

Advancing the Use of Artificial Intelligence & Machine Learning in Primary Care: *Roles & Opportunities for DFMs*

Andrew Bazemore MD MPH
Bob Phillips MD MSPH

The Opportunity

PRIMARY CARE is

“the provision of integrated, accessible health care services by clinicians who are accountable for addressing a large majority of personal health care needs, developing a sustained partnership with patients, and practicing in the context of family and community”

– Burnout

*Martin S, Phillips RL, Petterson S, Levin Z, Bazemore AW. Primary Care Spending in the United States, 2002-2016. *JAMA Intern Med.* 2020;180(7):1019–1020.

The Opportunity

AI/ML has

- Revolutionized industries, including medicine, but has yet to transform primary care.
 - Review of primary care & AI/ML concluded...the field remains in “early stages of maturity,” despite a 35 yr history^{*}
 - Only 1 out of every 7 of these papers includes a primary care author; therefore, one barrier to greater impact is engagement from the primary care community.
- Infrequently involved PC end-users and researchers in development to date
- Scarcely tapped the wealth of data & technology available from PC practices

*Kueper J, Terry AL, Zwarenstein M, Lizotte DJ. Artificial Intelligence and Primary Care Research: A Scoping Review. *Ann Fam Med*.

The Opportunity

The **Quintuple Aim*** for U.S. Healthcare includes

- Better Health
- Better Patient Experience
- Lower Costs
- Improved Clinician Wellbeing
- Equity in Outcomes

*<https://www.ahrq.gov/ncepcr/tools/workforce-financing/white-paper.html>

Pathways connecting PC, AI/ML, & the Quintuple Aim?



*We aim to align how the professions are valued
with the values of the professions*

NASEM Report

About ▾

Products & Activities ▾

Measures That Matter

Work With Us

Laboratory ▾

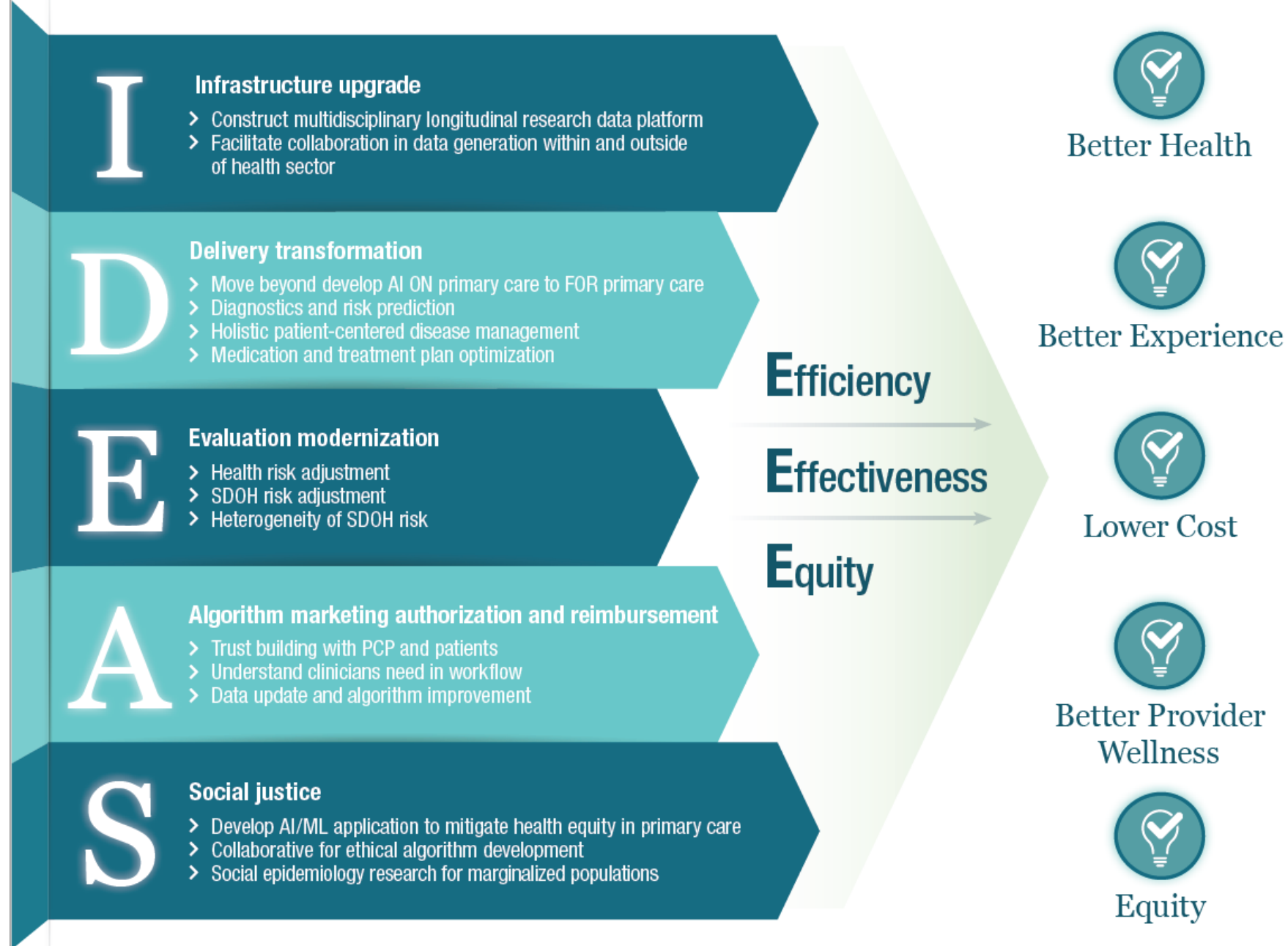
News & Events ▾



SETTING A RESEARCH AGENDA FOR THE USE OF ARTIFICIAL INTELLIGENCE & MACHINE LEARNING IN PRIMARY CARE

Virtual Summit: March 18-19, 2021

FOR QUESTIONS CONTACT: Andrew Bazemore, & Mikel Severson at 1-202-600-9447



Ongoing ABFM Investment in Advancement of AI/ML in Depts of Family Medicine

- Primary Care Specific Data Laboratories
 - PRIME Registry, Supporting National Labs(AHRQ)
- Convenings
- Presentations in AI/ML Communities
- Human Capital Investment



Family Medicine Artificial Intelligence and Machine Learning Faculty Support

2022 Grant Awards Announcement



American Board of Family Medicine Inc.



Why?

Enhance the capacity for AI/ML methods in Family Medicine to study primary care research questions using real-world, primary care data.



Expected Outcomes

Per Department/Division



One AI/ML researcher embedded for at least five years



Two proposals for externally funded research



Three peer-reviewed publications



University of Houston

PI: Winston Liaw, MD, MPH

Project Title: Primary Care Forecast: Using Social Risk Factors and Actionable, Explainable Artificial Intelligence/Machine Learning to Prevent the Progression of Diabetes Complications

Co-Investigators: Ioannis A. Kakadiaris, PhD; LeChauncy Woodard, MD, MPH; Omolola Adepoju, PhD, MPH

American Board of Family Medicine Inc.





University of Pittsburgh

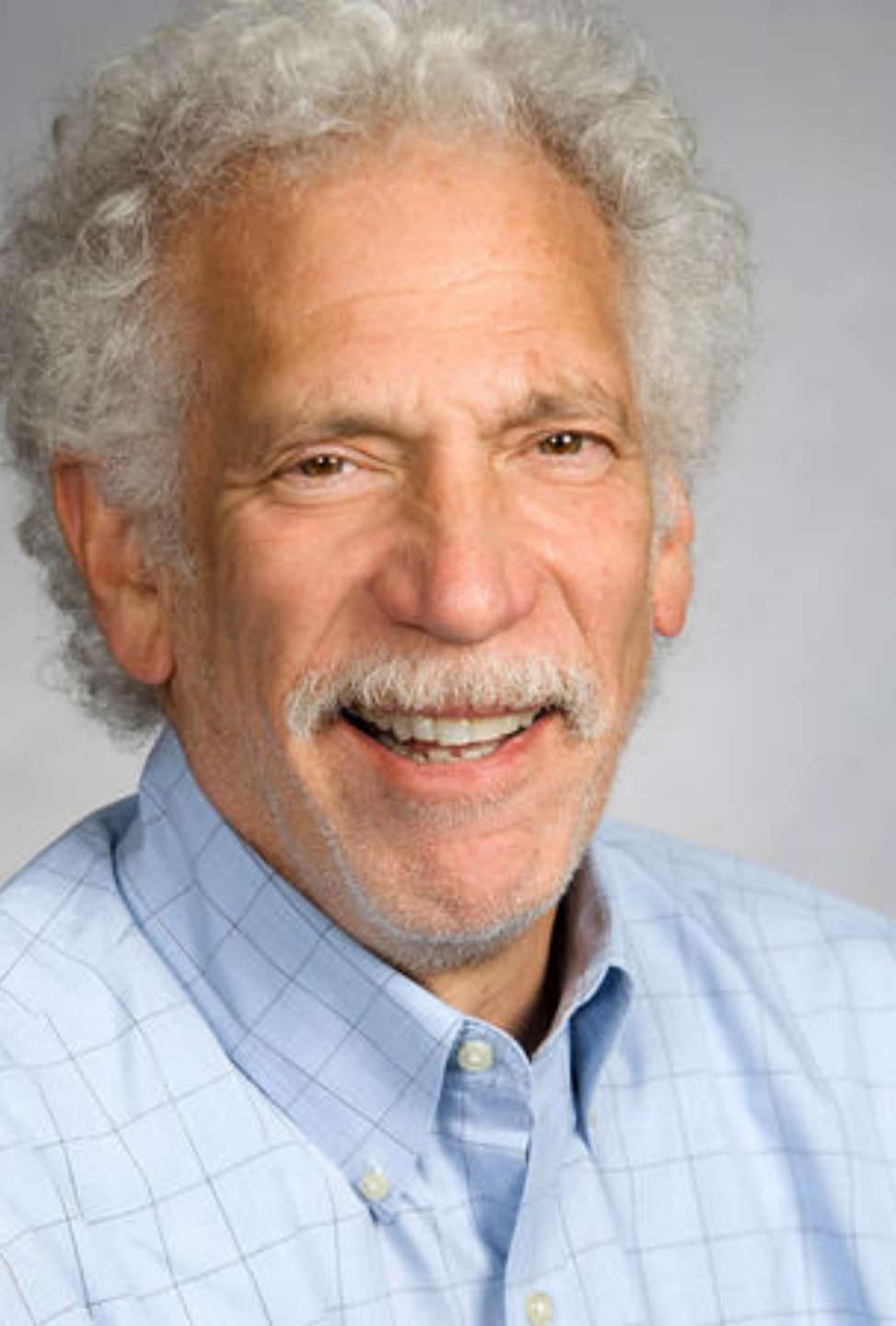
PI: John S Maier, PhD, MD

Project Title: Growing Primary Care Informatics using AI/ML to Understand Patients Not Just Diseases

Co-Investigators: Tracey Conti, MD; Shyam Visweswaran, MD, PhD; José Abad, MD

American Board of Family Medicine Inc.





University of California, San Diego

PI: Gene Kallenberg, MD

Project Title: Building AI/ML Capacity in the UCSD Department of Family Medicine

Co-Investigators: Ming Tai-Seale, PhD, MPH;
Lucila Ohno-Machado, MD, PhD, MBA;
Christopher Longhurst, MD

AI/ML Fellow: Ammar Mandvi, MD



University of Texas, San Antonio

PI: Carlos Roberto Jaén, MD, PhD

Project Title: Harnessing Complexity: Applying AI/ML to discover solutions of multi-morbidity in Primary Care

Co-Investigators: Meredith Nahm Zozus, PhD; Zhu Wang, PhD; Robert L. Ferrer, MD, MPH; David A. Katerndahl, MD, MA

AI/ML Fellows: Shorabuddin Syed, PhD; Yun Shi, MD, PhD

American Board of Family Medicine Inc.





