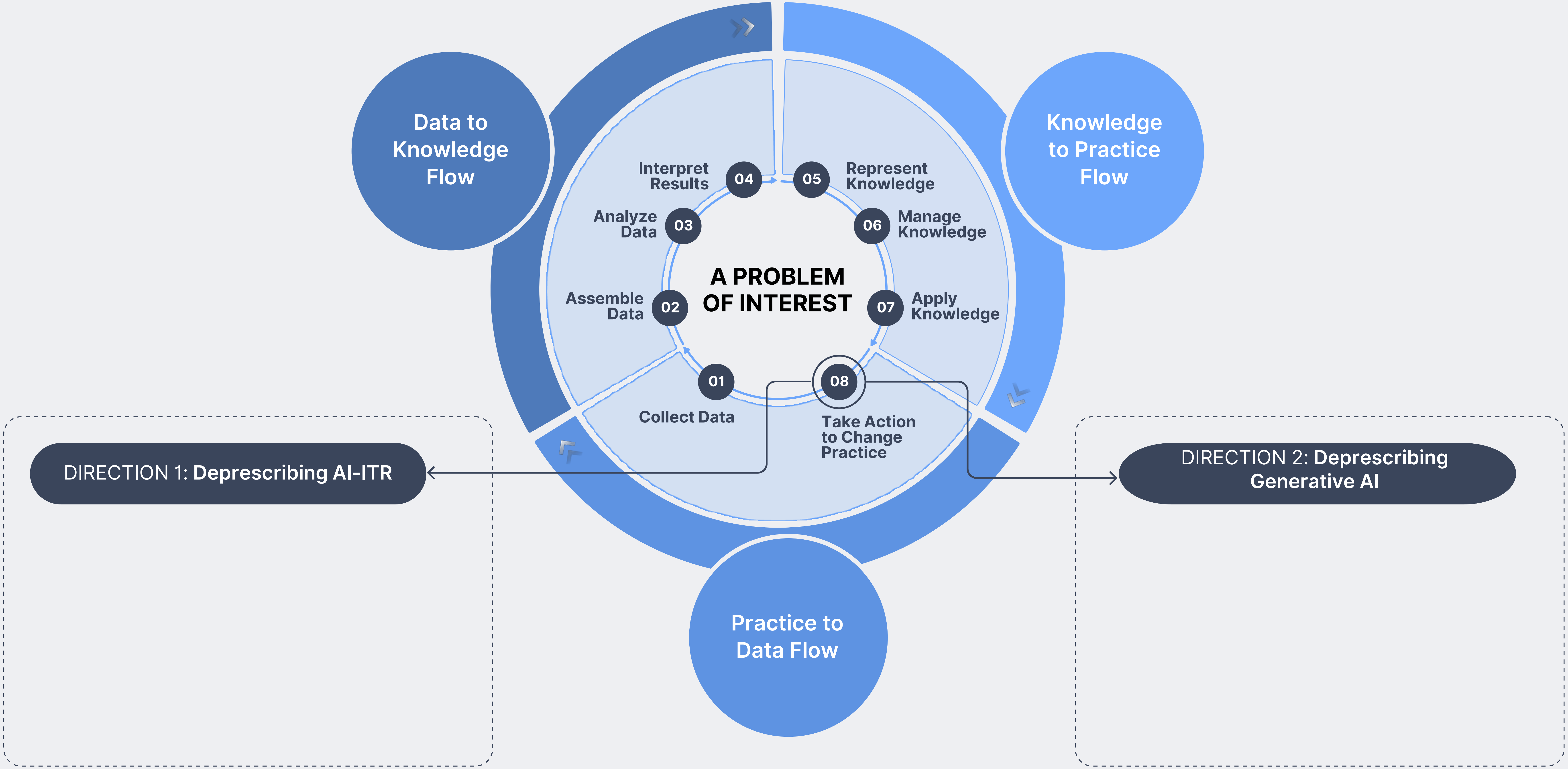
PEW RESEARCH CENTER, 2022

06

Provide real-life examples: 44% trust AI in healthcare, 43% are unsure of its uses

