Leveraging Implementation and Community Engagement to Advance Equitable Artificial Intelligence

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Outline

- Implementation Science and Community Engagement
- Leveraging IS and CE to advance AI
- Future Direction
- AI and ML

Equitable Implementation Science

IMPLEMENTATION SCIENCE


A Glossary for Dissemination and Implementation Research in Health

Borsika A. Rabin, Ross C. Brownson, Debra Haire-Joshu, Matthew W. Kreuter, and Nancy L. Weaver

Implementation science is an **integrated concept that links research and practice to accelerate the development and delivery of public health approaches.**

Implementation science focuses on **practical approaches** to improve **implementation and to enhance equity, efficiency, scale-up, and sustainability of programs, policies and practices.**

Four **categories/objectives**: 1) informing policy design and implementation (assessment), 2) improving people's health (patient/population outcome), 3) strengthening health service delivery (systems and structures), and 4) empowering communities and beneficiaries (dissemination/empowerment).


Evidence-Based Public Health: A Fundamental Concept for Public Health Practice

Ross C. Brownson,[1] Jonathan E. Fielding,[2] and Christopher M. Maylahn[3]

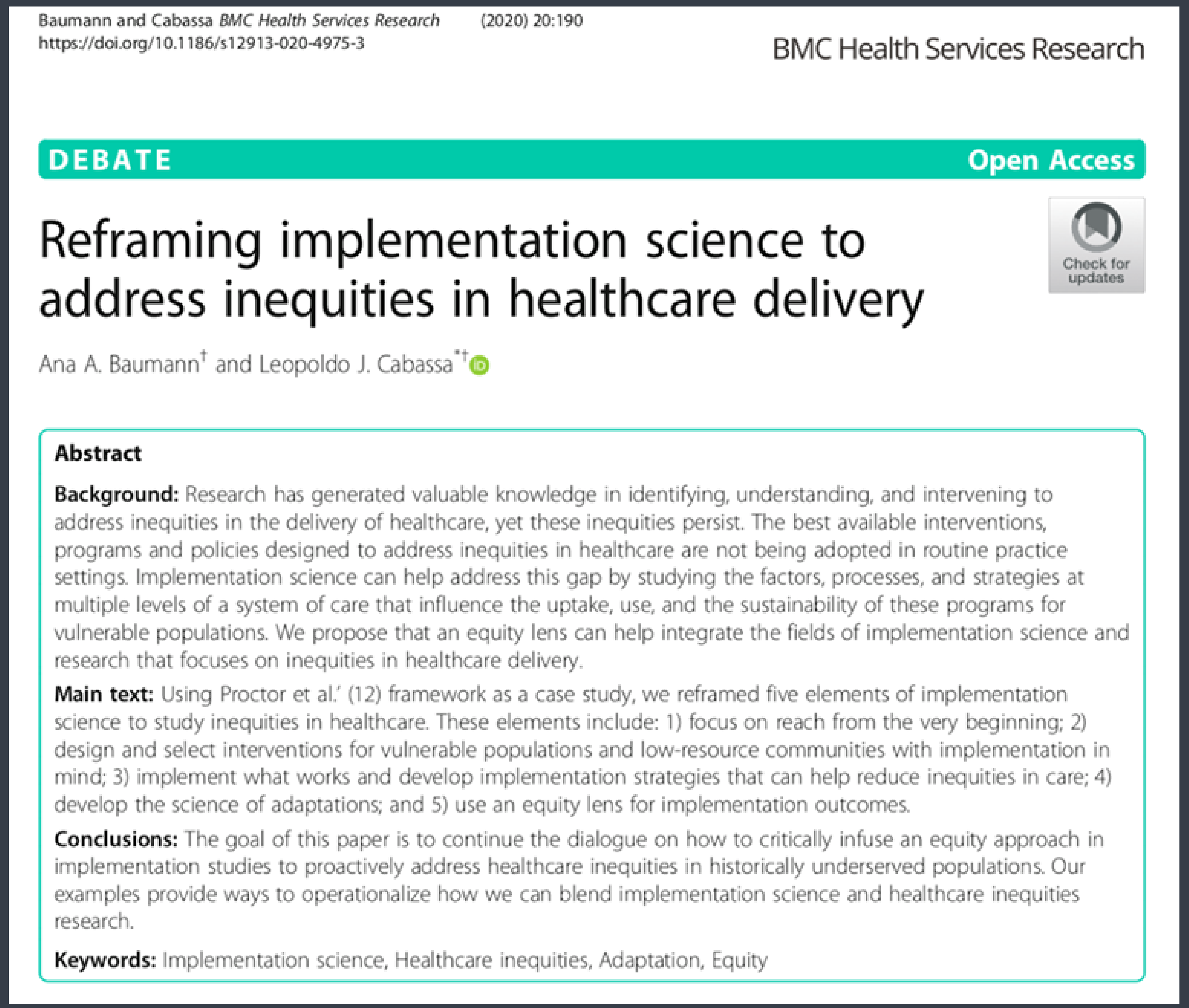
IMPLEMENTATION SCIENCE

Growing calls to reframe elements of implementation science to address inequities:

1. Focus on reach from the very **beginning.**
2. Design and select intervention for vulnerable populations with **implementation in mind**.
3. Implement **what works** and develop implementation strategies that can help reduce inequities.
4. Develop the **science of rapid adaptation and rapid qualitative analysis.**
5. Use **equity lens** for implementation outcomes.

Health Equity Implementation Framework integrates three health equity domains to existing implementation determinant frameworks:

1. Culturally relevant factors of recipients,
2. Clinical encounter or patient-provider interaction, and
3. Societal context (including but not limited to social and structural determinants of health).


Baumann and Cabassa *BMC Health Services Research* (2020) 20:190
https://doi.org/10.1186/s12913-020-4975-3
BMC Health Services Research

DEBATE Open Access

Reframing implementation science to address inequities in healthcare delivery

Ana A. Baumann[†] and Leopoldo J. Cabassa[*†]

Abstract

Background: Research has generated valuable knowledge in identifying, understanding, and intervening to address inequities in the delivery of healthcare, yet these inequities persist. The best available interventions, programs and policies designed to address inequities in healthcare are not being adopted in routine practice settings. Implementation science can help address this gap by studying the factors, processes, and strategies at multiple levels of a system of care that influence the uptake, use, and the sustainability of these programs for vulnerable populations. We propose that an equity lens can help integrate the fields of implementation science and research that focuses on inequities in healthcare delivery.

Main text: Using Proctor et al.' (12) framework as a case study, we reframed five elements of implementation science to study inequities in healthcare. These elements include: 1) focus on reach from the very beginning; 2) design and select interventions for vulnerable populations and low-resource communities with implementation in mind; 3) implement what works and develop implementation strategies that can help reduce inequities in care; 4) develop the science of adaptations; and 5) use an equity lens for implementation outcomes.

Conclusions: The goal of this paper is to continue the dialogue on how to critically infuse an equity approach in implementation studies to proactively address healthcare inequities in historically underserved populations. Our examples provide ways to operationalize how we can blend implementation science and healthcare inequities research.

Keywords: Implementation science, Healthcare inequities, Adaptation, Equity


Implementation Science Communications

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Methodology | Open Access | Published: 05 June 2021

A more practical guide to incorporating health equity domains in implementation determinant frameworks

Eva N. Woodward, Rajinder Sonia Singh, Phiwinhlanhla Ndebele-Ngwenya, Andrea Melgar Castillo, Kelsey S. Dickson & JoAnn E. Kirchner

Implementation Science Communications **2**, Article number: 61 (2021) | Cite this article

Abstract

Background

Due to striking disparities in the implementation of healthcare innovations, it is imperative that researchers and practitioners can meaningfully use implementation determinant frameworks to understand why disparities exist in access, receipt, use, quality, or outcomes of healthcare. Our prior work documented and piloted the first published adaptation of an existing implementation determinant framework with health

IMPLEMENTATION SCIENCE

Intervention Mapping is a systematic approach that facilitates planning and design for dissemination, implementation and maintenance of EBIs in practice. Five steps:

(1) conduct an **implementation needs assessment and identify program adopters and implementers**;

(2) identifying implementation **outcomes and objectives**, identify determinants, and create matrices of change objectives;

(3) choose theoretical methods (mechanisms of change) to design implementation strategies;

(4) produce **implementation protocols and materials; and**

(5) evaluate implementation outcomes.

Adaptation of an effective school-based sexual health promotion program for youth in Colombia

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ARTICLE INFO

Keywords:
Sexual health
Adolescents
Intervention
Adaptation
COMPAS
Colombia

ABSTRACT

Rationale: Given the disproportionate impact of HIV and STIs among youth in Latin America, there is a compelling need for effective sex education programs. In particular, Colombia lacks a nationally standardized youth sex education program, despite the fact that 15 to 24-year-olds accounted for the highest incidence and prevalence rates of HIV and STIs in the nation. In an attempt to fill this void, our team adapted COMPAS, a Spanish school-based sexual health promotion intervention, for Colombian adolescents. *Objective:* This study describes the adaptation process that resulted in a modified version of COMPAS for youth in Colombia. *Method:* We employed a systematic cultural adaptation process utilizing a mixed methods approach, including intervention adaptation sessions with 100 young adolescents aged 15–19. The process included six steps: 1) consulting international researchers and community stakeholders; 2) capturing the lived experiences of a diverse sample of colombian youth; 3) identifying priorities and areas in need of improvement; 4) integrating the social cognitive theory, information-motivation-behavioral skills model, and an ecological framework for colombian youth; 5) adapting intervention content, activities, and materials; and 6) quantitative evaluation of COMPAS by Colombian youth. *Results:* The adapted intervention incorporates elements common to effective youth sex education interventions, including: a solid theoretical foundation, sexual communication skills and social support for protection, and guidance on how to utilize available cultural- and linguistic-appropriate services. In addition, the adapted intervention incorporates cultural and linguistic appropriate content, including an emphasis on tackling *machismo* to promote risk reduction behaviors. *Conclusions:* The systematic adaptation approach to sexual health intervention for youth can be employed by researchers and community stakeholders in low-resource settings for the promotion of health wellness, linkage to care, and STI and unplanned pregnancy prevention for youth.

NIH Public Access
Author Manuscript
AIDS Educ Prev. Author manuscript; available in PMC 2014 April 15.

Published in final edited form as:
AIDS Educ Prev. 2014 February ; 26(1): 68–80. doi:10.1521/aeap.2014.26.1.68.

ADAPTATION AND IMPLEMENTATION OF HoMBReS: A COMMUNITY-LEVEL, EVIDENCE-BASED HIV BEHAVIORAL INTERVENTION FOR HETEROSEXUAL LATINO MEN IN THE MIDWESTERN UNITED STATES

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University of California San Diego

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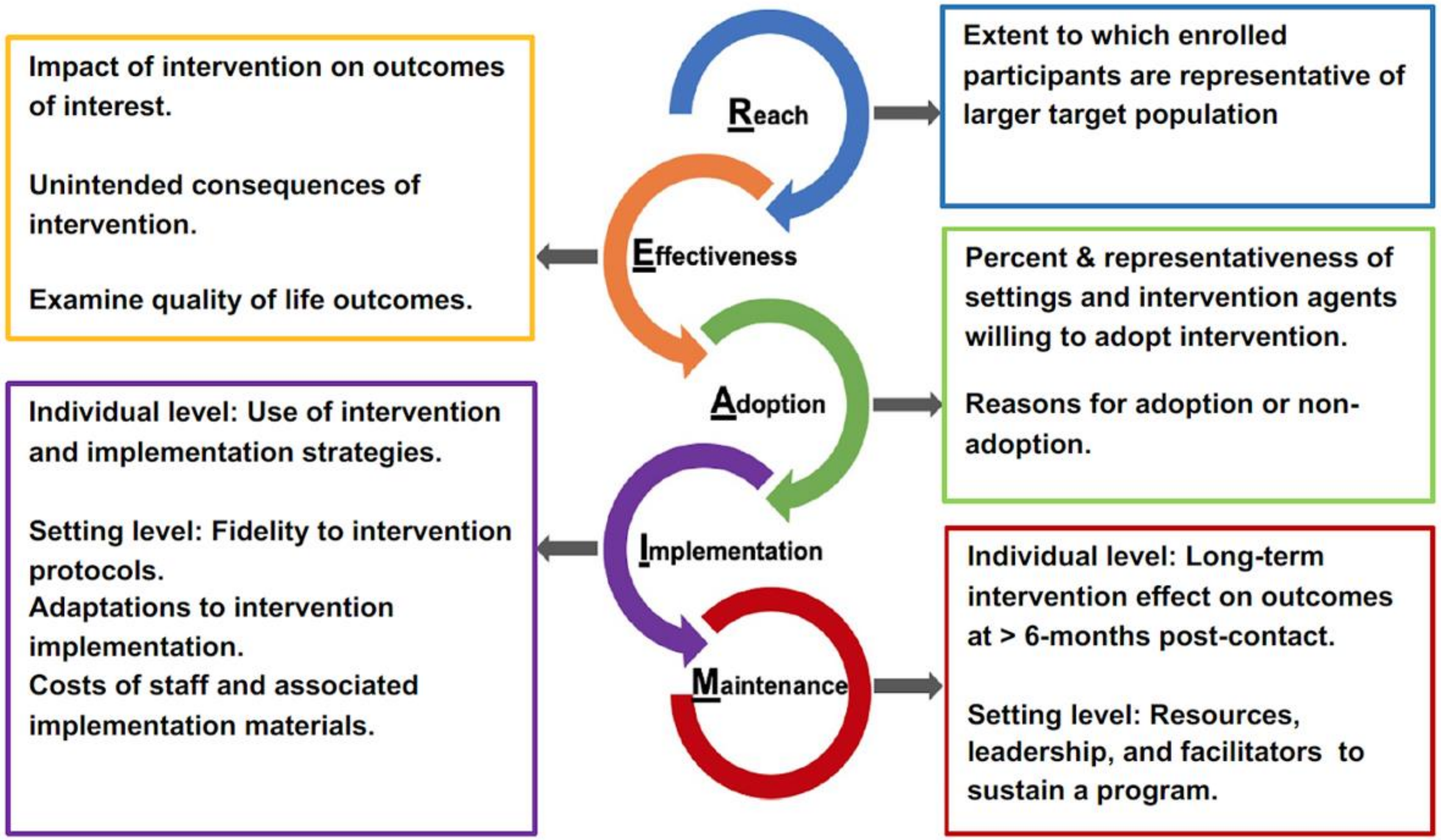
Abstract

Over the past decade, the midwestern United States has witnessed a dramatic increase in its Latino population. The lack of culturally and linguistically congruent resources coupled with high incidence and prevalence rates of HIV among Latinos living in the Midwest merits attention. HoMBReS: Hombres Manteniendo Bienestar y Relaciones Saludables (Men Maintaining Wellbeing and Healthy Relationships) is a community-level social network intervention designed for Latino men. We describe the adaptation and implementation of HoMBReS for Latino men living in Indianapolis, Indiana, the second largest city in the Midwest. Five *Navegantes* (lay health educators) were trained; they provided a total of 34 educational *charlas* (small group didactic sessions). A total of 270 Latino men attended the charlas and were offered no-cost screening for HIV and sexually transmitted infections (STI). Three participants tested HIV positive and 15 screened positive for STI. The charlas coupled with the testing initiative, served as a successful method to increase sexual health knowledge among Latino men and to link newly-diagnosed HIV/STI-positive individuals to treatment and care. The adaptation and implementation of HoMBReS respond to the CDC and NIH call to increase HIV testing and service provision among vulnerable populations.

IMPLEMENTATION SCIENCE

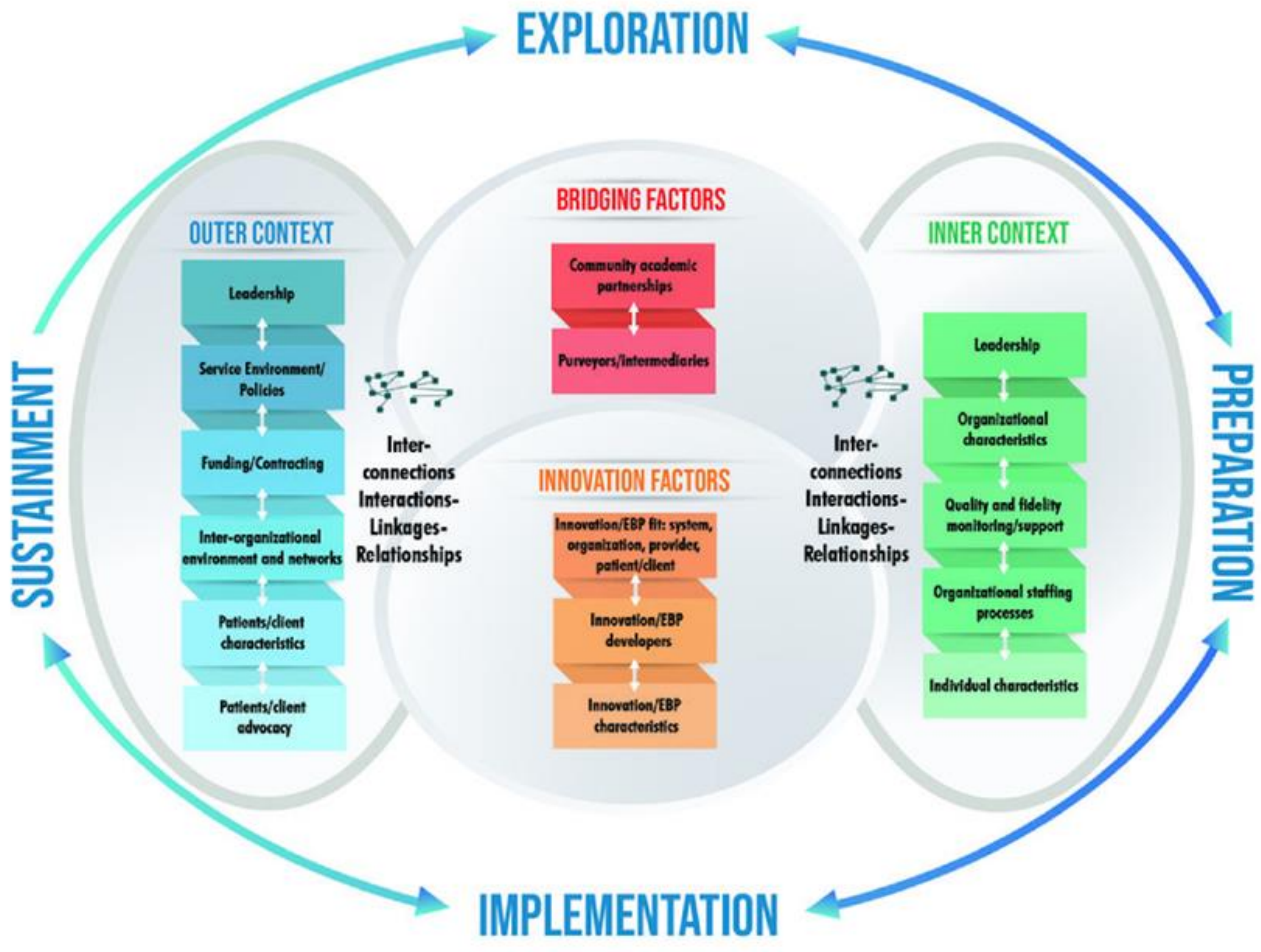
RE-AIM Framework



Glasgow RE, Vogt TM, Boles SM. Evaluating the public health impact of health promotion interventions: the RE-AIM framework. Am J Public Health. 1999;89(9):1322-7. https://www.re-aim.org/

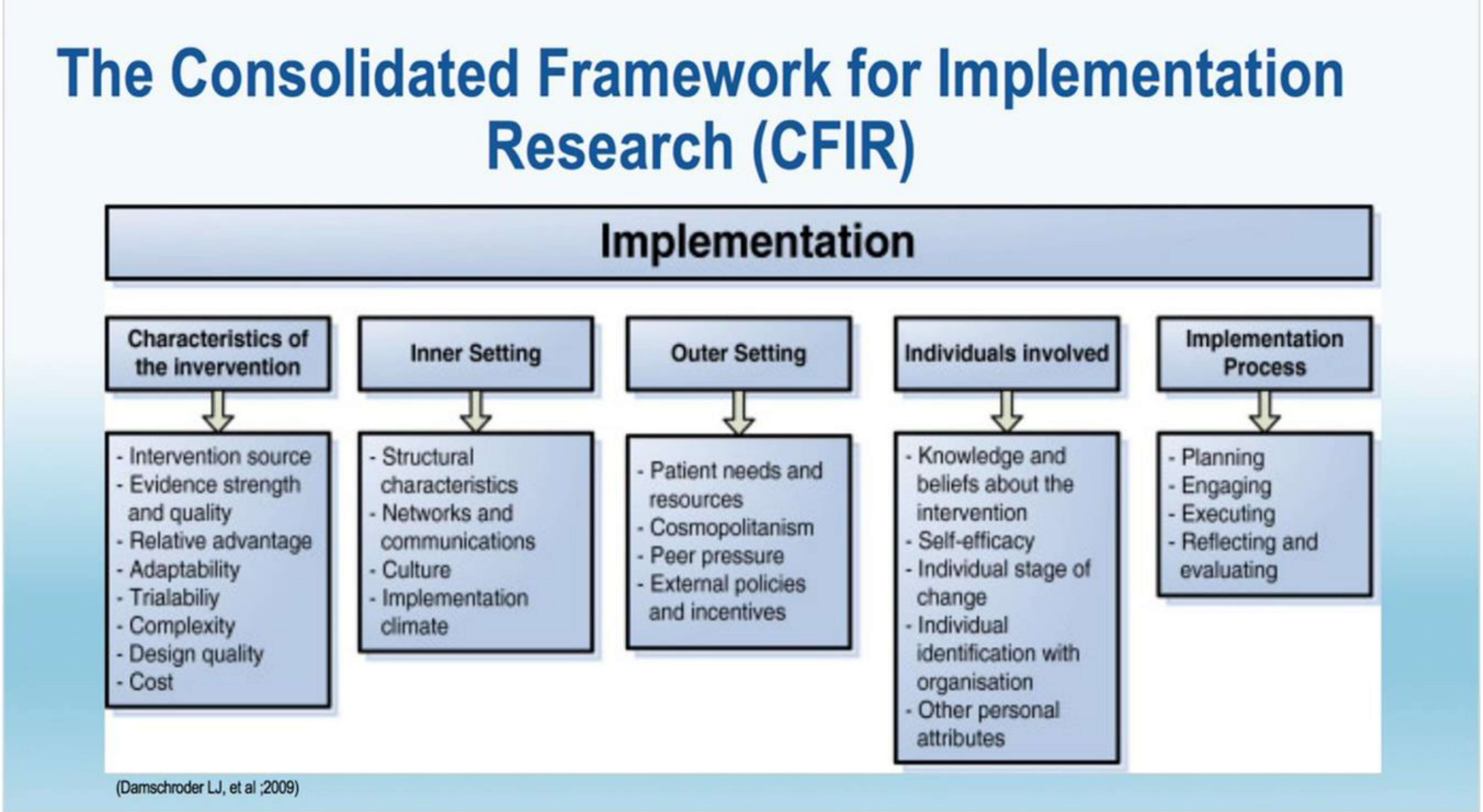
IMPLEMENTATION SCIENCE

EPIS Framework



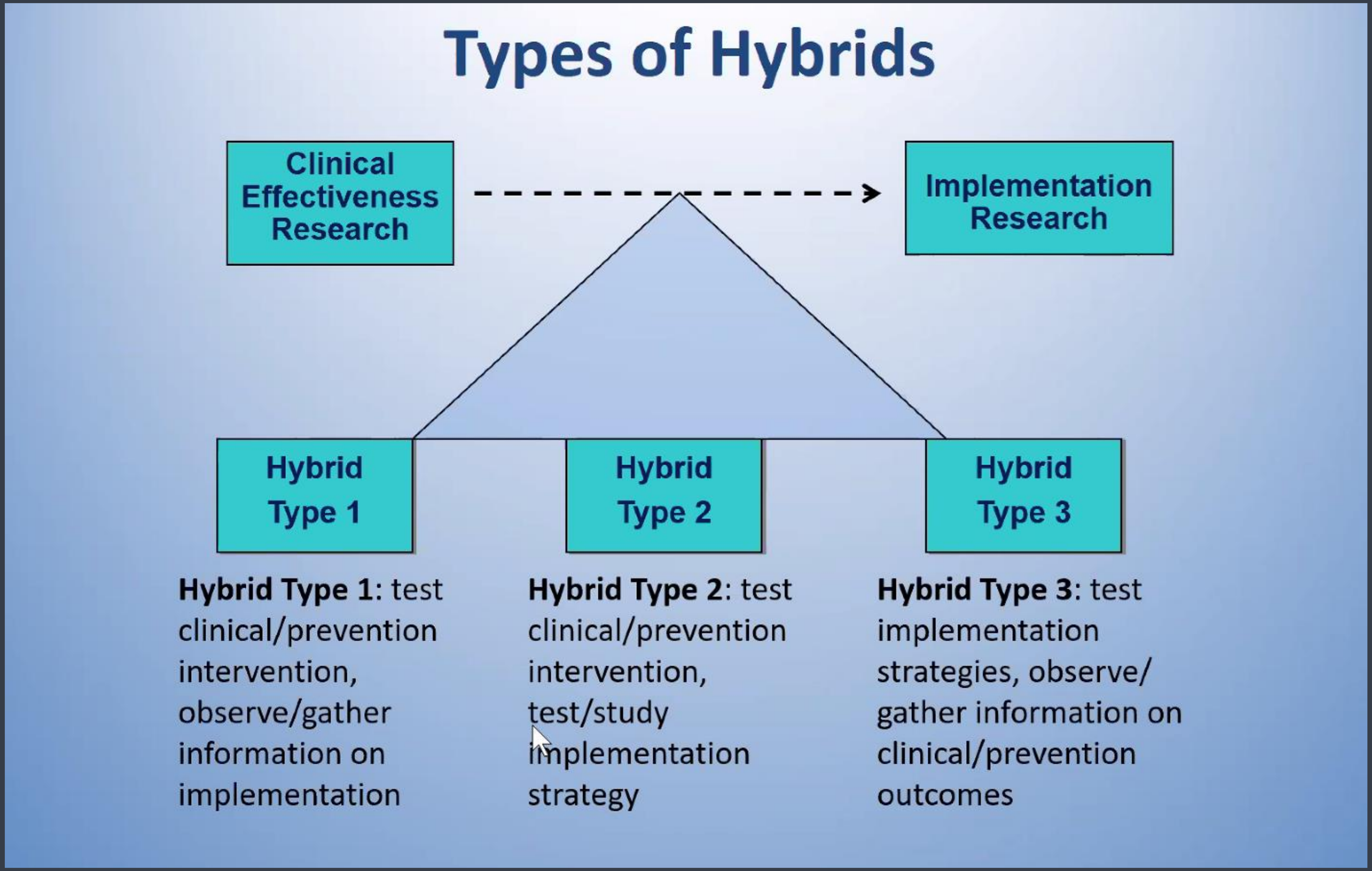
Aarons GA, Hurlburt M, Horwitz SM. Advancing a conceptual model of evidence-based practice implementation in public service sectors. Adm Policy Ment Hlth. 2011;38:4–23. https://episframework.com/

IMPLEMENTATION SCIENCE



Damschroder LJ, Aron DC, Keith RE, Kirsh SR, Alexander JA, Lowery JC. Fostering implementation of health services research findings into practice: a consolidated framework for advancing implementation science. Implementation science. 2009 Dec;4(1):1-5. https://cfirguide.org/

HYBRID DESIGNS



Source: Research Talk by Dr. Geoffrey Curran

Community Engagement

Immigration

"Many people won't go and seek out services because they are afraid it will affect their immigration status…for fear of being found out as undocumented individuals, then don't seek help." (Alex, El Salvador, 45)

Discrimination and Stigma

"As trans individuals, we are constantly challenged by discrimination, stigma, violence, homelessness, and lack of comprehensive trans care. Support is needed to navigate through legal and medical systems, like name change and access to hormones and affirmation surgery" (Laritza, Latinx, 30).

MARCH 2019

HIV PREVENTION IN THE UNITED STATES

BOLSTERING LATINX GAY AND BISEXUAL MEN TO PROMOTE HEALTH AND REDUCE HIV TRANSMISSION

National Library of Medicine
National Center for Biotechnology Information

PubMed.gov

Review > Expert Rev Anti Infect Ther. 2021 Mar;19(3):323-329.
doi: 10.1080/14787210.2020.1819790. Epub 2020 Sep 17.

A review of current strategies to improve HIV prevention and treatment in sexual and gender minority Latinx (SGML) communities

Omar Martinez[1]

PMID: 32902348 DOI: 10.1080/14787210.2020.1819790

HIV Spec. Author manuscript; available in PMC 2019 Aug 8.
Published in final edited form as:
HIV Spec. 2019 Jun; 11(2): 14–17.
PMCID: PMC6687337
NIHMSID: NIHMS1039142
PMID: 31396600

HIV-related Stigma as a Determinant of Health Among Sexual and Gender Minority Latinxs

OMAR MARTINEZ, JD, MPH, MS

SEXUAL AND GENDER MINORITY LATINXS (SGML) continue to be disproportionately impacted by HIV. While new HIV diagnoses stabilized for gay and bisexual men from 2012–2016, they increased by 12% during this period for Latinx gay and bisexual men.[1] According to U.S. epidemiological data, Latinx transgender individuals are also disproportionately impacted by HIV.[2–5] These disparities among SGML are the products of, and exacerbated by, social and structural conditions, including poverty, HIV-related stigma, discrimination, documentation status, lack of access to healthcare, and anti-immigration rhetoric.[6–9]

Among these conditions, HIV-related stigma serves as a determinant of health among SGML.[10, 11] HIV-related stigma includes negative attitudes and beliefs directed at people living with HIV (PLWH) and

THE LANCET

Ending the HIV epidemic in US Latinx sexual and gender minorities

HHS Public Access
Author manuscript
Drug Alcohol Depend. Author manuscript; available in PMC 2017 September 01.
Published in final edited form as:
Drug Alcohol Depend. 2016 September 1; 166: 258–262. doi:10.1016/j.drugalcdep.2016.06.033.

Syndemic Factors Associated with Adult Sexual HIV Risk Behaviors in a Sample of Latino Men who Have Sex with Men in New York City

Omar Martinez [Assistant Professor],

HHS Public Access
Author manuscript
J Immigr Minor Health. Author manuscript; available in PMC 2019 April 01.
Published in final edited form as:
J Immigr Minor Health. 2018 April ; 20(2): 497–501. doi:10.1007/s10903-017-0568-6.

Syndemic Conditions Reinforcing Disparities in HIV and other STIs in an Urban sample of Behaviorally Bisexual Latino Men

Miguel Muñoz-Laboy, Dr.P.H.[1], Omar Martinez, JD,MPH,MS[1], Ethan C. Levine, MA[1], Brian T. Mattera, BS[1], and M. Isabel Fernandez, PhD[2]

HHS Public Access
Author manuscript
Am J Prev Med. Author manuscript; available in PMC 2017 August 23.
Published in final edited form as:
Am J Prev Med. 2017 August ; 53(2): 225–231. doi:10.1016/j.amepre.2017.01.037.

Sexual and Behavioral Health Disparities Among Sexual Minority Hispanics/Latinos: Findings From the National Health and Nutrition Examination Survey, 2001–2014

Omar Martinez, JD, MPH, MS[1], Ji Hyun Lee, MD, MPH[2], Frank Bandiera, PhD, MPH[3], Karina Santamaria, MPH[2], Ethan C. Levine, MA[1], and Don Operario, PhD[2]

HHS Public Access
Author manuscript
EHQUIDAD. Author manuscript; available in PMC 2020 February 24.
Published in final edited form as:
EHQUIDAD. 2020 ; 13: 217–236. doi:10.15257/ehquidad.2020.0009.

Using Syndemics Theory to Examine HIV Sexual Risk Among Latinx Men Who Have Sex with Men in Philadelphia, PA: Findings from the National HIV Behavioral Surveillance

Omar Martinez[1], Kathleen A. Brady[2], Ethan Levine[1], Kathleen R. Page[3], Maria Cecilia Zea[4], Thespina J. Yamanis[5], Suzanne Grieb[3], Jennifer Shinefeld[2], Kasim Ortiz[6], Wendy W. Davis[3], Brian Mattera[1], Ana Martinez-Donate[7], Silvia Chavez-Baray[8], Eva M. Moya[8]

Open access — Original research

BMJ Open **More than just oral PrEP: exploring interest in rectal douche, dissolvable implant, removable implant and injection HIV prevention approaches among racially diverse men who have sex with men in the Northeast Corridor**

Omar Martinez,[1] Ethan Levine,[2] Miguel Munoz-Laboy,[3] Alex Carballo-Diéguez,[4] José Arturo Bauermeister,[5] Alexi Chacon,[6] Jeffrey Jacobson,[7] Robert Bettiker,[7] Madeline Sutton,[8] Abby E Rudolph,[9] Elwin Wu,[10] Scott D Rhodes,[11]

> AIDS Educ Prev. 2022 Oct;34(5):365-378. doi: 10.1521/aeap.2022.34.5.365.

Perceived Barriers to and Facilitators of Long-Acting Injectable HIV PrEP Use Among Black, Hispanic/Latino, and White Gay, Bisexual, and Other Men Who Have Sex With Men

Nguyen K Tran[1], Omar Martinez[2], Ayden I Scheim[1 3], Neal D Goldstein[1], Seth L Welles[1]

Editorial > Circ Cardiovasc Qual Outcomes. 2022 Dec;15(12):e009650.
doi: 10.1161/CIRCOUTCOMES.122.009650. Epub 2022 Dec 20.

Addressing the Unique Social and Structural Drivers of Hypertension Among Sexual Minority Adults in the United States

Humberto López Castillo[1 2], Omar Martínez[2]

PMID: 36538587 DOI: 10.1161/CIRCOUTCOMES.122.009650

PLOS ONE

RESEARCH ARTICLE

Feasibility and acceptability of CRiSOL: A pilot peer-based intervention to address syndemic health issues afflicting Latino immigrants in the U.S.

Ana P. Martinez-Donate[1*], Claudia Zumaeta-Castillo[1], Yoshiaki Yamasaki[2], Cristina Perez[2], Omar Martinez[3], Elizabeth McGhee Hassrick[1,4], Jonas Ventimiglia[4], Mariana Lazo-Elizondo[1,5]

COMMUNITY ENGAGEMENT

Community engagement is a collaborative process that actively involves community members in decision-making and program development, ensuring that their needs, values, and insights are meaningfully incorporated. It prioritizes equitable participation by acknowledging and addressing social and structural conditions—such as discrimination, marginalization, and historical inequities—that impact communities. Through this approach, community engagement seeks to build trust, foster inclusivity, and empower communities to co-create solutions that are responsive to their unique contexts and challenges.

Why It Matters in AI Development:
Ensures AI interventions are culturally relevant, ethical, and aligned with community needs.

Builds trust and increases the acceptance of AI solutions, particularly in healthcare and underserved populations.

KEY CONTRIBUTIONS OF COMMUNITY ENGAGEMENT TO AI

Cultural Relevance and Sensitivity:
Involving communities helps to tailor AI applications, particularly in healthcare, to consider social, cultural, and linguistic factors, making interventions more effective.

Building Trust and Transparency:
Transparent communication with communities builds trust in AI technologies, reducing fear or skepticism around AI use in sensitive areas like healthcare.

Co-Creation of Solutions:
Community engagement facilitates a collaborative approach where AI tools are co-developed with community members, ensuring that their voices influence the design and functionality of AI systems.

CHALLENGES OF COMMUNITY ENGAGEMENT IN AI

Data Privacy and Ethical Concerns:
Community members may be wary of how their data is used, especially when it involves sensitive health information. Building trust requires robust data protection measures and clear communication.

Ensuring Representation in Model Design:
Often, certain communities are underrepresented in AI model training data. This challenge highlights the need for proactive inclusion in the data collection process.

Technical Literacy and Accessibility:
AI concepts can be complex, and engaging communities with limited technical literacy poses challenges in ensuring meaningful participation and understanding.

Sustainability of Engagement Efforts:
Maintaining long-term community engagement is resource-intensive. It requires continuous collaboration, feedback loops, and compensation for community contributions to ensure sustained involvement.

ADDRESSING CHALLENGES

Transparent Communication:
Clearly communicate the purpose, risks, and benefits of AI tools to the community.

Incorporating Feedback Mechanisms:
Build in systems that allow community members to provide ongoing feedback on AI interventions, ensuring continuous refinement and relevance.

Building Capacity for Technical Literacy:
Offer workshops, resources, and support to help community members better understand AI technology, fostering more informed engagement.

Ensuring Ethical AI Practices:
Prioritize fairness, privacy, and accountability in AI development by implementing strong data protection policies and ethical guidelines.

IMPLEMENTATION SCIENCE AND COMMUNITY ENGAGEMENT FRAMEWORK TO ADVANCE AI

Phase 1: Design and Data Interpretation

Community helps identify key variables, identifying relevant data, and providing insights into local context, ensuring that AI models reflect real world needs.

Phase 2: Data Quality and Fairness

Community engagement enhances data quality by identifying faps, inconsistencies, and underrepresented populations. Advocating for data equity and improving accuracy in categorization of sensitive information like race/ethnicity, gender/sexual identity, and other SSDoH.