WAKING THE SLEEPING GIANT



ENGAGING FAMILY MEDICINE IN DIGITAL/ AI TRANSFORMATION

David Rushlow, MD
Chair, Family Medicine
Mayo Clinic
Rochester, Minnesota, USA

Presentation Overview

The Power of AI to Transform Primary Care

Challenges and Opportunities for AI in Family
Medicine

Overview of Mayo Clinic Midwest Dept. of Family
Medicine

Our Experience using AI and Pragmatic Trials to
Transform Practice

Example of the EAGLE study as a prototype project

Healthcare Delivery Innovation Laboratory (iLab)

Power of AI to Transform Primary Care

Most comprehensive care delivery platform in US*

Enormous clinical data repository largely unused.

Not limited by disease, age, geography, race, ethnicity, social determinants of health, etc.

Focus on wellness, disease prevention and chronic disease management leading to greater downstream impact on overall health

**Pettersen, et al. Washington: Robert Graham Center (2018).*

Power of AI to transform Primary Care



Primary care providers are burning out at record pace*



Breadth of knowledge base provides excellent opportunity for decision support



Evidenced-based decision support provides opportunity to reduce cost through lower hospitalizations and diagnostic testing.



Must be well aligned with front line workflow to reduce disruption and alert fatigue.

*Goldberg et al, JBFM 5/2020

Strategic Challenges for Mayo Clinic Family Medicine



Not meeting expectations
of the Quadruple Aim



Information overload!!



Gap between innovation and front-line practice
too long – 17 years*



Significant disparities in health equity



Disruptors are active and moving fast

**Morris ZS, Wooding S, J R Soc Med.*



AI Opportunities for Mayo Clinic Family Medicine

Leverage the value of a large integrated Family Medicine Department

- Leadership Infrastructure.
- Single EHR database.
- 400K patients
- 550 engaged provider pragmatists!

Leverage Mayo Clinic's Digital/AI Expertise

- Center for Digital Health
- Clinical and Pragmatic Trials Research Infrastructure
- Implementation Science
- Embedded expertise within specialty departments



Opportunities for Alignment cont.

Aligned Strategic Priorities

- Mayo Clinic Enterprise 2030 vision
- Department of Family Medicine
- Research shield
- Specialty departments

Proven Success

- EAGLE Study

Mayo Clinic Midwest Dept. of Family Medicine:



Mayo Midwest Family Medicine

Who are We?

| | Rochester | NWWI | SWWI | SEMN | SWMN | Total |
|--------------------|-----------|--------|--------|---------|--------|------------|
| Total Sites | 5 | 9 | 9 | 10 | 14 | 47 |
| MD/DO | 61 | 68 | 53 | 46 | 47 | 275 |
| NP/PA (APP) | 58 | 45 | 25 | 68 | 57 | 253 |
| Residents | 27 | 15 | 25 | 0 | 0 | 60 |
| Total Patient | 70,678 | 92,710 | 64,265 | 113,640 | 73,702 | 414,995 |
| Care Teams | 11 | 23 | 27 | 27 | 28 | 116 |
| Average Panel Size | 1843 | 1547 | 1475 | 2136 | 1386 | 1677 (ave) |

Path to AI Collaboration

- Mayo Clinic's strategy to improve care delivery and rapid diagnosis through Artificial Intelligence (AI)
- AI is most mature in the Cardiology and Radiology departments
- FM lacks personnel and resources to develop AI independently
- Approached by Cardiology to test ECG algorithm for detection of heart failure (low ejection fraction)
- Bringing cutting-edge Mayo innovation to the primary care level

Benefits of Collaboration

- Engaging clinicians in research
- Interdepartmental collaboration
- FM contributes to Mayo Clinic's strategic mission

The EAGLE Trial

ECG AI-Guided Screening for Low Ejection Fraction (EAGLE) trial

Primary care clinicians were recruited from 120 care teams in 45 clinics or hospitals

Patients with ECG obtained as part of routine care in subjects without a prior diagnosis of heart failure

Primary outcome: new diagnosis of low EF ($\leq 50\%$) within 90 days of the ECG

Study Outcomes

- Diagnosis of low EF

| | Intervention | Control | OR (95% CI) | P value |
|-------------|--------------|---------|---------------|---------|
| Overall | 2.1% | 1.6% | 1.3 (1.0-1.6) | .007 |
| Positive AI | 19.5% | 14.5% | 1.4 (1.1-1.9) | .01 |

- AI algorithm based on ECGs can enable the early diagnosis of low EF in patients in the setting of routine primary care

Outcomes

- Successful collaborative pragmatic trial
- 8 of 22 authors in Family Medicine



Artificial intelligence-enabled electrocardiograms for identification of patients with low ejection fraction: a pragmatic, randomized clinical trial

Xiaoxi Yao^{1,2}✉, David R. Rushlow³, Jonathan W. Inselman¹, Rozalina G. McCoy^{1,4}, Thomas D. Thacher³, Emma M. Behnken⁵, Matthew E. Bernard³, Steven L. Rosas⁶, Abdulla Akfaly⁷, Artika Misra⁸, Paul E. Molling⁹, Joseph S. Krien¹⁰, Randy M. Foss¹¹, Barbara A. Barry¹, Konstantinos C. Siontis², Suraj Kapa², Patricia A. Pellikka², Francisco Lopez-Jimenez², Zachi I. Attia², Nilay D. Shah¹, Paul A. Friedman² and Peter A. Noseworthy²

Healthcare Delivery Innovation Laboratory (iLab)

Accelerate the cycle from innovation to everyday practice.

Projects aimed at improving the Quadruple Aim.

Leverage our front-line care teams as the laboratory “bench”.

iLab Core Capabilities



Guide the development of pragmatic research designs for real world effectiveness.



Leverage Digital/AI technology



Develop evidence-based implementation plans to support adoption.



Disseminate best practice recommendations through collaboration and publications

iLab Infrastructure

iLab Executive Team

Center for Digital
Health.

Robert D. and Patricia
E. Kern Center for the
Science of Health Care
Delivery

Center for Clinical and
Translational Sciences
(CCaTS)

Specialty Departments
(Cardiology, Psychiatry
and Psychology,
Gastroenterology)

Example Projects

EAGLE Implementation

Depression treatment and assessment of remission

Point of care decision support tools

Patient identification for specific therapies (atrial fibrillation)

Early disease identification (fatty liver, osteoporosis, amyloidosis)

Digital clerical assistant to aid in documentation.

UAB THE UNIVERSITY OF
ALABAMA AT BIRMINGHAM.

The Impact of AI/ML in Family Medicine at UAB

Thursday | June 9 | 3:15 PM – 4:15 PM

Irfan Asif, M.D.

Professor and Chair; Department of Family and Community Medicine

Associate Dean for Primary Care and Rural Health

UAB Heersink School of Medicine

Team Physician: UAB Athletics, Birmingham Legion FC, USA Wheelchair Rugby

Outline

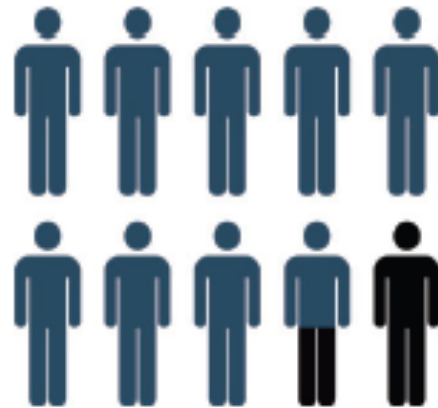
Describe 2 ways that AI/ML will impact Family Medicine at UAB

- Imaging
- Language Processing

Imaging

Diabetic Retinopathy

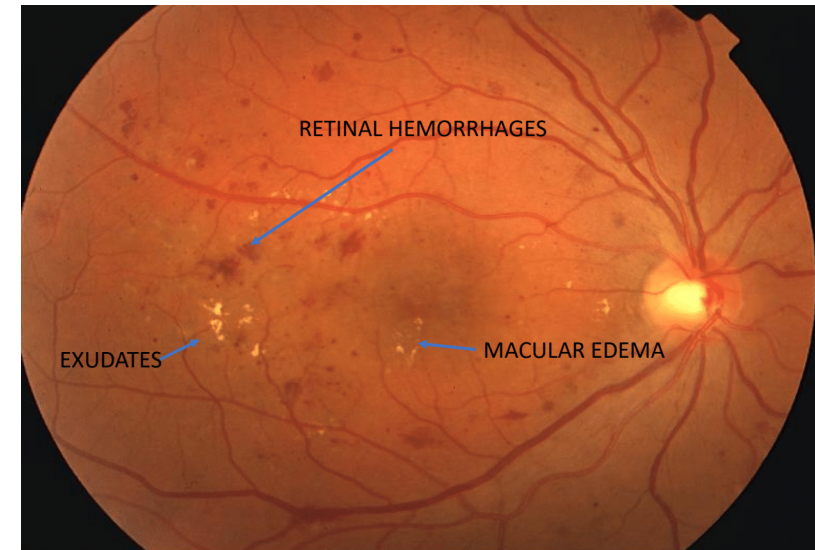
#1 cause of blindness in working age adults



Over **85%** of individuals
with diabetes will develop
DIABETIC RETINOPATHY
within 20 years

Diabetic Retinopathy: Barriers to Detection

- Lack of Access to Specialists
- Social Determinants of Health
 - Lack of insurance
 - Lack of transportation



Non-Proliferative Diabetic Retinopathy

<https://avruc.com/procedures/diabetic-retinopathy/>

Detecting Diabetic Retinopathy: Artificial Intelligence

**Normal:
Retest in 12 months**

**Diabetic Retinopathy or
Macular Edema:
Refer to Eye Specialist**



Robotic fundus camera captures two images per eye

<https://www.darkdaily.com/2019/01/02/fda-clears-ai-device-for-diagnosis-of-diabetic-retinopathy-is-this-favorable-for-use-of-ai-in-digital-pathology/>

Preliminary Results: 3 Months

| | FQHC #1 | FQHC #2 | Total |
|------------------------------|----------|----------|----------|
| Identified Diabetic Patients | 529 | 272 | 801 |
| Exams Performed | 73 | 32 | 105 |
| Positive Results | 20 (27%) | 10 (31%) | 30 (29%) |

Benefits

- Immediate results and contributes to comprehensive diabetes management
- Potential to save time and quality of care for patients

Challenges

Benefits

- Immediate results and contributes to comprehensive diabetes management
- Potential to save time and quality of care for patients

Challenges

- Need to develop clear workflows, including space and staff training (e.g. eye dilation)
- Does not detect mild diabetic retinopathy

Cardiomegaly on CT Scans

- At UAB, 80,000 CT exams of the chest or abdomen per year
- UAB Radiology will begin a pilot of an image-based AI algorithm to opportunistically screen for cardiomegaly on routine CT exams of the chest or abdomen obtained for other purposes
- The AI algorithm has 97% specificity for cardiomegaly