HEATH, 2024

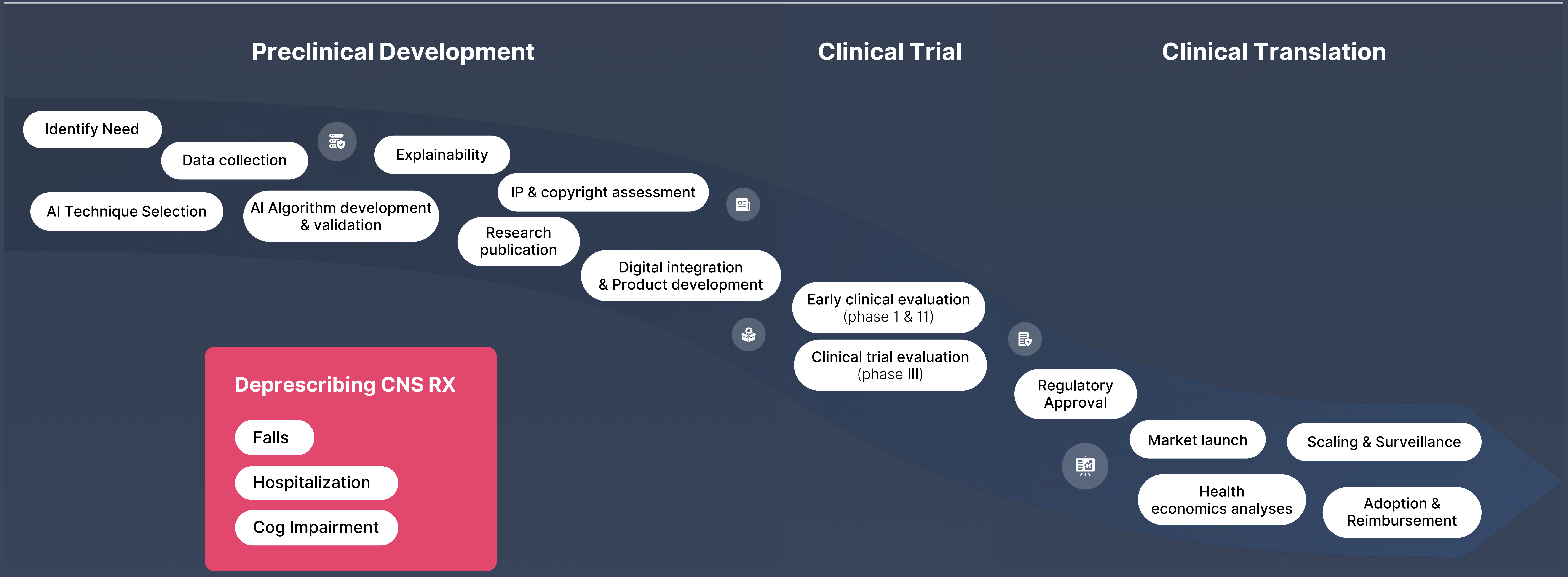
Data Science/Learning Health



Translational Pathway: AI-Driven Solutions for Geriatrics

AI developmental lifecycle which transitions technology from algorithm development to bedside use, and takes over five years from concept to implementation.