Phase 3: AI Development and Model Implementation

Ongoing feedback loops between researchers and community ensure that AI models are developed in ways that are culturally sensitive and contextually appropriate. Providing insights to make AI models fair, equitable, and interpretable, while ensuring biases are minimized.

Phase 4: Dissemination and Uptake

Community plays a vital role in dissemination of findings, ensuring that the knowledge generated is accessible and actionable for local stakeholders, policymakers and the public. Facilitating widespread adoption by leveraging trusted networks, ensuring sustainability, and promoting buy-in for the AI interventions.

Implementation Science and Community Engagement Framework to Advance AI

AI

AI and Homelessness (NSF Grant)

Proto-OKN Theme 1: DREAM-KG: Develop Dynamic, REsponsive, Adaptive, and Multifaceted Knowledge Graphs to address homelessness with Explainable AI

PI: Yuzhou Chen (Temple)
Co-PIs: Chiu C. Tan (Temple), **Huanmei Wu** (Temple), **Ying Ding** (UT)

SP & Consultants: Karin Eyrich-Garg (Temple), **Omar Martinez** (UCF), **Shak Ragoler** (Shelter App), **Prithviraj Lanka** (Shelter App)

NSF Proto-OKN First Quarter Reviews
January 17, 2024

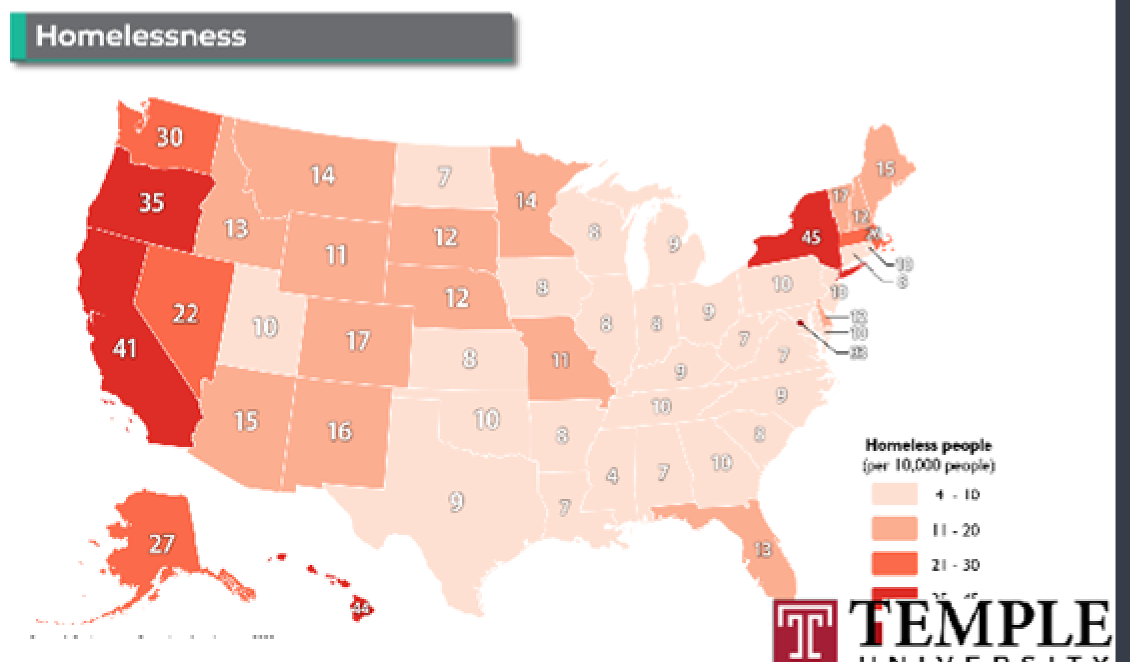
TEMPLE UNIVERSITY

Project Overview

- **Objective:** to create a knowledge graph (KG) system (i.e., **D**ynamic, **RE**sponsive, **A**daptive, and **M**ultifaceted **K**nowledge **G**raph (**DREAM-KG**)) that will help
  - provide a comprehensive understanding of the social, economic, and political factors that contribute to homelessness
  - triage existing services and resources to support people experience homelessness (PEH)

Challenges

- Many PEHs heavily rely on local community services to meet their essential needs.
- Homeless service resources are subject to frequent changes due to several factors,
  - e.g., available funding, seasonal changes, etc
- Challenges for data collection and processing
  - e.g., outdated information
- Police needs:
  - better policies and partnerships



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AI and Homelessness (NSF Grant)

Building the DREAM-KG: A Community-Engaged Approach to Addressing Homelessness Through Knowledge Graphs

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Abstract. Homelessness is a multifaceted issue influenced by social, economic, and political factors, necessitating innovative and integrative solutions. This study introduces the Dynamic, REsponsive, Adaptive, and Multifaceted Knowledge Graph (DREAM-KG) system, designed to provide a comprehensive understanding of homelessness, triage existing services, and implement an automated knowledge graph/graph AI pipeline. Through engagement with a community advisory board (N=10) comprising clinicians, nonprofit leaders, and policy advocates, we gathered valuable insights to ensure DREAM-KG's effectiveness and responsiveness. Our findings highlight the importance of community engagement, ethical considerations, and the integration of explainable AI techniques to enhance transparency and accountability. The DREAM-KG project aims to offer an adaptive, community-driven approach to supporting unhoused individuals, with significant implications for policy and practice.

Keywords: Homelessness, knowledge graph, community-driven approach.

COMMUNITY ENGAGEMENT OVERVIEW

Objective: Establish regular communication with diverse stakeholders to ensure the DREAM-KG project is inclusive, responsive to the community's needs, and sustainable.

Stakeholders:

National Institute of Justice (NIJ): Legal and policy insights on homelessness.

Findhelp Inc.: Expertise on connecting individuals with essential services.

DREAM-KG Community Advisory Board: Continuous feedback from clinicians, nonprofit leaders, and policy advocates.

NJ Department of Community Affairs: Focus on data management, privacy, and state-level system integration.

STRATEGY

NIJ: Insights into legal considerations and policy alignment.

Findhelp: Operational challenges in providing community services.

Community Advisory Board: Feedback on project alignment with community needs.

NJ Department of Community Affairs: Data integration and privacy practices.

Presentation and Feedback Process:
Presented the project to each group.
Gathered reactions, concerns, and assessment of the DREAM-KG’s usefulness.
Summarized feedback from each stakeholder group.

QUESTIONS FOR STAKEHOLDERS

How do you envision the DREAM-KG project making a positive impact on homelessness?

What considerations ensure the knowledge graphs are dynamic and responsive to unhoused individuals' evolving needs?

How can explainable AI enhance transparency and accountability in interventions?

How can we ensure the knowledge generated is accessible to all users?

What resources or partnerships could enhance the success of DREAM-KG?

What outcomes or indicators would be most meaningful in evaluating DREAM-KG’s effectiveness?

RAPID QUALITATIVE ANALYSIS

Process Overview:

Initial Review: Two researchers independently reviewed transcripts.

Coding Framework: Collaboration to create a comprehensive framework, including major themes and sub-themes.

RESULTS

Engaging communities potentially impacted by homelessness is vital for the project's success. The community advisory board with 10 members provides ongoing guidance and advice, ensuring that our approach is informed by those directly affected by homelessness – people with lived homelessness experience, service providers, agency administrative leaders, and policymakers. This engagement helps us design interventions that are not only effective but also respectful and supportive of the community's needs. Figure 1 provide three recommendations from the CAB meetings, which emphasized the importance of comprehensive services integrated into the KG.

Fig. 1. Three suggestions from a CAB meeting with 10 members regarding the expectations for the DREAM-KG infrastructure.

NIH R01: AI to Advance Health Equity in Cardiovascular Risk Prediction

Aim 1: To develop a social-ecological AI model to improve health equity (AI2Equity) in CVD risk prediction. Our hypothesis is that integrating social risk factors can help improve CVD risk prediction accuracy especially for marginalized populations. We will test this hypothesis by: (1) developing state-of-the-art NLP systems to extract SDOH factors from unstructured clinical notes; (2) exploring novel deep learning architecture with hierarchical attention mechanism to integrate multi-level and multi-domain (following NIMHD's Research Framework) social and clinical factors and their complex interactions; and (3) assessing the model's fairness and accuracy.

Aim 2: To enhance the AI2Equity model's fairness and interpretability. Our hypothesis is that model fairness can be further improved through data transformation and algorithmic optimization, and new insights can be obtained through enhanced model interpretability and stakeholder engagement. We will test this hypothesis by: (1) integrating adversarial adaptation and fairness-constrained optimization to mitigate potential bias following ethical AI principles; 16 (2) making the model more transparent and understandable through "Explainable AI" techniques; 17,18 and (3) employing iterative, qualitative, and Delphi panel methodologies and engaging a wide range of community stakeholders to explain the quantitative results, to further understand the impact of SDOH on CVD incidence.

Aim 3: To broaden AI2Equity's generalizability across multiple healthcare systems/settings. We hypothesize that our novel AI solution can be generalized across different healthcare institutions and perform more accurately and equitably compared with existing clinical tools. We will test this hypothesis by: (1) developing transfer learning techniques to reduce the performance variance across institutions/settings due to data heterogeneity and population diversity; (2) benchmarking AI2Equity's accuracy against four common CVD risk tools (QRISK3, 19 FRS-CVD, 20 SCORE 21 and ACC/AHA PCE 22) using observed real-world EHR data; and (3) gauging the impact of AI2Equity with different thresholds on predicted statin therapy for primary prevention retrospectively.

ENGAGEMENT

Stakeholder Engagement

We will implement a modified, innovative Delphi approach using mixed methods based on our prior experiences. We propose to conduct an interactive online Delphi panel via Zoom focus groups with patients impacted by CVD, physicians, case managers, behavioral health providers, patient navigators, and social workers. We focus on AA and Latinx populations as they experience higher CVD risk and are underrepresented in risk calculator models.

Conducting the focus groups will accomplish three goals: (1) soliciting perspectives and lived experiences from patients, (2) assessing providers' understanding of barriers and facilitators to CVD prevention, and (3) obtaining feedback to improve CVD prevention. A key contribution of Delphi and focus group data will be to identify SDOH associated with CVD risk among diverse groups of AA and Latinx individuals (e.g., low socioeconomic status, lack of insurance, at risk of CVD, and living in densely populated urban areas).

AI and Diabetes (AIM-AHEAD Consortium)

DETERMINE: Diabetes prEdicTion and Equity through Responsible MachINe lEarning

AIM-AHEAD Consortium Development Project (2023.9-2025.8)

Problems

- Existing clinical guidelines for T2D preventive measures rely on problematic "prediabetes" definition
- Limited SDOH are integrated in diabetes prevention and control to address root causes of diabetes inequities
- Lacking solutions to address model fairness and generalizability

Solutions

To develop an AI-powered multivariable risk prediction model for accurate, fair, generalizable, and interpretable T2D risk prediction.

Responsible AI can help identify those at risk for diabetes and personalize care plans to improve outcomes and health equity.

UMass Chan Medical School | Temple University | OCHIN | University of Illinois Chicago | University of Central Florida | Brown

Specific AIMS

Aim 1
- **Develop responsible AI to predict diabetes risk**
  - SDOH+clinical data integration
  - Interpretable and fair AI model development

Aim 2
- **Perform external validation and assessment on DETERMINE**
  - Generalizability validation
  - Simulation analysis

Predict diabetes risk | Identify risk factors | Responsible AI | Personalize care plans

UMass Chan Medical School | Temple University | OCHIN | University of Illinois Chicago | University of Central Florida | Brown

ENGAGEMENT WITH COMMUNITY ADVISORY BOARD

Key Challenges and Considerations:

Addressing variability in clinical definitions (pre-diabetes, diabetes) and inconsistencies in electronic health records (EHR) across healthcare providers.

Importance of incorporating social determinants of health (SDoH) into diabetes prevention and control models.

Ensuring fairness and generalizability in AI-driven models, particularly in diverse populations.

COMMUNITY ADVISORY BOARD

Inclusivity and Disparities

The importance of capturing gestational diabetes and addressing racial/ethnic disparities in diabetes prevalence.

Need to consider the unique needs of underserved populations when developing and validating the tool.

Focus on creating a tool that is dynamic and responsive to community needs.

COMMUNITY ADVISORY BOARD

Adoption and Impact

Discussion on the intended user of the tool, ensuring that the tool is practical and easy to adopt.

The tool should build on individual strengths and align with user desires for health improvements.

Differentiating the tool from existing solutions and assessing its long-term impact on diabetes care outcomes.

COMMUNITY ADVISORY BOARD

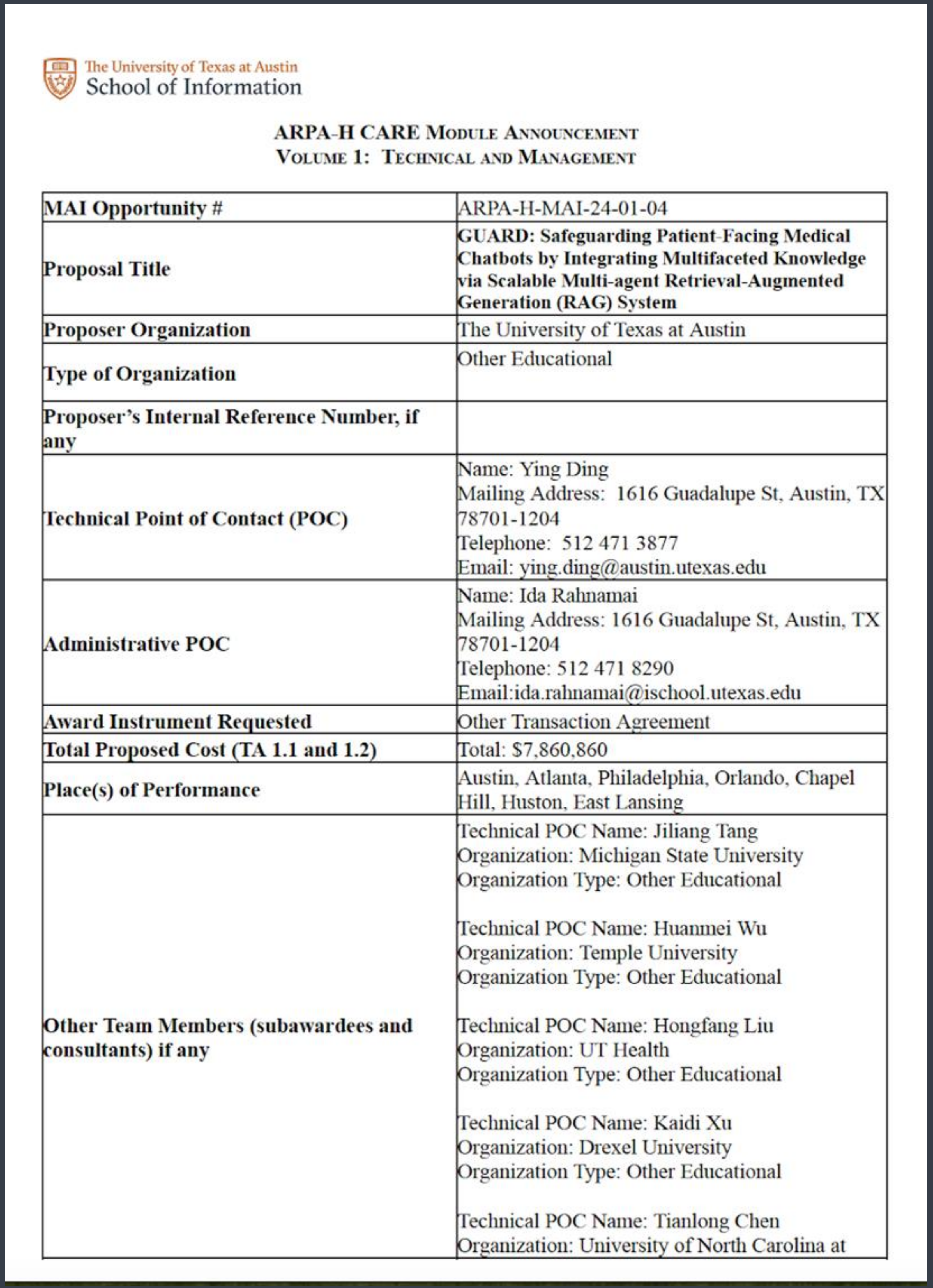
Next Steps and Focus Areas

Focus on ensuring data accuracy and reducing discrepancies in medical records and race/ethnicity categorization.

Continue efforts to address gestational diabetes and racial/ethnic disparities in diabetes prevalence.

Gather effectiveness data to ensure the tool helps in identifying undiagnosed cases and benefits the target population.

CHATBOTS（Advanced Research Projects Agency for Health, Department of Health and Human Services, Co-PI）



The University of Texas at Austin
School of Information

ARPA-H CARE Module Announcement
Volume 1: Technical and Management

MAI Opportunity #	ARPA-H-MAI-24-01-04
Proposal Title	GUARD: Safeguarding Patient-Facing Medical Chatbots by Integrating Multifaceted Knowledge via Scalable Multi-agent Retrieval-Augmented Generation (RAG) System
Proposer Organization	The University of Texas at Austin
Type of Organization	Other Educational
Proposer's Internal Reference Number, if any	
Technical Point of Contact (POC)	Name: Ying Ding Mailing Address: 1616 Guadalupe St, Austin, TX 78701-1204 Telephone: 512 471 3877 Email: ying.ding@austin.utexas.edu
Administrative POC	Name: Ida Rahnamai Mailing Address: 1616 Guadalupe St, Austin, TX 78701-1204 Telephone: 512 471 8290 Email:ida.rahnamai@ischool.utexas.edu
Award Instrument Requested	Other Transaction Agreement
Total Proposed Cost (TA 1.1 and 1.2)	Total: $7,860,860
Place(s) of Performance	Austin, Atlanta, Philadelphia, Orlando, Chapel Hill, Huston, East Lansing
Other Team Members (subawardees and consultants) if any	Technical POC Name: Jiliang Tang Organization: Michigan State University Organization Type: Other Educational Technical POC Name: Huanmei Wu Organization: Temple University Organization Type: Other Educational Technical POC Name: Hongfang Liu Organization: UT Health Organization Type: Other Educational Technical POC Name: Kaidi Xu Organization: Drexel University Organization Type: Other Educational Technical POC Name: Tianlong Chen Organization: University of North Carolina at

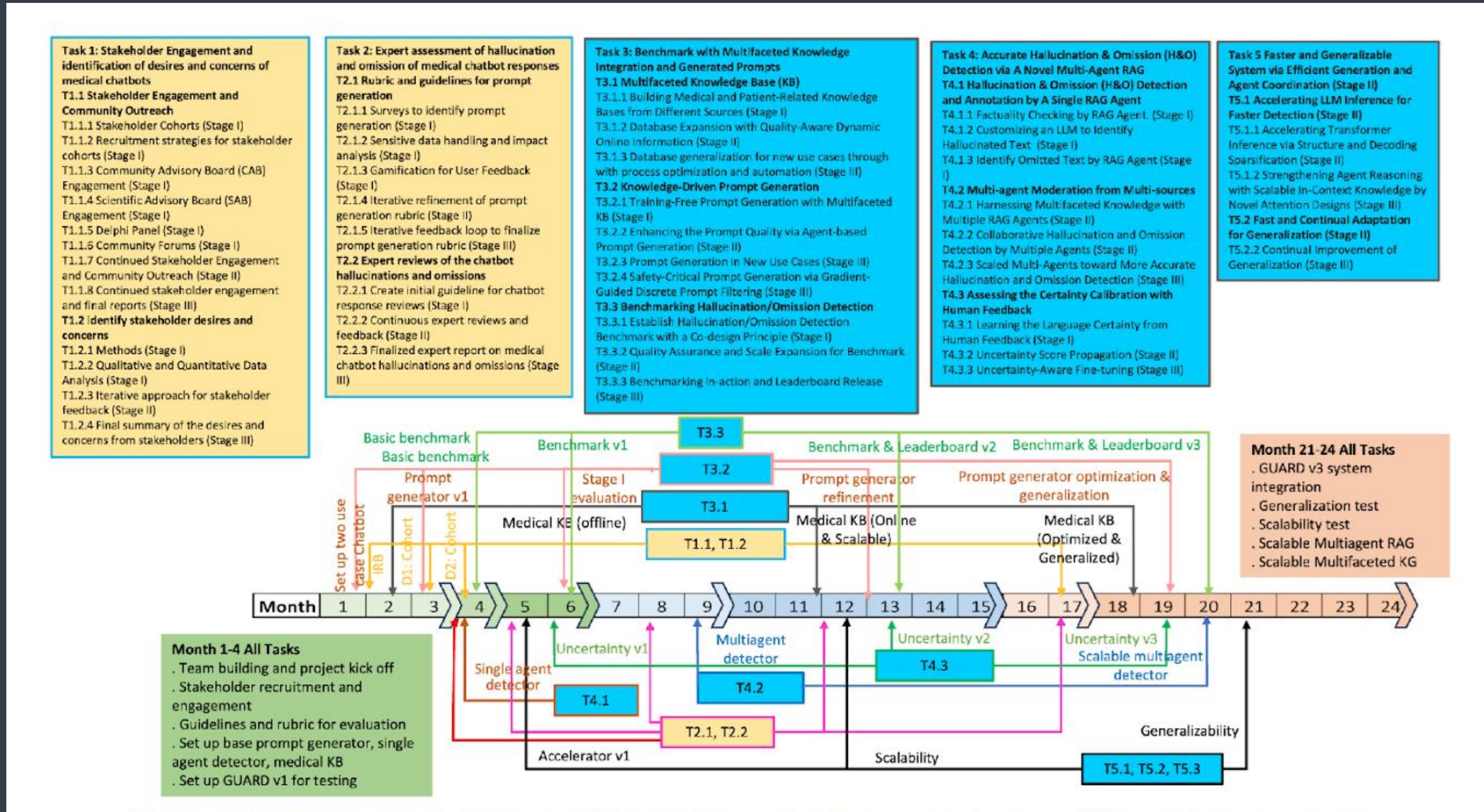


Figure 2. Overview of Task 1-5 in monthly activities and milestones and responsibility of the consortium

This proposal aims to develop innovative technologies to evaluate high-risk inaccuracies (hallucinations and omissions) for medical advice provided by the Large-Language -Model (LLM) chatbots.

COMMUNITY ENGAGEMENT

Community Advisory Board (CAB) Engagement. The CAB, comprising frontline staff, advocacy groups, and community leaders, ensures chatbots align with community needs, cultural competencies, ethics, and accessibility.
Expected Outcomes: **The first CAB meeting will introduce the project, followed by a chatbot demonstration and discussions on meeting community needs, credibility assessment, and ethical considerations.**

Scientific Advisory Board (SAB) Engagement. The SAB consists of experts in AI, clinical practice, and implementation science, guiding technical development and real-world deployment. They ensure scientific rigor and scalability.
Expected Outcomes: **Their prompts, revisions of prompts, and any chatbot hallucinations or omissions will be recorded using the chatbot's annotation function. Discussions will cover response quality, hallucinations or omissions, criteria for assessing responses, and technical feasibility. SAB members will also provide trusted medical information sources for maternal health and depression.**

COMMUNITY ENGAGEMENT

Delphi Panel. To ensure a comprehensive and informed approach to developing a safeguard ecosystem for medical chatbots, we will establish a Delphi panel consisting of three distinct subgroups.

Table 1. The Delphi panel groups and related information.

Delphi Groups	Participant Information
Expert Group A: Medical and AI Ethics Experts	**Participants**: 20 experts **Identification**: Through NIH Reporter, PubMed **Role**: Ensure high ethical standards for chatbots
Expert Group B: Technological and Clinical Experts	**Participants**: 20 professionals **Identification**: Background in AI technology and clinical practice in healthcare settings **Role**: Address technical and practical aspects of chatbot functionality
Expert Group C: Stakeholders and End-Users	**Participants**: 20 clinicians, patients, healthcare policymakers **Identification**: Direct interaction with or impact from medical chatbots **Role**: Understand practical needs and concerns, ensure user-friendliness & effectiveness

Table 2. The procedure for each Delphi Panel

Step 1. Create Survey	Created based on the analysis of stakeholder Cohorts, CAB, and SAB meetings, including demographics; trusted sources for medical advice; concerns and desires regarding medical chatbots.
Step 2. Questions & annotations	Each panel member will receive three questions, use our chatbot to seek information to answer these questions, and annotate when they spot hallucinations or omissions in the chatbot responses.
Step 3. Feedback	Each member will provide feedback to describe their overall strategies to interact with the chatbot to obtain satisfactory answers, criteria for evaluating chatbot quality, and ethical considerations.
Step 4. Discussions	The expert groups will examine different aspects of designing medical chatbots.
Group A	Focus participants' desires and concerns associated with medical chatbots; ethical considerations in development and potential risks with data privacy, user manipulation, and response accuracy.
Group B	Focus on ethical considerations; hallucination types; omission types; prompt formulation and reformulation and best practices; criteria to assess chatbot response quality; and risk mitigation.
Group C	Focus on using chatbots; chatbot UI design; prompt generation and best practices; response credibility, perception concerning chatbot hallucination and omission; socio-ethical concerns
Step 5. Report	Data analysis, stakeholders' desires and concerns, and criteria/rubric for prompt and assessment.

Collaborative Research: DSC: National Student Data Corps - Data and Knowledge for Social Good (NSDC-DAKS)

Project Summary

Overview

This "Collaborative Research: DSC: National Student Data Corps - Data and Knowledge for Social Good (NSDC-DAKS") project brings together 10 institutions, including 2 in EPSCoR states, to engage underrepresented minorities to learn how to leverage data to develop knowledge and insights to address societal challenges. Through a collaborative partnership bringing together real-world data from 14 NSF-funded Open Knowledge Network (OKN), Proto-OKN, Harnessing the Data Revolution (HDR) and Technology Innovation and Partnership (TIP) projects, we will proactively engage and enable underrepresented students with flexible educational pathways to build a robust national STEM and data science pipeline. We will empower undergraduate, community college and grade 6-12 students with a focus on minority serving institutions with basic to advanced methods to create actionable knowledge from data, giving them hands-on experience in using real-world data to enable learning in the community and address societal challenges. The societal challenges we will address include homelessness, health disparities, social and structural determinants of health, pandemic response and recovery, criminal justice, and climate resilience related to agriculture. Leveraging the collaborative and open Northeast Big Data Innovation Hub's (NEBDHub) National Student Data Corps (NSDC) portal and program, we will extend the learning to support data science and knowledge graph education, fostering robust project outcomes through data discovery, knowledge access, data sharing and data-based insights. Training resources and programs from the base NEBDHub and NSDC, as well as Proto-OKN use case, Education Gateway and Fabric teams, will provide foundational data science education and training across the data lifecycle for undergraduate, community college, MSI, and grade 6-12 students, teaching them how to work with real-world data for real-world societal challenges, including practical training with hands-on projects. Students will earn certificates of participation and completion for their engagement and success in projects offered through the program. Topics will include data science ethics, data science pipeline, artificial intelligence, geospatial analysis, as well as topics aligned with the Proto-OKN such as knowledge graph and knowledge network creation, usability and interoperation. By bridging the data-to-knowledge gap, we will build capabilities in the community to enable more effective decision-making for urban and rural communities at local, state, and national levels. Leveraging the diverse and inclusive NEBDHub and NSDC community of over 10,200 individuals including 217 MSIs, 171 institutions in 26 EPSCoR states, 51 community colleges, and 27 K-12 organizations, including educators, students, data scientists, computer scientists, social scientists, domain experts, community stakeholders, and professionals, we will develop a workforce-ready cohort of data scientists and technologists, equipped with practical experience.

Collaborative Research: DSC: National Student Data Corps - Data and Knowledge for Social Good (NSDC-DAKS)

Table 1. RE-AIM (Reach, Effectiveness, Adoption, Implementation, and Maintenance) Framework [8-11]

RE-AIM Constructs	Questions	Measures	Data Collection Methods
Reach	How many and what types of students participated in the DSC program?	Number of students enrolled, demographic characteristics, participation rates.	Enrollment records, demographic surveys, participation logs.
Effectiveness	What is the impact of the DSC experience on student gains in data science, KG/OKN, societal impact knowledge, and other skills?	Pre- and post-assessment scores, self-reported skill improvements, project evaluations, increased knowledge of societal challenges and learning of how to apply data science to address these issues.	Surveys, assessments, project reports.
Adoption	How widely has the DSC curriculum been adopted by institutions?	Number of institutions integrating the curriculum, educator/facilitator feedback.	Institutional reports, educator surveys.
Implementation	Was the DSC program delivered as intended across institutions?	Adherence and fidelity to curriculum, quality of project implementation.	Monitoring logs, site visits, educator and facilitator interviews.
Maintenance	Is the DSC program sustainable and are its materials reusable and generalizable?	Long-term skill retention, institutionalization of the curriculum, ongoing engagement.	Follow-up surveys, institutional feedback, community engagement metrics.

FUTURE DIRECTION

FUTURE DIRECTION

Enhance the impact of implementation strategies.

Conduct Effectiveness Research

Integration of IS, CE and AI

Harness implementation science to promote health equity

Increase economic evaluations of implementation strategies

FUTURE DIRECTION

Leverage implementation science and AI to address health disparities in biomedical prevention or treatment research, including noncommunicable diseases such as **cancer, Alzheimer and diabetes.**

NIH Public Access
Author Manuscript
AIDS Educ Prev. Author manuscript; available in PMC 2014 April 15.
Published in final edited form as:
AIDS Educ Prev. 2014 February ; 26(1): 68–80. doi:10.1521/aeap.2014.26.1.68.

NIH-PA Author Manuscript

ADAPTATION AND IMPLEMENTATION OF HoMBReS: A COMMUNITY-LEVEL, EVIDENCE-BASED HIV BEHAVIORAL INTERVENTION FOR HETEROSEXUAL LATINO MEN IN THE MIDWESTERN UNITED STATES

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Abstract

Over the past decade, the midwestern United States has witnessed a dramatic increase in its Latino population. The lack of culturally and linguistically congruent resources coupled with high incidence and prevalence rates of HIV among Latinos living in the Midwest merits attention. HoMBReS: Hombres Manteniendo Bienestar y Relaciones Saludables (Men Maintaining Wellbeing and Healthy Relationships) is a community-level social network intervention designed for Latino men. We describe the adaptation and implementation of HoMBReS for Latino men living in Indianapolis, Indiana, the second largest city in the Midwest. Five *Navegantes* (lay health educators) were trained; they provided a total of 34 educational *charlas* (small group didactic sessions). A total of 270 Latino men attended the charlas and were offered no-cost screening for HIV and sexually transmitted infections (STI). Three participants tested HIV positive and 15 screened positive for STI. The charlas coupled with the testing initiative, served as a successful method to increase sexual health knowledge among Latino men and to link newly-diagnosed HIV/STI-positive individuals to treatment and care. The adaptation and implementation of HoMBReS respond to the CDC and NIH call to increase HIV testing and service provision among vulnerable populations.

Baumann and Cabassa *BMC Health Services Research* (2020) 20:190
https://doi.org/10.1186/s12913-020-4975-3
BMC Health Services Research

DEBATE Open Access

Reframing implementation science to address inequities in healthcare delivery

Check for updates

Ana A. Baumann[†] and Leopoldo J. Cabassa[*†]

Abstract

Background: Research has generated valuable knowledge in identifying, understanding, and intervening to address inequities in the delivery of healthcare, yet these inequities persist. The best available interventions, programs and policies designed to address inequities in healthcare are not being adopted in routine practice settings. Implementation science can help address this gap by studying the factors, processes, and strategies at multiple levels of a system of care that influence the uptake, use, and the sustainability of these programs for vulnerable populations. We propose that an equity lens can help integrate the fields of implementation science and research that focuses on inequities in healthcare delivery.

Main text: Using Proctor et al.' (12) framework as a case study, we reframed five elements of implementation science to study inequities in healthcare. These elements include: 1) focus on reach from the very beginning; 2) design and select interventions for vulnerable populations and low-resource communities with implementation in mind; 3) implement what works and develop implementation strategies that can help reduce inequities in care; 4) develop the science of adaptations; and 5) use an equity lens for implementation outcomes.

Conclusions: The goal of this paper is to continue the dialogue on how to critically infuse an equity approach in implementation studies to proactively address healthcare inequities in historically underserved populations. Our examples provide ways to operationalize how we can blend implementation science and healthcare inequities research.

Keywords: Implementation science, Healthcare inequities, Adaptation, Equity

Adaptation of an effective school-based sexual health promotion program for youth in Colombia

Check for updates

Alexandra Morales[a], Eileen Garcia-Montaño[b], Cristian Barrios-Ortega[b], Janivys Niebles-Charris[b], Paola Garcia-Roncallo[b], Daniella Abello-Luque[b], Mayra Gomez-Lugo[c], Diego Alejandro Saavedra[c], Pablo Vallejo-Medina[c,*], José Pedro Espada[a], Marguerita Lightfoot[e], Omar Martínez[d]

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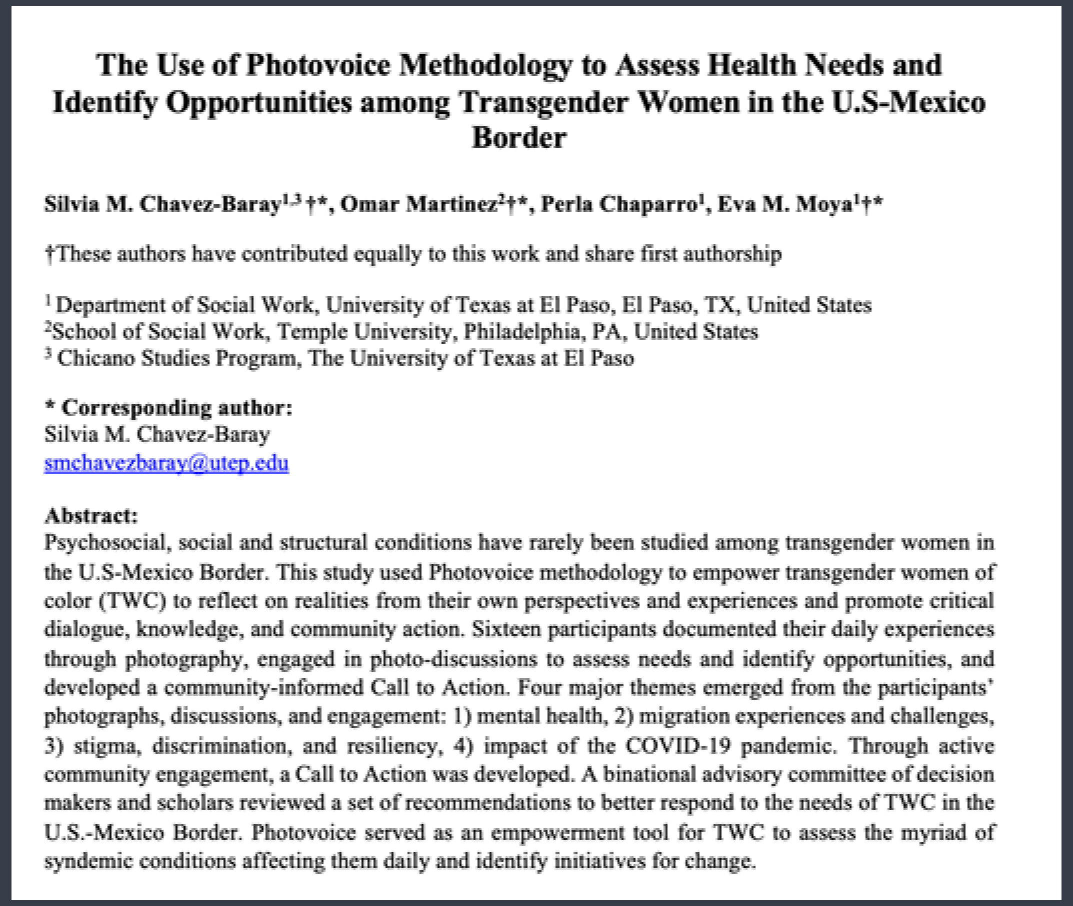
HHS Public Access
Author manuscript
Commonhealth (Phila). Author manuscript; available in PMC 2022 July 07.
Published in final edited form as:
Commonhealth (Phila). 2022 June ; 3(2): 75–86.

Dissemination and Implementation Science to Advance Health Equity: An Imperative for Systemic Change

GABRIELLA M. MCLOUGHLIN, PHD, MS[1,2], OMAR MARTINEZ, JD, MPH, MS[3]

FUTURE DIRECTION

Integrating AI to support existing **locally-developed, homegrown prevention and treatment interventions can enhance their responsiveness to environmental and structural conditions,** including approaches like Photovoice and peer-led approaches. AI can personalize interventions, analyze community-generated data, and provide adaptive, real-time support while maintaining the strengths of these participatory, community-driven models. This integration ensures interventions remain contextually relevant and scalable while addressing local needs and challenges.