Cardiomegaly on CT Scans

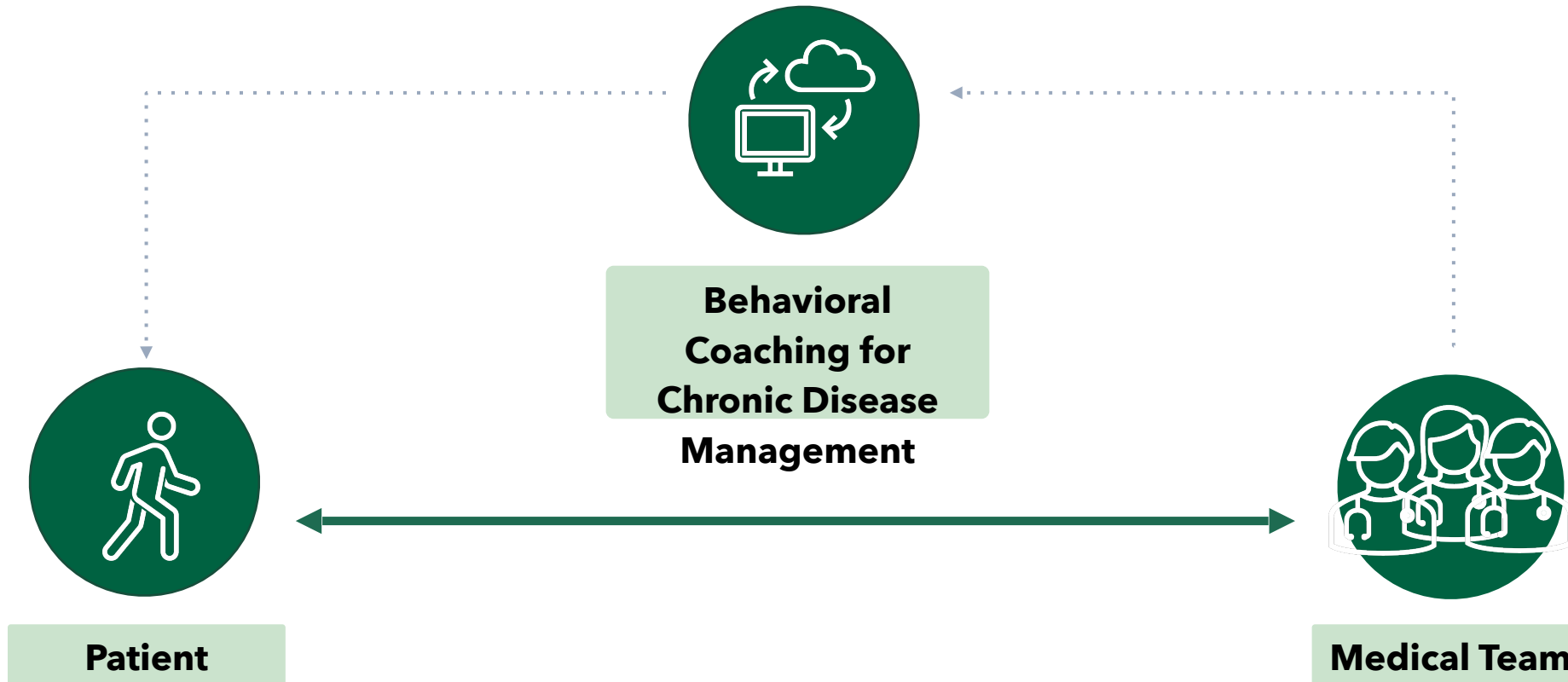
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Colorectal Screening

- Screening for colorectal cancer can identify premalignant lesions and improve survival
- Computer aided AI platform being used by UAB GI to enhance polyp detection

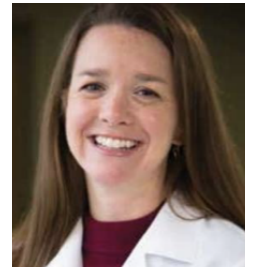
Language Processing

AI-Based Language Processing: Health Promotion and Chronic Disease Management



Tapan Mehta PhD

Vice Chair for Research
Family & Community Medicine

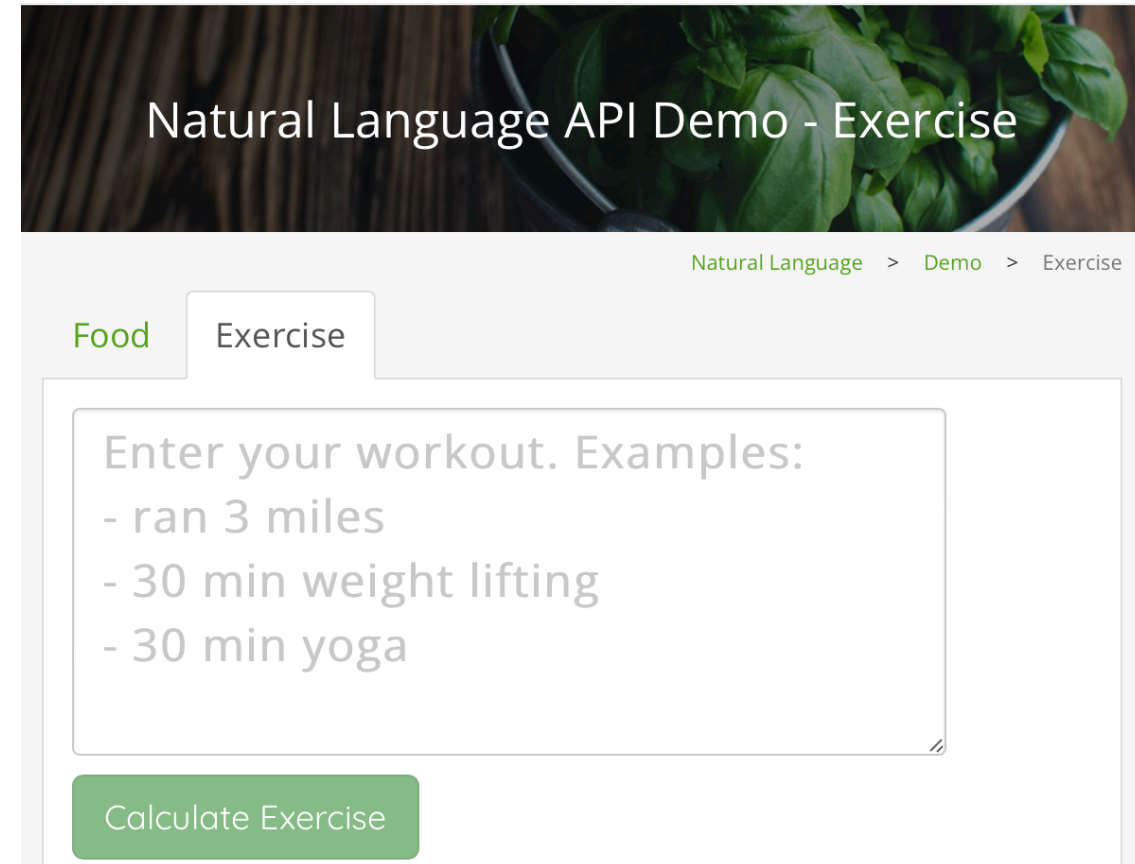


Erin Delaney, MD

Vice Chair for Clinical Affairs &
Quality
Family & Community Medicine

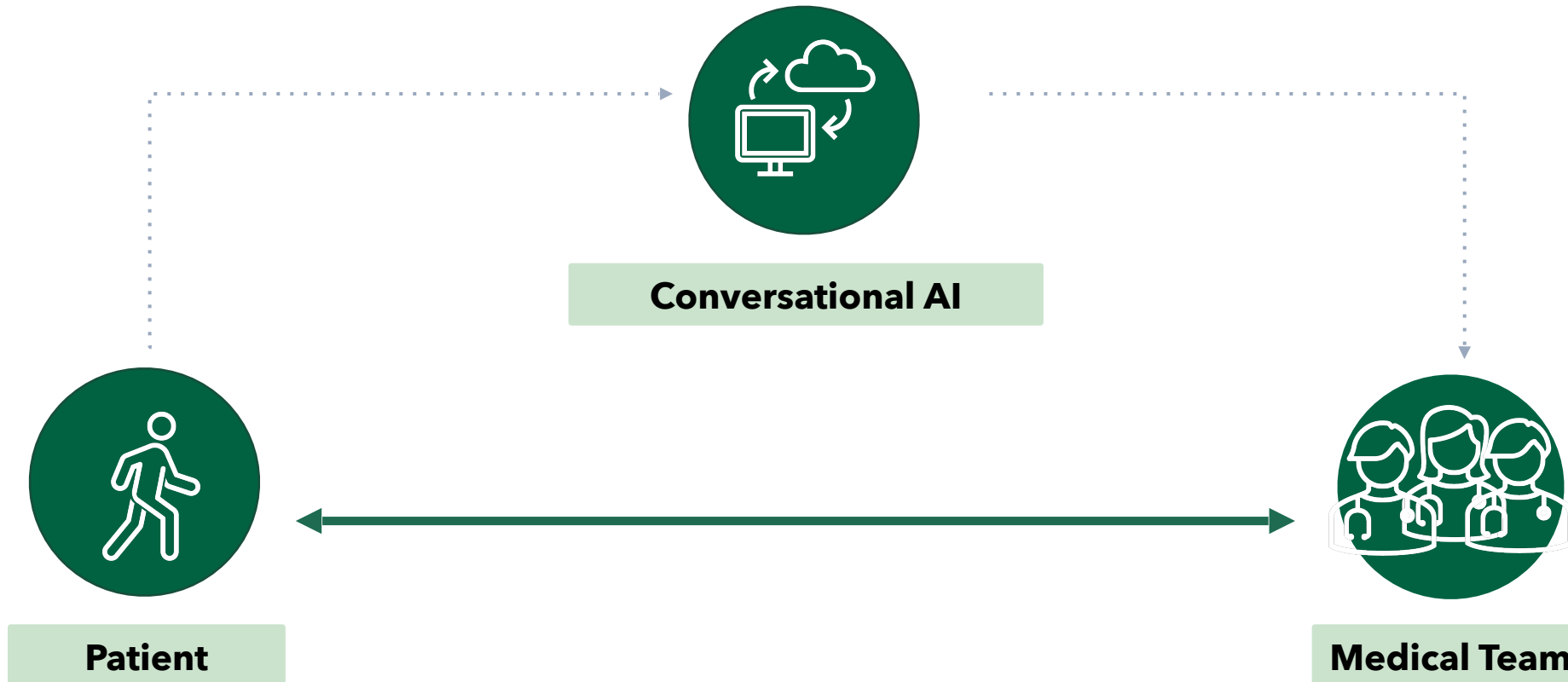
Gamified Optimized Diabetes management with Artificial Intelligence-powered Rural Telehealth (GODART)

- AI-assisted individualized lifestyle modification for glycemic control
 - Smart phone
 - Landline phone
- Key Features
 - Interactive voice response
 - Natural language processing
 - Conversational features for motivational coaching



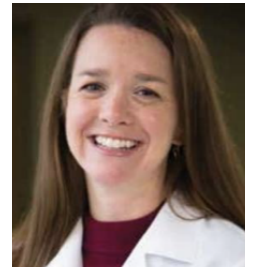
The screenshot shows a web interface for the GODART system. At the top, there's a header with the title "Natural Language API Demo - Exercise" over a background image of green basil. Below the header is a breadcrumb trail: "Natural Language > Demo > Exercise". There are two tabs: "Food" (highlighted in green) and "Exercise". The "Exercise" tab is active, showing a text input area with the prompt "Enter your workout. Examples:" followed by three examples: "- ran 3 miles", "- 30 min weight lifting", and "- 30 min yoga". Below the input area is a green button labeled "Calculate Exercise".

