Precision Medicine for all Oklahomans: Leveraging Artificial Intelligence and Health Information Exchange

AI: Friend or Foe?

Disclosures

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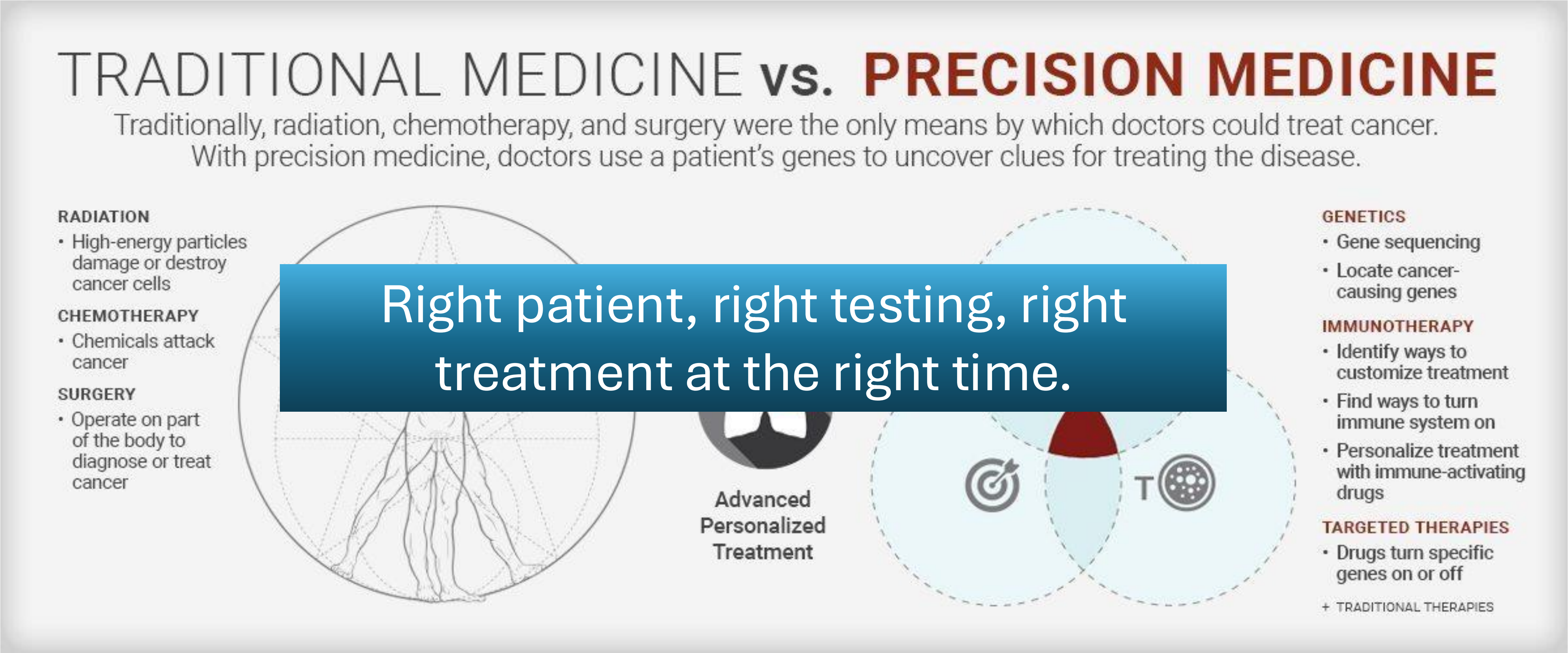
- Founder & CEO, MyHealth Access Network, Oklahoma’s 501c3 State Designated Entity for HIE/HDU
- Founder & Chair, Department of Informatics, OU School of Community Medicine
- Associate Vice-Provost for Strategic Planning, OU Health Sciences Center
- Technical Assistance Consultant for ONC
- Founder of MedUnison and developer of Doc2Doc
- Board, National Committee for Quality Assurance (NCQA)
- Board, CIVITAS Networks for Health
- Board, Patient Centered Data Home

Agenda

- What is AI?
- Can AI help me?
- Can AI replace me?
- Where should I invest?
- How do we leverage AI in Oklahoma?