The Use of Photovoice Methodology to Assess Health Needs and Identify Opportunities among Transgender Women in the U.S-Mexico Border

Silvia M. Chavez-Baray[1,3] †*, Omar Martinez[2]†*, Perla Chaparro[1], Eva M. Moya[1]†*

†These authors have contributed equally to this work and share first authorship

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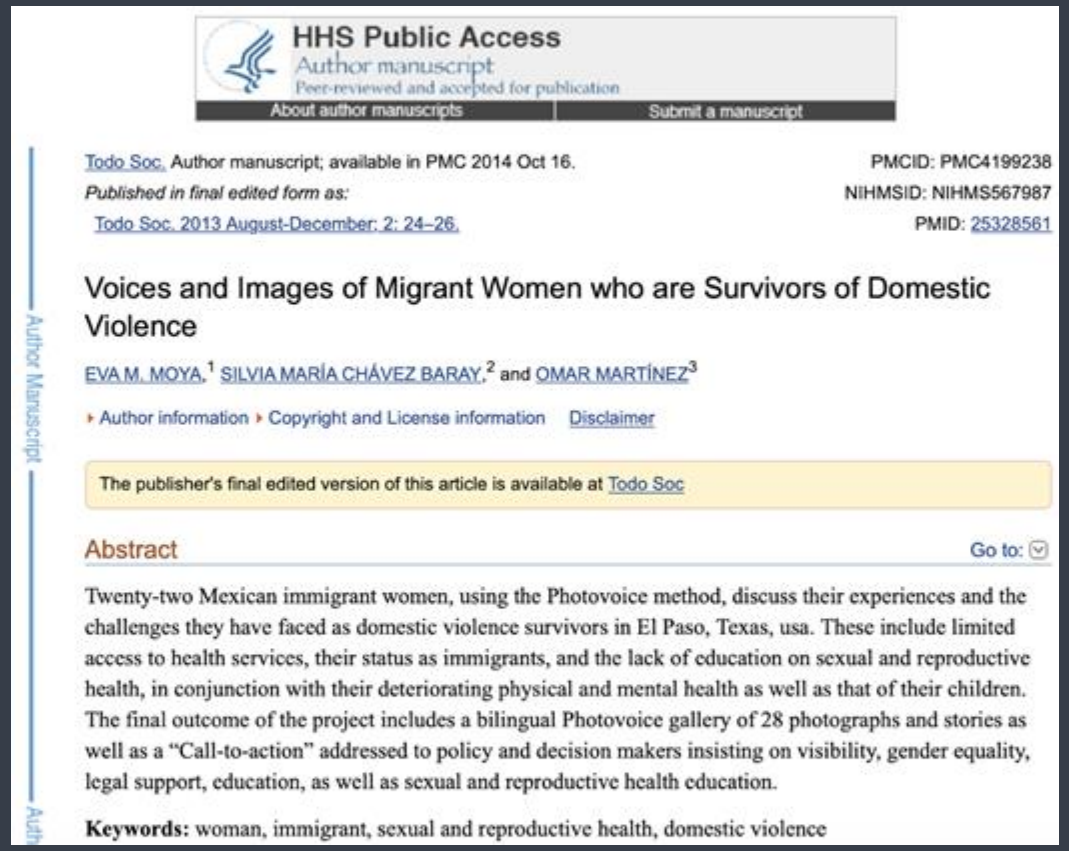
Abstract:
Psychosocial, social and structural conditions have rarely been studied among transgender women in the U.S-Mexico Border. This study used Photovoice methodology to empower transgender women of color (TWC) to reflect on realities from their own perspectives and experiences and promote critical dialogue, knowledge, and community action. Sixteen participants documented their daily experiences through photography, engaged in photo-discussions to assess needs and identify opportunities, and developed a community-informed Call to Action. Four major themes emerged from the participants' photographs, discussions, and engagement: 1) mental health, 2) migration experiences and challenges, 3) stigma, discrimination, and resiliency, 4) impact of the COVID-19 pandemic. Through active community engagement, a Call to Action was developed. A binational advisory committee of decision makers and scholars reviewed a set of recommendations to better respond to the needs of TWC in the U.S.-Mexico Border. Photovoice served as an empowerment tool for TWC to assess the myriad of syndemic conditions affecting them daily and identify initiatives for change.



Todo Soc. Author manuscript; available in PMC 2014 Oct 16. PMCID: PMC4199238
Published in final edited form as: NIHMSID: NIHMS567987
Todo Soc. 2013 August-December; 2: 24–26. PMID: 25328561

Author Manuscript

Voices and Images of Migrant Women who are Survivors of Domestic Violence

EVA M. MOYA,[1] SILVIA MARÍA CHÁVEZ BARAY,[2] and OMAR MARTÍNEZ[3]

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The publisher's final edited version of this article is available at Todo Soc

Abstract Go to:

Twenty-two Mexican immigrant women, using the Photovoice method, discuss their experiences and the challenges they have faced as domestic violence survivors in El Paso, Texas, usa. These include limited access to health services, their status as immigrants, and the lack of education on sexual and reproductive health, in conjunction with their deteriorating physical and mental health as well as that of their children. The final outcome of the project includes a bilingual Photovoice gallery of 28 photographs and stories as well as a "Call-to-action" addressed to policy and decision makers insisting on visibility, gender equality, legal support, education, as well as sexual and reproductive health education.

Keywords: woman, immigrant, sexual and reproductive health, domestic violence

FUTURE DIRECTION

Journal of Racial and Ethnic Health Disparities (2021) 8:1456–1466
https://doi.org/10.1007/s40615-020-00908-2

Check for updates

Vital Voices: HIV Prevention and Care Interventions Developed for Disproportionately Affected Communities by Historically Underrepresented, Early-Career Scientists

Madeline Y. Sutton[1] · Omar Martinez[2] · Bridgette M. Brawner[3] · Guillermo Prado[4] · Andres Camacho-Gonzalez[5] · Yannine Estrada[4] · Pamela Payne-Foster[6] · Carlos E. Rodriguez-Diaz[7,8] · Sophia A. Hussen[9] · Yzette Lanier[10] · Jacob J. van den Berg[11] · Souhail M. Malavé-Rivera[8] · DeMarc A. Hickson[12] · Errol L. Fields[13]

Mentoring and supporting the next generation of underrepresented scientists.

FUTURE DIRECTION

Expand **robust community-research collaborations** defined by: 1) recognition that community development is an important focus of research, 2) commitment to build upon strengths and resources of individuals and communities, 3) promotion of a process that actively addresses social inequalities, and 4) dissemination of findings and knowledge to all partners.

FUTURE DIRECTION

Scaling Community Engagement: How can we develop scalable models of community participation to ensure that AI interventions remain inclusive and effective?

AI Policy and Advocacy: How can community voices influence policy decisions on AI, particularly in healthcare settings?

Empowering Communities as Co-Developers: Future AI tools should not only serve communities but be co-developed with them, ensuring continuous relevance and impact.

ACKNOWLEDGEMNTS

COMMUNITY MEMBERS AND PARTNERS

MENTORS

Participants and Community Members
alaei familia
CDC MARI Family
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Florida International University
    Nelson and Sheilla Rodriguez
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    Erin Loubier
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Nova Southeastern University
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THANK YOU!

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"Living on borders and in margins, keeping intact one's shifting and multiple identity and integrity, is like trying to swim in a new element, an 'alien' element."

Gloria E. Anzaldúa

Applications of Social Determinants of Health and AI/ML in Public Health

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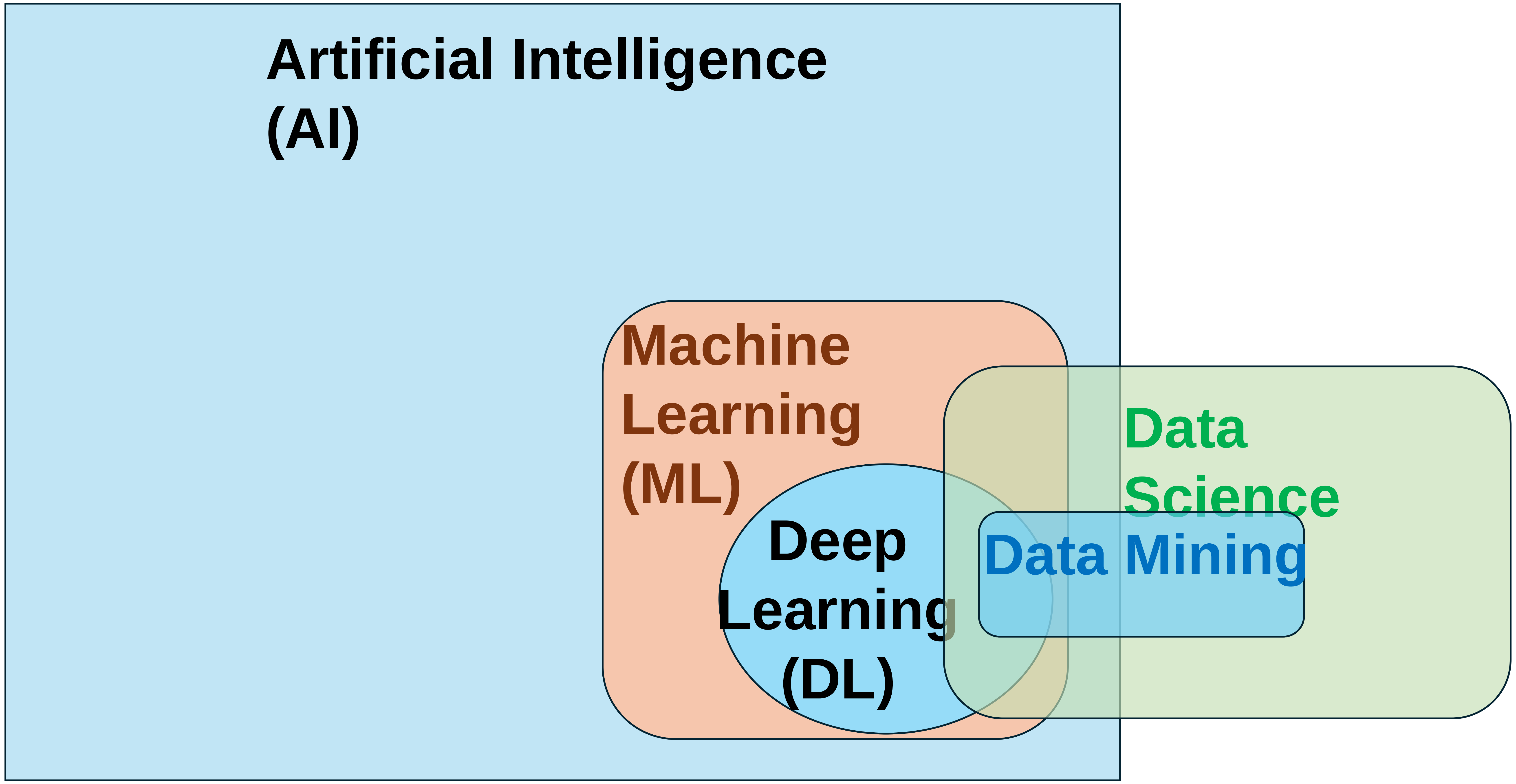
Introduction to AI/ML

Introduction of Artificial Intelligence (AI)

- Artificial intelligence is the science of making computers act like humans.
  - The ability for a computer to think, learn, and simulate human mental processes, such as perceiving, reasoning, and learning.
- AI can be used to solve problems that humans solve using their intelligence.
  - Independently perform
  - complex tasks that once
  - required human input

Relations between AI and Other Technologies
(i.e., ML, DL, DS, and DM)



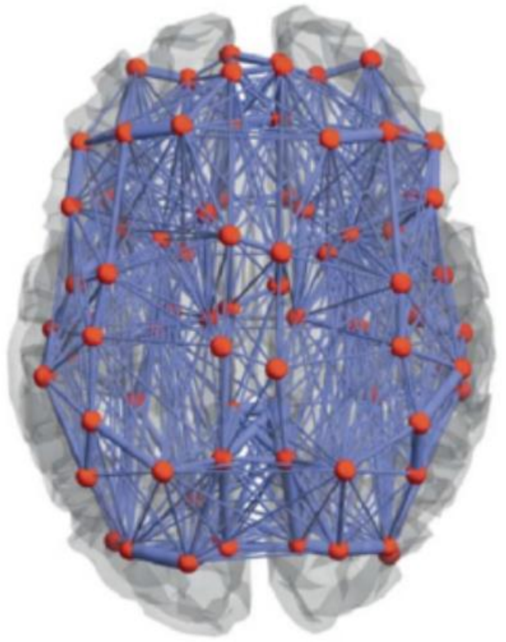
Introduction of ML and Examples

Typical applications of ML

Image classification
https://www.image-net.org/index.php

Speech recognition
https://www.analyticsinsight.net/nlp-augments-the-power-of-chatbots-and-voice-in-2019/

Robotics
https://arxiv.org/pdf/1504.00702.pdf



Bioinfomatics
https://www.ncbi.nlm.nih.gov/pubmed/22565236

Using ML for predictive modeling

Data → Input → Apply an ML Model → Output → Prediction

Data

Examples:
- Infectious diseases
- ED utilization
- Electronic healthcare records
- …

Apply an ML Model

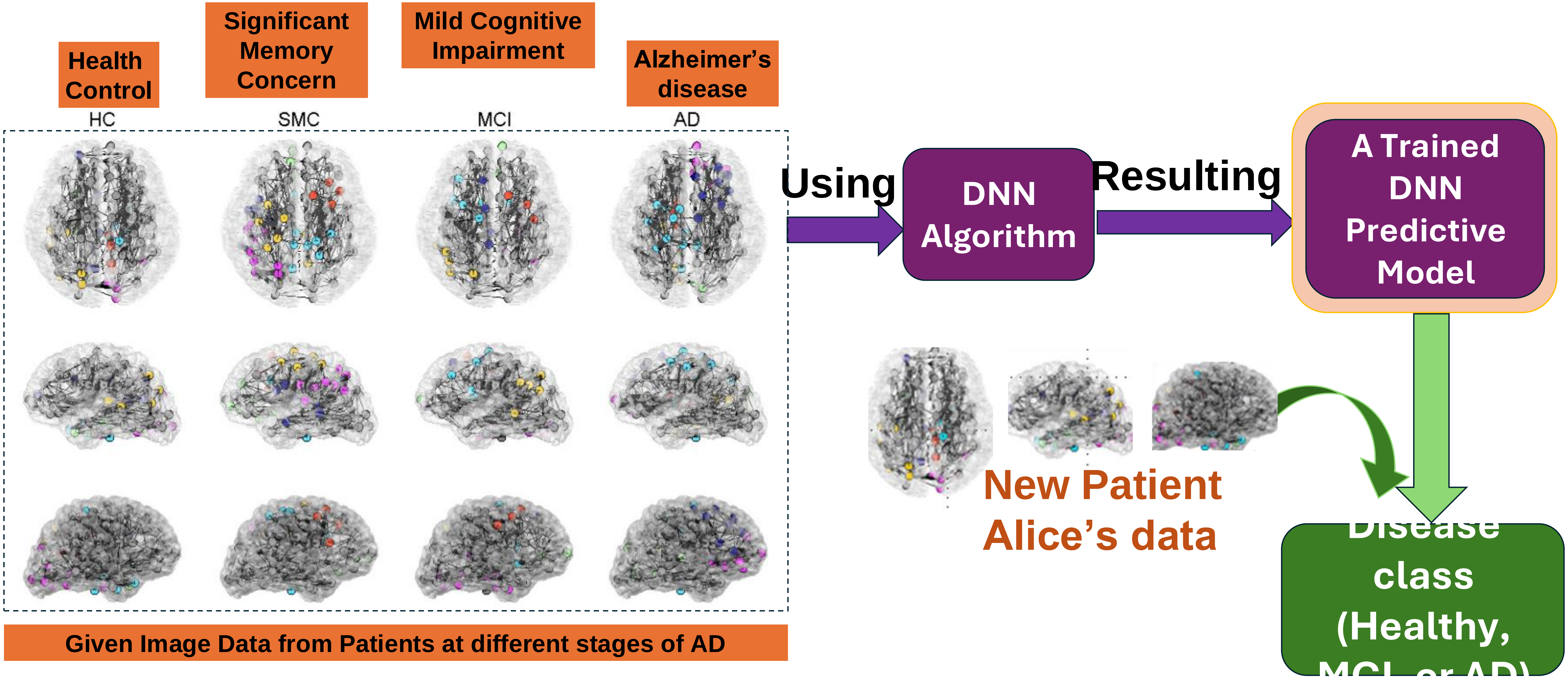
Examples:
- Linear regression
- Logistic regression
- K nearest neighbor
- Deep neural network
- …

Prediction

Examples:
- Disease class
- Heart failure rate
- …

Example: Alzheimer’s disease prediction

- Building a Deep Neural Network (DNN) for AD prediction



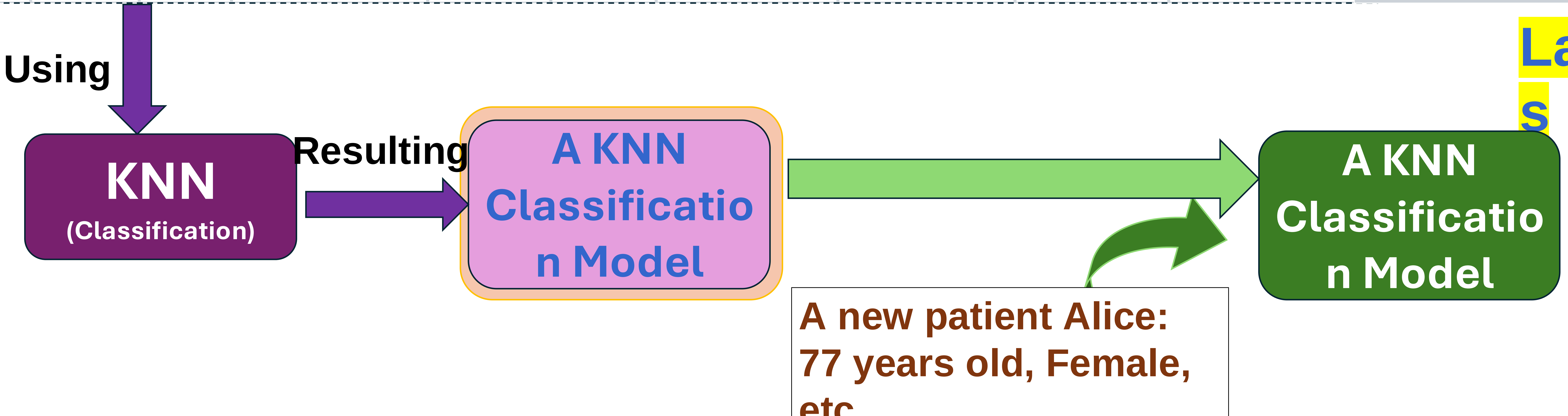
Another example

- Building a K-Nearest Neighbor (KNN) for heart disease classification

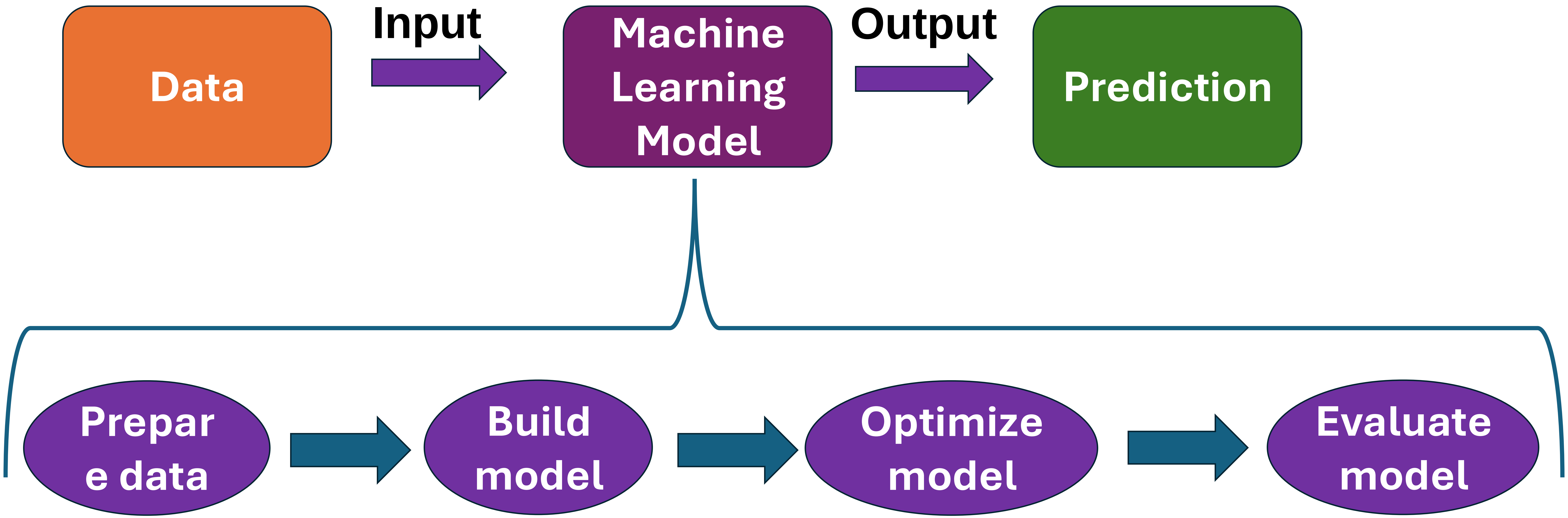
Features

age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	HeartDisease
63	1	3	145	233	1	0	150	0	2.3	Yes
37	1	2	130	250	0	1	187	0	3.5	No
41	0	1	130	204	0	0	172	0	1.4	No

Labels

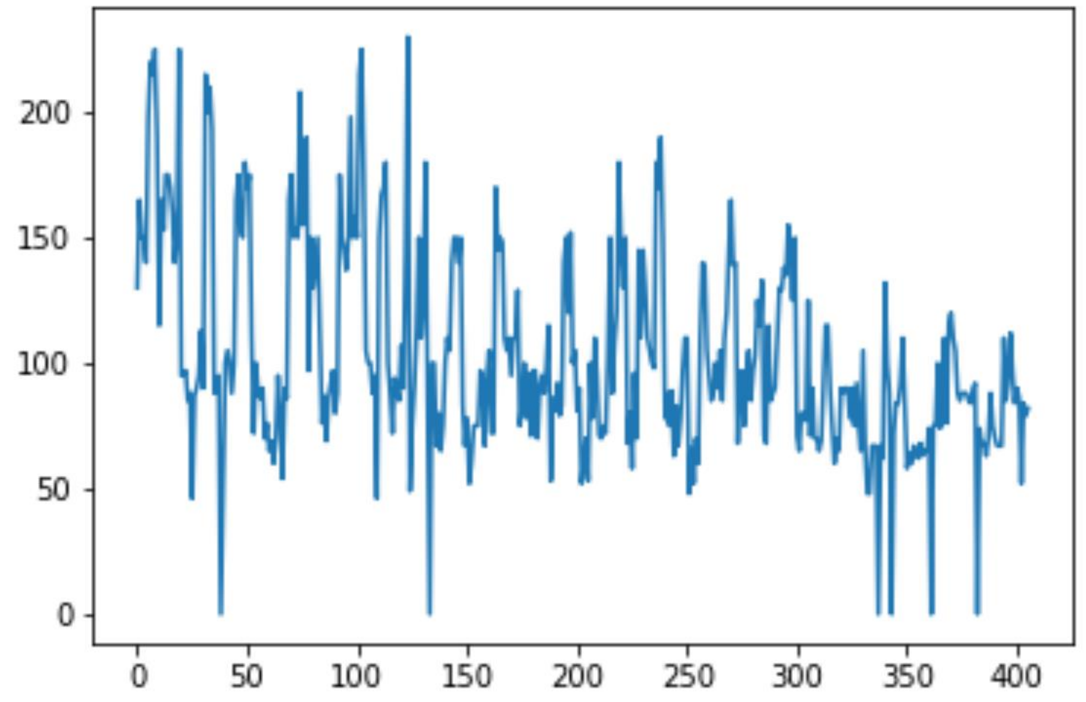


Basic ML workflow



Step 1: Prepare data

- Data used to train the ML model needs to be processed or cleaned before they can be used effectively. Here are some common steps



Remove noises/outliers

```
ocean_proximity
            NaN
            NaN
            NaN
            NaN
       NEAR BAY
```

Handle missing values

```
ocean_proximity
       NEAR BAY
       NEAR BAY
       NEAR BAY
       NEAR BAY
       NEAR BAY
```

Categorical → numerical feature

Feature-1	Feature-2
126.0	8.3252
1138.0	8.3014
177.0	7.2574
219.0	5.6431
259.0	3.8462

Different scales

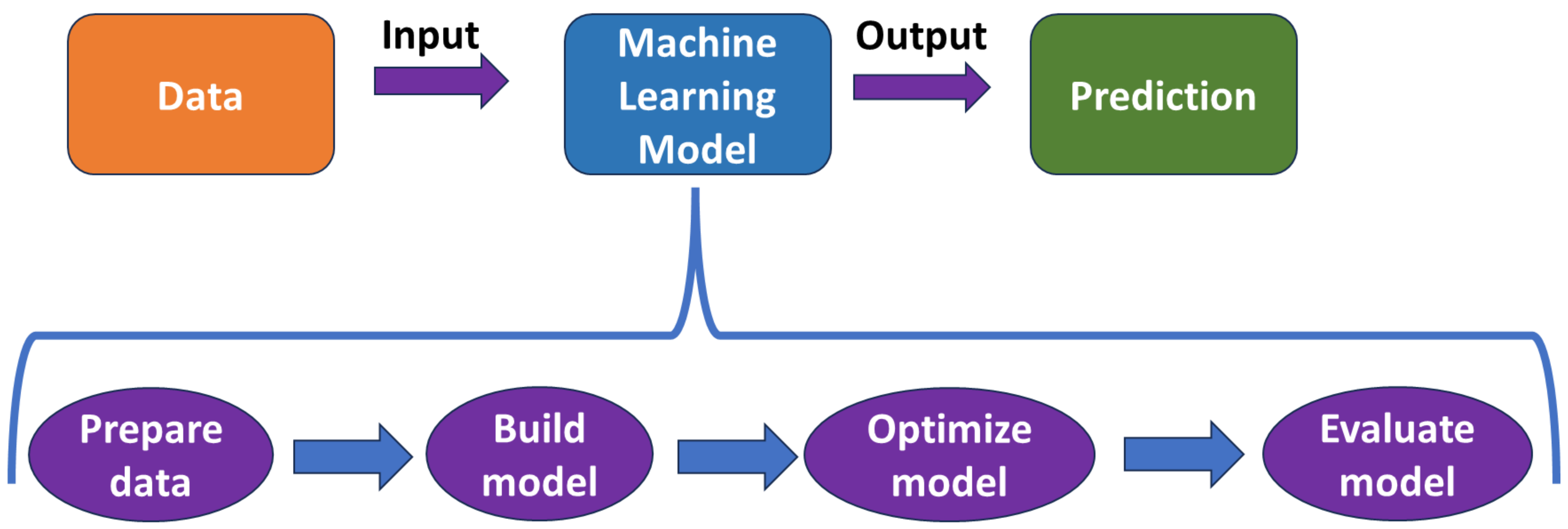
Feature normalization

After cleaning, data is partitioned into training set and test set

- Training set is used to train the ML model.
- The testing set is used to validate the ML model after training is completed

Training set	Testing set

Step 2: Build Models



- Different models have different performance

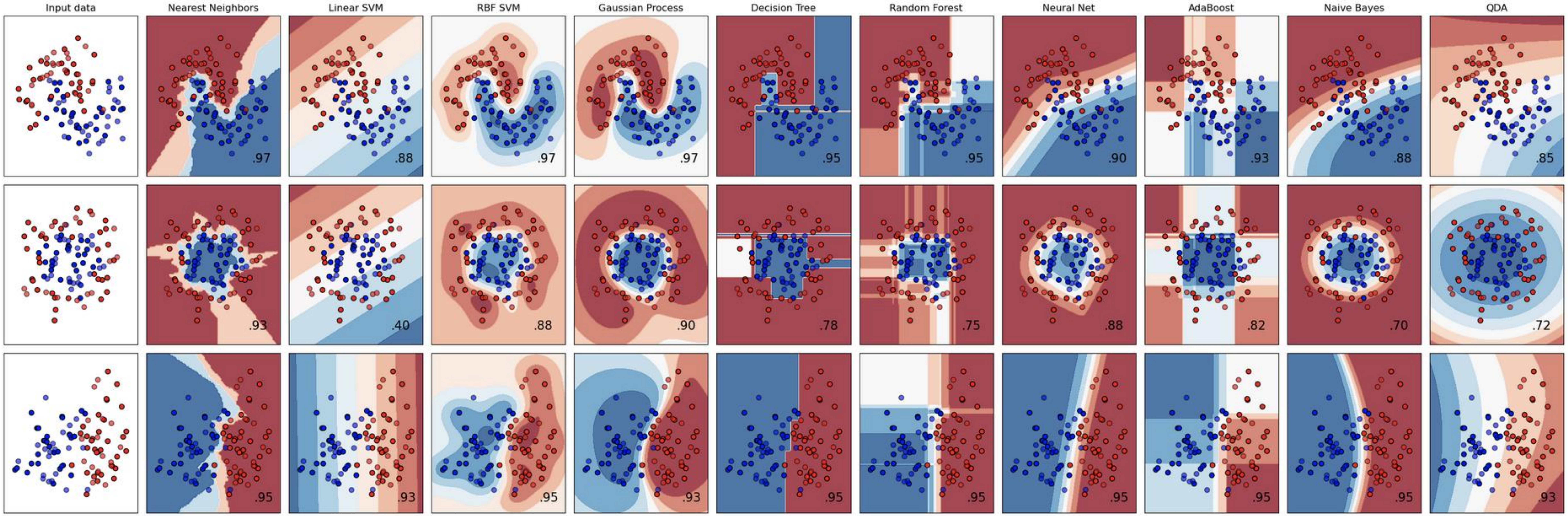


Fig: https://scikit-learn.org/stable/auto_examples/classification/plot_classifier_comparison.ht

Step 3: Optimize model

Use the optimizer to find the optimal model

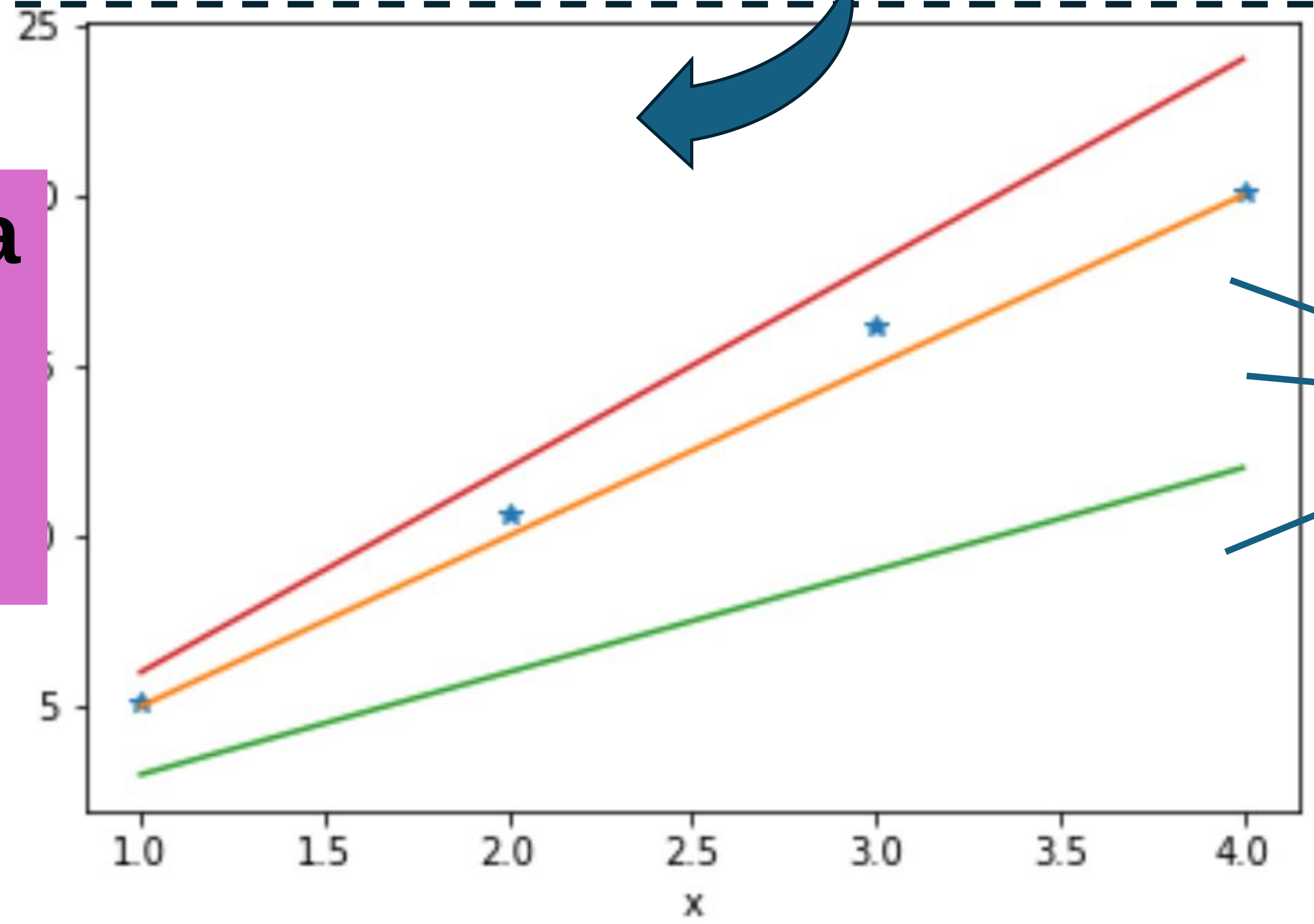
Training Data

ML Model

Black-box Optimizer (Gradient Descent)

Optimal Model

Use optimizer



- Blue dots: training data
- Red line: model-1
- Orange line: model-2
- Green line: model-3

Optimizer finds an optimal model, i.e., the orange line

Step 4. Evaluate model

- There are many different ways of
- evaluating a ML model.
- Some commonly used metrics are
  - Accuracy
  - Precision
  - Recall

Ground-truth	Prediction	Correct?
1	0	N
1	1	Y
0	0	Y
0	0	Y
1	1	Y
1	1	Y
0	1	N

- When the data is **balanced**, we can use accuracy metric
  - **Balanced** means that # of positive samples is almost the same with # of negative samples

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} = 5/7$$

odel (continued)

Ground-truth	Prediction	Correct?
1	0	N
0	0	Y
0	0	Y
0	0	Y
0	0	Y
0	0	Y
0	0	Y

- **What happens if data is not balanced?**
  - A poor ML model that always predicts negative (0) will still have a high accuracy because the underlying data is not balanced

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} = 6/7$$

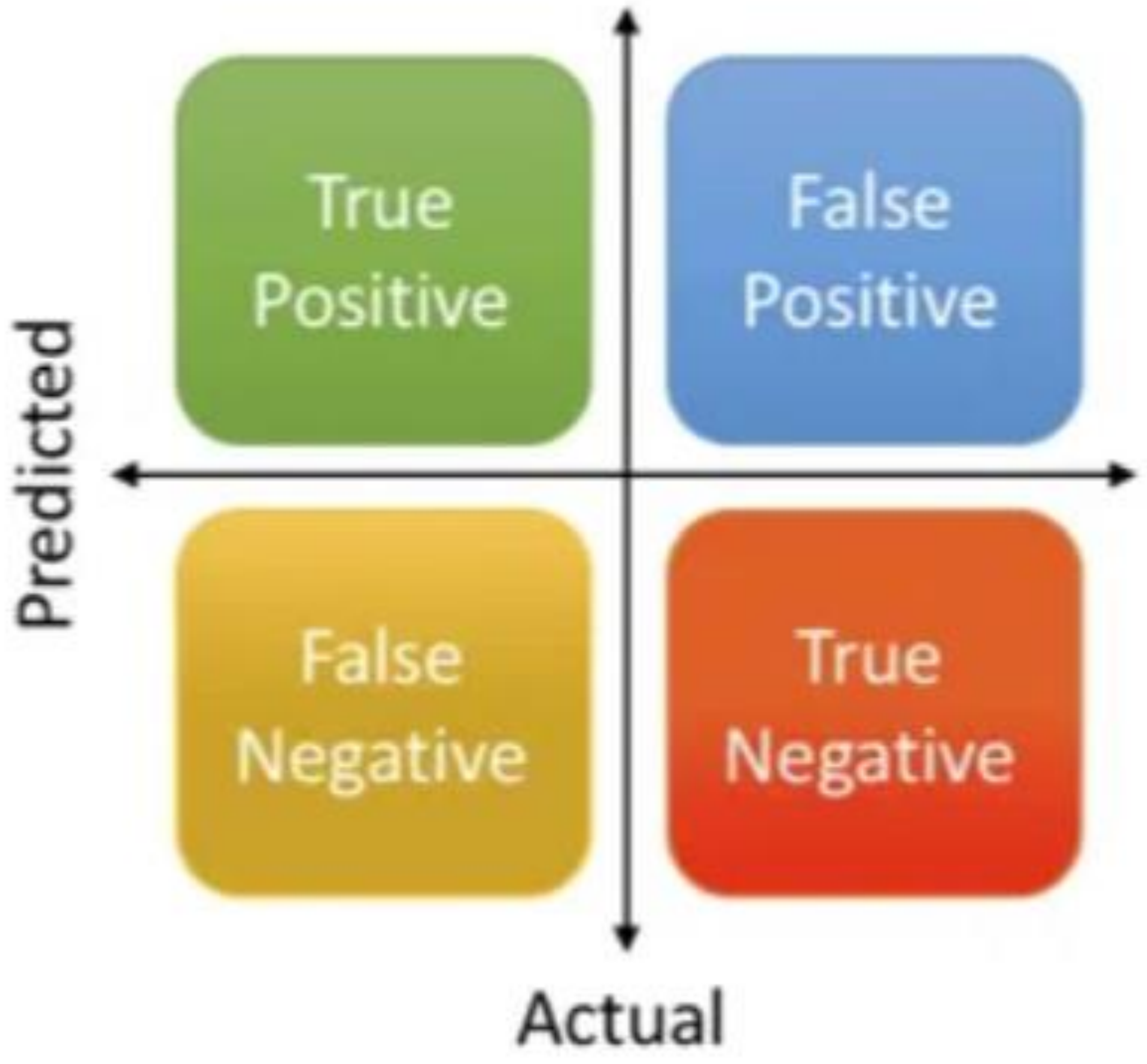
The proportion of positive predictions is actually correct

$$\textbf{Precision} = \frac{\text{True Positive}}{\text{Actual Results}} \text{ or } \frac{\text{True Positive}}{\text{True Positive + False Positive}}$$

The proportion of positive predictions is classified correct

$$\textbf{Recall} = \frac{\text{True Positive}}{\text{Predicted Results}} \text{ or } \frac{\text{True Positive}}{\text{True Positive + False Negative}}$$

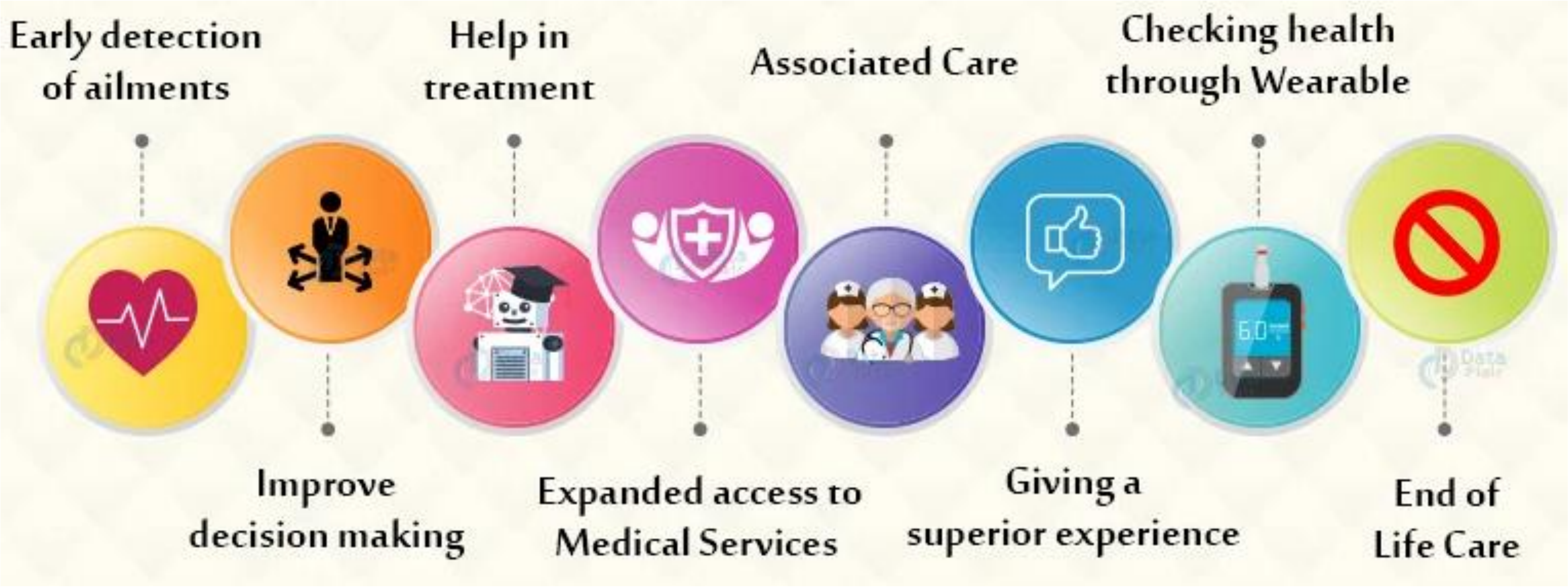
$$\textbf{Accuracy} = \frac{\text{True Positive + True Negative}}{\text{Total}}$$



Fairness of ML/AI

Role of AI in Healthcare

- **Quick question:** What are some examples of AI applications in Healthcare?