AI-Based Language Processing: Patient Portal Assistance



Tapan Mehta PhD

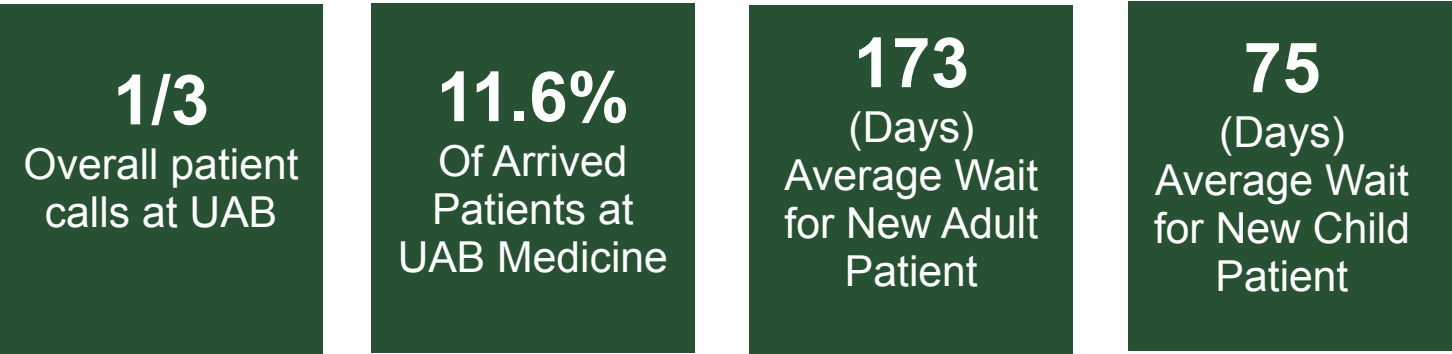
Vice Chair for Research
Family & Community Medicine



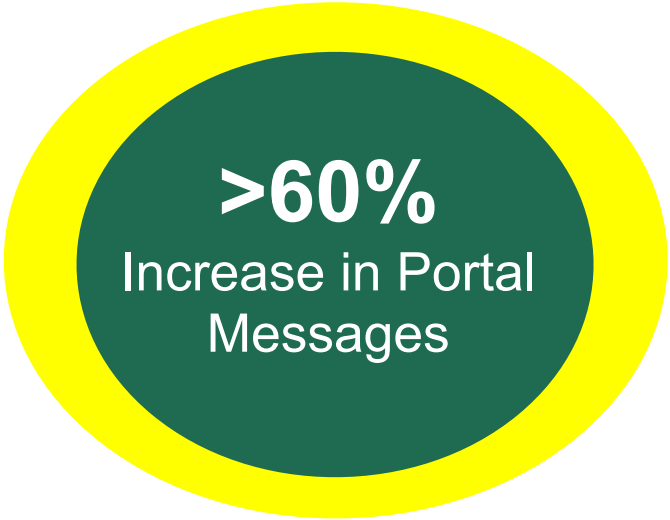
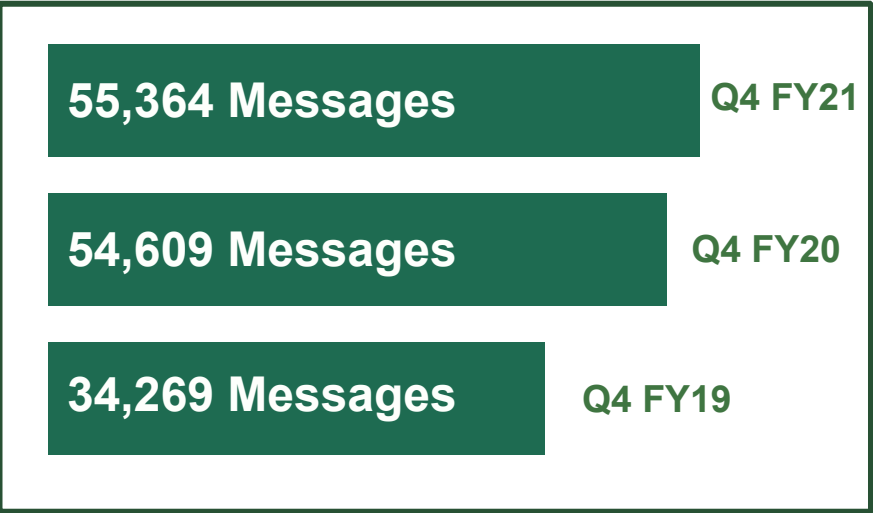
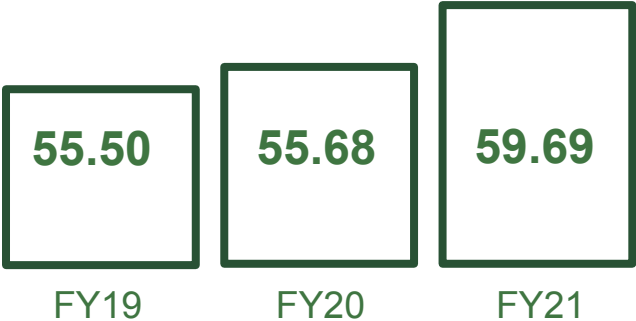
Erin Delaney, MD

Vice Chair for Clinical Affairs &
Quality
Family & Community Medicine

By the Numbers: UAB Primary Care Service Line



Clinical Full Time Equivalents

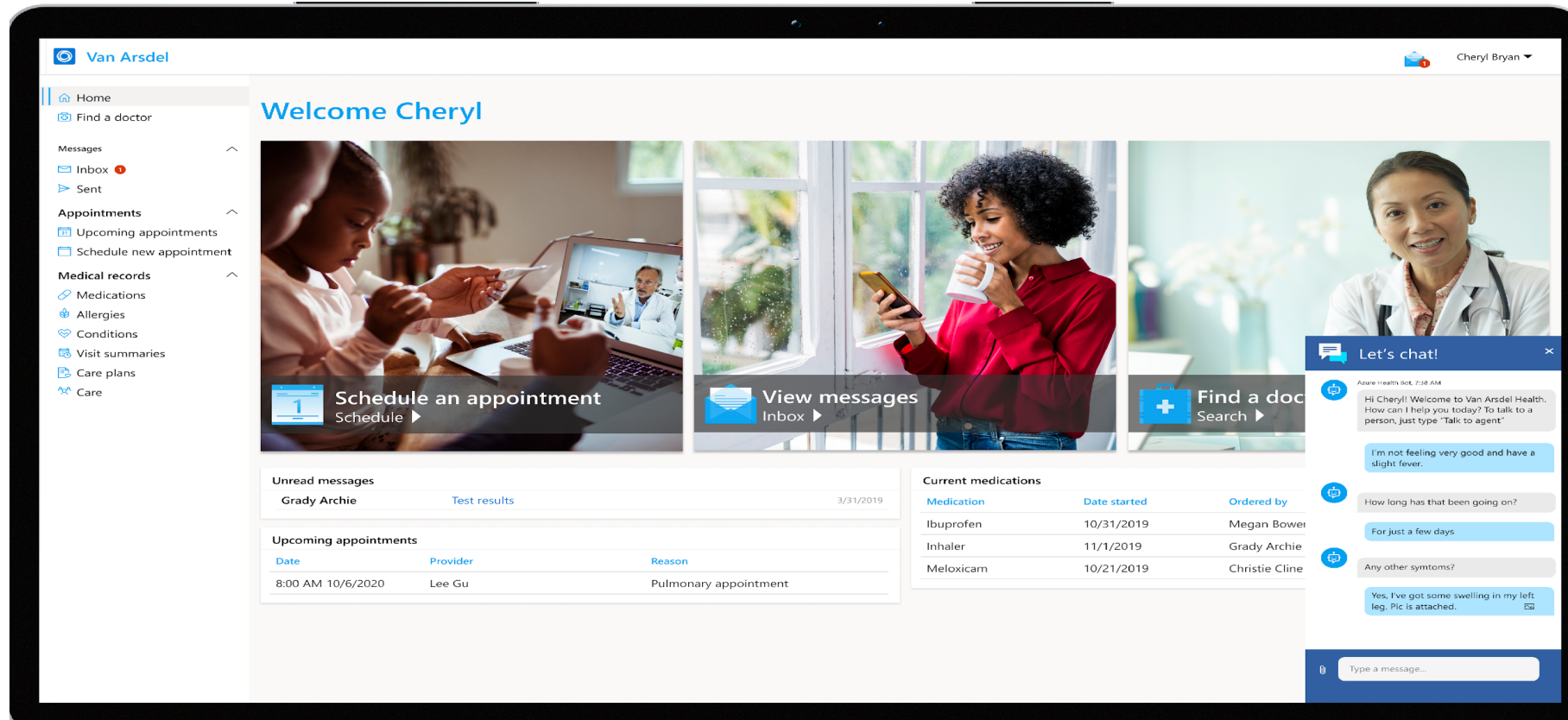


188,860
FY21 Arrived Patients

185,989
FY20 Arrived Patients



Conversational AI can aid in more meaningful patient engagement through the patient portal and help prioritize messages that may require a provider team (human) response.



- Lab, Imaging, and Result Retrieval
- Appointment Scheduling
- Message Routing
- Sentiment Analysis
- Health Query Response

Benefits

- Address major issues in current clinical practices
- Increased quality of care and potential to save time

Challenges

Benefits

- Address major issues in current clinical practices
- Increased quality of care and potential to save time

Challenges

- Need to develop clear workflows
- Provider/staff/patient education

Conclusions

- Imaging and language processing are 2 key areas where artificial intelligence will affect Family Medicine in the future
- Our role as a family physician will likely change
 - We may encroach on the territory of other specialties
 - Embrace our discipline's core ability to communicate to patient



Go Blazers and Thank You!

AI and ML at Howard University

Mark S. Johnson, MD MPH

It started with one individual

Abiodun Otolorin, MD MS

- BS, Computer Science, Georgia Tech
 - MS, Bioengineering, Georgia Tech
 - MD, Eastern Virginia Medical School
 - Howard Family Medicine Residency Program
-

It continues with training

- Grant Generating Project
 - AIM-AHEAD Training
 - Washington University PRIDE Program
 - NIH Health Disparities Training Scholars
-

It's supported with infrastructure

- Research Centers in Minority Institutions (RCMI)
 - Georgetown-Howard University Center for Clinical and Translational Science (GHUCCTS)
-

Howard involvement in collaboratives

- NIH Artificial Intelligence/Machine Learning Consortium to Advance Health Equity and Researcher Diversity (AIM-AHEAD)
 - Howard University Center for Applied Data Science and Analytics (CADSA)
 - Georgetown University Massive Data Institute (MDI)
-

Grant funded

- Addressing Health Disparities via Development of a Geospatial Analysis Application for Visualization of Environmental and Social Determinants of Health: District of Columbia Pilot Study, \$180,000
-

Grants submitted

- Improving African American Health: Use of Artificial Intelligence and SMART on FHIR Application to Detect and Monitor Statin Nonadherence for Cardiovascular Disease Prevention, PI, Otolorin,
 - The relative impact of biological factors and social determinants on reducing health disparities in COVID-19, PI Johnson
 - Howard University Clinical Research Network for Health Equity, PI Johnson
-

Departmental research faculty

- TyWanda McLaren-Jones, PhD – clinical psychology
 - Latita Kaul, PhD – nutrition
 - Abiodun Otolorin, MD MS
 - Finie Richardson, MPH PhD – health communication
-