RESEARCH & DEVELOPMENT | **CLINICAL IMPLEMENTATION**



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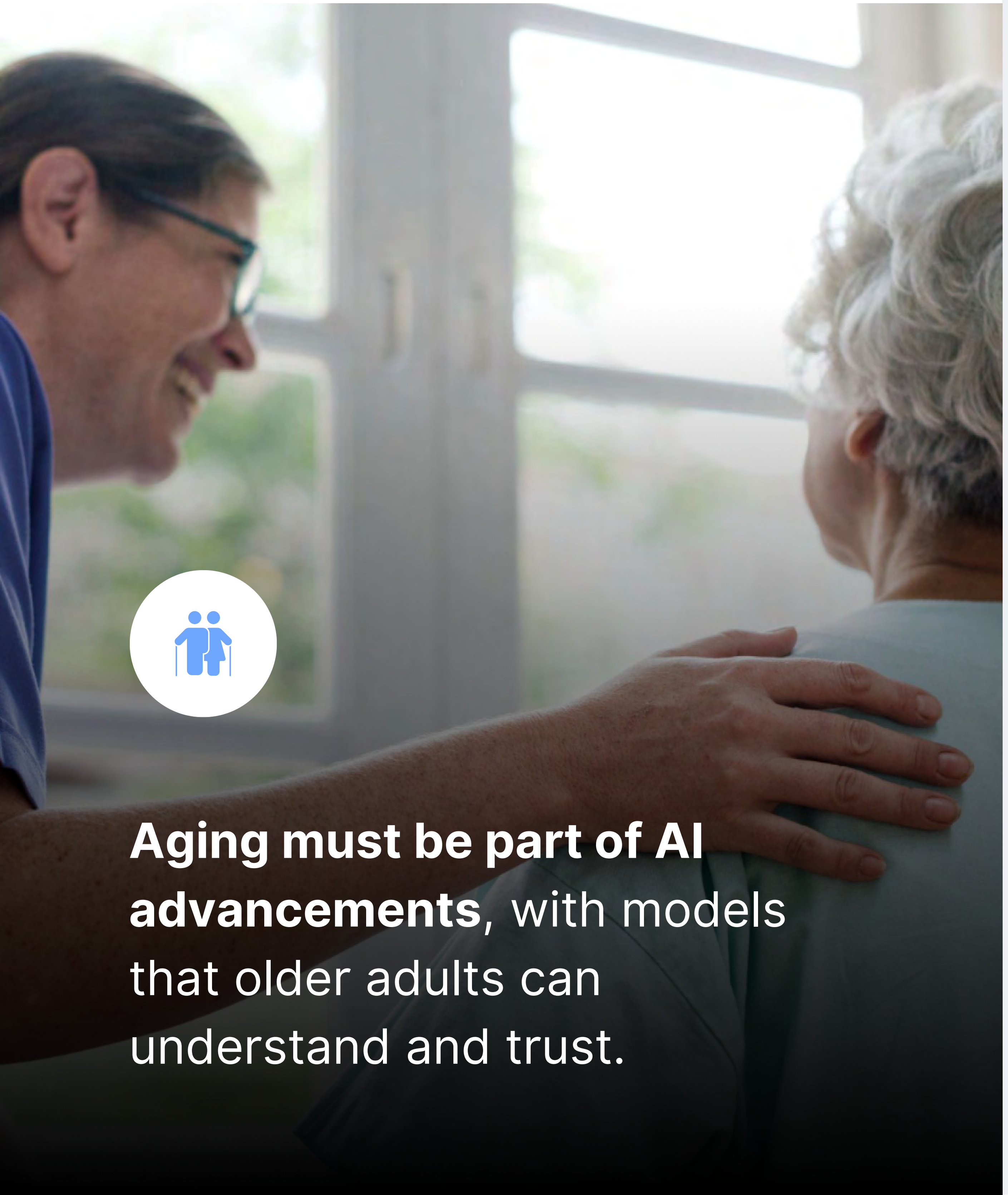
Program Goals



Aging must be part of AI advancements, with models that older adults can understand and trust.

Build AI + Aging Community

Match Ideas with Resources

Translational Pathway Algorithm to Bedside

AI tools are like frogs - some turn into princes and are worth pursuing, while others are not.

Focus on tools that work and move forward

Pavon

Thank you

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Cathleen Colón-Emeric, MD

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Infrastructure

NIH National Institutes of Health
Turning Discovery Into Health
1R01-AG088214-01

Duke Aging Center
Duke University School of Medicine

pcornet
The National Patient-Centered Clinical Research Network

US Deprescribing Research Network

Duke Resources

Duke University School of Medicine

Department of Biostatistics & Bioinformatics
Duke University School of Medicine
Department of Population Health Sciences
Duke University School of Medicine

Duke Clinical & Translational Science Institute

Duke AI HEALTH

Clinical Data Research Networks (CDRN)

Behavioral Health and Survey Research Core

PopHealth DataShare™
explore • analyze • discover

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