A Motivating Example

A pulse oximeter is a device used to measure the level of oxygen in the blood stream.

SHORT WAVE

LISTEN & FOLLOW

COVID-19 made pulse oximeters ubiquitous. Engineers are fixing their racial bias

FEBRUARY 13, 2023 · 12:30 AM ET

By Anil Oza, Emily Kwong, Thomas Lu, Gabriel Spitzer

During the covid pandemic, pulse oximeters were used to determine the severity of patients with covid.

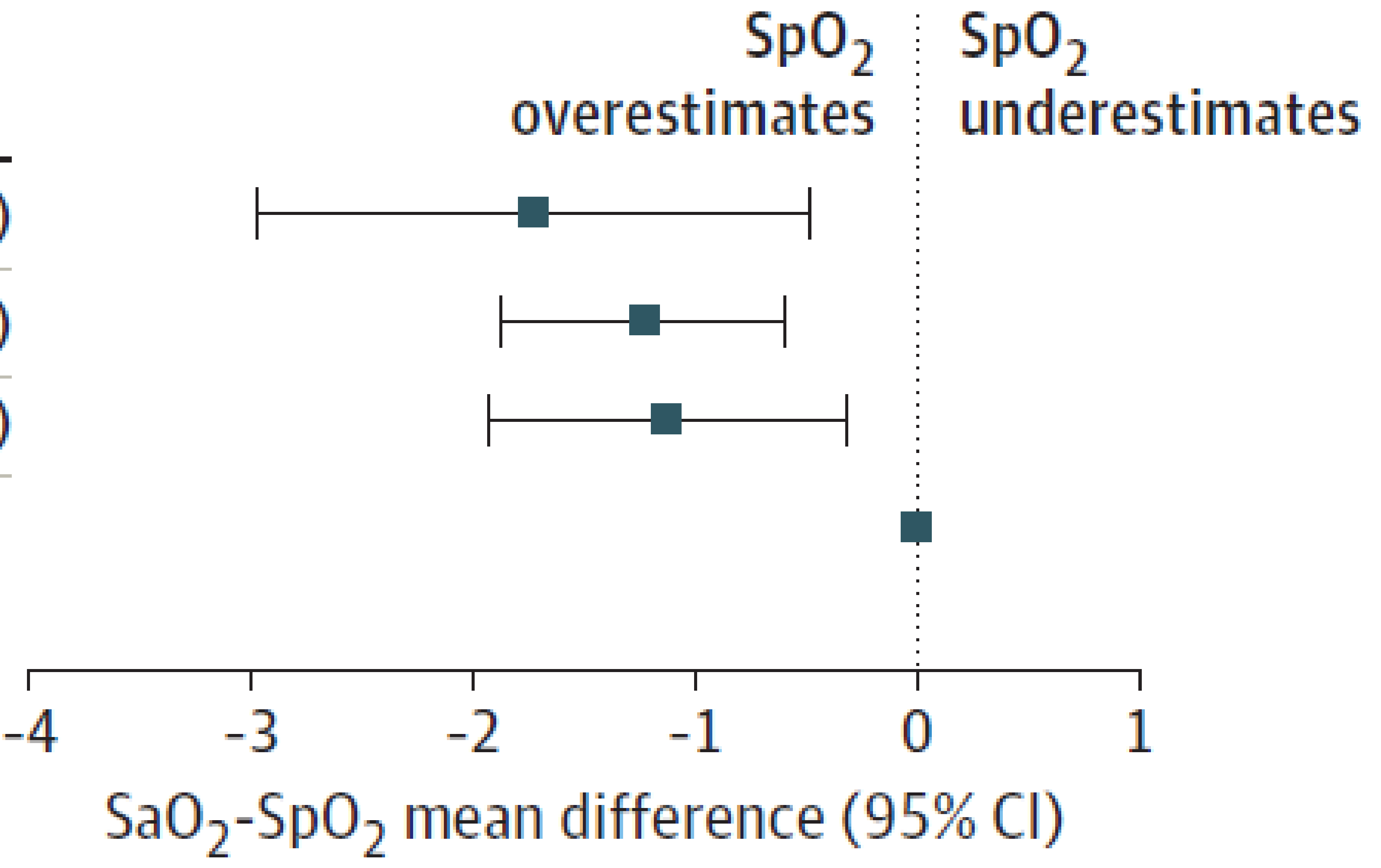
https://www.npr.org/2023/02/10/1156166554/covid-19-pulse-oximeters-racial-bias

Example of bias

- Technology was tested using populations that were not racially diverse. People with darker skin color were not adequately represented.
- Oximeter readings were less accurate for peoples of color.

Figure 3. Relative Mean Differences With 95% CIs of SaO_2-SpO_2 for Patients of Racial and Ethnic Minority Groups Based on the Adjusted Parsimonious Linear Mixed-Effects Model

Race and ethnicity	Patients, No.	Observations, No.	Mean difference (95% CI)	*P* value
Asian	54	1696	-1.73 (-2.98 to -0.48)	.007
Black	399	10517	-1.23 (-1.87 to -0.59)	<.001
Hispanic	188	6693	-1.13 (-1.93 to -0.32)	.006
White	363	8461	0 [Reference]	



Fawzy, Ashraf, et al. "Racial and ethnic discrepancy in pulse oximetry and delayed identification of treatment eligibility among patients with COVID-19." *JAMA internal medicine* 182.7 (2022): 730-738.

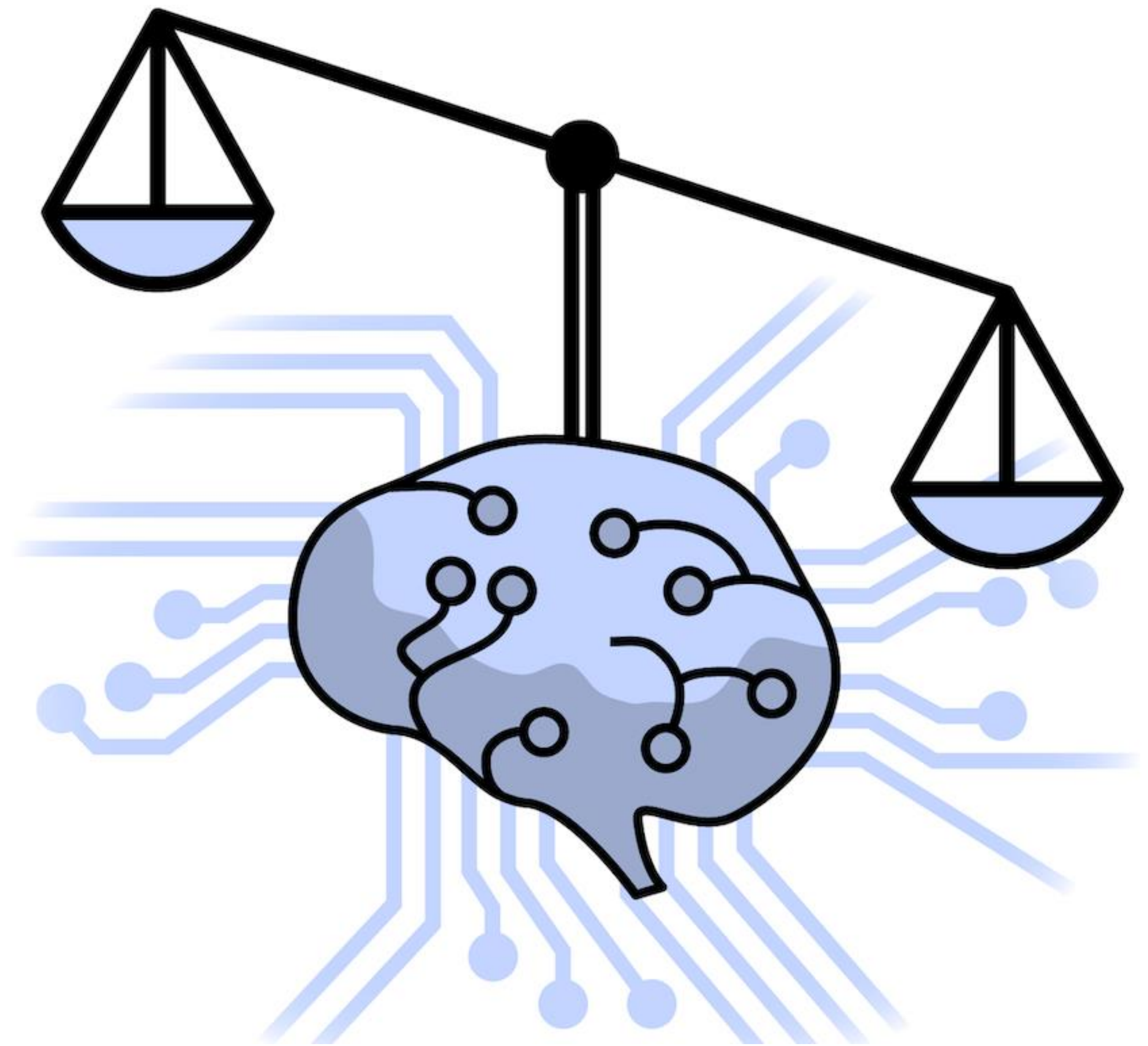
Different types of biases for ML/AI

- **Prejudicial Bias:**
  - Data: with prejudices, stereotypes, or faulty societal assumptions
  - It can influence any stage of developing a ML application
  - The most complex and important source to correct.
- **Sampling Bias**:
  - Data: Intentionally or unintentionally, oversample or under sample from a population
  - leading to the predictions being biased towards the characteristic's representative of that group
- **Algorithm Bias:**
  - There are certainly use cases that fit an algorithm better
  - The wrong choice of algorithm can also lead to bias in predictions.
- **Confirmation Bias:**
  - After train our model and evaluate its predictions, we may tend to retain information that affirms our preconceived notions.
  - start to exclude or remove data that goes against our theory in the process
  - lead to a certain bias in the data, and therefore our application’s predictions

https://censius.ai/wiki/machine-learning-bias

Machine Learning Fairness

- Machine learning fairness is the process of correcting and eliminating algorithmic bias from ML models
  - In the context of decision-making, fairness is *the absence of any prejudice or favoritism toward an individual or group based on their inherent or acquired characteristics*.
  - Especially bias of race and ethnicity, gender, sexual orientation, disability, religion, class, disability status, genetic information, ...
- An unfair algorithm is one whose decisions are
- skewed toward a particular group of people



Mehrabi et al. A Survey on Bias and Fairness in Machine Learning. ACM Comput. Surv. 54,6, Article 115 (July2021), https://doi.org/10.1145/3457607

Fairness Metrics

- **Demographic parity:** Our prediction is independent of any sensitive features (S) (e.g., age, gender, etc.)

Probability person has cancer given that person is a man = **Probability person has cancer given that person is a woman**

- **Equalized odds:** Given the true label, the prediction outcome (Y) is independent of sensitive features (S) (e.g., age, gender, etc.)

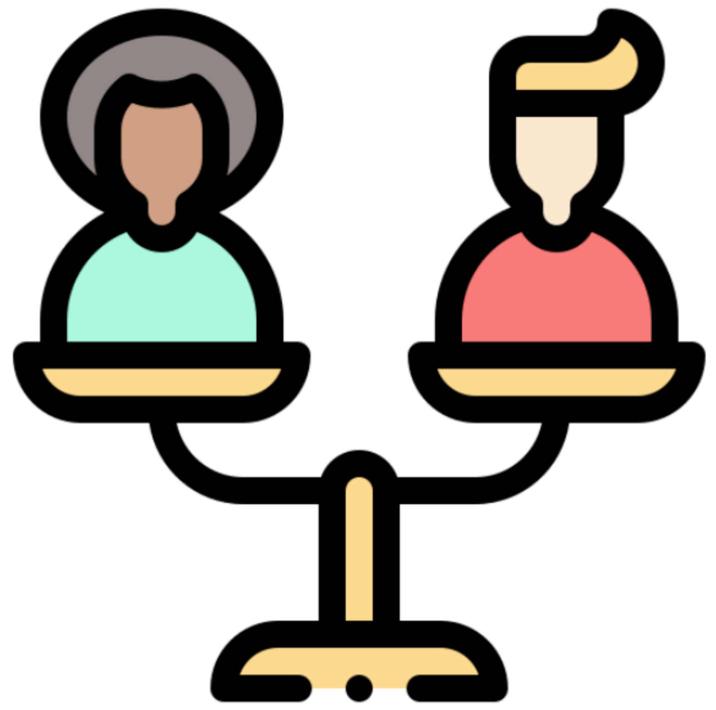
Probability person has cancer given that person is a man with cancer = **Probability person has cancer given that person is a woman with cancer**

&

Probability person don't have cancer given that person is a man with cancer = **Probability person don't have cancer given that person is a woman with cancer**

Probability a man truly has cancer given that this person is predicted "have cancer" with a score y = **Probability a woman truly has cancer given that this person is predicted "have cancer" with a score y**

- Mitigating biases is based on the idea of **sensitive or protected variables**. E.g.,
  - Age, Gender, Race, sexual orientation, etc.



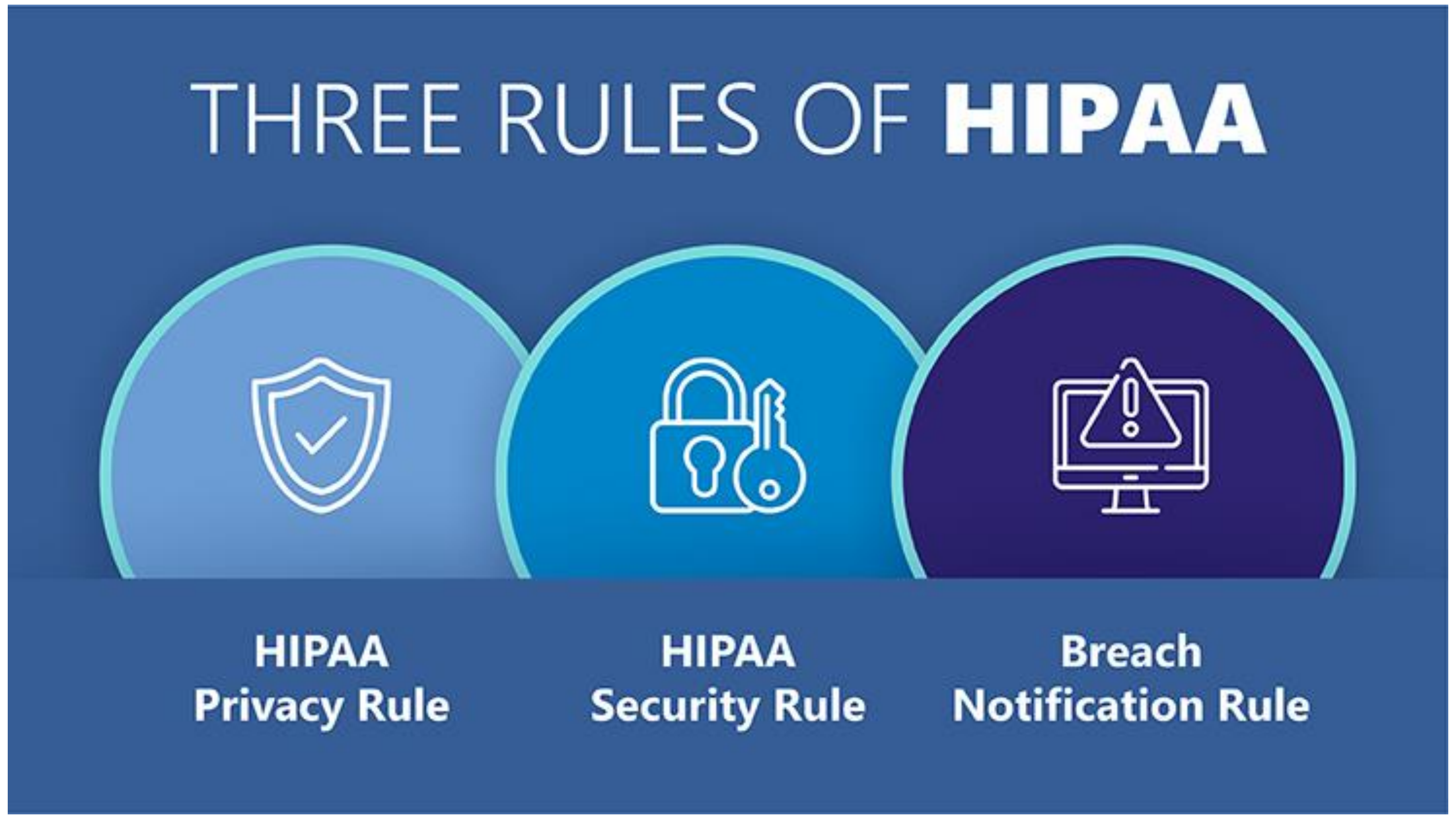
- **Equal calibration:** Given the prediction score (Y), the sample with different sensitive features (S) should have the same probability to truly belong to the positive class.

- PHI stands for Protected Health Information.
- The HIPAA Privacy Rule provides federal protections for personal health information held by covered entities and gives patients an array of rights with respect to that information. At the same time, the Privacy Rule is balanced so that it permits the disclosure of personal health information needed for patient care and other important purposes.
- Learn more about protected health information at: https://www.hhs.gov/hipaa/for-professionals/privacy/special-topics/de-identification/index.html#protected

Source: https://www.hhs.gov/answers/hipaa/what-is-phi/index.html

Ethical Consideration of AI in Healthcare

The HIPAA Privacy Rule



- The HIPAA Privacy Rule protects most "individually identifiable health information" held or transmitted by a covered entity or its business associate, in any form or medium, whether electronic, on paper, or oral. The Privacy Rule calls this information *protected health information* (PHI). Protected health information is information, including demographic information, which relates to:
  - the individual's past, present, or future physical or mental health or condition,
  - the provision of health care to the individual, or
  - the past, present, or future payment for the provision of health care to the individual, and that identifies the individual or for which there is a reasonable basis to believe can be used to identify the individual. Protected health information includes many common identifiers (e.g., name, address, birth date, Social Security Number) when they can be associated with the health information listed above.

Covered Entities, Business Associates, and PHI

In general, the protections of the Privacy Rule apply to information held by covered entities and their business associates.

HIPAA defines a covered entity as

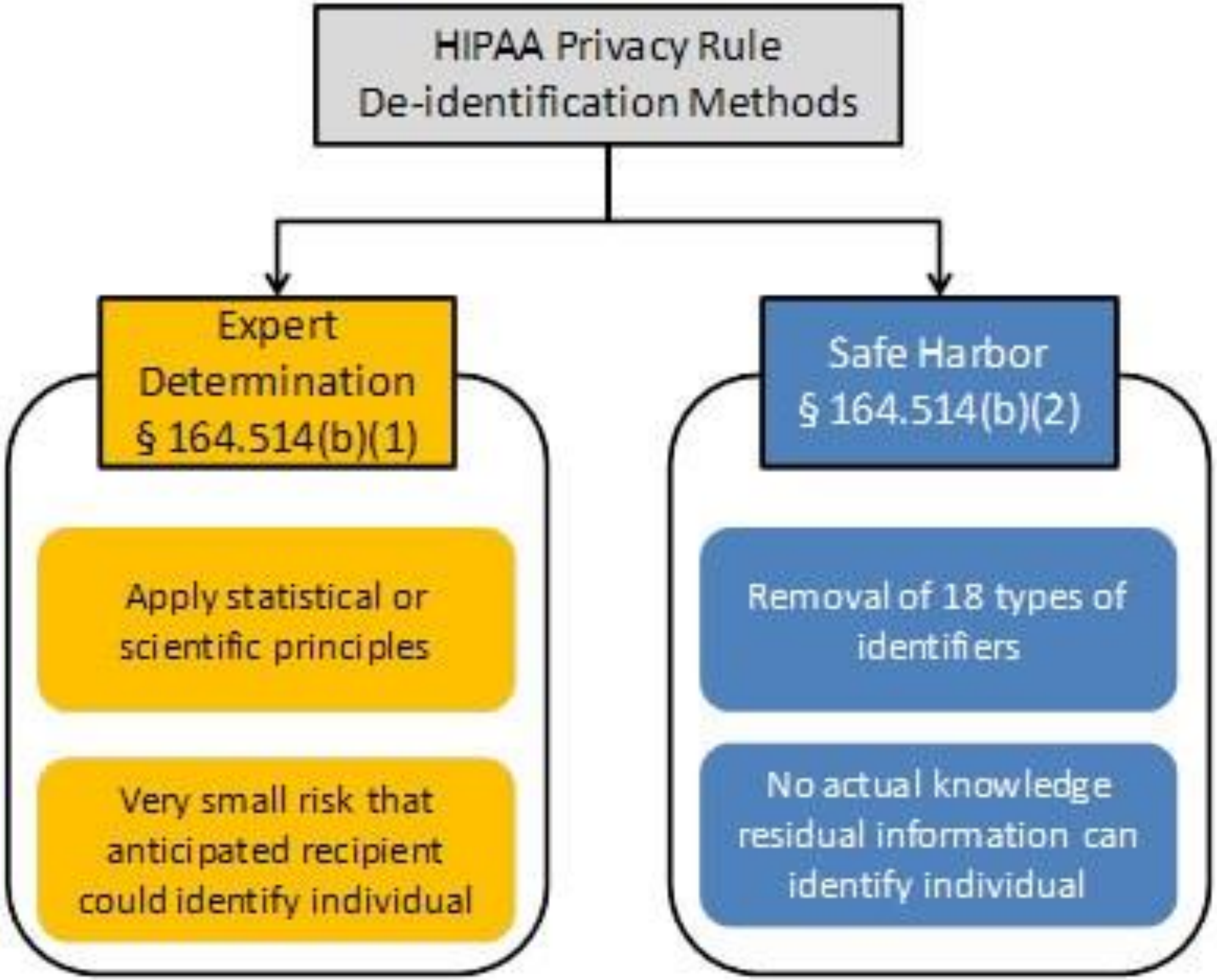
1) a health care provider that conducts certain standard administrative and financial transactions in electronic form;

2) a health care clearinghouse; or

3) a health plan.

A business associate is a person or entity (other than a member of the covered entity’s workforce) that performs certain functions or activities on behalf of, or provides certain services to, a covered entity that involve the use or disclosure of protected health information.

A covered entity may use a business associate to de-identify PHI on its behalf only to the extent such activity is authorized by their business associate agreement.



Source: https://www.hhs.gov/hipaa/for-professionals/privacy/special-topics/de-identification/index.html#protected

PHI elements for Safe Harbor

The following identifiers of the individual or of relatives, employers, or household members of the individual, are removed:

Names	Telephone numbers and Fax numbers
Vehicle identifiers & serial numbers, & license plate numbers	Email addresses
Device identifiers and serial numbers	Web Universal Resource Locators (URLs)
Social security numbers	Internet Protocol (IP) addresses
Account numbers and Medical record numbers	Any other unique identifying number, characteristic, or code
Biometric identifiers, including finger and voice prints	Certificate/license numbers
Health plan beneficiary numbers	Full-face photographs and any comparable images
All geographic subdivisions smaller than a state, including street address, city, county, precinct, ZIP code, and their equivalent geocodes, except for the initial three digits of the ZIP code if, according to the current publicly available data from the Bureau of the Census: (1) The geographic unit formed by combining all ZIP codes with the same three initial digits contains more than 20,000 people; and (2) The initial three digits of a ZIP code for all such geographic units containing 20,000 or fewer people is changed to 000	All elements of dates (except year) for dates that are directly related to an individual, including birth date, admission date, discharge date, death date, and all ages over 89 and all elements of dates (including year) indicative of such age, except that such ages and elements may be aggregated into a single category of age 90 or older

PHI data applications, such as public surveillance, cancer registry

Public Health Surveillance
- Waiver for PHI

Cancer and other disease registries
- De-identified

Research studies
- Requires approval from an IRB

Clinical systems
- For patient care

Administrative systems
- For billing and claims

Mobile Applications
- Secure method for communicating

Text/SMS
- Requires HIPAA compliant service

List the impacts of human errors in protecting PHI

Human Error	Impact to business	Impact to patient
• ***Incorrect de-identification method***	Fines, bad press	Patient usually unaware
• ***Incorrect data collection or storage***	Fines, bad press, loss of trust	Loss of trust
• ***Sending data outside of a closed system***	Data breach from using 3rd party system	Loss of trust, exposed data
• ***Transferring data without a Data Use Agreement***	Legal/contractual	Patient usually unaware
• ***Linking data/re-identification***	Loss of anonymity	Loss of trust, exposed data, Loss of anonymity, job loss or other personal impact

- Database was not password protected
- Had no form of authentication in place
- Hosted by a 3rd party vendor

- **How to avoid:**
- Vendors must be vetted, sign Business Associate Agreements, have cyber insurance
- Vendors must follow all cyber program requirements
- Cyber program requirements must include passwords and multifactor authentication or other authentication protocols where appropriate

Sample Applications of AI in Healthcare

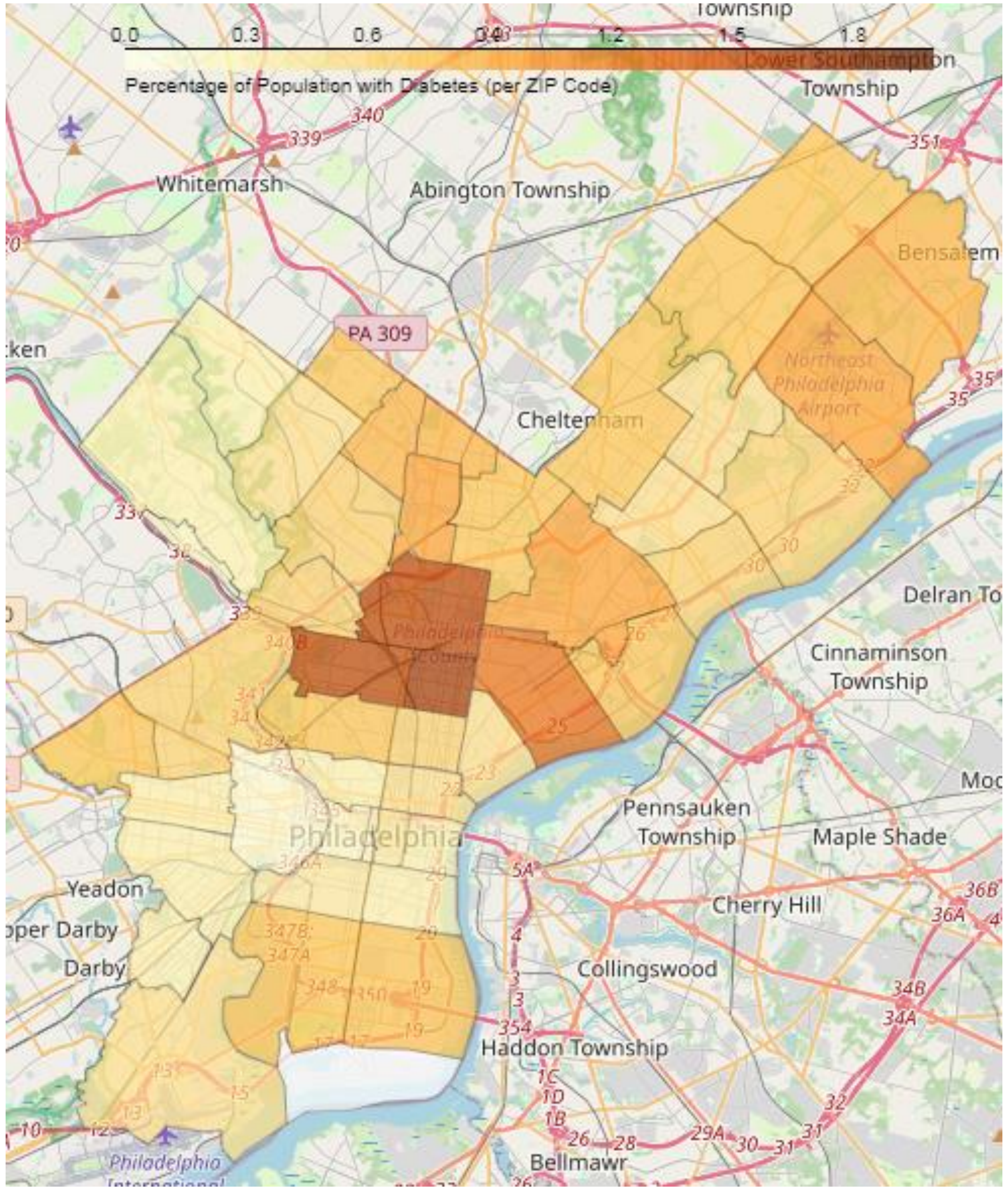
Sample Project 1:

Forecasting Emergency Department Visits Among Patients with T2D and/or Hypertension

Javad M Alizadeh, Huanmei Wu, Jay Patel, Gabriel Tajeu, Yuzhou Chen, Ilene L Hollin Huanmei.wu@temple.edu

Study Objectives

- To develop predictive models for ED visit risk for patients with T2D, specifically
    1) Establish a pipeline for preprocessing complex clinical data from various healthcare facilities
    2) Integrate patients' demographic information, SDoH factors, clinical encounters, medical history, and vital signs.
    3) Identify risk factors for ED visits among patients with T2D



- Leverage data from HSX Clinical Data Repository (CDR)
    - Data from over 200 healthcare facilities

EHR + SDoH

Encounter
encounter_key
encounter_code
panel_key
zip_code
patient_class
facility
encounter_date
visit_reason
chief_complaint
admission_type
admit_source
discharge_disposition
death_indicator
discharged_to_location
attending_phys_name
attending_phys_npi
encounter_notes

Patient_Panel
panel_key
Age
Gender
Race
Ethnicity
Zip Code

Diagnosis
encounter_key
panel_key
diagnosis_date
dx_code
dx_label
dx_code_system
dx_code_system_label
dx_type

Procedure
encounter_key
panel_key
procedure_date
px_code
px_label
px_code_system

Vital
encounter_key
panel_key
value
units
vitals_code
code_system
vitals_label

Individual-level and Zip-code SDoH

Log_Population	pct_overcrowding	pct_English first language
ICE income	pct_Native American	pct_living in poverty
ICE race (Black)	pct_service workers	pct_Asian and Pacific Islander
ICE race (Hispanic)	pct_production workers	Median household income(HH_income)
ICE occup+race (Black)	pct_health workers	Median home value (HH_value)
ICE income+race (Black)	pct_uninsured	Average PM2.5 (pm25_mean)
ICE income+race (POC)	pct_using public transit	SVI1 – socioeconomic status
pct_Hispanic	pct_high school	SVI2 – household composition
pct_non-Hispanic white	pct_college	SVI3 – minority status
pct_Black	pct_foreign born	SVI4 – housing type and transportation

Data quality Issues:
Patient Race - 106 unique values

B
AF
2 Black Or African American
African American
African American/Black
African
Black
Black or African American
BLACK OR AFRICAN-AMERICAN
Black, not of Hispanic Origin
Black/African American
Black/African American (Not Hispanic)
2054-5

W
WH
White
3 White / Caucasian
Caucasian
Non-Minority (White, non-Hispanic)
White (Not Hispanic / Latino)
White / Caucasian
WHITE OR CAUCASIAN
White Race
White, non-Hispanic
White, not of Hispanic Origin
2106-3

A
AS
Asian
Asian (uds)
Asian Americ
CHINESE
FILIPINO
Korean
Vietnamese
Pakistani
Other Asian
2028-9

9999-1

Alaskan Native
AM
American Indian
American Indian or Alaska Native
American Indian or Alaskan Native
American Indian/Alaskan Native
5 American Indian Or Alaskan Native
INDIAN
N
Native Hawaiian
Native Hawaiian or Other Pacific Islander
NATIVE HAWAIIAN OR PACIFIC ISLANDER
Other Pacific Islander (Not Hawaiian)
OTHER PACIFIC ISLANDER
2076-8
1002-5

H
HISPANIC
Hispanic Black
Hispanic or Latino
Hispanic Or Latino (All Races)
Hispanic Other
Hispanic Unknown
Hispanic White
HISPANIC/ASIAN
HISPANIC/BLACK
HISPANIC/OTHER
HISPANIC/UNKNOWN
HISPANIC/WHITE
HS
LATINO
White-Hispanic
PUERTO RICAN
2135-2

Patient Declined
Patient Refused
Refused to Report /Unreported
U
UN
Unable to Determine
Undefined
Unknown
UNKNOWN/NOT CLASSIF.
Unknown/Not Reported
Unspecified
Decline to Answer
Declined
Declined to Provide
Declined to specify
1 Declined To Specify
Intake- Not Asked
(blank)

Other
Other Race
OTHER RACES
2131-1

More than one race
Multiracial
Multi-racial
TWO OR MORE RACES

C	D	G	O
P	X	CA	ZZ

Data quality Issues:
Ethnicity - 97 unique values

H
HL
HS
HIS
Hisp
Hispanc or Latino
HISPANIC
Hispanic or Latino
Hispanic or Latino Hispanic or Latino
Hispanic or Latino/Spanish
Cuban
Central American
Puerto Rican
YES Hispanic or Latino
Yes, Hispanic or Latino
Mexican, Mexican American, or Chicano/a
Other Hispanic, Latino/a, or Spanish origin
2135-2