The language of research

FIU | THRIVE

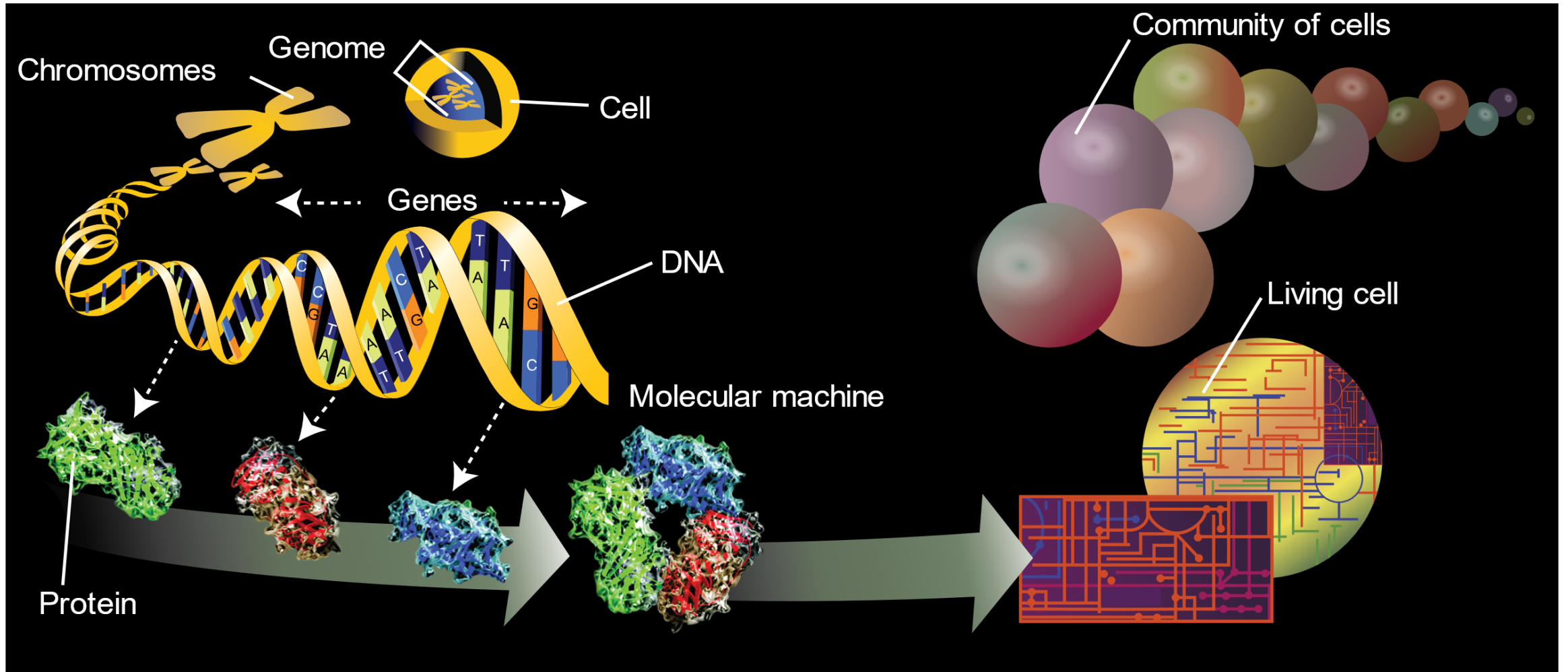
Social Determinants of Health Machine Learning Use Case

David Brown, MD; Troy Stefano, PhD; Cynthia LeRouge, PhD; M. Hadi Amini, PhD, DEng; Rachel Clarke, PhD; Staci Morris, PsyD; and Nana Aisha Garba, MD, PhD