NHL
Non-Hisp
NON-HISPANIC
NOT HISPANIC
Not Hispanic (uds)
Non Hispanic or Latino
Not Hispanic or Latino
Not Hispanic, Latino/a, or Spanish origin
XNot Hispanic or Latino
Black, not of Hispanic Origin
2186-5

CA
CAU
White, not of Hispanic Origin
White/Caucasian

AF
Black/African-American
AS
Asian
AM
ASKU
IND
N

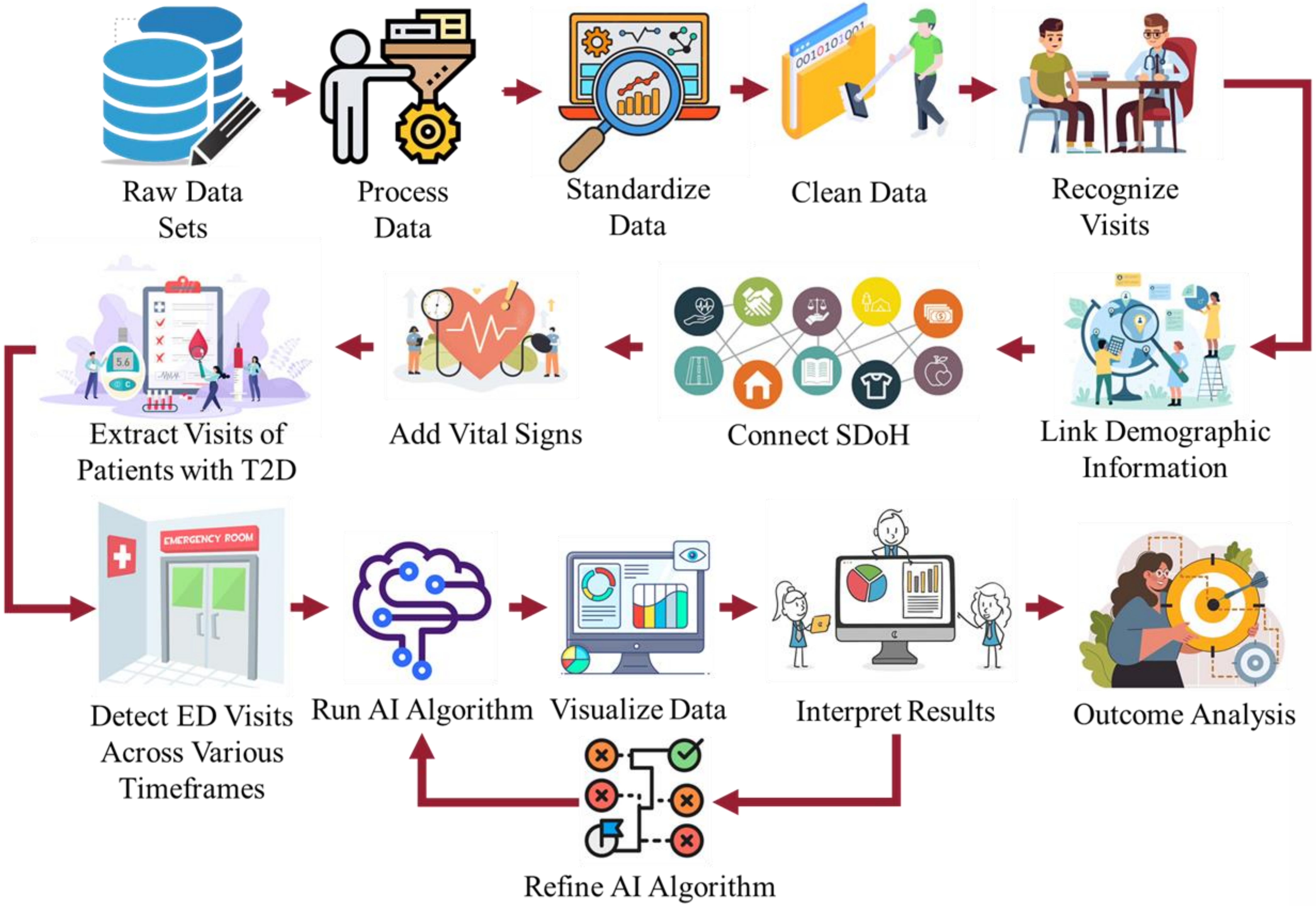
ANOTHER
Other
ZZ
PT
0
4

D
Decline to Answer
DECLINED
Declined to specify
Patient Declined
Patient Refused
Refused
Refused to Report
U
Unable to Determine
Unavailable
undefined
UNK
Unknown
Unknown / Not Reported
UNREPORTED
Unspecified
Pt Unavailable
NOT
Not Available

Data Cleaning and Standardization

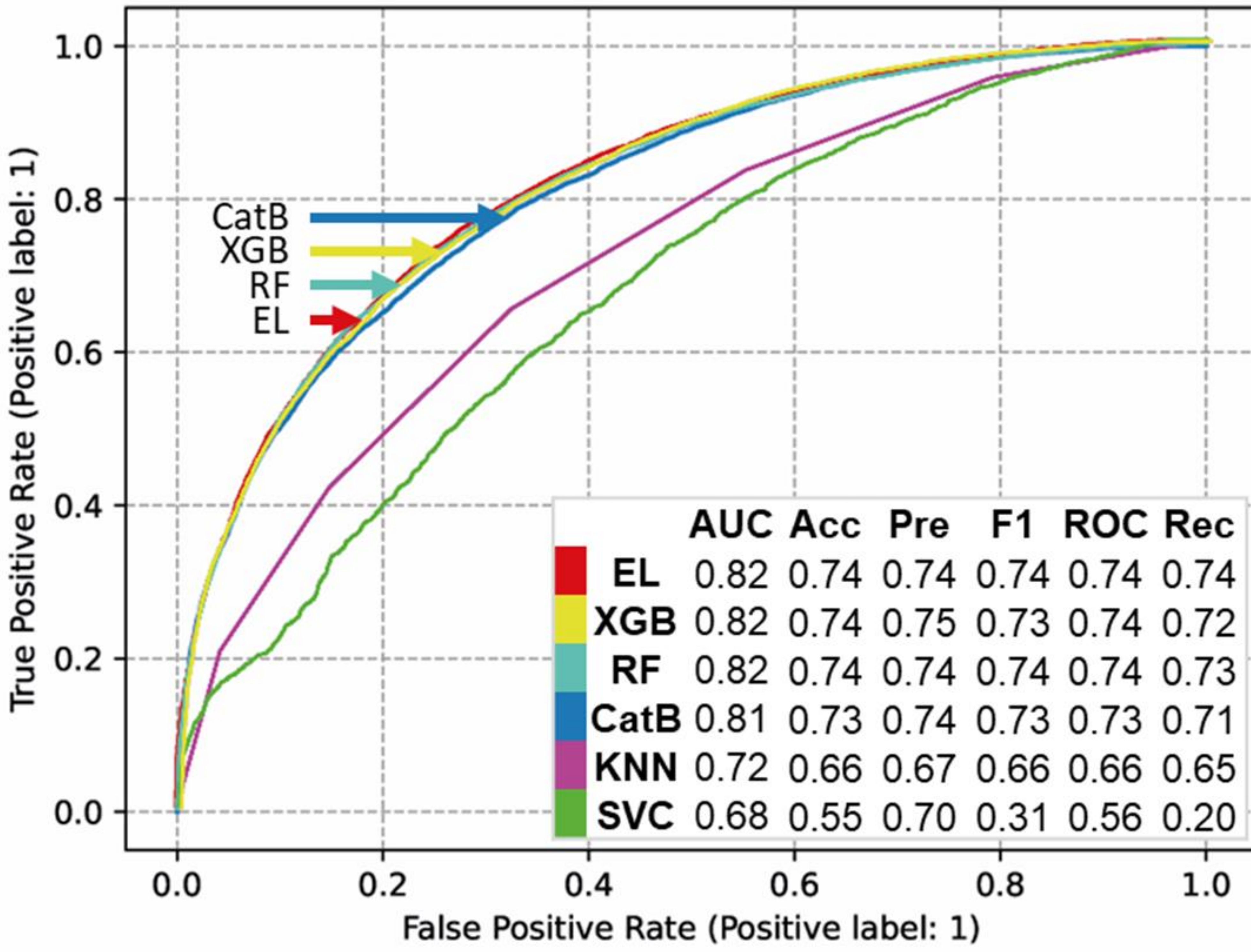
Variables	*Distinct values in raw Data*	*Distinct values in clean data*
Gender	8	3
Race	154	7
Ethnicity	97	3
Diagnosis coding systems	17	1
Patient class	7,443	32
Admission Types	263	30
Diagnosis codes	29,784	2,465
Vital Types	55	12

Data Processing Pipeline

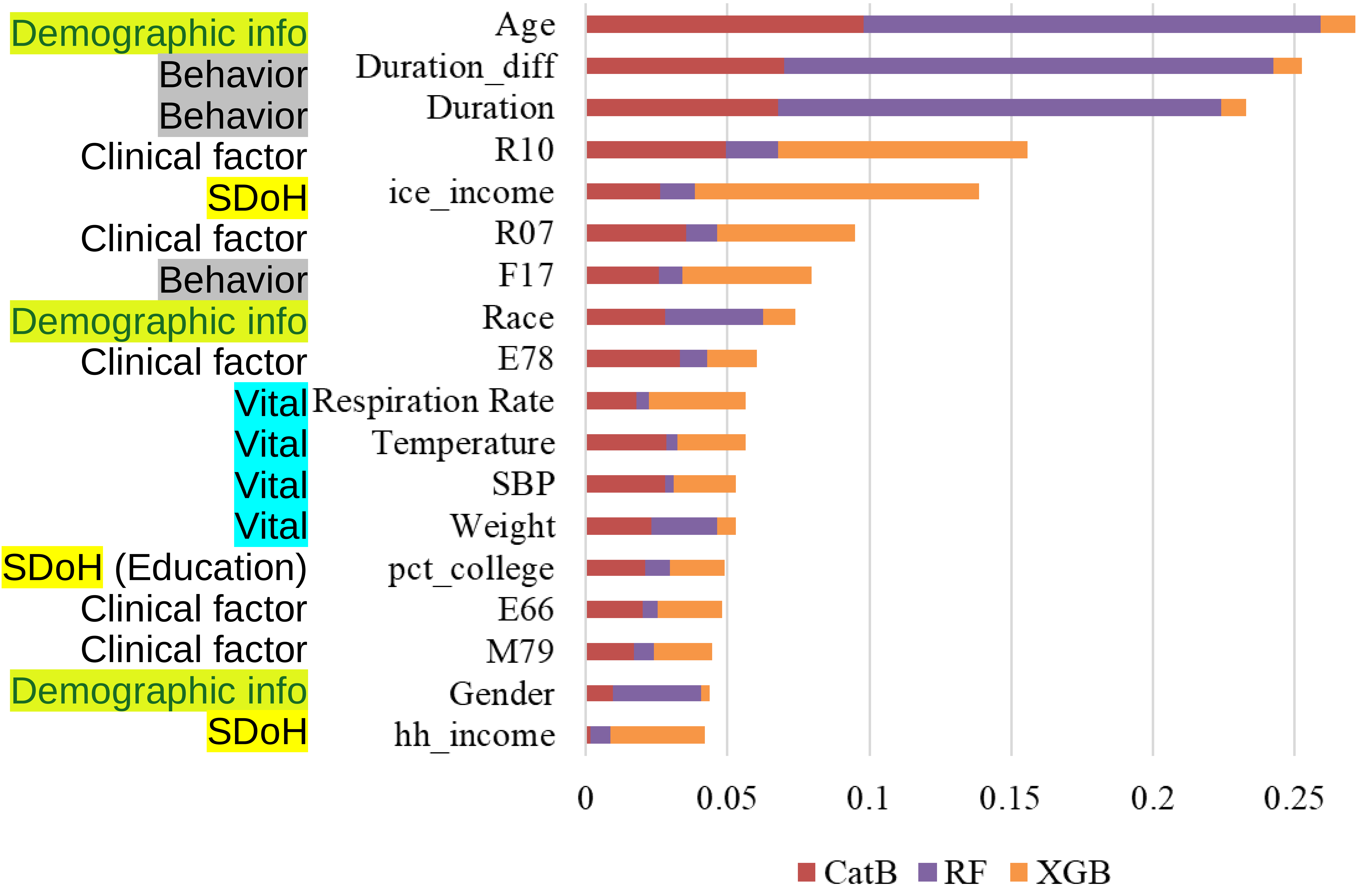


Machine learning methods:

- K-nearest Neighbors
- Support Vector Classification
- Random Forest
- XGBoost
- CatBoost
- Ensemble Learning

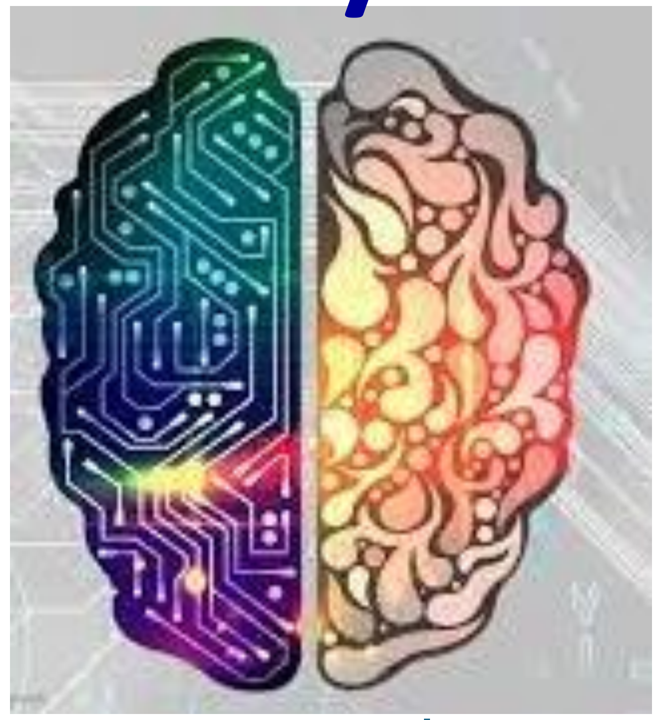


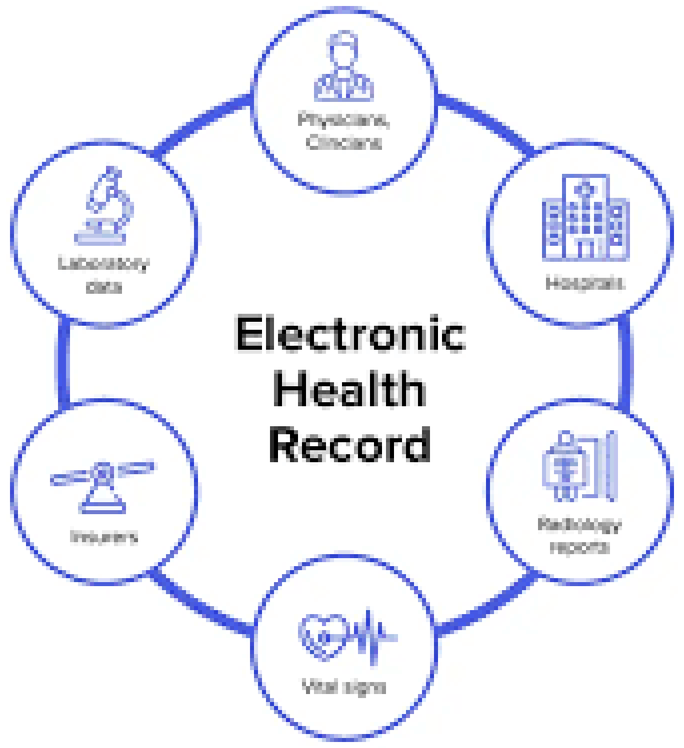
Influential Factors

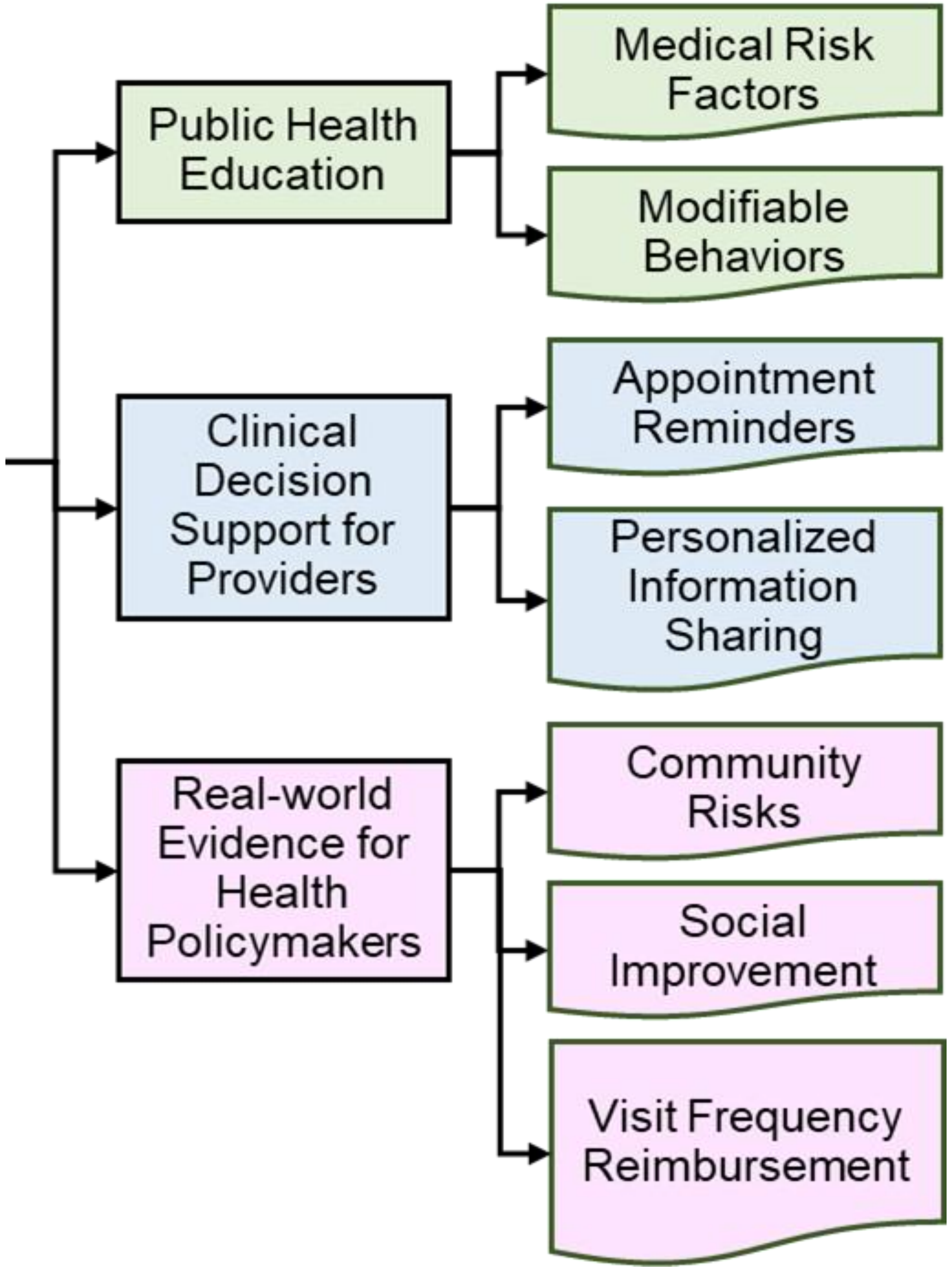


Conclusions

ML/AI







- To predict risk for ED visits
- To identify different risk factors
- To develop potential intervention

- to reduce ED utilization

Acknowledgements

- The project is supported by the Robert Wood Johnson Foundations Health Data for Action (HD4A) program
  - Robert Wood Johnson Foundation (RWJF)
  - AcademyHealth
  - The HealthShare Exchange
- Temple University

Robert Wood Johnson Foundation

AcademyHealth

HSX

TEMPLE UNIVERSITY

Sample Project 2

Machine Learning Models for Predicting Post-Amputation Stump Complications

Junchao Fei, Ronald Renzi, Susan VonNessen-Scanlin, Huanmei Wu

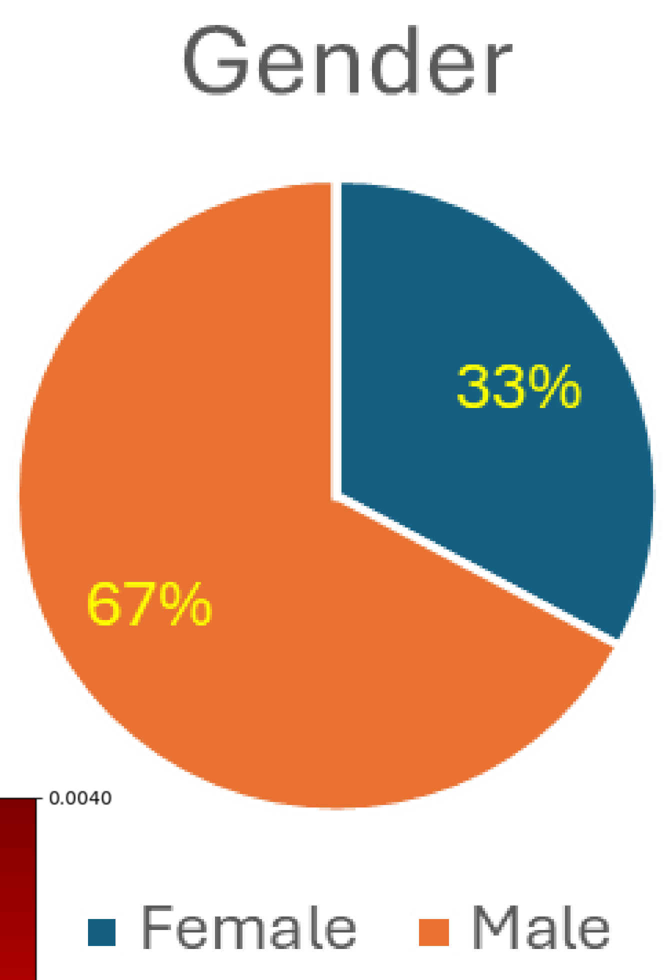
Intro of Post-amputation Stump Complications

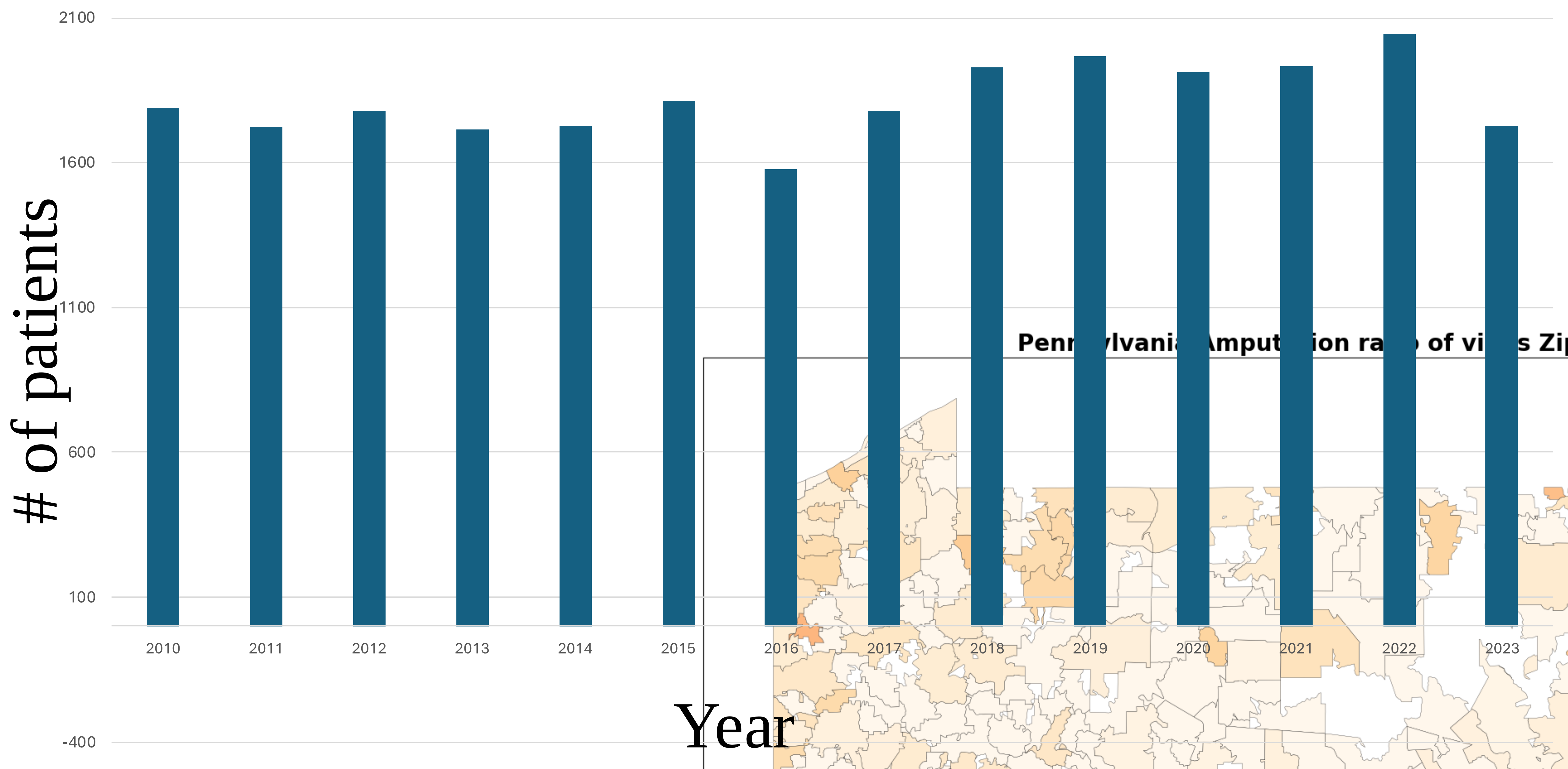
- The prevalence of limb amputations
  - at 0.7% in the global population
- Common complications
  - Infection
  - Residual limb pain
  - Phantom limb pain
  - Skin problems.
- Stump wound infections
  - leading to morbidity, bad quality of life, & additional health care costs

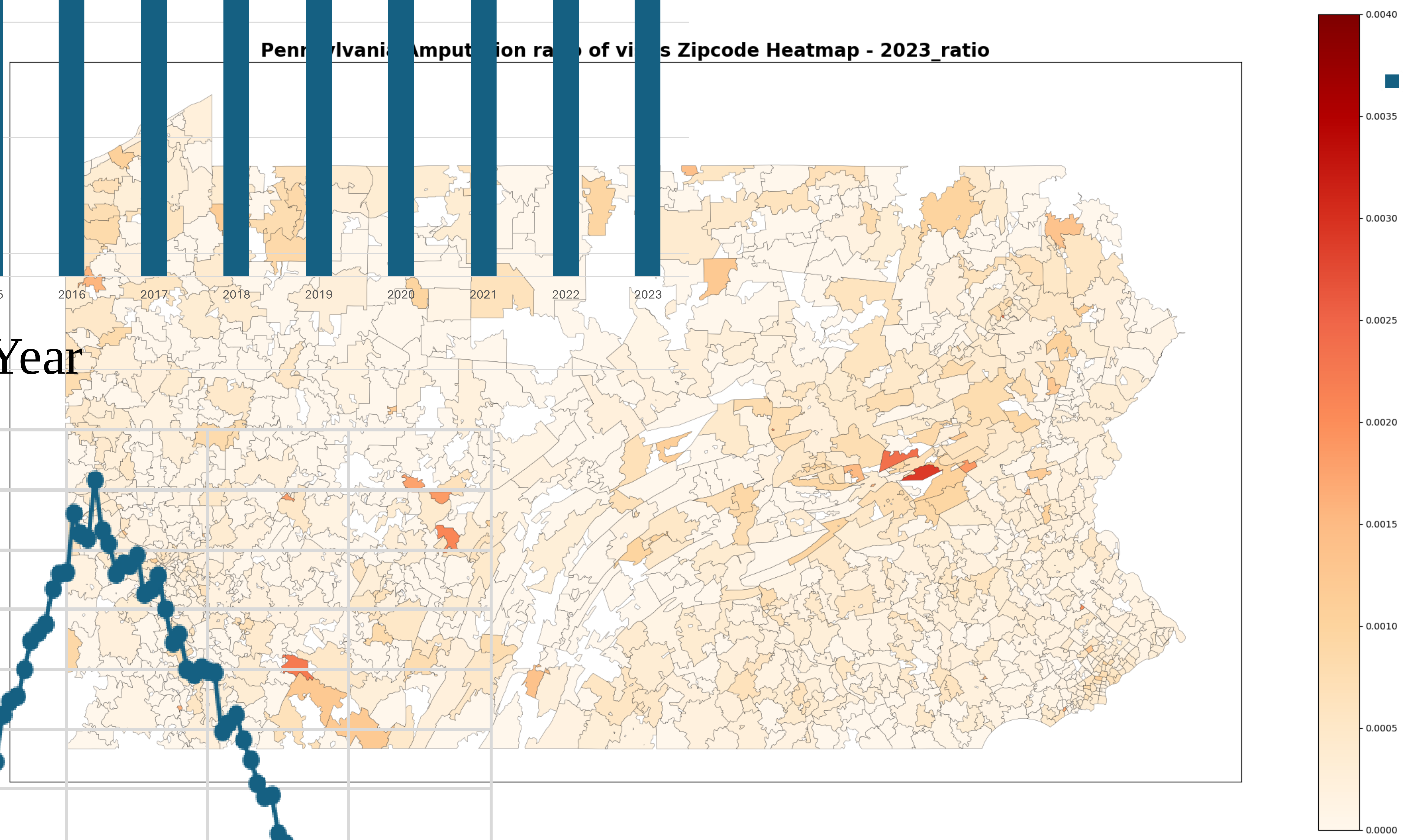
Objective: Use machine learning to predict complications by integrating clinical and SDoH data

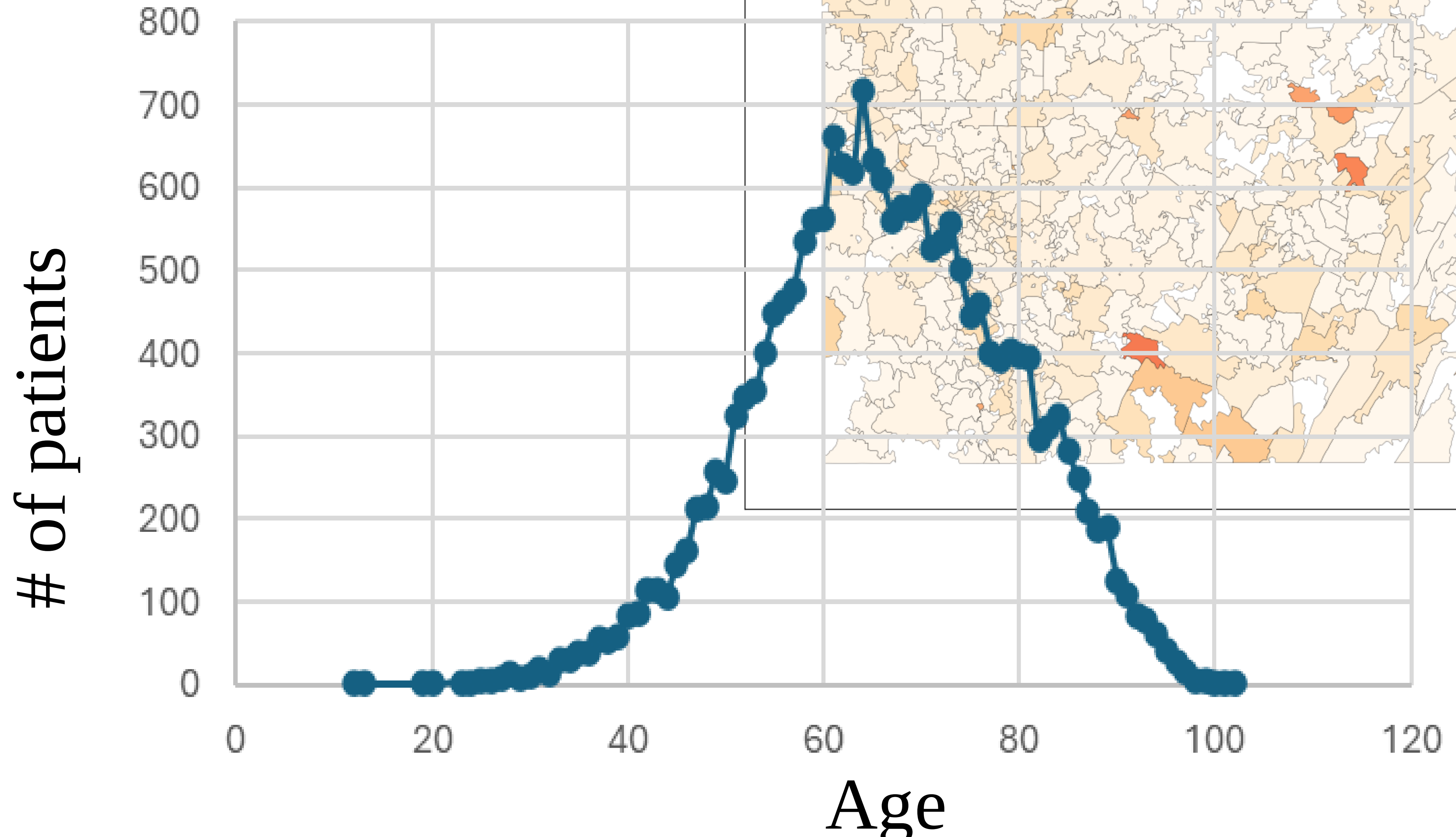
Dutronc, H., et al. "Stump infections after major lower-limb amputation: a 10-year retrospective study." Médecine et maladies infectieuses 43.11-12 (2013): 456-460.

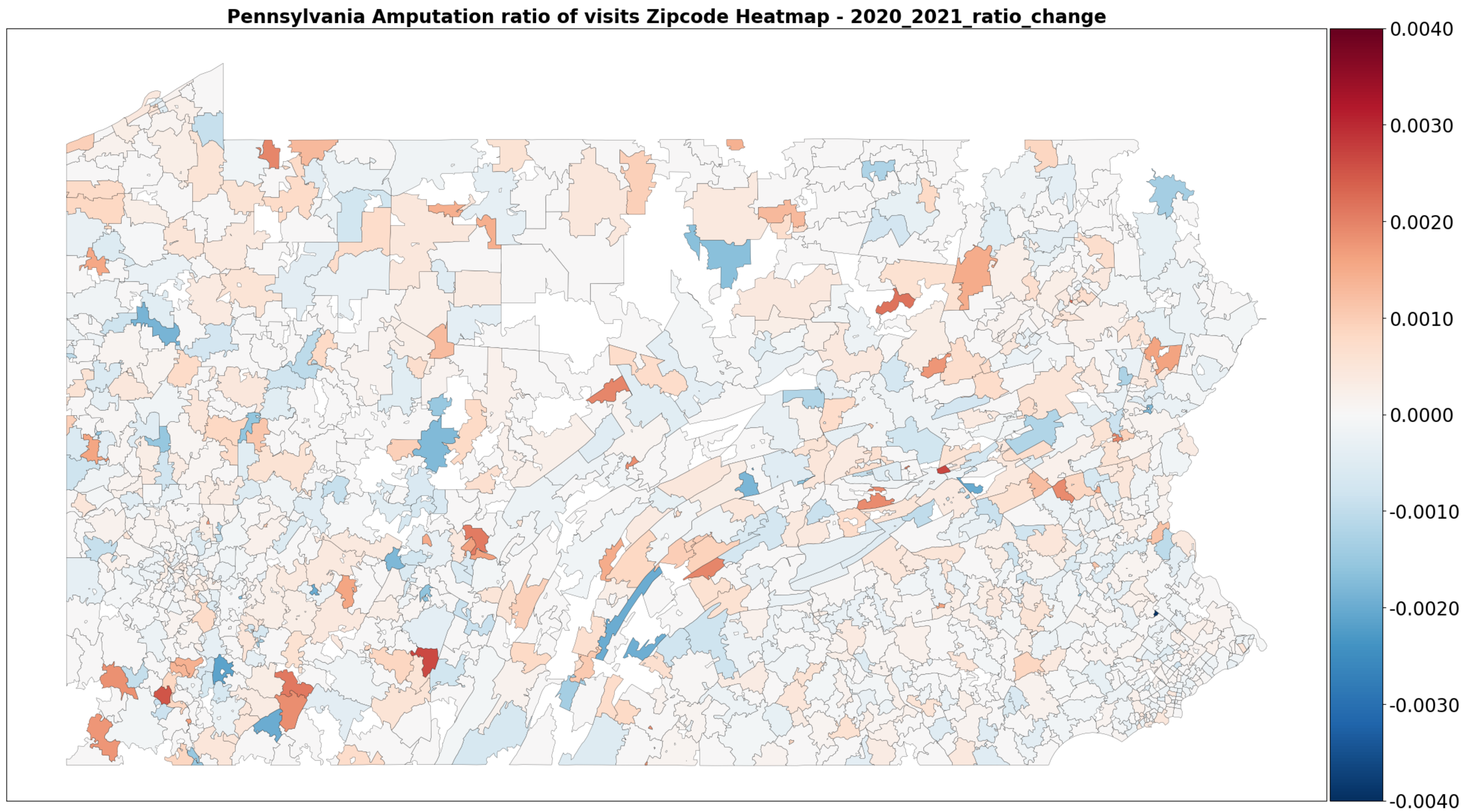
Dataset Description

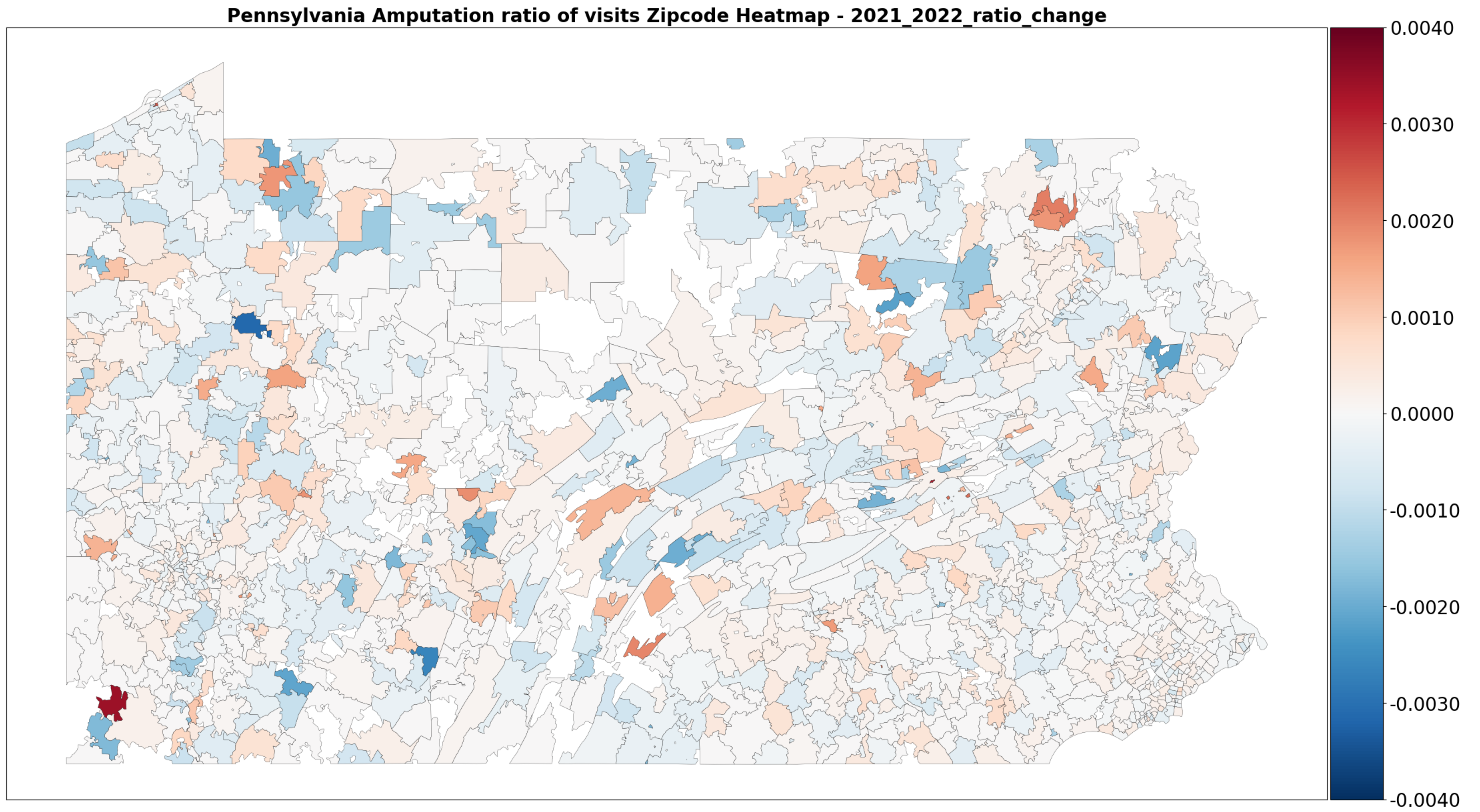


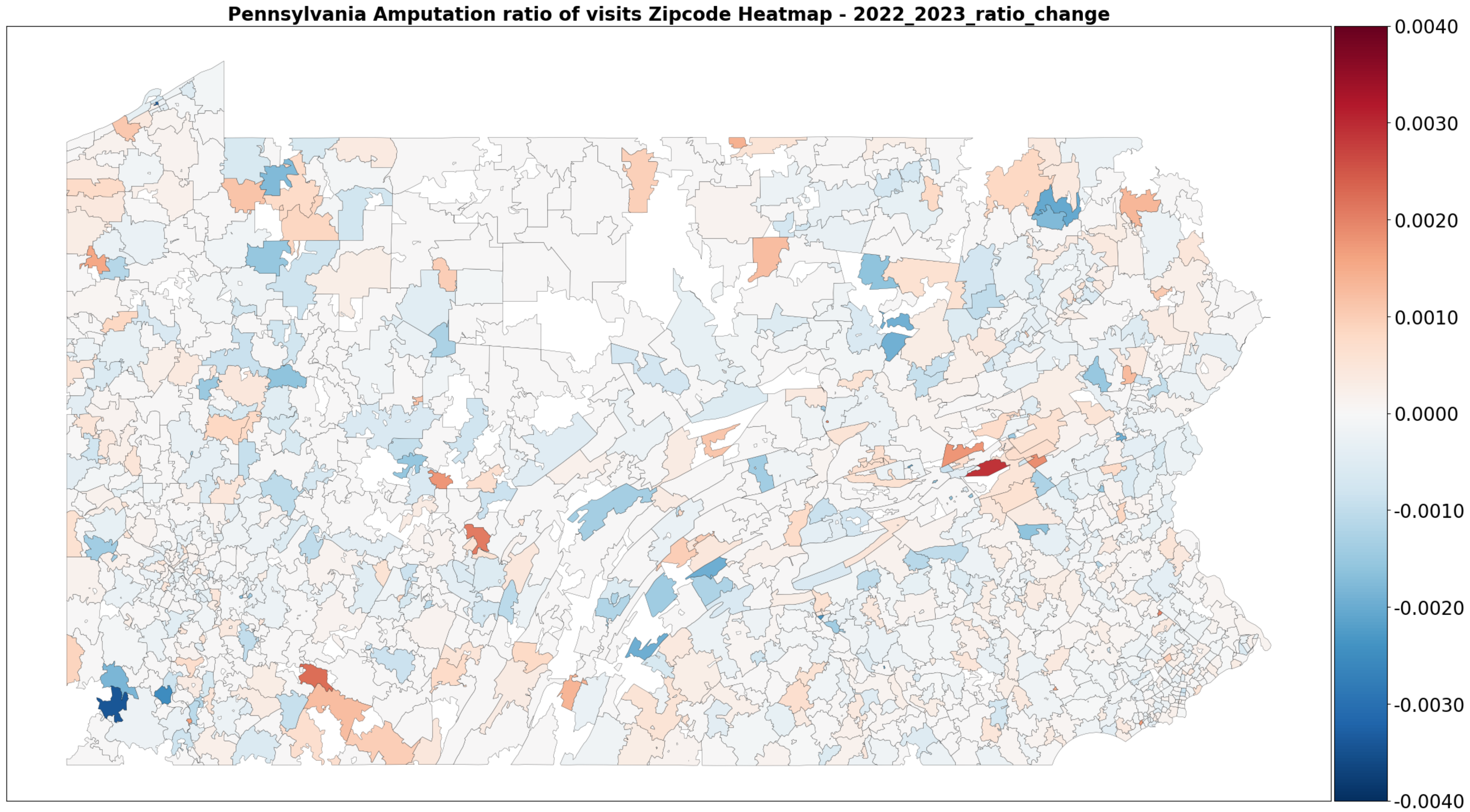


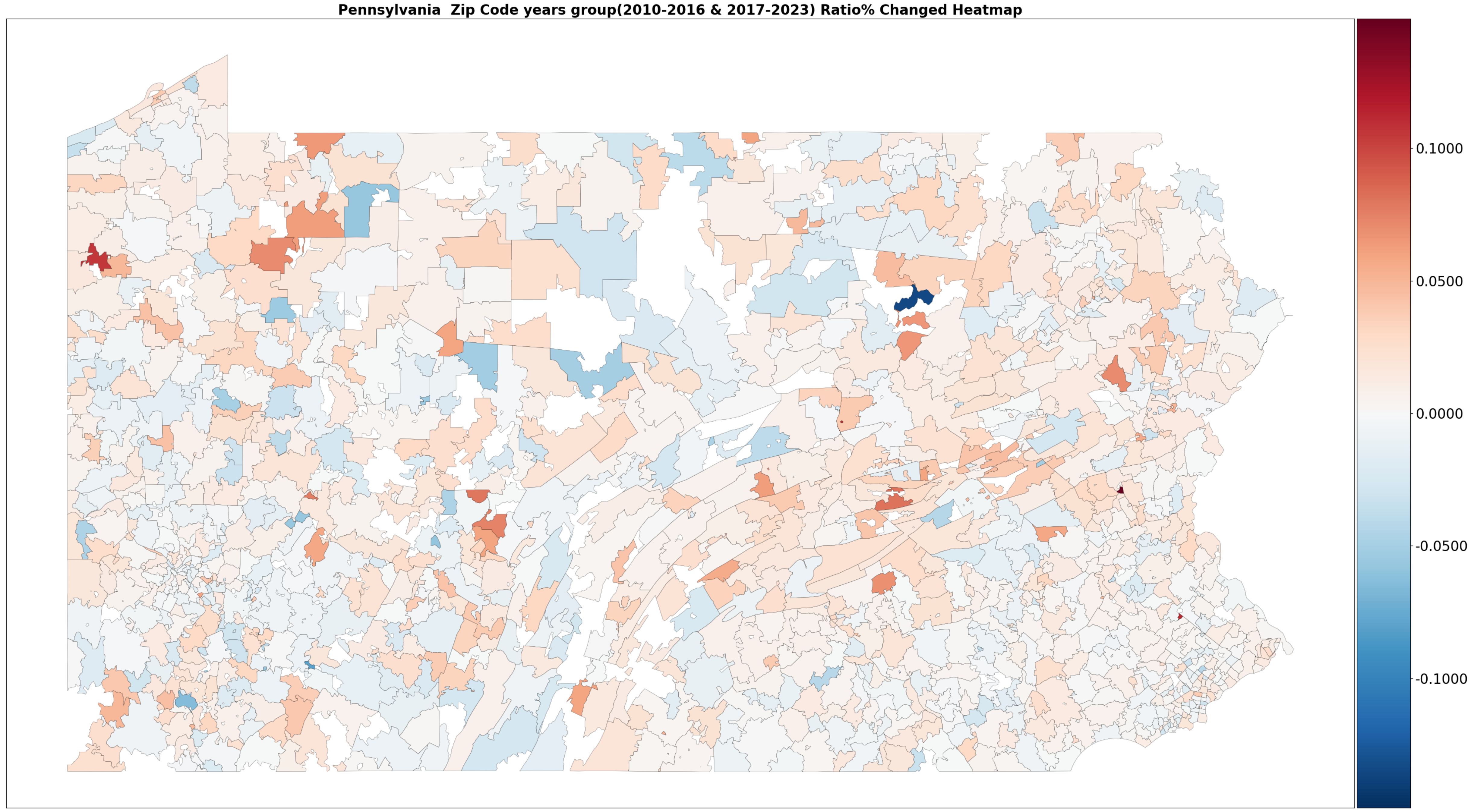


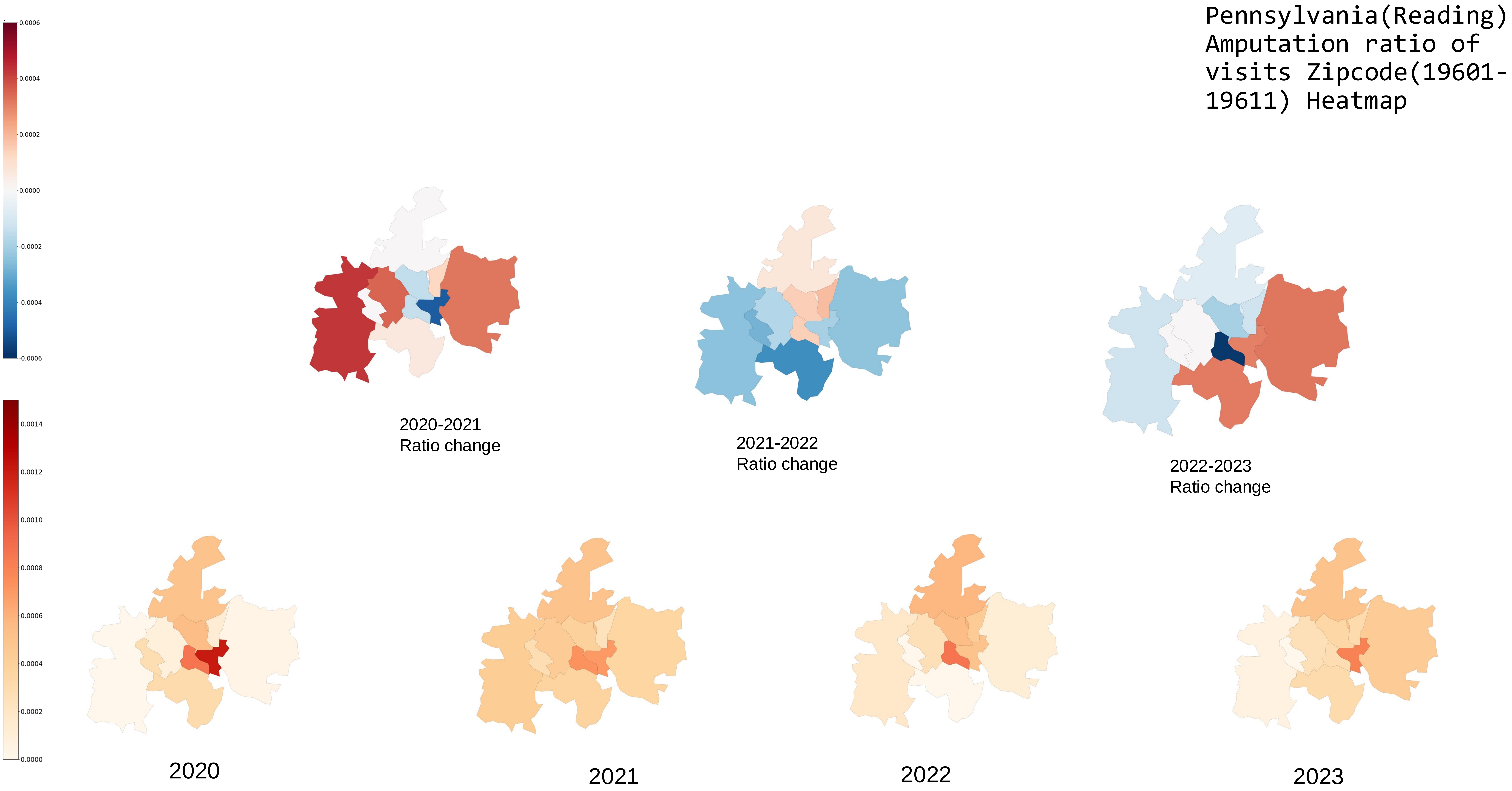



Pennsylvania Amputation ratio of visits Zipcode Heatmap - 2020_2021_ratio_change
0.0040
0.0030
0.0020
0.0010
0.0000
-0.0010
-0.0020
-0.0030
-0.0040


Pennsylvania Amputation ratio of visits Zipcode Heatmap - 2021_2022_ratio_change
0.0040
0.0030
0.0020
0.0010
0.0000
-0.0010
-0.0020
-0.0030
-0.0040


Pennsylvania Amputation ratio of visits Zipcode Heatmap - 2022_2023_ratio_change
0.0040
0.0030
0.0020
0.0010
0.0000
-0.0010
-0.0020
-0.0030
-0.0040


Pennsylvania Zip Code years group(2010-2016 & 2017-2023) Ratio% Changed Heatmap
0.1000
0.0500
0.0000
-0.0500
-0.1000


Pennsylvania(Reading) Amputation ratio of visits Zipcode(19601-19611) Heatmap
0.0006
0.0004
0.0002
0.0000
-0.0002
-0.0004
-0.0006
2020-2021
Ratio change
2021-2022
Ratio change
2022-2023
Ratio change
0.0014
0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
2020
2021
2022
2023

Data Preprocessing

3072 with Stump
17311 without Stump

↓

3072 with Stump
3072 without Stump

Random Undersampling

3072 with Stump
17311 without Stump

↓

Obtain unique population value (25+ years)
& Calculate weight of each ZIP code

↓

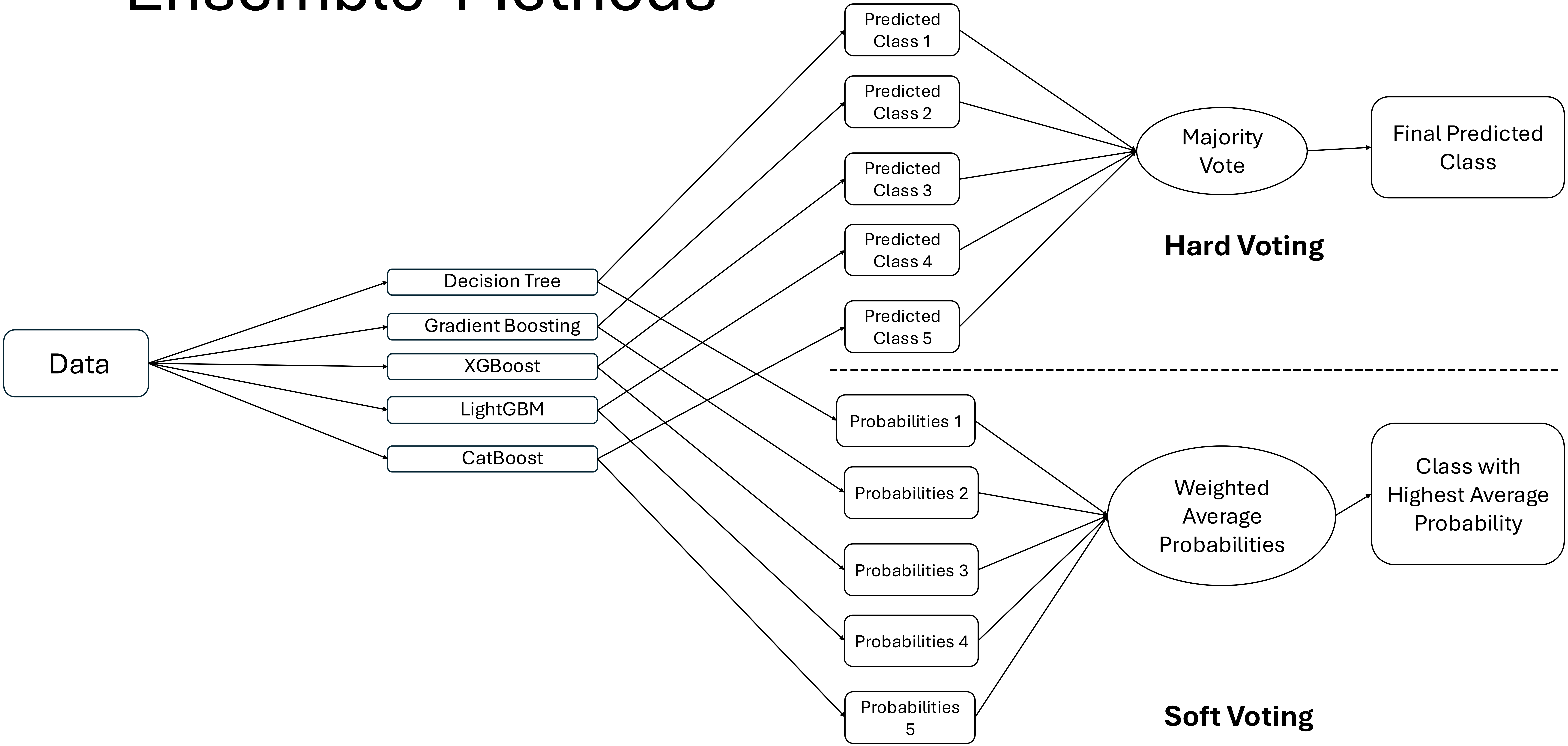
Determine number of samples per ZIP code
& Perform stratified sampling within each ZIP

↓

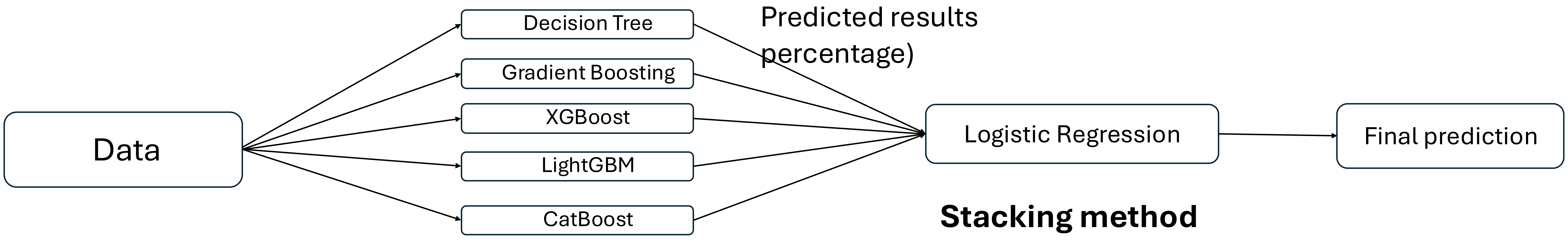
1921 with Stump
2795 without Stump

Stratified Random Sampling

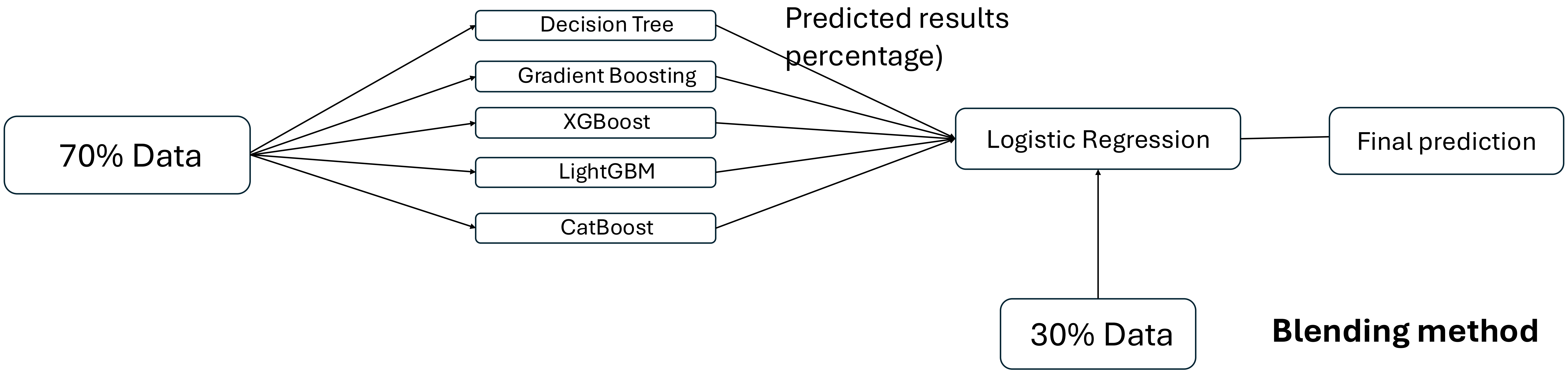
Ensemble Methods



Ensemble Methods



Stacking method



Blending method

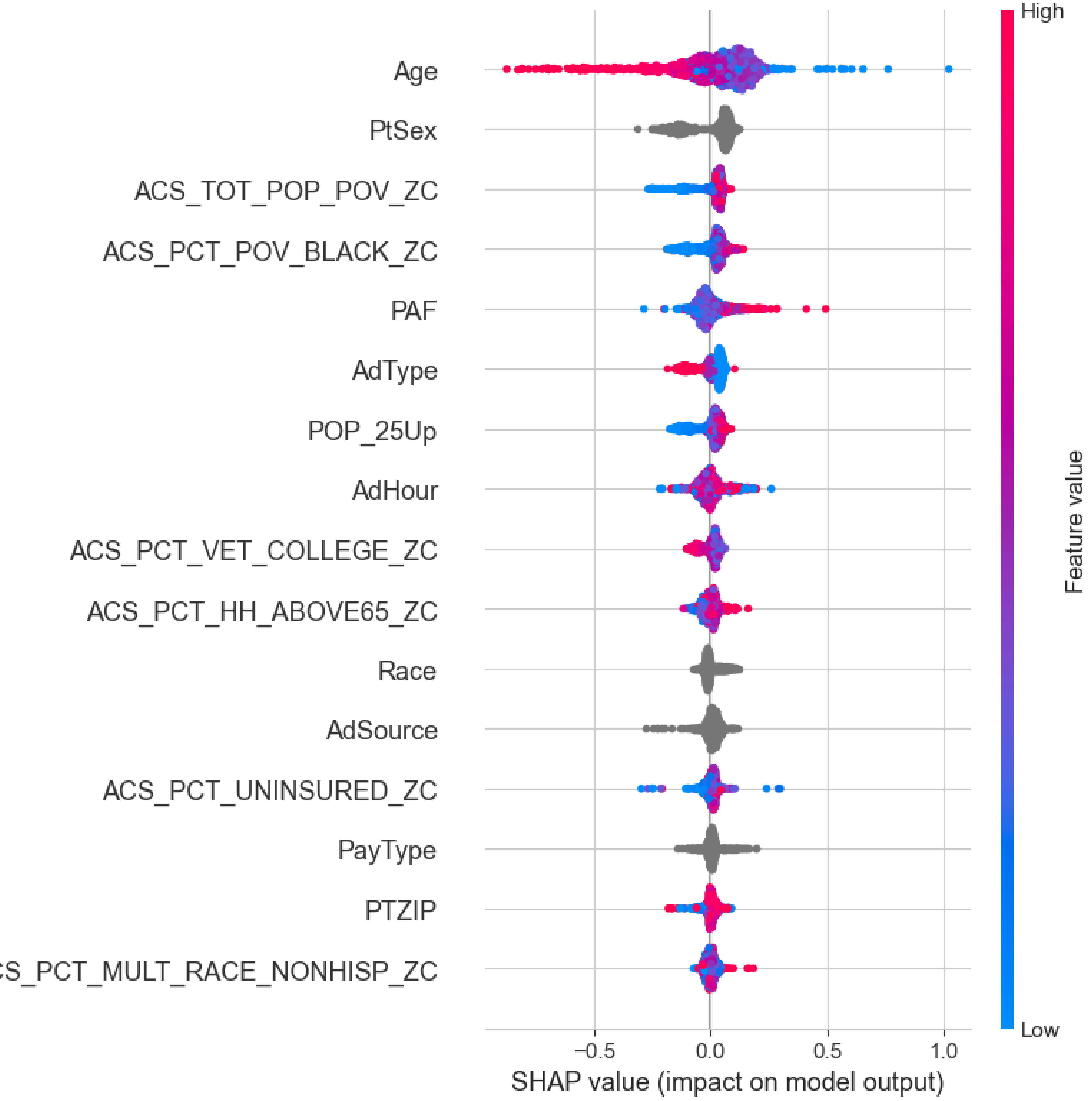
Model Construction

- **ML algorithms:**
  - Decision Tree
  - Gradient Boosting
  - XGBoost
  - LightGBM
  - CatBoost

- **Data split:**
  - 80% training, 20% testing
- **Cross-validation:**
  - Five-fold for optimal parameters
- **Metrics:**
  - Accuracy, Precision, Recall, F1 Score, ROC AUC

Sampling methods	Model	Accuracy	Precision	Recall	F1 Source	Roc AUC
Ensemble Methods	Voting (hard)	0.810	0.816	0.791	0.798	NA
	Voting (soft)	0.805	0.806	0.788	0.794	0.826
	Stacking	0.824	0.837	0.802	0.811	0.838
	Blending	0.821	0.828	0.802	0.809	0.824

Feature Importance



- **Top SDoH features:**
  - Socioeconomic status, insurance, race, education.

ACS_PCT_HH_ABOVE65_ZC: Percentage of households with one or more people 65 years and over (ZCTA level)

ACS_PCT_UNINSURED_ZC: Percentage of population with no health insurance coverage (ZCTA level)

ACS_PCT_POV_BLACK_ZC: Percentage of Black or African American population below poverty level (ZCTA level)

ACS_PCT_MULT_RACE_NONHISP_ZC: Percentage of non-Hispanic population reporting multiple races (ZCTA level)

ACS_TOT_POP_POV_ZC: Total population for whom poverty status is determined (ZCTA level)

ACS_PCT_VET_COLLEGE_ZC: % of civilian veterans that have some college education or an associate's degree (ages 25 and over, ZCTA level)

HIFLD_DIST_UC_ZP: Distance in miles to the nearest urgent care, calculated using population weighted ZIP centroids

POS_DIST_TRAUMA_ZP: Distance in miles to the nearest designated trauma center, calculated using population weighted ZIP centroids

ACS_TOT_POP_ABOVE25_ZC: Total population (ages 25 and over, ZCTA level)

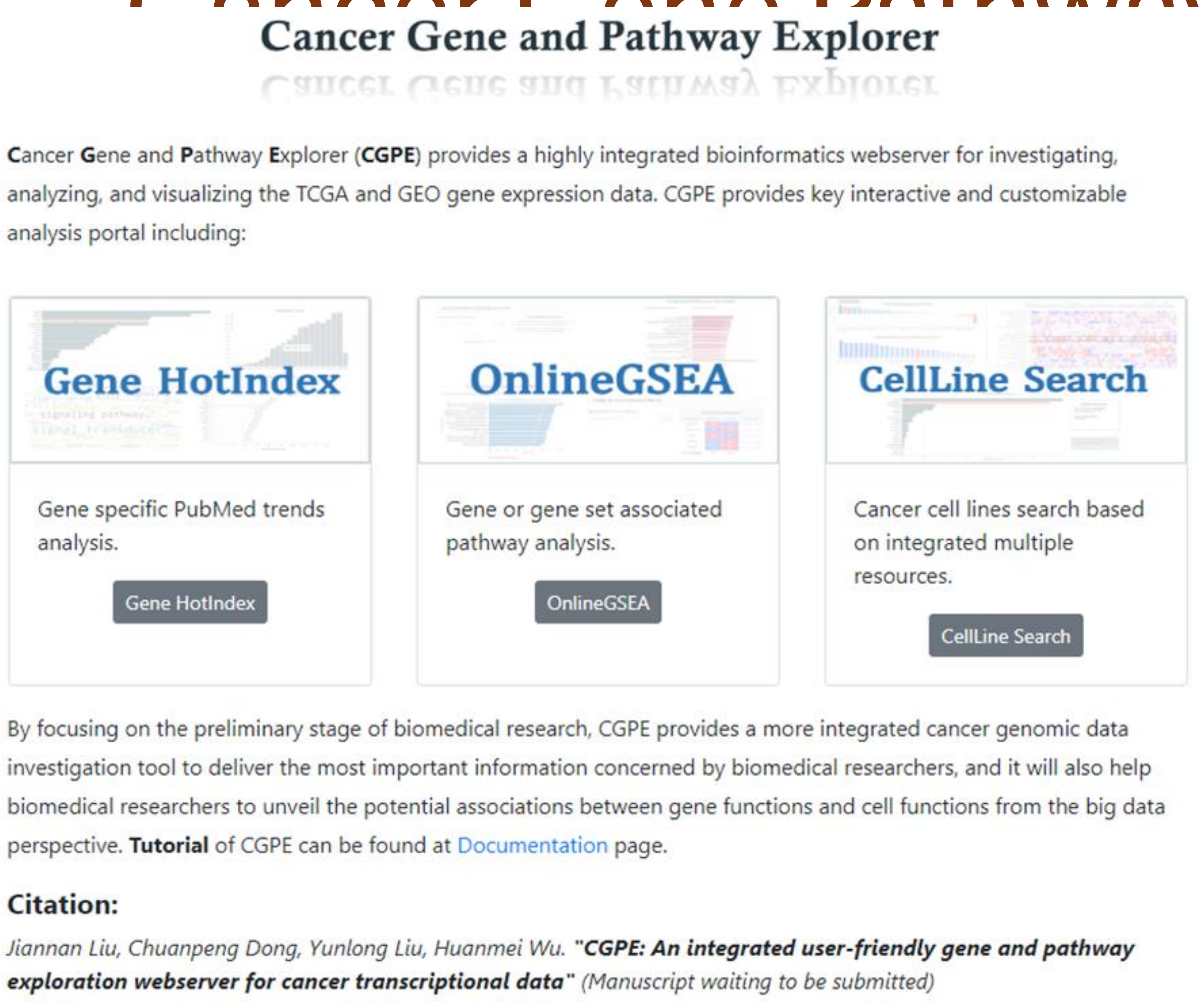
ACS_PCT_VET_ZC: Percentage of the civilian population consisting of veterans (ages 18 and over, ZCTA level)

Sample project 3

Bioinformatics Tool Development

Bioinformatics Tools:

Cancer Gene Pathway Explorer (CGPE)



Cancer Gene and Pathway Explorer

Cancer **G**ene and **P**athway **E**xplorer (**CGPE**) provides a highly integrated bioinformatics webserver for investigating, analyzing, and visualizing the TCGA and GEO gene expression data. CGPE provides key interactive and customizable analysis portal including:

Gene HotIndex

Gene specific PubMed trends analysis.

Gene HotIndex

OnlineGSEA

Gene or gene set associated pathway analysis.

OnlineGSEA

CellLine Search

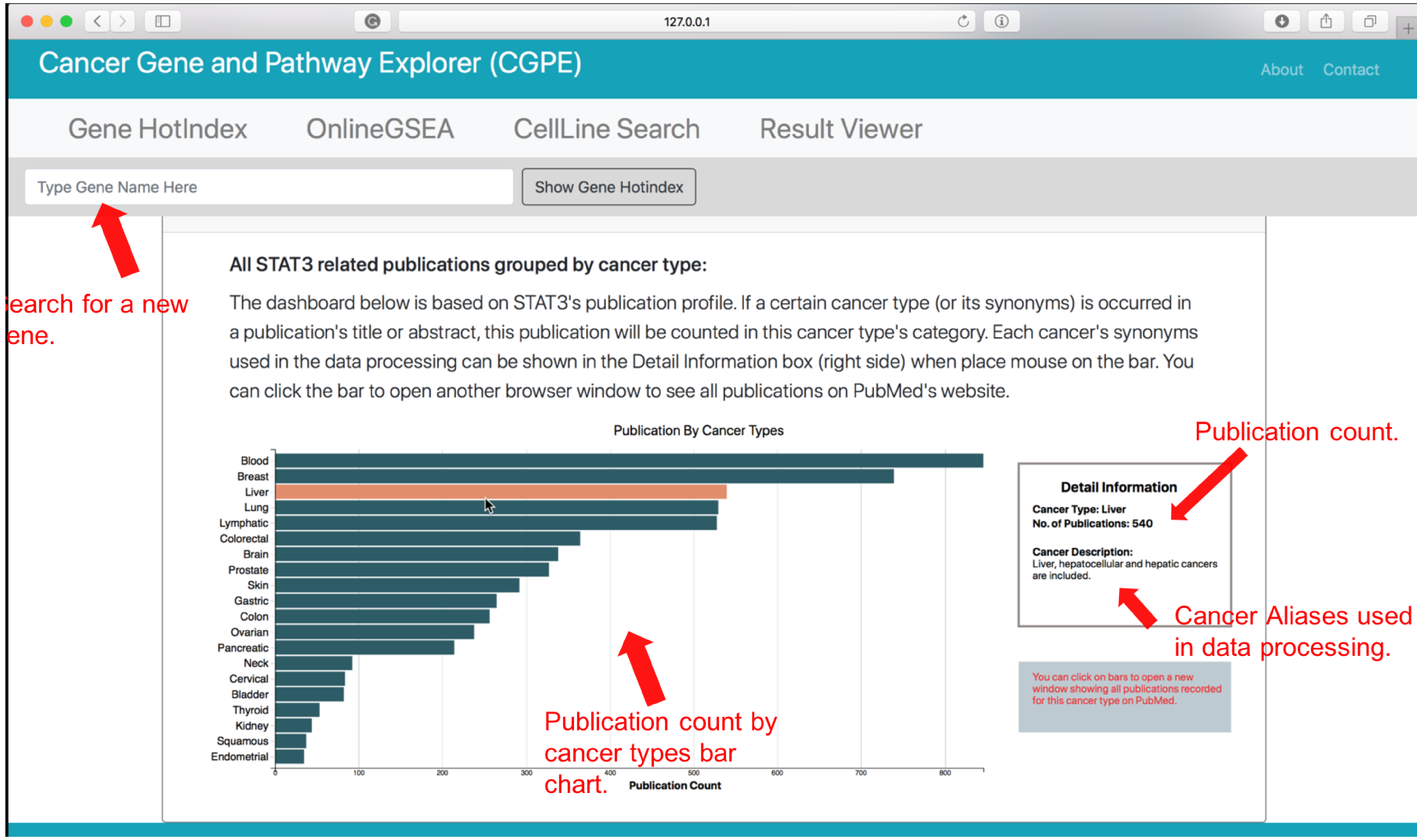
Cancer cell lines search based on integrated multiple resources.