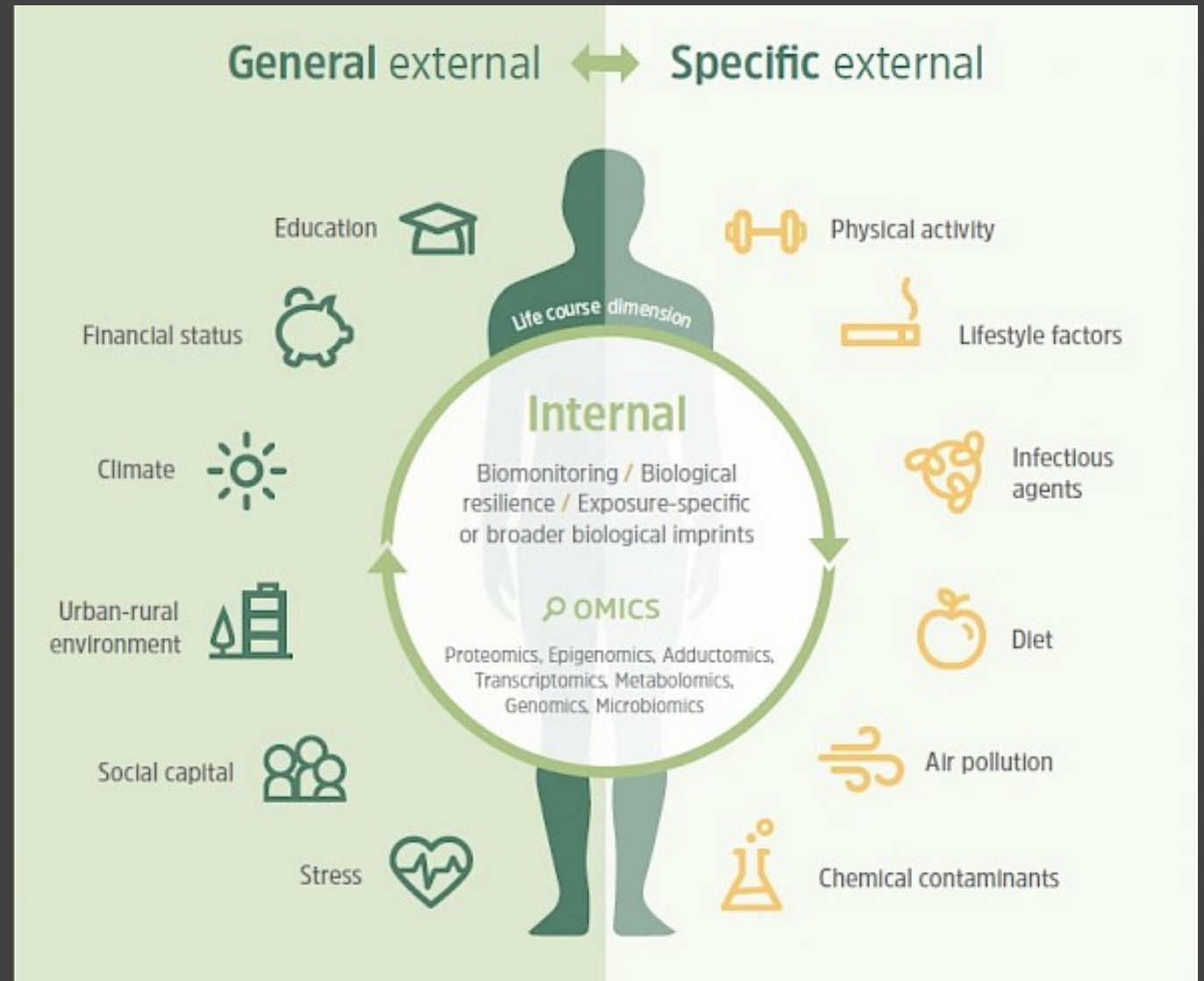
drbrown@fiu.edu

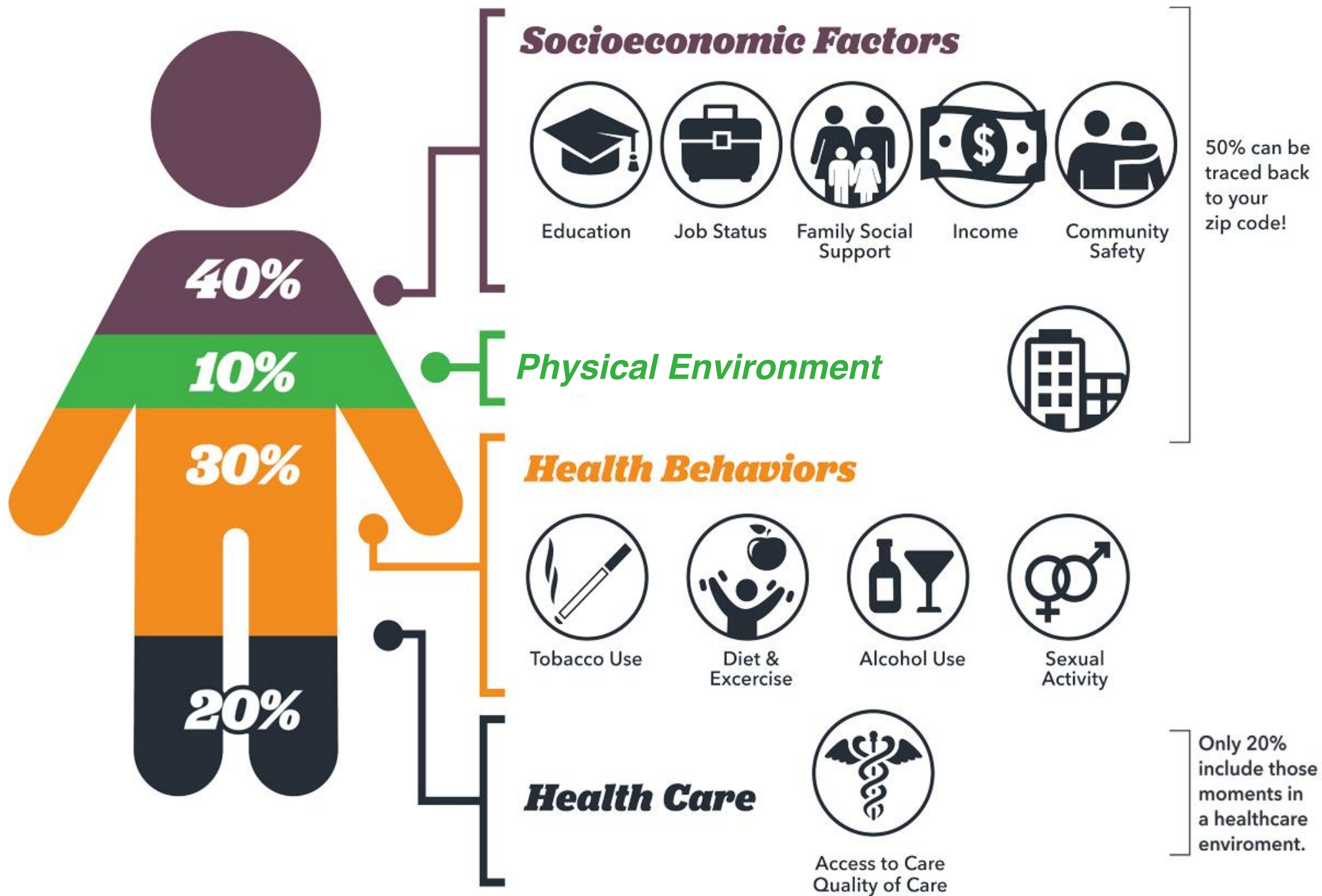


Myth of Simple Genetic Associations

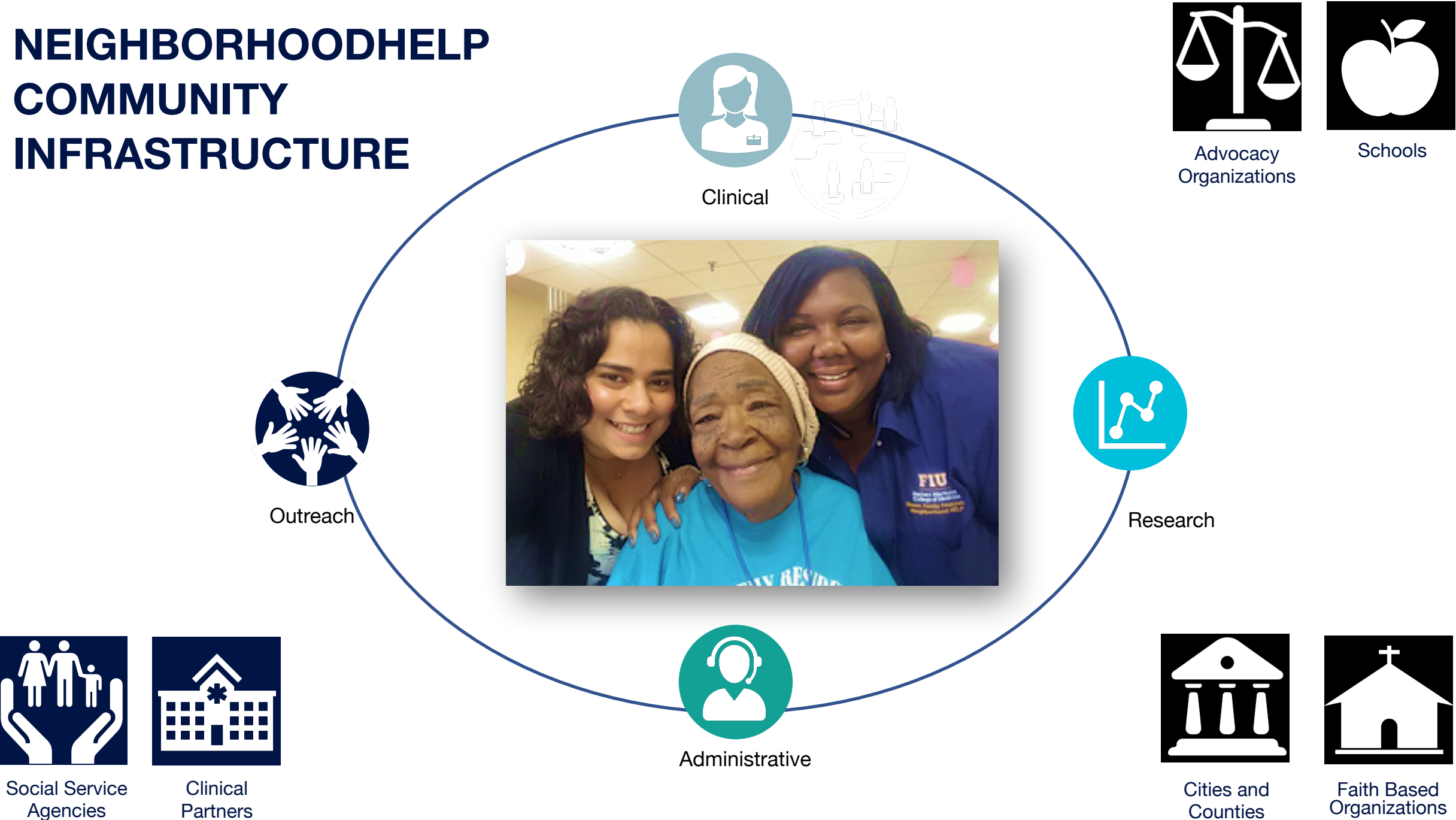


Exposure to the environment is “embodied” through multiple complex “omic” pathways





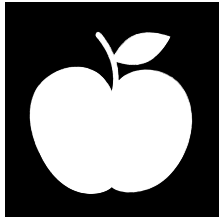
NEIGHBORHOODHELP COMMUNITY INFRASTRUCTURE



Clinical



Advocacy
Organizations



Schools



Research



Administrative



Outreach



Social Service
Agencies



Clinical
Partners



Cities and
Counties



Faith Based
Organizations



HEALTH RISK PROFILE

Linked to Needs and Service Navigation



Food



Daily Activities



Housing



Transportation



Education



Healthcare



Employment



Income



Technology



Legal



Secure Nutrition



Stable Housing



Graduate Degree



Career



Digitally Engaged



Easily Performs All Daily Activities



Comfortably Gets Transportation



Active Prevention



Savings and Planning



Civic Engagement

5



Nutrition Quality



Housing Needs Minor Repairs



Bachelor's Degree or License



Stable Employment Savings



2+ Sites/Apps for Health, Social Resources Understands Rights



Readily Performs Most Activities



Usually Gets Transportation



Engaged with Care



4



Enough Food Assistance



Subsidized Housing or Significant Issues



Associate's Degree or Vocational Training



Difficult Work Environment



Has Access to Information, but...



Stress or Discomfort with Daily Activities



Frequent Difficulty Getting Transportation



Has Access, but...



Meeting Basic Needs



Low Legal Literacy

3



Temp Need for Food



Housing Insecurity



HS or GED Only



Underemployed



Phone Internet Only



Difficulty Performing Daily Activities



Hard Time Getting Transportation



Difficulty Accessing Healthcare



Inconsistently Meeting Basic Needs



Legal Issues

2



Severely Short of Food



Homelessness



No HS Diploma or Vocation



Unemployed



No Internet



Unable to Perform Most Daily Activities



Can't Get Transportation



No Access to Care



Unable to Meet Basic Needs



Legal Barriers

1



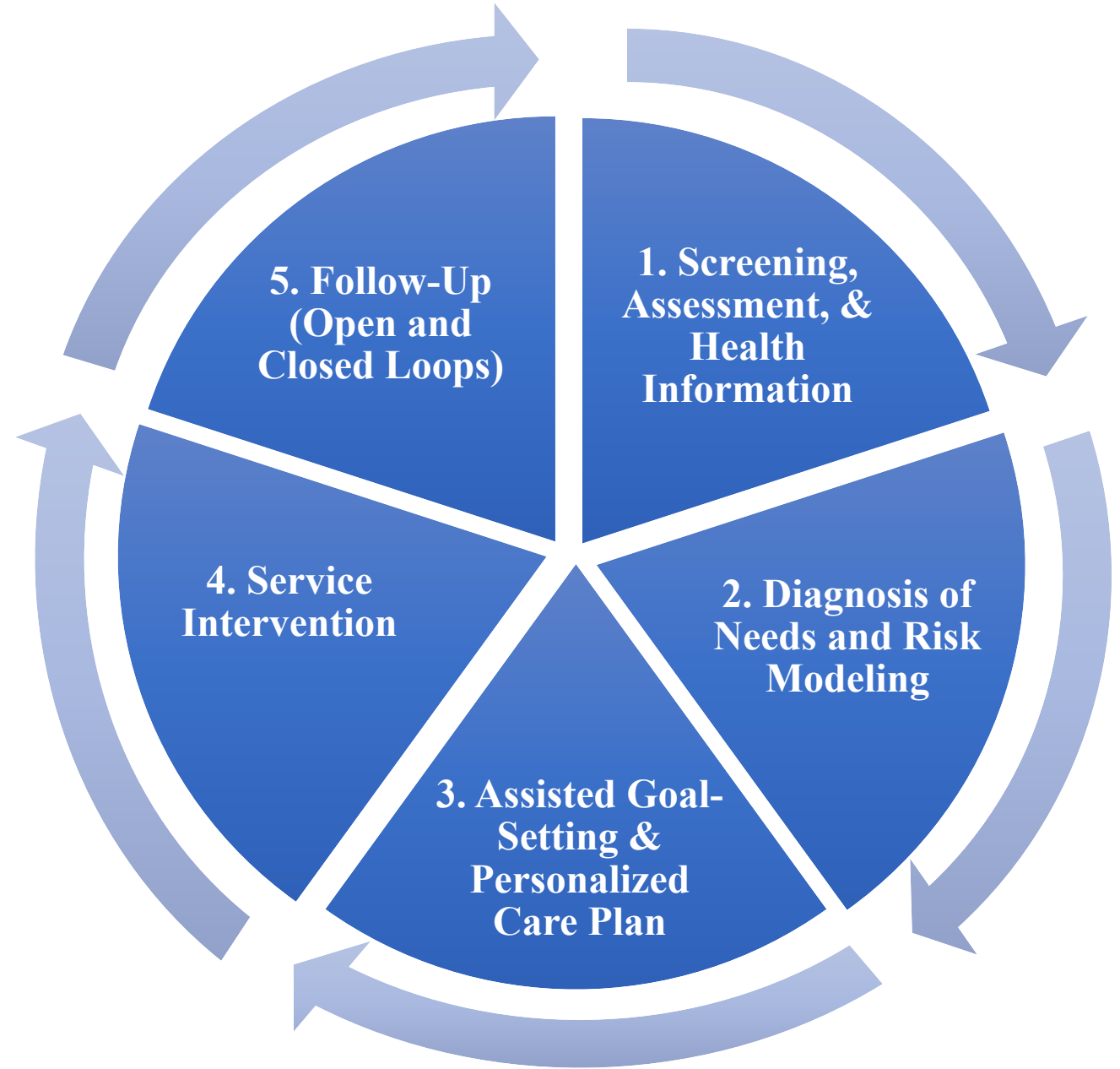
Social support for a healthier you

FIU Thrive helps connect people to accessible, valuable, and usable health and social care when and where it matters most.



| Thrive Domains | <u>Gravity Domains</u> | | | Additional Concepts |
|--------------------|---|----------------------------------|------------------------|---|
| Demographics | | | | <u>Veteran Status</u> |
| Food and Nutrition | <u>Food Insecurity</u> | | | *Food Insecurity (accessibility, affordability); Nutrition (access, literacy, and health behaviors); structural barriers (food swamp) |
| Daily Activity | | | | Physical Function, (Independence), Exercise |
| Education | <u>Educational Attainment</u> | | | Life Skills |
| Work | <u>Employment Status</u> | | | Retirement; Occupational Prestige |
| Financial Health | <u>Financial Insecurity</u> | <u>Material Hardship</u> | | financial health and financial well-being; |
| Technology | | | | Technological access, technological literacy, cell phone, technological adequacy, technological affordability |
| Transportation | <u>Transportation Insecurity</u> | | | |
| Housing | <u>Housing Instability & Homelessness</u> | <u>Inadequate Housing</u> | | Housing security (housing affordability); housing safety; neighborhood safety |
| Neighborhood | | | | GIS-Based Deprivation Index |
| Relationships | <u>Social Connection</u> | <u>Intimate Partner Violence</u> | <u>Elder Abuse</u> | Social Function, Household Composition, Support Structures, Social isolation |
| Wellness | <u>Stress</u> | | | Mental Health, Wellness, Substance Misuse |
| Healthcare | <u>Health Insurance Status</u> | <u>Medical Cost Burden</u> | <u>Health Literacy</u> | Engagement with Healthcare, Healthcare Access |