CellLine Search

By focusing on the preliminary stage of biomedical research, CGPE provides a more integrated cancer genomic data investigation tool to deliver the most important information concerned by biomedical researchers, and it will also help biomedical researchers to unveil the potential associations between gene functions and cell functions from the big data perspective. **Tutorial** of CGPE can be found at Documentation page.

Citation:

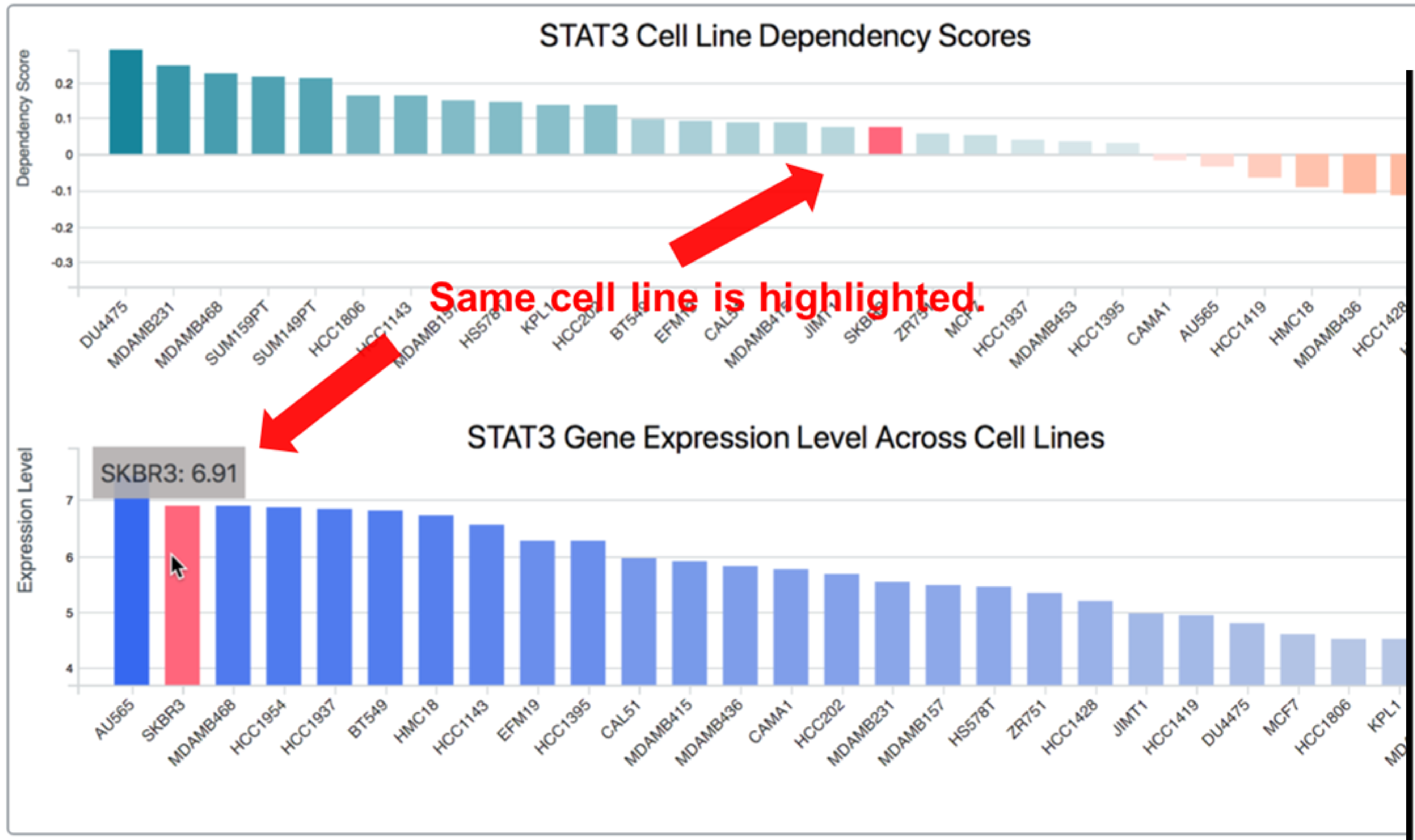
Jiannan Liu, Chuanpeng Dong, Yunlong Liu, Huanmei Wu. ***"CGPE: An integrated user-friendly gene and pathway exploration webserver for cancer transcriptional data"*** *(Manuscript waiting to be submitted)*



https://cgpe.soic.iupui.edu/

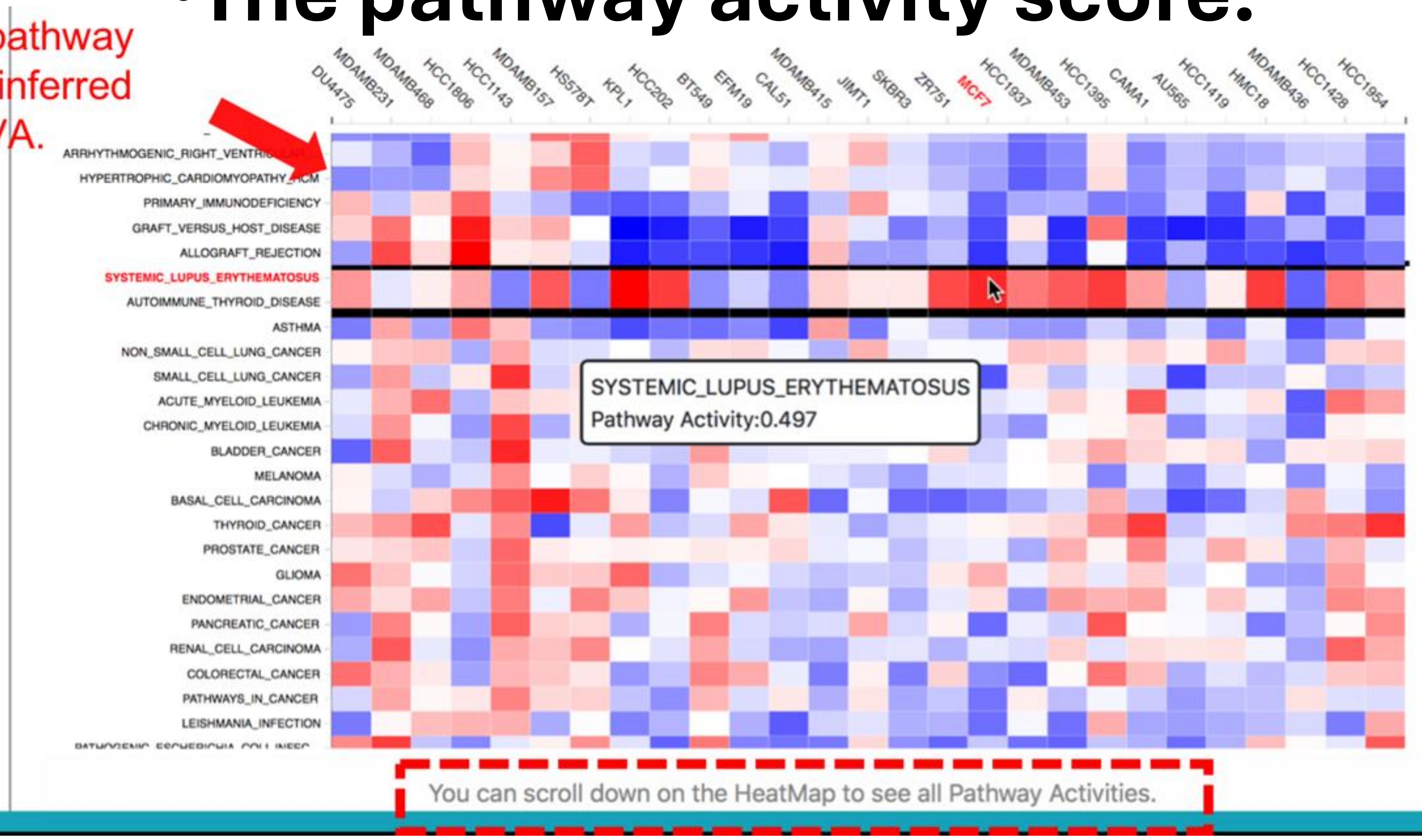
Liu et al, 2019

•The pathway activity score:

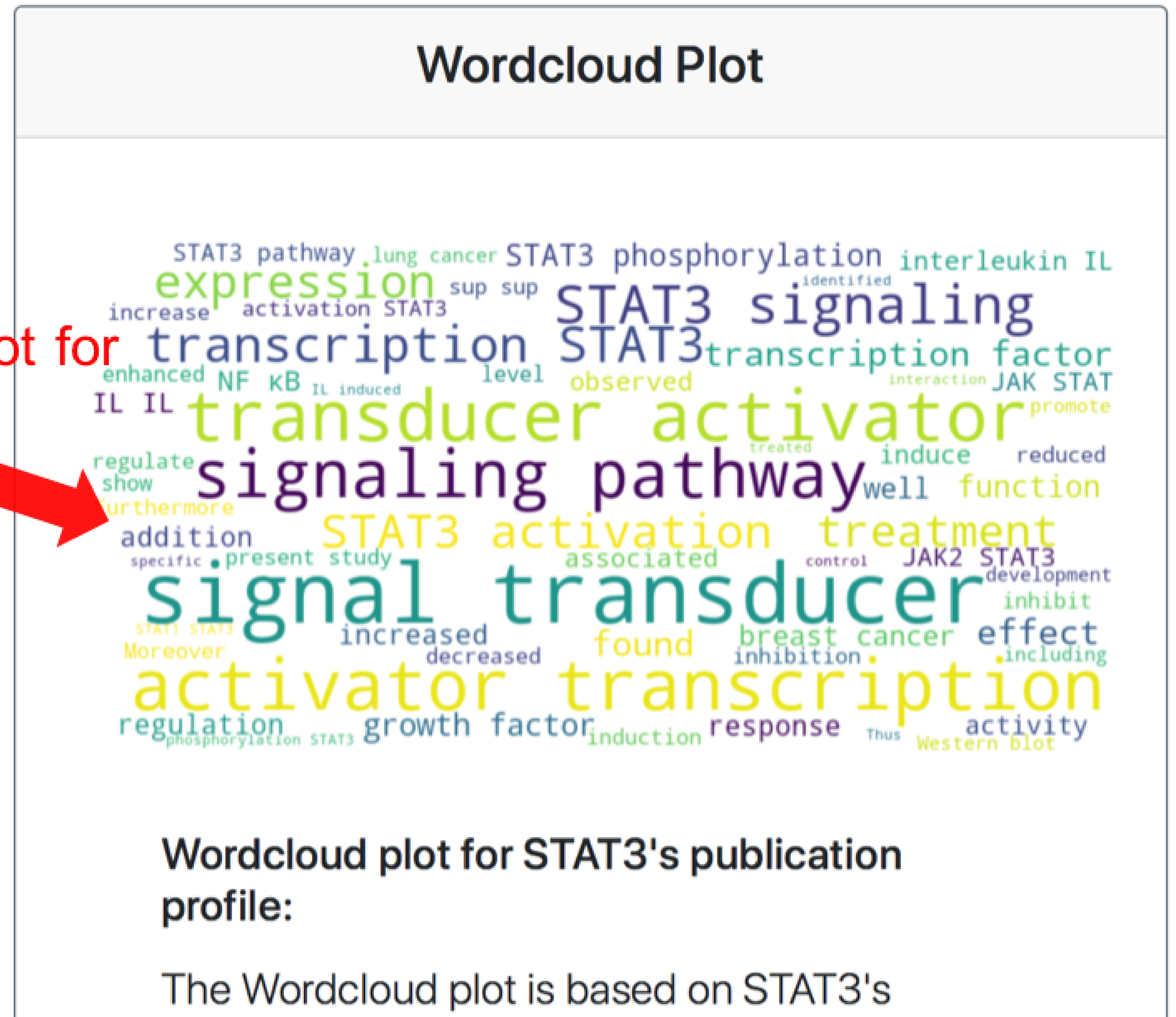


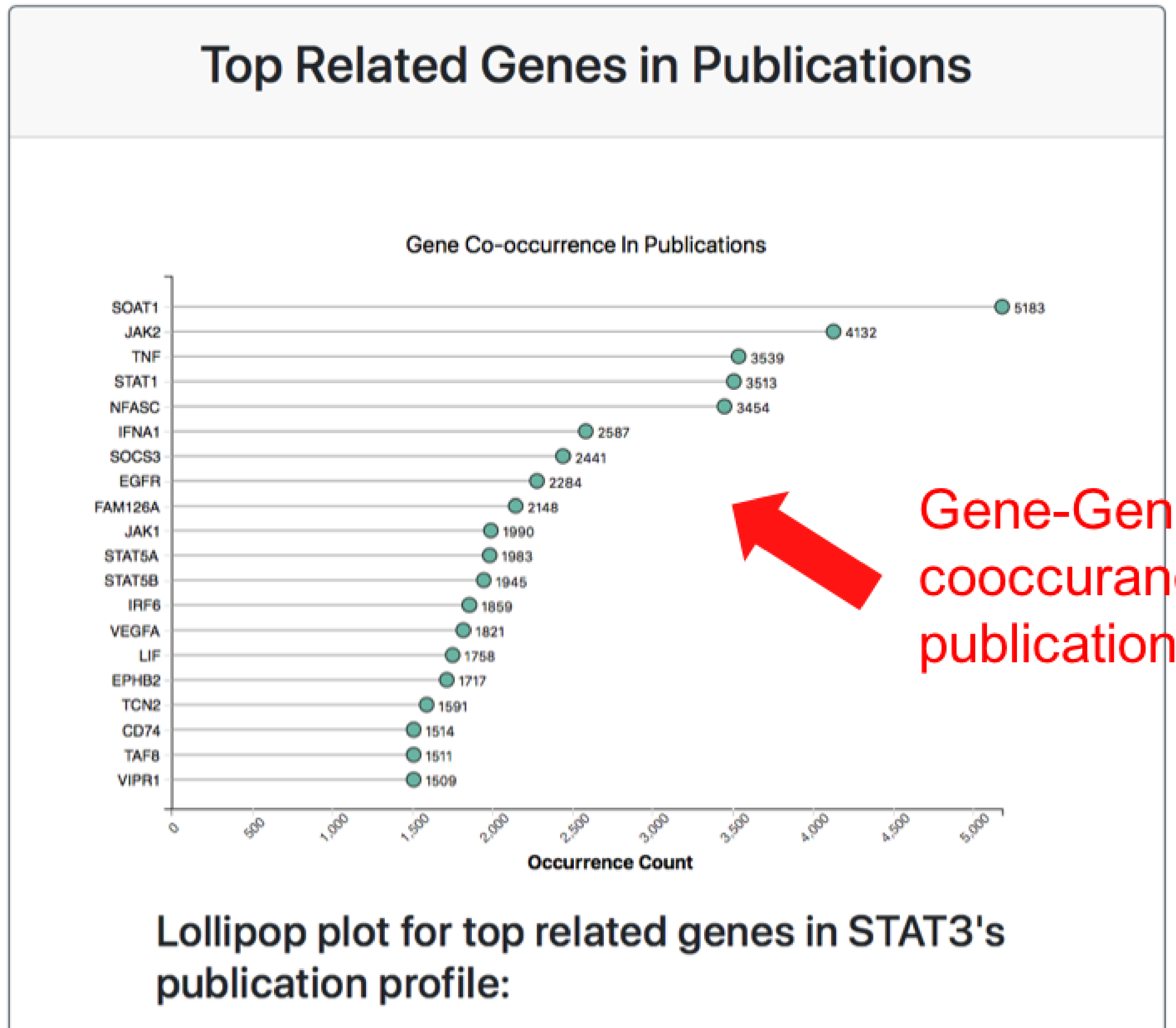
Cell Line Dependency (Interactive)

Cell line pathway activities inferred from GSVA.

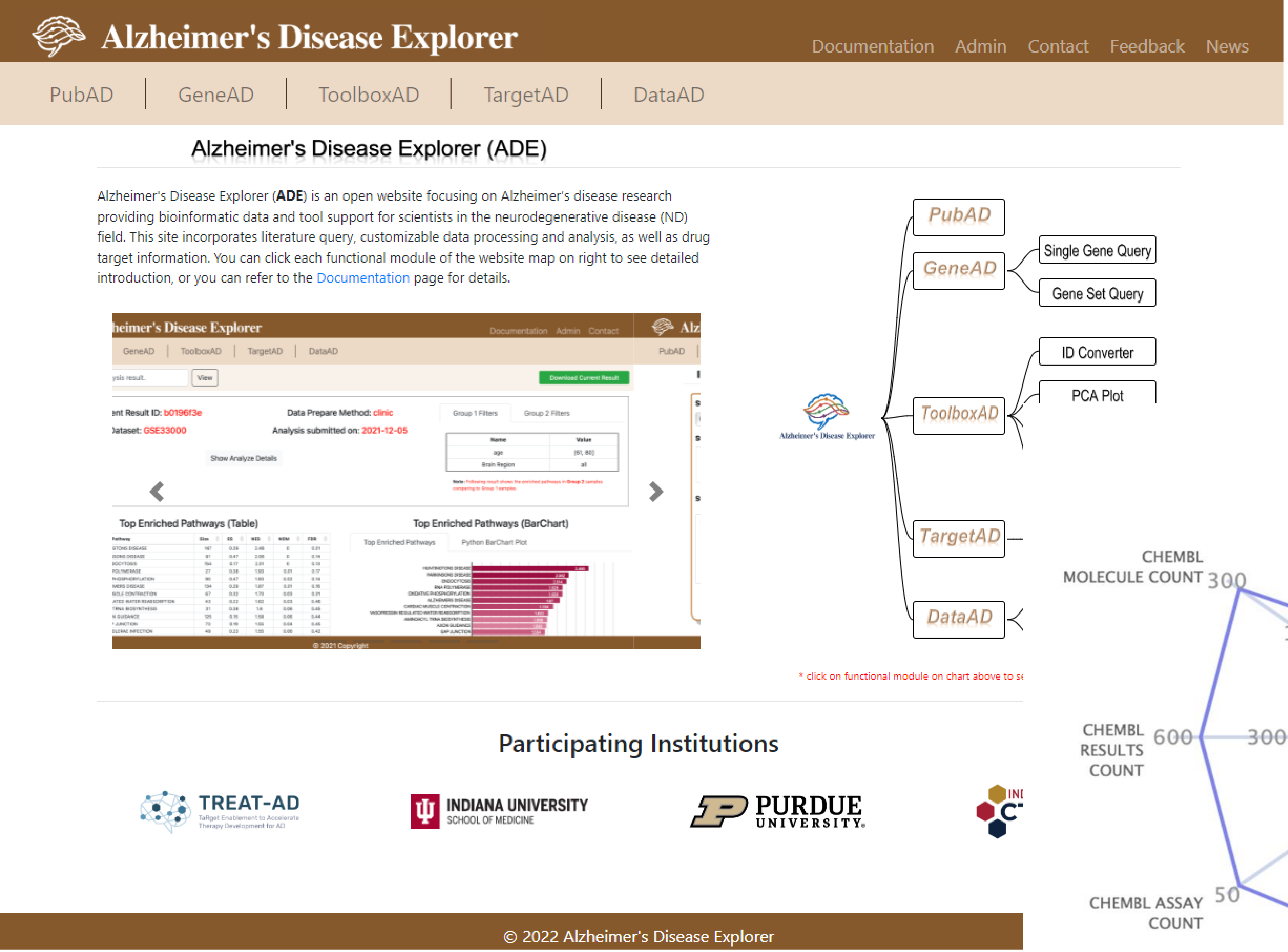


Wordcloud plot for query gene.

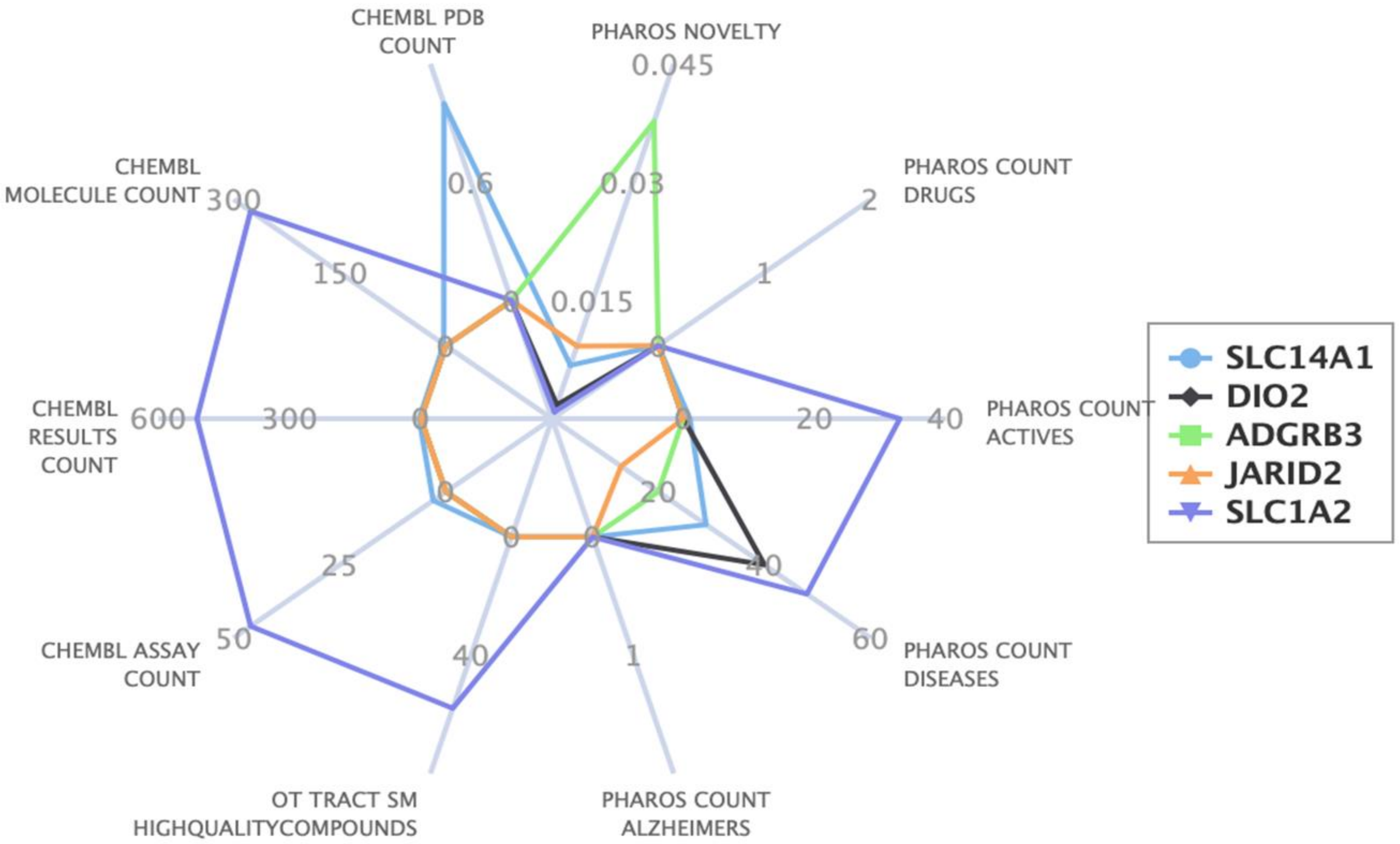




Gene-Gene cooccurance count in publication profiles.



https://adexplorer.medicine.iu.edu/



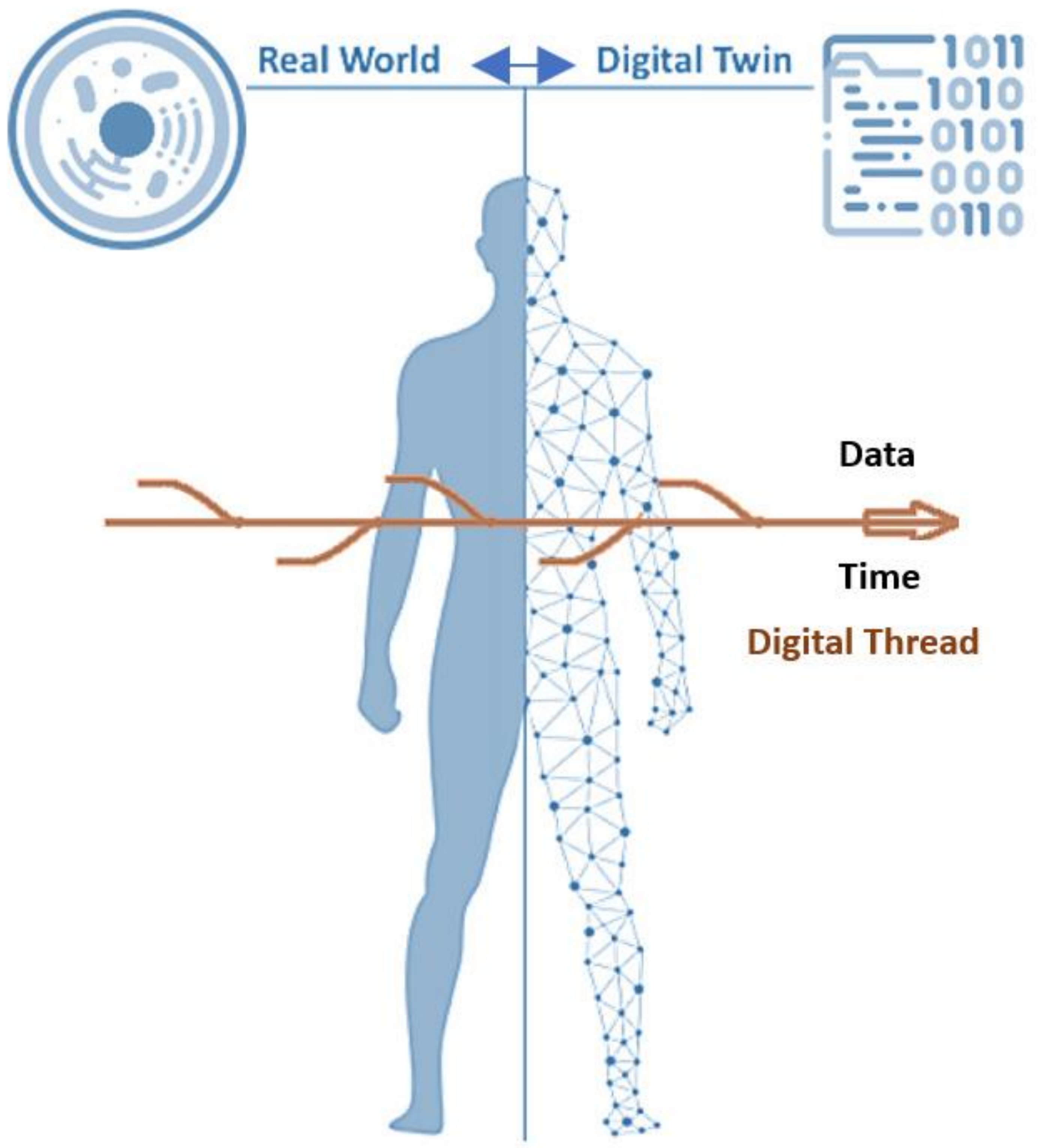
Drug target profiling using TargetAD

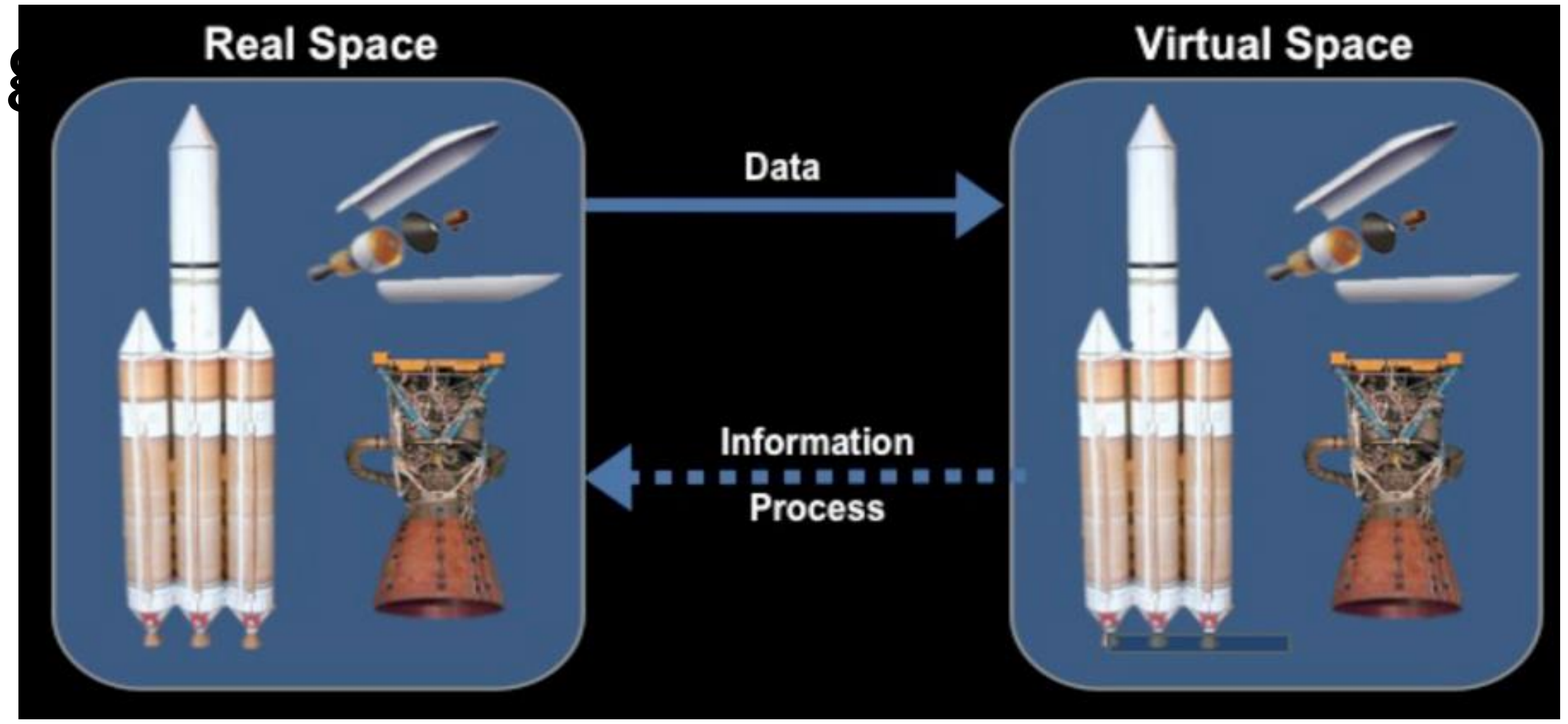
Vision:

Digital Twins for Personalized Pandemic Response

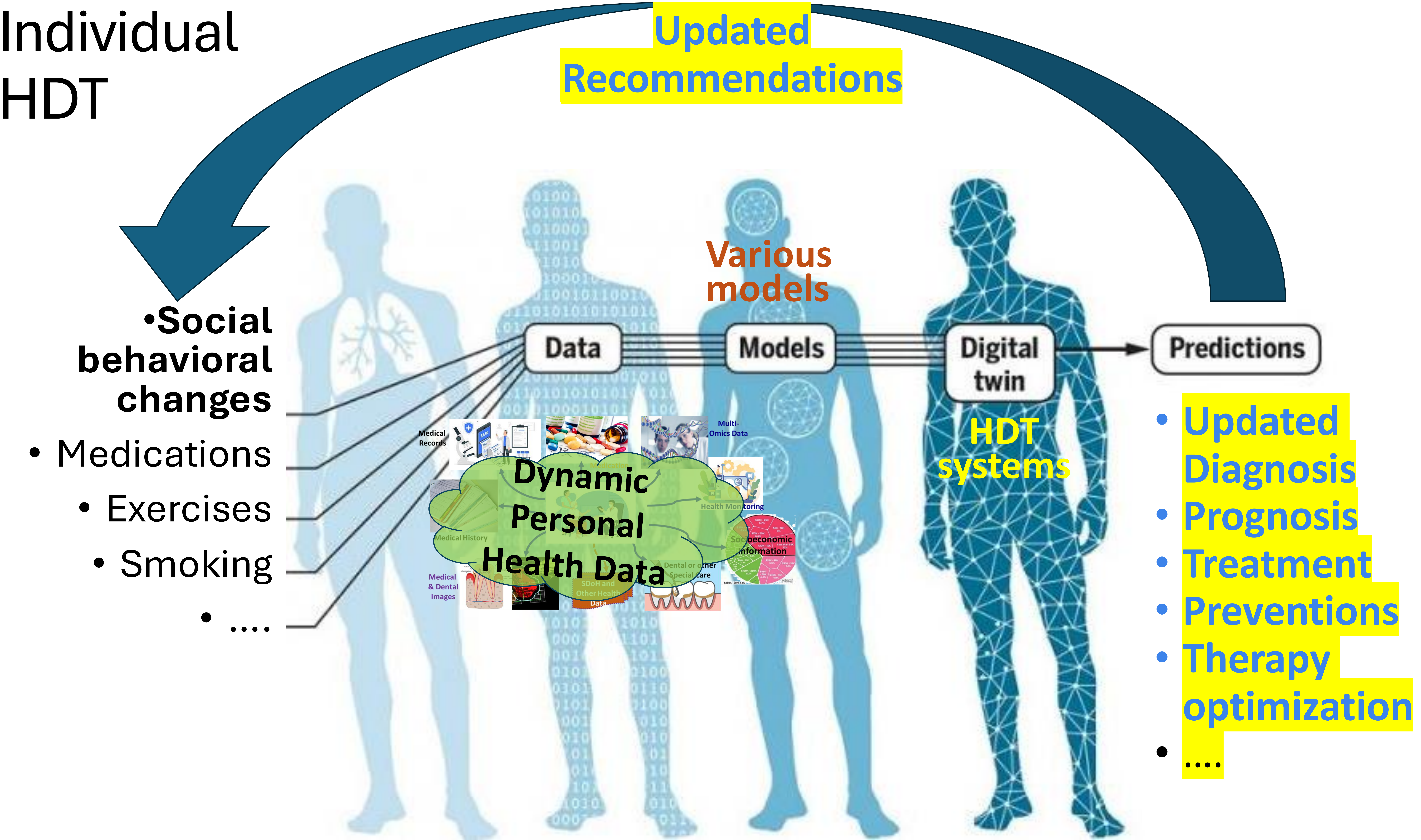
Introduction of Digital Twins

- A digital twin is a
  - A virtual representation of a real-world item or process
  - A convergence technology, which promises to bridge the gap between real and virtual
  - A virtual representation of an object or system that spans its lifecycle, is updated from real-time data, and uses simulation, machine learning and reasoning to help decision-making