Automated Care Plan Process

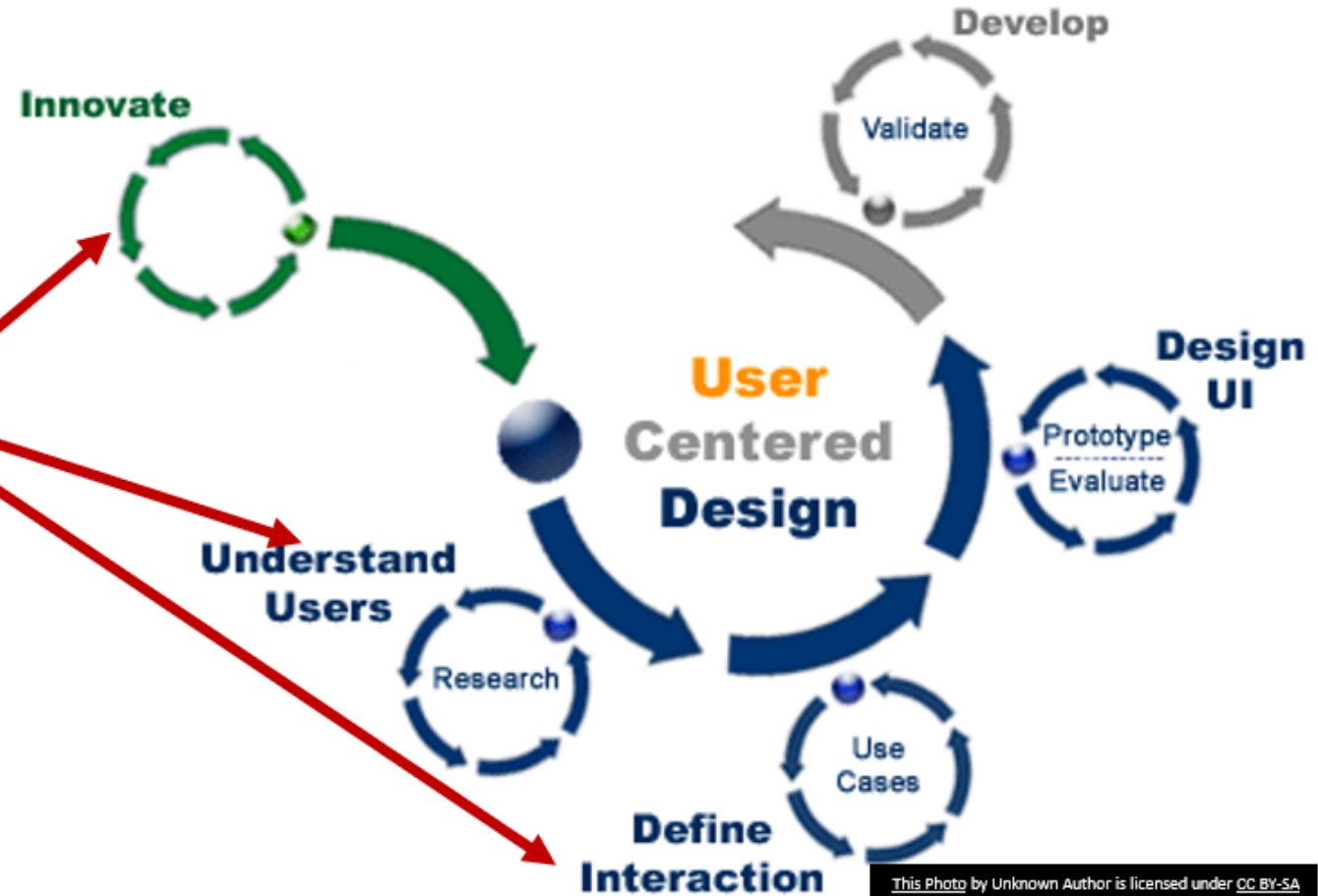


MI/SBIRT conceptual model for application design

- Engagement: assessing social needs
- Focusing/Evoking
 - sharing results for user to prioritize
 - user defines goals
- Planning/Directionality
 - Pre-set list of potential needs/goals
 - Offer a menu of options
 - Provide referral to services
 - Follow up

User Centered Design

Create for the
user and and
with the user



gband score:

2916 score

Bottom score

High score

| Core Validated Need-Based Assessment Instruments | | | | | | | | | | Structural |
|--|--|--|--|---|--|-----------------------------------|--|---|--|--|
| Set 1: Income & Wealth | | | Set 2: Financial Health | | | | | Set 3: FWB | | |
| Annual Family Income | Household Wealth | Spend Score: | Save Score | | Borrow Score | | Plan Score | | Financial Well-Being | ◀▶ Concentrated Poverty |
| | | Indicator 1= spend less than income; | indicator 2= pay bills on time. | Indicator 3: Have sufficient liquid savings | Indicator 4: Have sufficient long-term savings | Indicator 5: Have manageable debt | Indicator 6: Have a prime credit score | Indicator 7: Have appropriate insurance | Indicator 8: Plan ahead financially | |
| National Health Interview Survey (NHIS) Family Questionnaire, 2020 (PhenX) | Panel Study of Income Dynamics (PSID), wealth supplement, 2019 | Financial Health Network's FinHealth Score Toolkit | Financial Health Network's FinHealth Score Toolkit | | Financial Health Network's FinHealth Score Toolkit | | Financial Health Network's FinHealth Score Toolkit | | CFPB Financial Well-Being Scale, Abbreviated Version | American Community Survey (ACS), 5-year estimates, Concentrated Poverty, 2009-2018 |
| | | 2 Qs: Take Average Score of Qs 1A-1.B. | 2 Qs: Take Average Score of Qs 3-4 | | 2 Qs: Take Average Score of Qs 5-6 | | 2 Qs: Take Average Score of Qs 7-8 | | 5 Q | |

| Core Validated Need-Based Assessment Instruments | | | | | | | | | | Structural |
|--|--|--|--|---|--|-----------------------------------|--|---|--|--|
| Set 1: Income & Wealth | | | Set 2: Financial Health | | | | | Set 3: FWB | | |
| Annual Family Income | Household Wealth | Spend Score: | Save Score | | Borrow Score | | Plan Score | | Financial Well-Being | ◀▶ Concentrated Poverty |
| | | Indicator 1= spend less than income; | Indicator 2= pay bills on time. | Indicator 3: Have sufficient liquid savings | Indicator 4: Have sufficient long-term savings | Indicator 5: Have manageable debt | Indicator 6: Have a prime credit score | Indicator 7: Have appropriate insurance | Indicator 8: Plan ahead financially | |
| National Health Interview Survey (NHIS) Family Questionnaire, 2020 (PhenX) | Panel Study of Income Dynamics (PSID), wealth supplement, 2019 | Financial Health Network's FinHealth Score Toolkit | Financial Health Network's FinHealth Score Toolkit | | Financial Health Network's FinHealth Score Toolkit | | Financial Health Network's FinHealth Score Toolkit | | CFPB Financial Well-Being Scale, Abbreviated Version | American Community Survey (ACS), 5-year estimates, Concentrated Poverty, 2009-2018 |
| | | 2 Qs: Take Average Score of Qs 1A-1.B. | 2 Qs: Take Average Score of Qs 3-4 | | 2 Qs: Take Average Score of Qs 5-6 | | 2 Qs: Take Average Score of Qs 7-8 | | 5 Q | |

| | | | | | | | | | |
|---|---|--|--|---|---|---|---|--|---|
| HH income is equal to or greater than 2 SD higher than median HH income [100] HH income is a SD higher than median HH income [80]; | [Q1.A] Spending was much less than income [100]; | [Q1.B] Pay all bills on time [100]; | [Q2.A] 6 months or more of living expenses [100] | [Q2.B] Very confident of meeting longer-term goals [100] | [Q3.A] Do not have any debt [100] | [Q3.B] Excellent credit score [100] | [Q4.A] Very confident in HH insurance coverage [100]; | [Q4.B] Plans ahead financially? Agree strongly [100] | [Q8] Thriving [Score < 62] [Q8] Focused [Score: 45-62] |
| HH income is about equal to median HH income [75]; | [Q1.A] Spending was a little less than income [75]; | [Q1.B] Pay nearly all of our bills on time [60]; | [Q2.A] 3-5 months of living expenses [75] | [Q2.B] Moderately confident of meeting longer-term goals [75] | | [Q3.B] Very good credit score [80] | [Q4.A] Moderately confident in HH ins. coverage [75]; | [Q4.B] Plans ahead financially? Agree somewhat [65]; | [Q8] Striving [Score > 52] |
| HH income is above PL but below median HH income; | [Q1.A] Spending was about equal to income [50]; | [Q1.B] Pay most of our bill son time [40]; | [Q2.A] 1-2 months of living expenses [50] | [Q2.B] Somewhat confident of meeting longer term goals [50] | | [Q3.B] Good credit score [60] | [Q4.A] Somewhat confident in HH ins. coverage [50]; | | [Q8] Tenuous [Score < 52] |
| BPL [20] | [Q1.A] Spending was a little more than income [25]; | [Q1.B] Pay some of our bills on time [20] | [Q2.A] 1-3 weeks of living expenses [25] | [Q2.B] Slightly confident of meeting longer term goals [25] | [Q3.A] Have a bit more debt than is manageable [40] | [Q3.B] Fair credit score [40] | [Q4.A] Not at all confident in HH ins. coverage [10]; | [Q4.B] Plans ahead financially? Neither agree nor disagree [35] | |
| RBPL [0] | [Q1.A] Spending was much more than income [0]; | [Q1.B] Pay very few of our bills on time [0] | [Q2.A] Less than 1 week of living expenses [0] | [Q42.B] Not at all confident of meeting longer term goals [0] | [Q3.A] Have far more debt than is manageable [0] | [Q3.B] Poor credit score [0] [Q3.B] I don't know [0] | [Q4.A] No one in my HH has any insurance [0] | [Q4.B] Plans ahead financially? Disagree somewhat [15]; Plans ahead financially? Disagree strongly [0]; | |

| Description (Needs to be fine tuned in light of changes) | Sub-Segments | Status (3-Segments) | Risk-based Framework (Life Course View: Risk to Resiliency) |
|--|---------------------------------------|---|--|
| | Thriving (FWB Subjective Score: < 62) | Healthy (FinHealth Score: 80-100) | |
| | Focused (FWB Subjective Score: 45-62) | | |
| | Stable (FWB Score: < 45) | | |
| | Striving (FWB Subjective Score > 52) | Coping (FinHealth Objective: Score 40-79) | |
| | Tenuous (FWB Subjective Score < 52) | | |
| | Unengaged | Vulnerable (FinHealth Objective: Scores 0-39) | |
| | At risk | | |

| Description (Needs to be fine tuned in light of changes) | Sub-Segments | Status (3-Segments) | Risk-based Framework (Life Course View: Risk to Resiliency) |
|--|---------------------------------------|---|--|
| | Thriving (FWB Subjective Score: < 62) | Healthy (FinHealth Score: 80-100) | |
| | Focused (FWB Subjective Score: 45-62) | | |
| | Stable (FWB Score: < 45) | | |
| | Striving (FWB Subjective Score > 52) | Coping (FinHealth Objective: Score 40-79) | |
| | Tenuous (FWB Subjective Score < 52) | | |
| | Unengaged | Vulnerable (FinHealth Objective: Scores 0-39) | |
| | At risk | | |