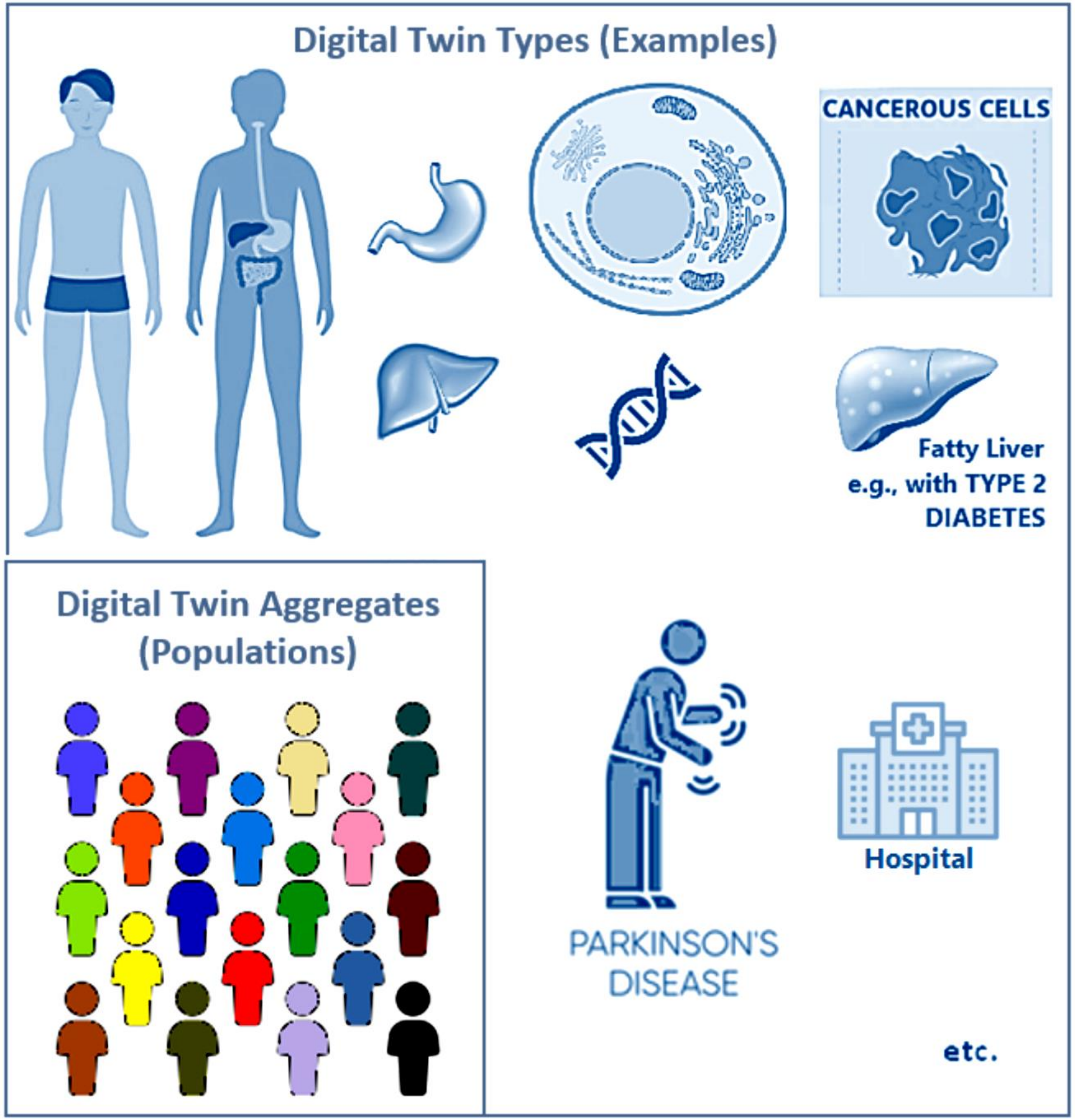


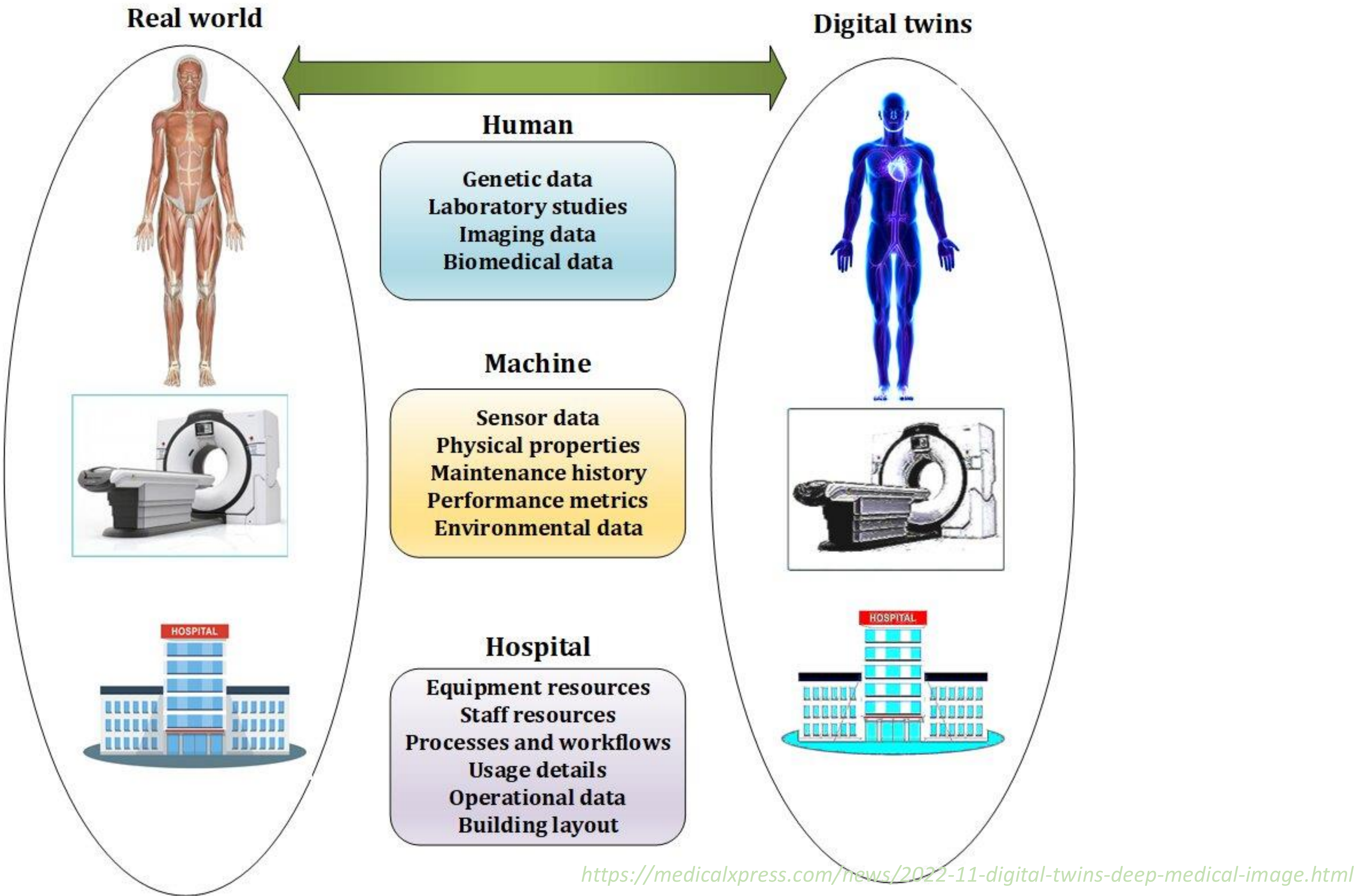
Individual HDT



Different Types of DTs four Healthcare

- Human DTs
  - the whole human body,
  - one body system (e.g., digestive system)
  - one body organ (e.g., stomach or liver)
  - one cell of a given type
  - some specific subcellular
  - Molecular level
- Disease DTs
  - Healthy or diseased entities
- Population DTs:
  - Aggregates
- Healthcare institutions
  - e.g., a hospital or department



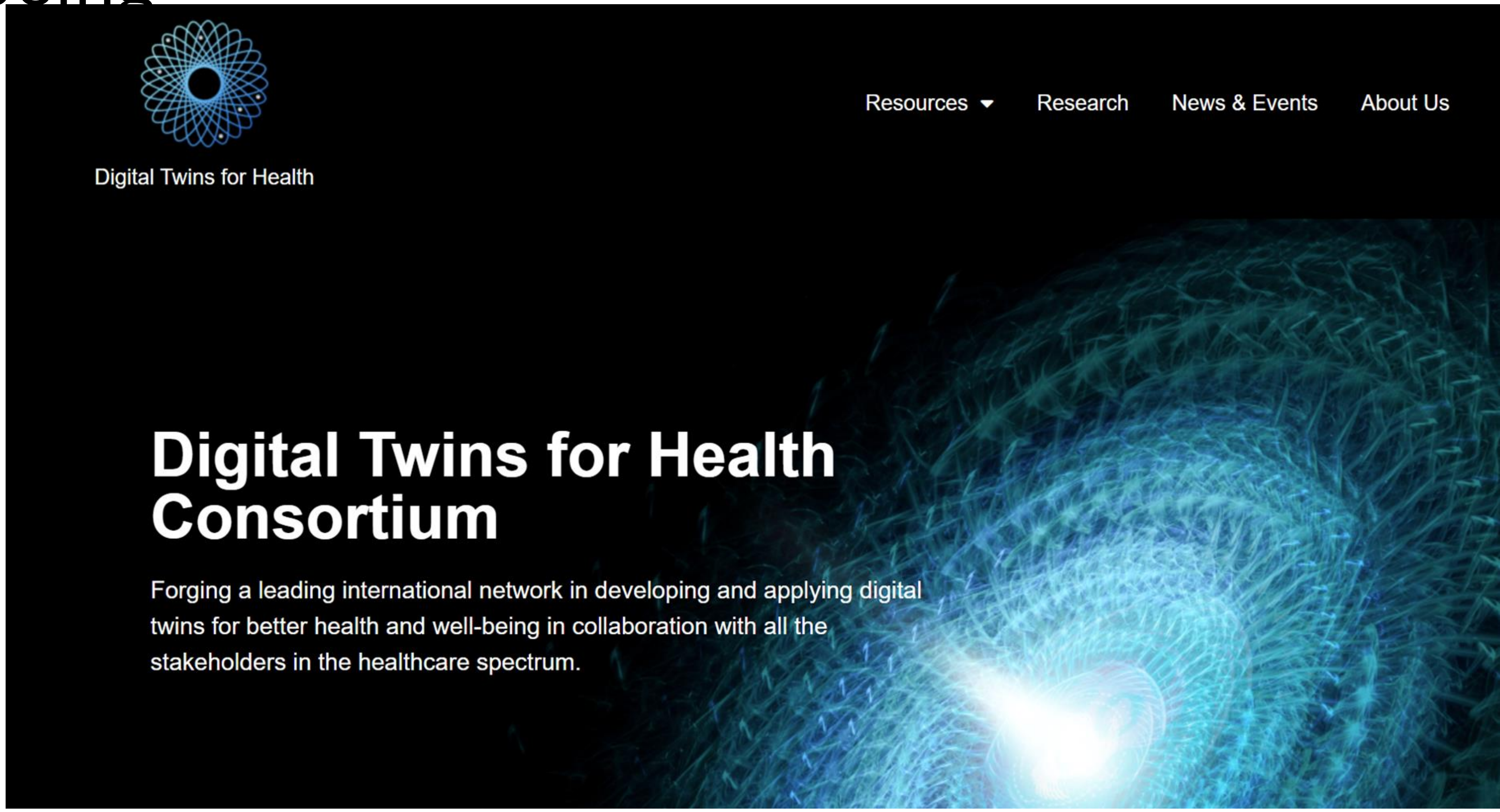

Real world
Digital twins
Human
Genetic data
Laboratory studies
Imaging data
Biomedical data
Machine
Sensor data
Physical properties
Maintenance history
Performance metrics
Environmental data
Hospital
Equipment resources
Staff resources
Processes and workflows
Usage details
Operational data
Building layout
HOSPITAL
HOSPITAL
https://medicalxpress.com/news/2022-11-digital-twins-deep-medical-image.html

Digital Twins for Health Consortium

- Digital Twins for health and well-being
  - An emerging area

- A lot of exciting areas
  - Data
  - Modeling (ML/AI)
  - Tools
  - …

- Challenging
  - Collaborations are needed
  - to identify needs and opportunities



dt4h.org

DT4H Consortium Activities

npj | digital medicine

Review artic

Published in partnership with Seoul National University Bundang Hospital

https://doi.org/10.1038/s41746-024-010

Digital twins for health: a scoping review

Check for upd

Evangelia Katsoulakis[1,2], Qi Wang[3], Huanmei Wu[4], Leili Shahriyari[5], Richard Fletcher[6,7], Jinwei Liu[8], Luke Achenie[9], Hongfang Liu[10], Pamela Jackson[11], Ying Xiao[12], Tanveer Syeda-Mahmood[13], Richard Tuli[2] & Jun Deng[14]

The use of digital twins (DTs) has proliferated across various fields and industries, with a recent surge in the healthcare sector. The concept of digital twin for health (DT4H) holds great promise to revolutionize the entire healthcare system, including management and delivery, disease treatment and prevention, and health well-being maintenance, ultimately improving human life. The rapid growth of big data and continuous advancement in data science (DS) and artificial intelligence (AI) have the potential to significantly expedite DT research and development by providing scientific expertise, essential data, and robust cybertechnology infrastructure. Although various DT initiatives have been underway in the industry, government, and military, DT4H is still in its early stages. This paper presents an overview of the current applications of DTs in healthcare, examines consortium research centers and their limitations, and surveys the current landscape of emerging research and development opportunities in healthcare. We envision the emergence of a collaborative global effort among stakeholders to enhance healthcare and improve the quality of life for millions of individuals worldwide through pioneering research and development in the realm of DT technology.

Advancing Healthcare with Human Digital Twins: Strategies and Insights

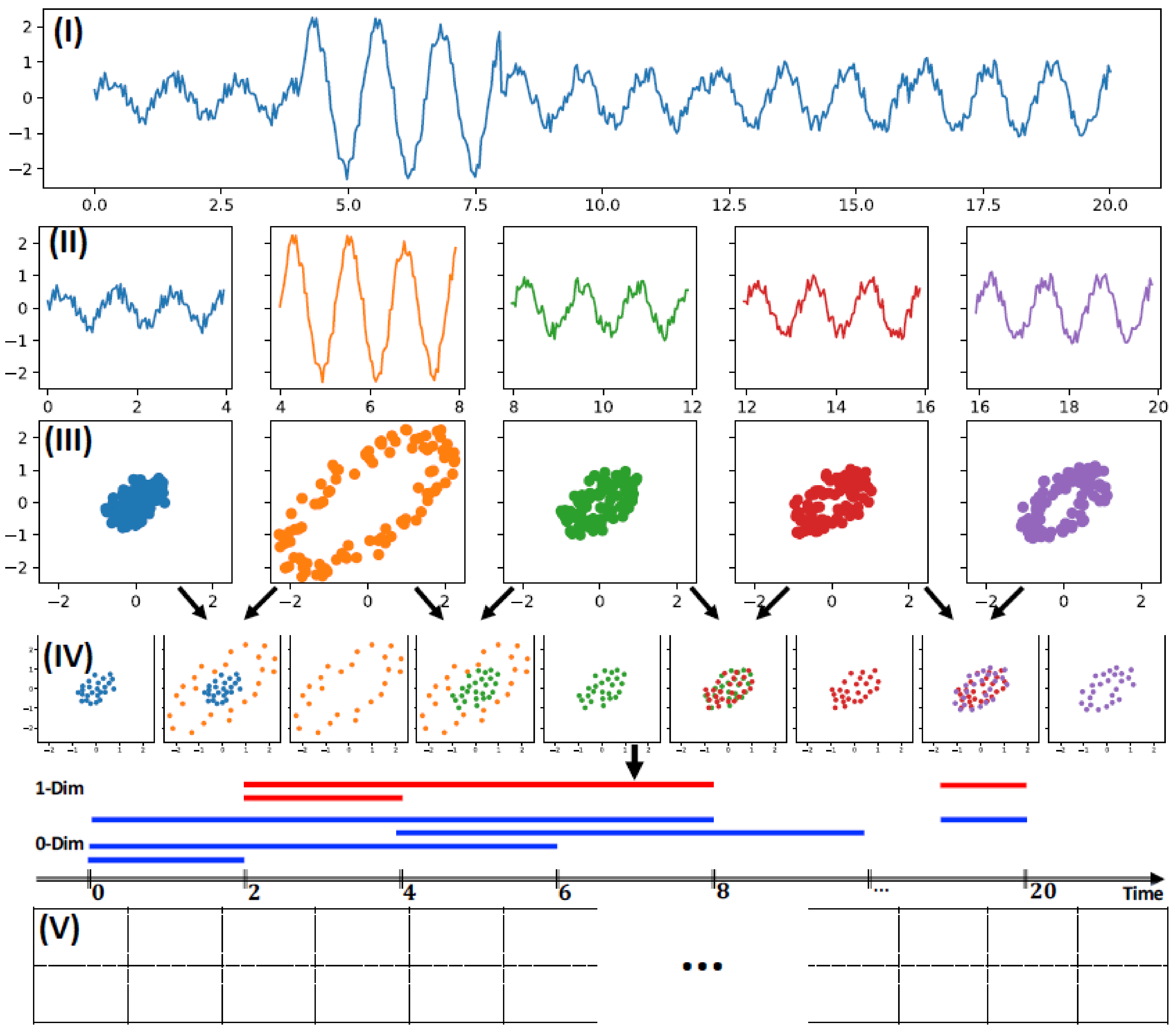
Abstract

A human digital twin (HDT) is a dynamic virtual representation of a human-based physical system, being a human body, an organ system, a single organ, or a tissue. Since its inception, a digital twin has been envisioned to replicate the underlying physical system in its entirety through dynamic synchronization enabling analysis and predictions for the system. When implemented in healthcare, the HDT can serve as a comprehensive representation of the target system across all healthcare phases, spanning diagnosis, prognosis, treatment and prevention. Its purpose is to ad ... ent int ... ial ap ... ne sig ... on of

DT-Brain: A Topology-Empowered Digital Twin for Brain Health Monitoring and Neurological Diseases Prevention

Time-series data and their corresponding time-delay embeddings

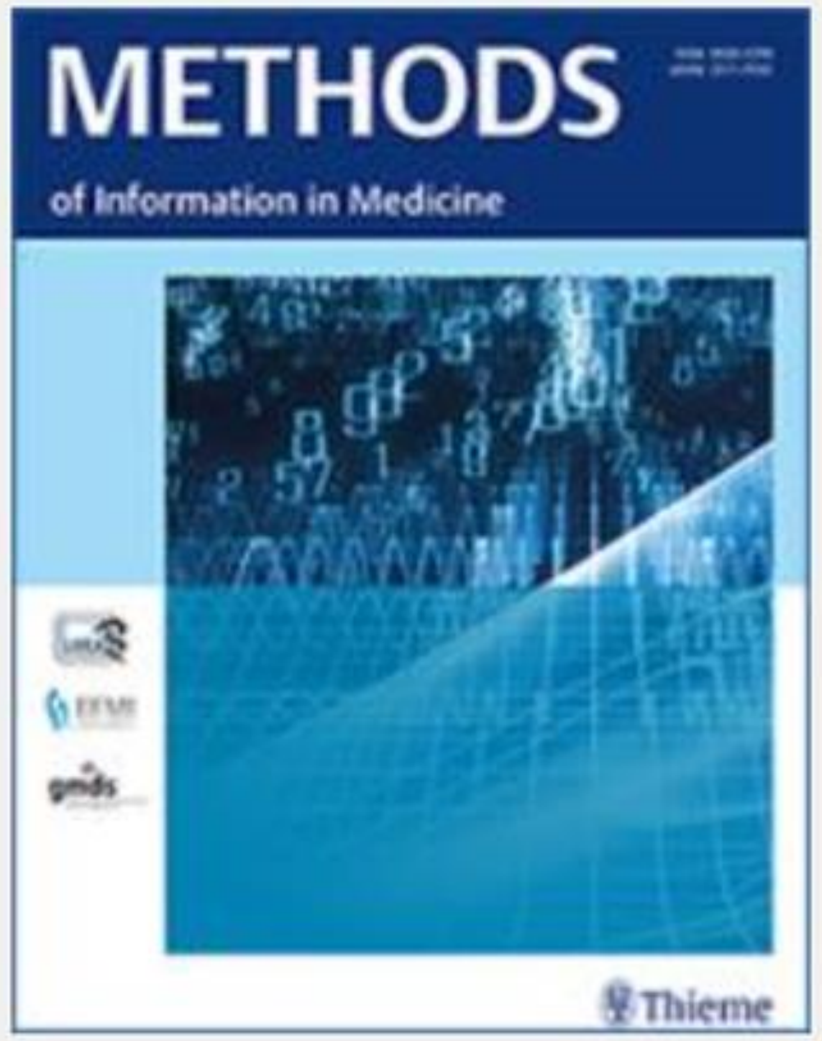
Types	Sub-types	Examples
Neuroimaging	MRI (Magnetic Resonance Imaging): Structural and functional brain images	A high-resolution T1-weighted MRI scan showing the brain's anatomy
	fMRI (Functional MRI): Measures brain activity by detecting changes in blood flow	An fMRI scan showing brain regions activated during a cognitive task
	DTI (Diffusion Tensor Imaging): Diffusion of water molecules to map white matter tracts	A DTI scan highlighting the brain's white matter pathways
Electrophysio-logical	EEG (Electroencephalography): Records electrical activity of the brain	An EEG recording showing brain waves in different frequency bands (alpha, beta, delta, theta)
	MEG (Magnetoencephalography): Measures magnetic fields produced by neuronal activity	A MEG scan displaying brain activity patterns during sensory processing
Genomic	Genotyping: Genetic variants associated with brain health and disease	SNP (Single Nucleotide Polymorphism) array indicating variants linked to Alzheimer's diseas
	Transcriptomics: AGene expression profiles in brain tissue	RNA-Seq data showing differentially expresse genes in healthy vs diseased brain tissue
Cognitive Assessments	Tests measuring memory, attention, executive function, and other cognitive abilities	Results from a memory recall test showing sco over time in a longitudinal study
Behavioral Observations	Recorded behaviors during specific tasks or daily activities	Video recordings and annotations of motor skil patients with Parkinson's disease
Clinical	Medical Records: Patient histories, diagnoses, treatment plans, and outcomes	Electronic health record (EHR) data summariz the clinical history of a patient with epilepsy
	Neurological Exams: Detailed examinations assessing neurological functions	Neurological examination results indicating m and sensory deficits
Biomarker	CSF (Cerebrospinal Fluid) Biomarkers: Levels of proteins and other molecules in CSF	CSF amyloid-beta and tau protein levels in pat with Alzheimer's disease
	Blood Biomarkers: Blood tests indicating markers associated with brain health	Plasma levels of neurofilament light chain (Nf individuals with traumatic brain injury
Lifestyle	Lifestyle Surveys: Data on diet, exercise, sleep, and other lifestyle factors	Survey results detailing the physical activity patterns of participants in a brain health study
	Substance Use: Alcohol, tobacco, and drug use can have detrimental effects on brain health	Chronic alcohol abuse leads to neurodegenerat conditions like Wernicke-Korsakoff syndrome
Environmental Exposure	Information on exposure to pollutants, toxins, and other environmental factors	Data on air quality and its correlation with cognitive decline in an urban population
Psychometric	Mental Health Assessments: Standardized questionnaires and scales for mental health	Scores from the Beck Depression Inventory (B in a patient cohort with major depressive disor
SDoHs	Various social determinants of health (SDoHs) to be describe more in the text.	



Data Types used in DT-Brain

Thanks!

Other Project 4:
Machine Learning and Natural Language Processing on Real World Data to Identify Adverse Events



Year (Archive)

Methods Inf Med
DOI: 10.1055/s-0042-1760248

Download PDF

Original Article

Automatic Identification of Self-Reported COVID-19 Vaccine Information from Vaccine Adverse Events Reporting System

Jay S. Patel , Sonya Zhan , Zasim Siddiqui , Bari Dzomba , Huanmei Wu

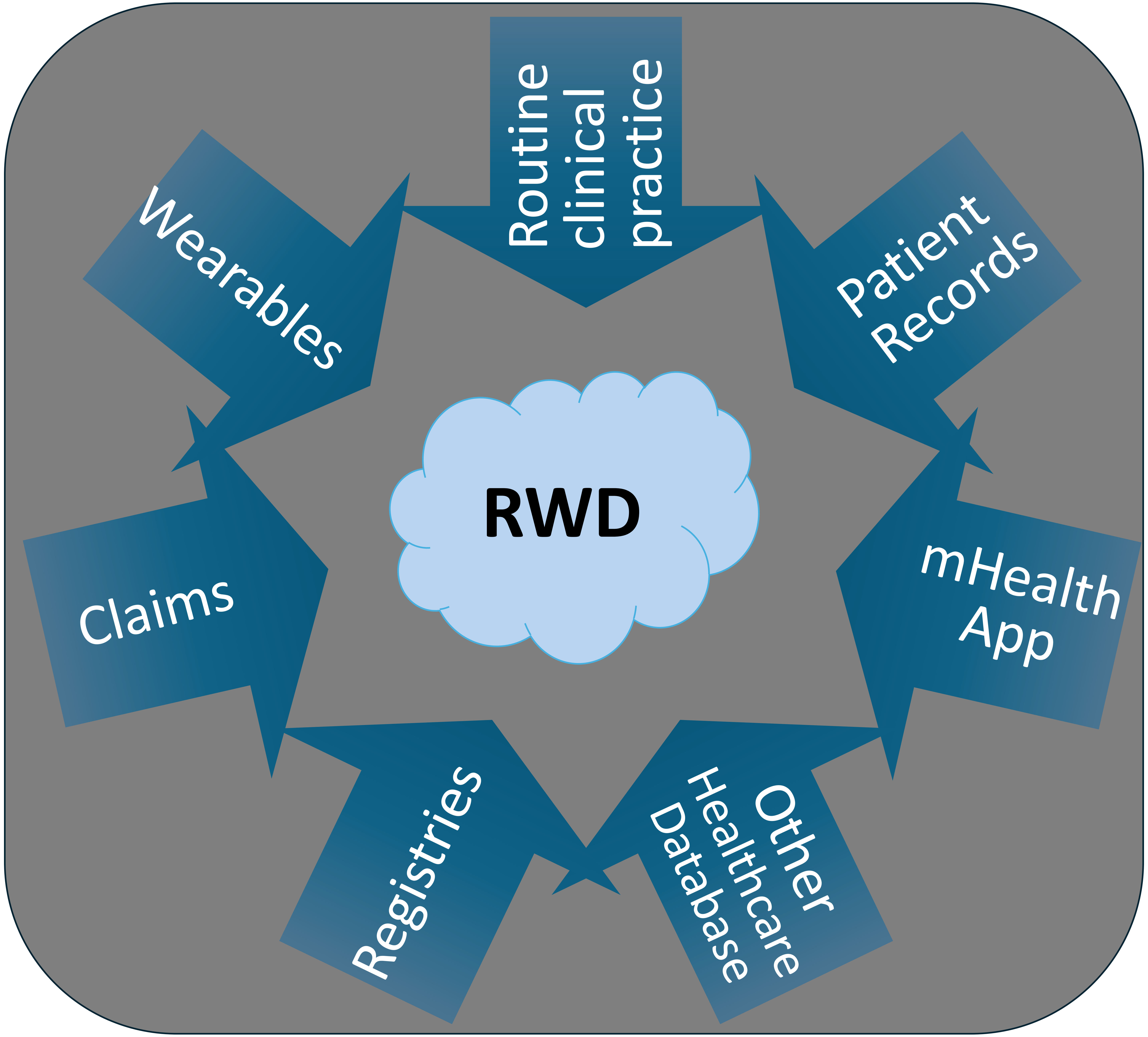
› Author Affiliations

› Further Information

Abstract | Full Text | References

Sample Project 4: RWD

- Health-related information collected from various sources outside of traditional clinical trials in real-world settings.



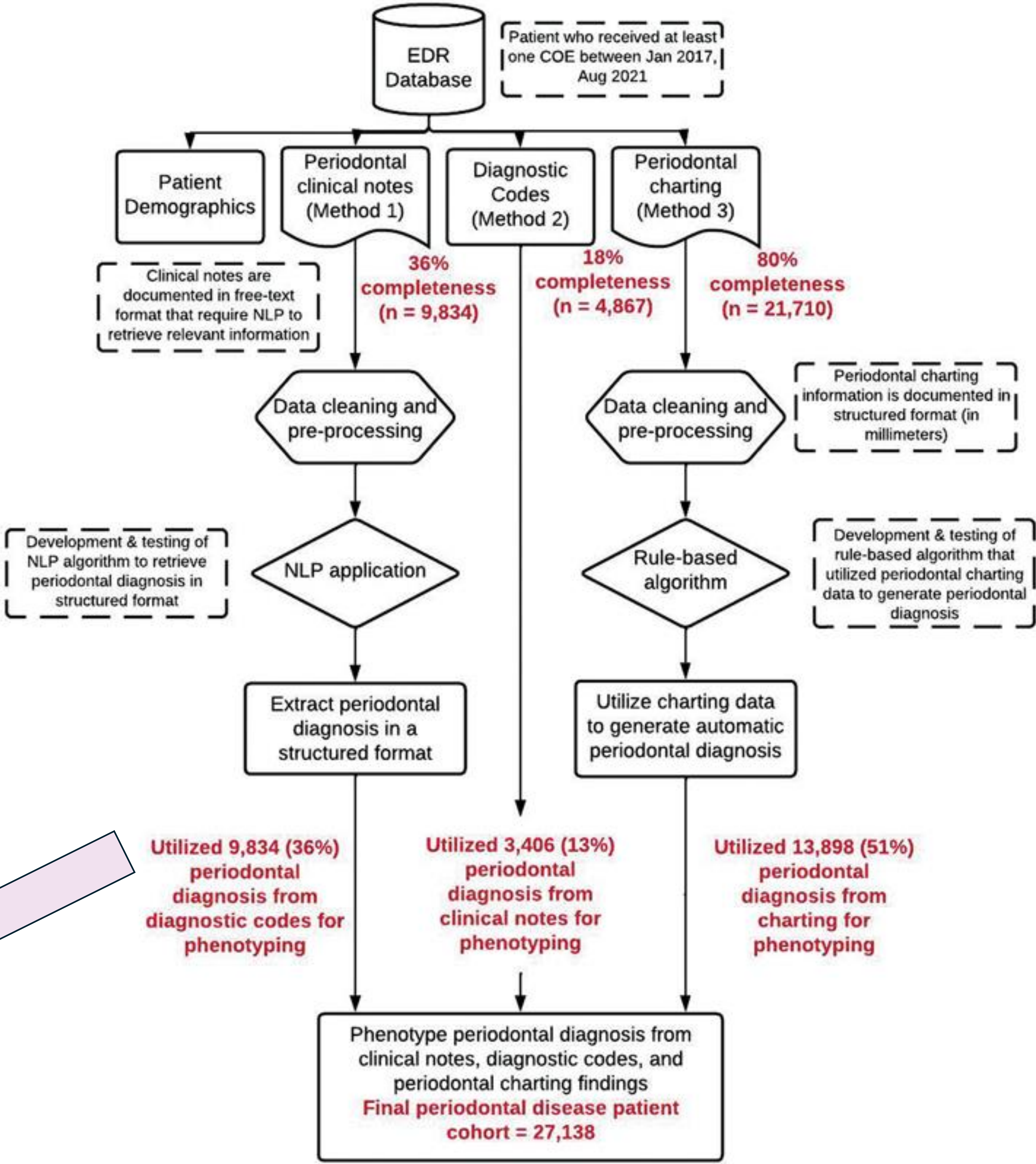
Article published online: 2022-11-22

THIEME OPEN ACCESS

Developing Automated Computer Algo
Phenotype Periodontal Disease Diagno
Electronic Dental Records

Jay Sureshbhai Patel[1] Ryan Brandon[2] Marisol Tellez[2] Jasim M. Albanda
Joachim Krois[4] Huanmei Wu[1]

RWD Used:
Electronic Dental Records
(Temple University)



Complete periodontal disease (PD) diagnoses from diagnosis codes, clinical notes, and periodontal charting of EDR

Sample Project 5

NSF Award Search: Award # 233

nsf.gov/awardsearch/showAward?AWD_ID=2333703&HistoricalAwards=false

Awards

Search Awards

Recent Awards

Presidential and Honorary Awards

About Awards

How to Manage Your Award

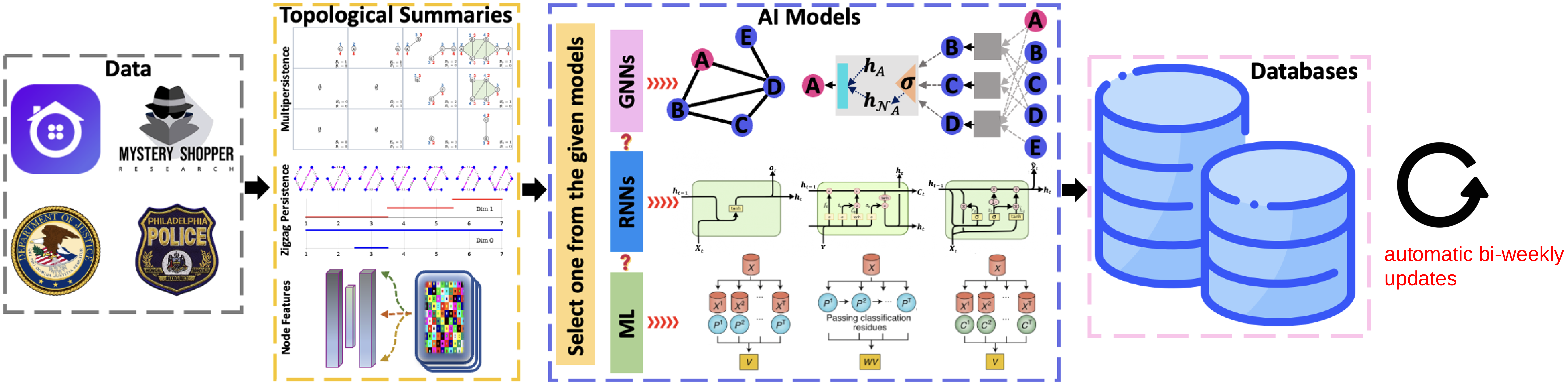
Grant General Conditions

Award Abstract # 2333703

Proto-OKN Theme 1: DREAM-KG: Develop Dynamic, REsponsive, Adaptive, and Multifaceted Knowledge Graphs to address homelessness with Explainable AI

NSF Org:	ITE Innovation and Technology Ecosystems
Recipient:	TEMPLE UNIVERSITY-OF THE COMMONWEALTH SYSTEM OF HIGHER EDUCATION
Initial Amendment Date:	September 8, 2023
Latest Amendment Date:	September 8, 2023
Award Number:	2333703
Award Instrument:	Cooperative Agreement

Thrust A: Data Integration and Explainable ML/DL



- Collect dynamic data and feedback from volunteers
- Merge multi-view features
- Develop topological data analysis (TDA) tools and explainable ML/DL models for accurate data self-correction and human-intelligible explanations

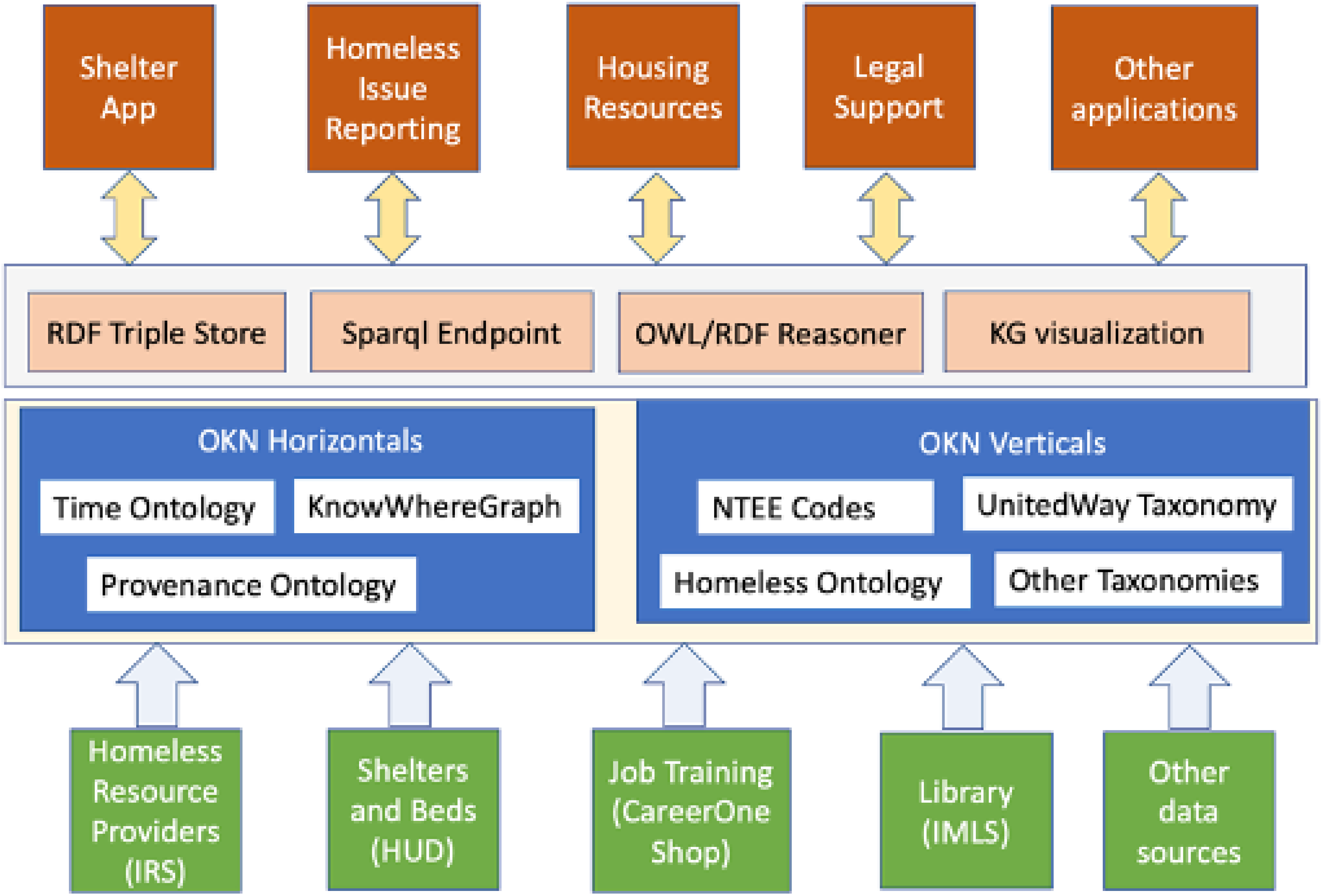
Thrust B: DREAM-KG Development

- **Develop the OKN Ontology and Taxonomy**
  - Incorporating dynamic and multifaceted information into the ontology

  ➔ a comprehensive view of homelessness

- **Build the DREAM-KG**
  - Allow users to contribute datasets

  ➔ community-centric and user-driven platform



Thrust C: Customized App Development

- A one-stop shop for serving PEH
  - Emergency Shelters
  - Serving Returning Citizens for USDOJ
  - Utilizing Dynamic Providers and Mobile Offices/Services
  - Leveraging KG for Law Enforcement
  - Evidence-based Policymaking