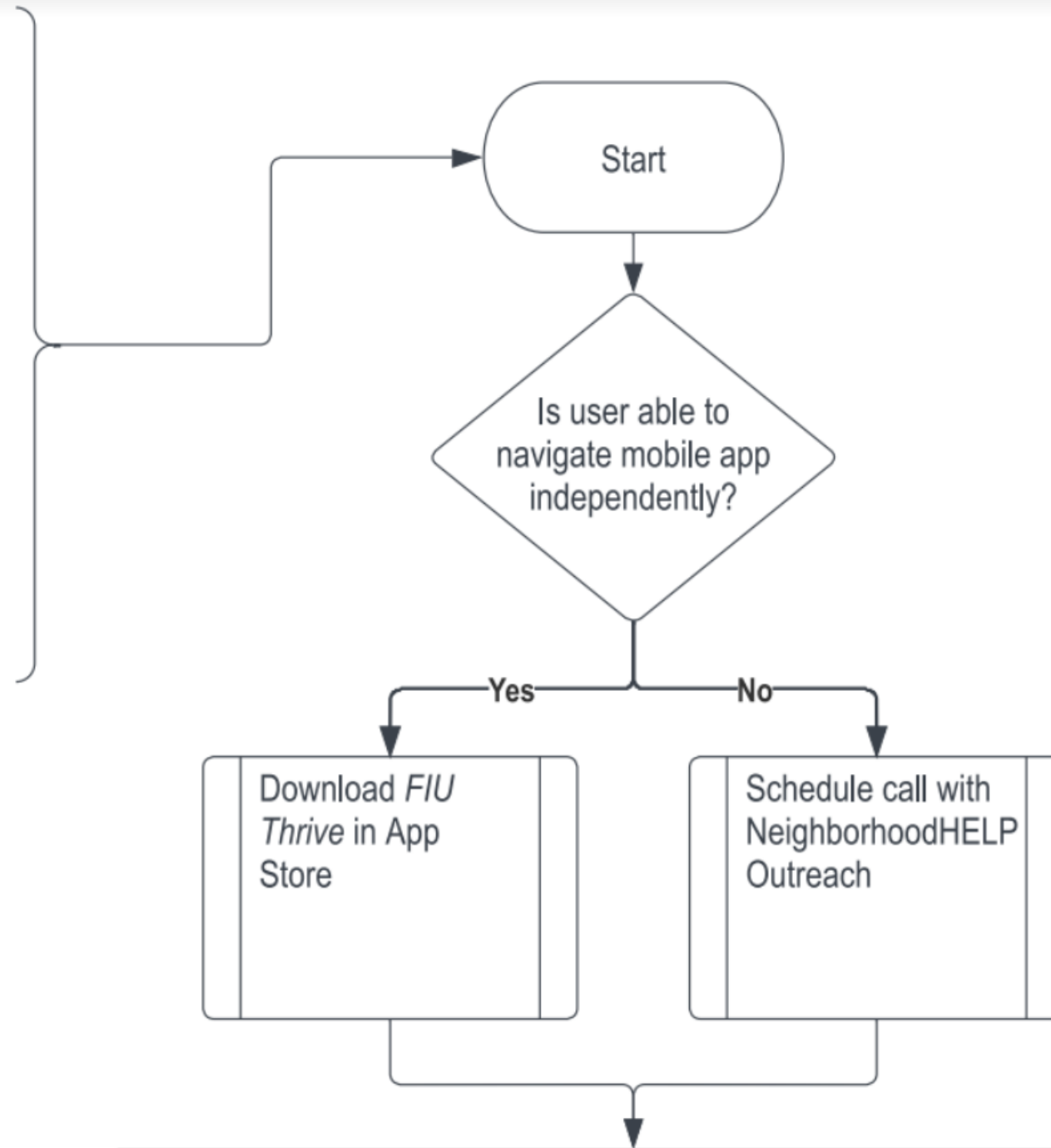
Healthy (FinHealth Score: 80-100)

Coping (FinHealth Objective: Score 40-79)

Vulnerable (FinHealth Objective: Scores 0-39)

Risk-Based Framework
(Life Course View: Risk to Resiliency)

User Journey





FHIR
Compliant
API capacity

↓

0. Enrollment
-Description: Permissions/ Consent & Baseline Profile
-Description: after appropriate permissions, disclosures, and consent, baseline profile questions will be filled in as part of the enrollment process.

-Source: Validated, open-source instruments (such as PhenX), wherever possible; team-developed to fill in gaps.

↓



1. Screening/ Assessment

-Description: screening questions with conditional flows for 12 domains of SDOH. Questions and conditional flows are built into the database design and software.

-Source: Validated, open-source instruments wherever possible.



v1: expert-based look-up tables for filtering relevant needs based on conditional logic of assessment

v2: ML-based risk modeling and need identification



2. Need Identification

-Description: assessment results lead to a need identification (per subdomain) from a pre-set list of need identification options and a three-tiered risk designation (per domain); users then select priority needs from identified need list.

-Source: Gravity project (HL7's consensus-based standards), where possible; team-developed to fill in gaps.



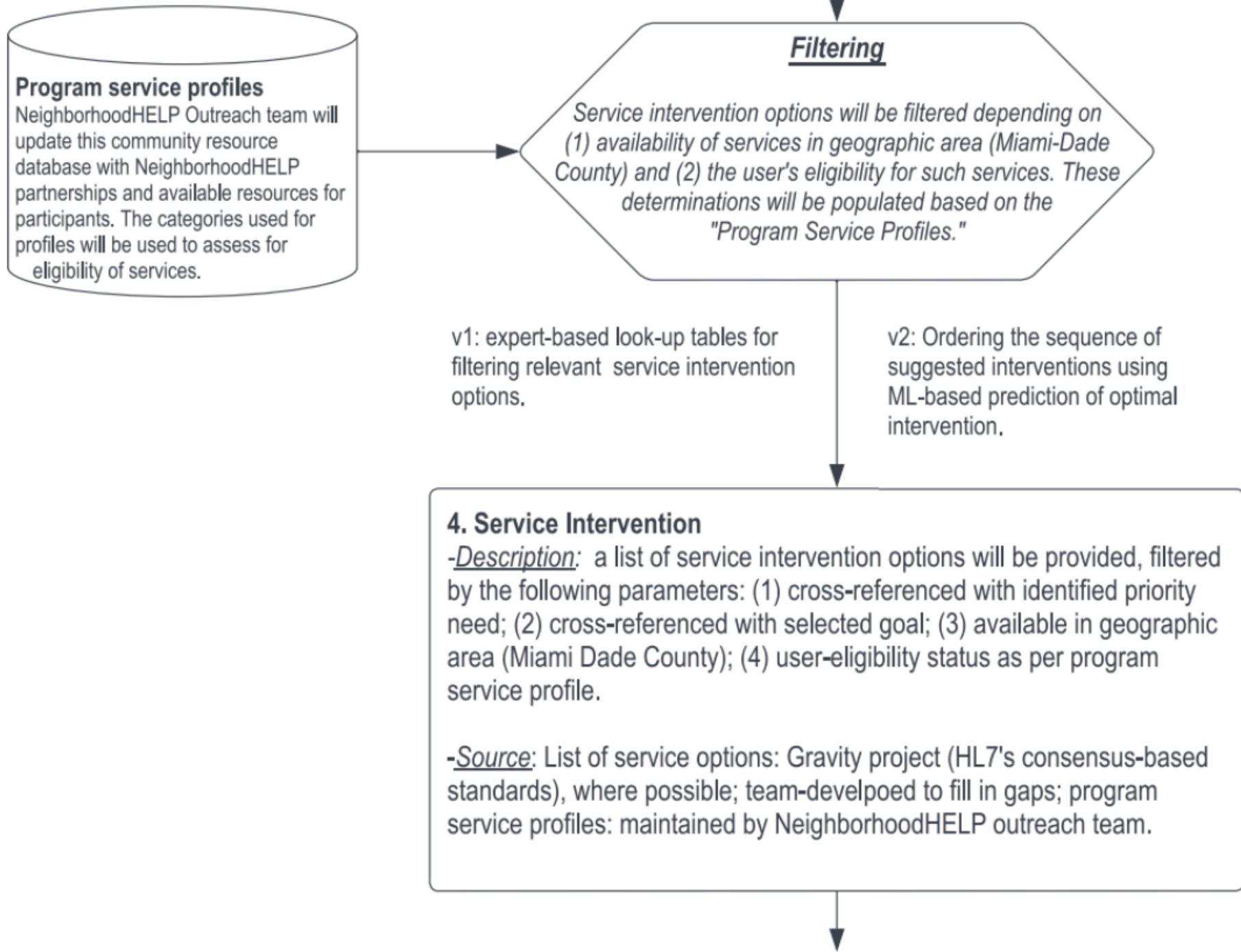
Look-up tables for filtering relevant goals based on selected priority needs.

Look-up tables for filtering milestone options based on risk level, goals, and domain.

3. Goal-setting & milestones

-Description: user to select a goal from a list of goal-options that corresponds to selected priority needs. A milestone for follow-up is selected per goal.

-Source: Gravity project (HL7's consensus-based standards), where possible; team-developed to fill-in gaps. Milestones to be determined based on secondary literature.





5. Follow-up

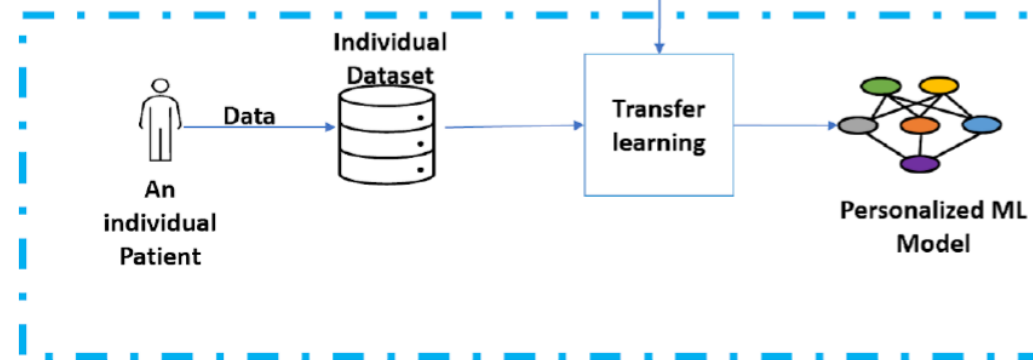
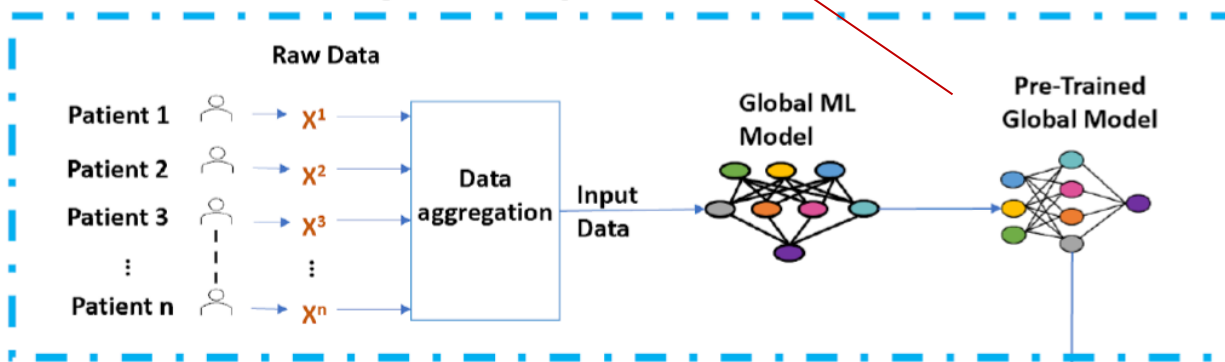
-Description: follow-up will take place at the time determined in the milestone selection (step 3). Questions would ask about other SDOH domain areas and would update the assessment accordingly.

-Source: Adapted questions similar to screening/assessment questions (i.e., validated, open-source instruments), wherever possible.

Artificial Intelligence (AI)

ML 0: Pre-
Training for
Functions 1-3 via
Transfer Learning.

Level 1: Global Machine Learning Model Training



Level 2: Personalized Machine Learning Model Training

ML 1: Complex
health risk
modeling and
simulation using
data-driven tools

ML 2: Assisted
Goal-Setting and
Personalized Care
Plan

ML 3:
Personalized
Intelligent
Learning for
Patient-users

Q&A