Precision Medicine



Right patient, right testing, right treatment at the right time.

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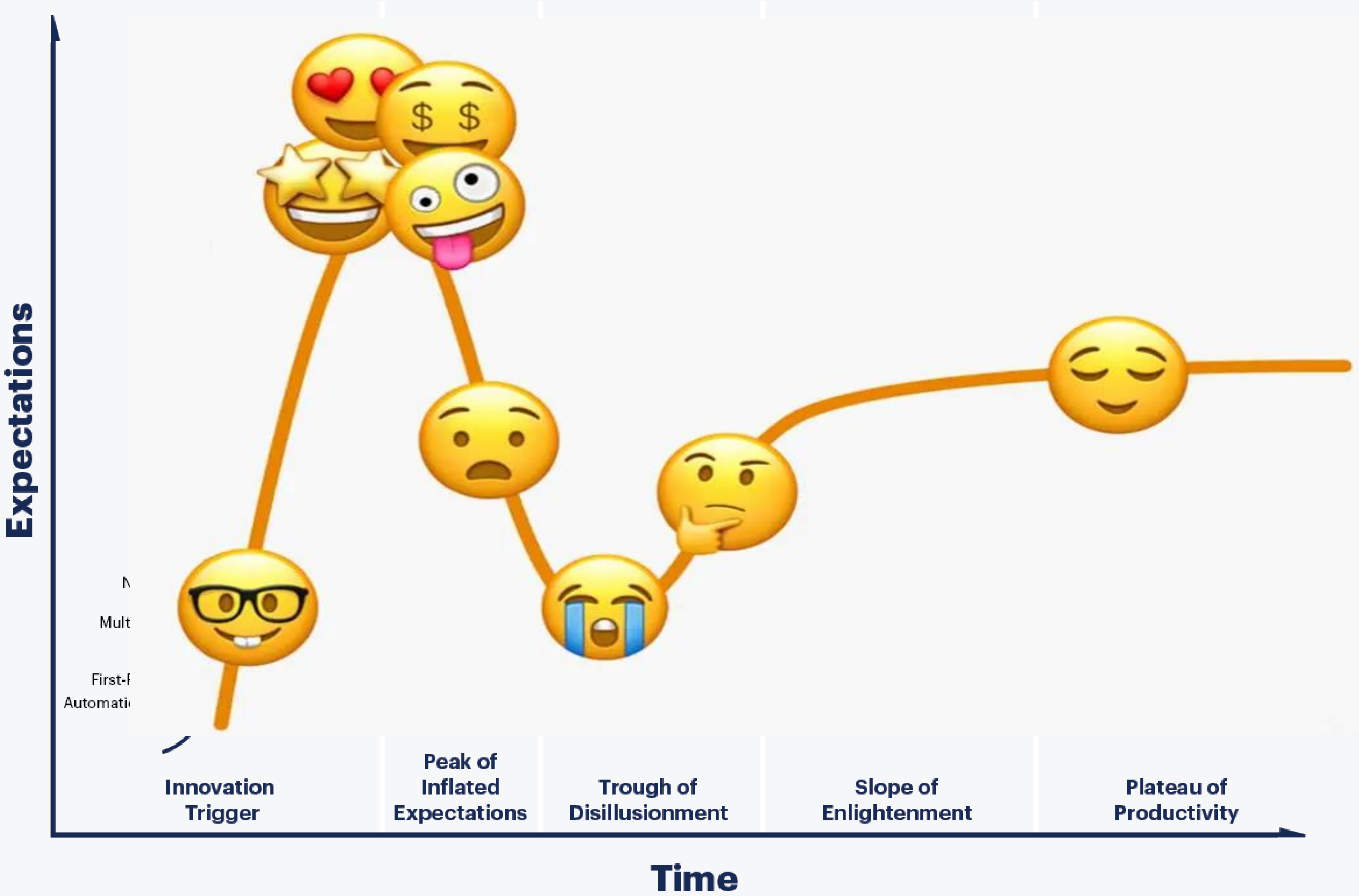
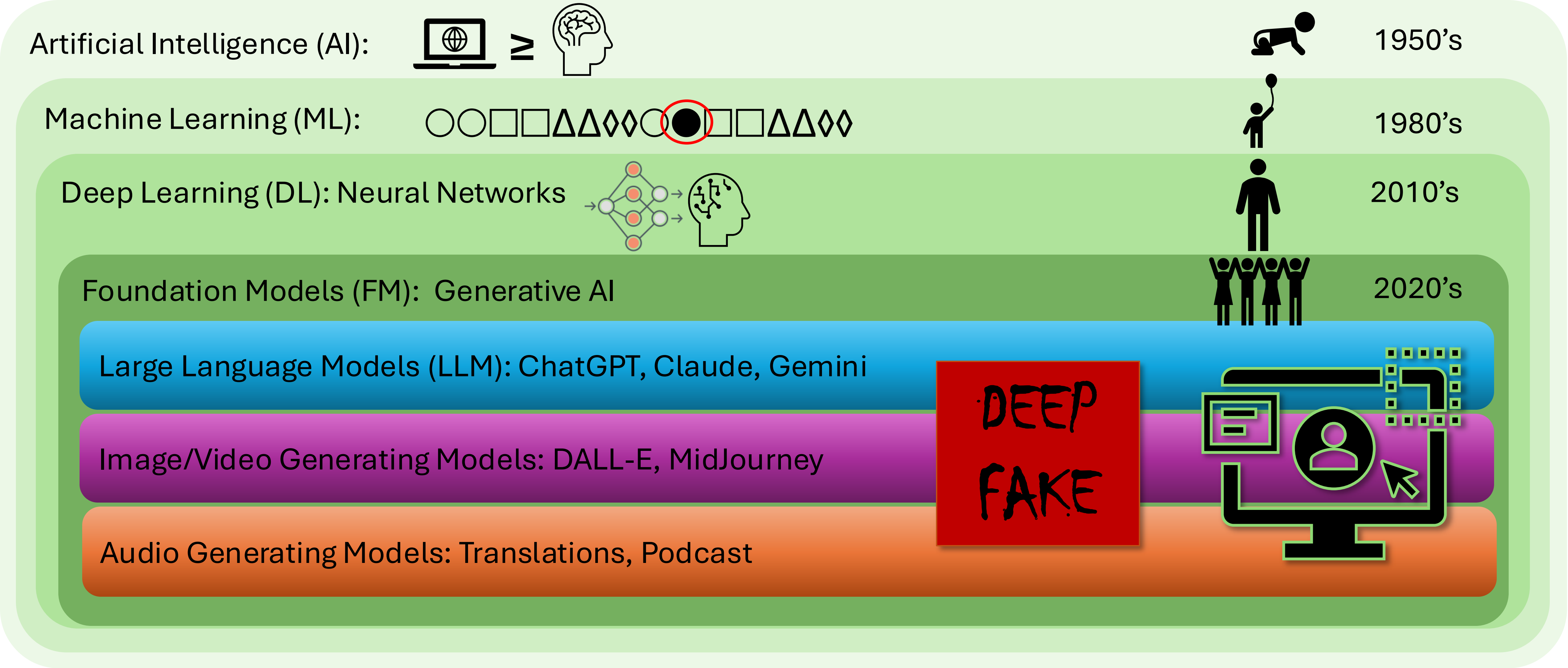
To be useful AI should improve health and quality of life for all through . . .

- Earlier and more accurate detection of disease
  - Cancer, CV, complex diseases as yet unknown
- Earlier and more accurate detection of dis-ease
  - Mental health, social needs, human interactions
- Better treatments
  - Effective, fewer side effects, cost effective
- Reductions in the cost of care and services & Improvement in Access
  - Democratization not just of information but of interpretation of information
- Reductions in provider burden
  - Documentation, proving performance, coordination and communication
- Improve policy-making and policy-un-making
  - Evidence-based policy-making

Hype Cycle for Artificial Intelligence, 2023

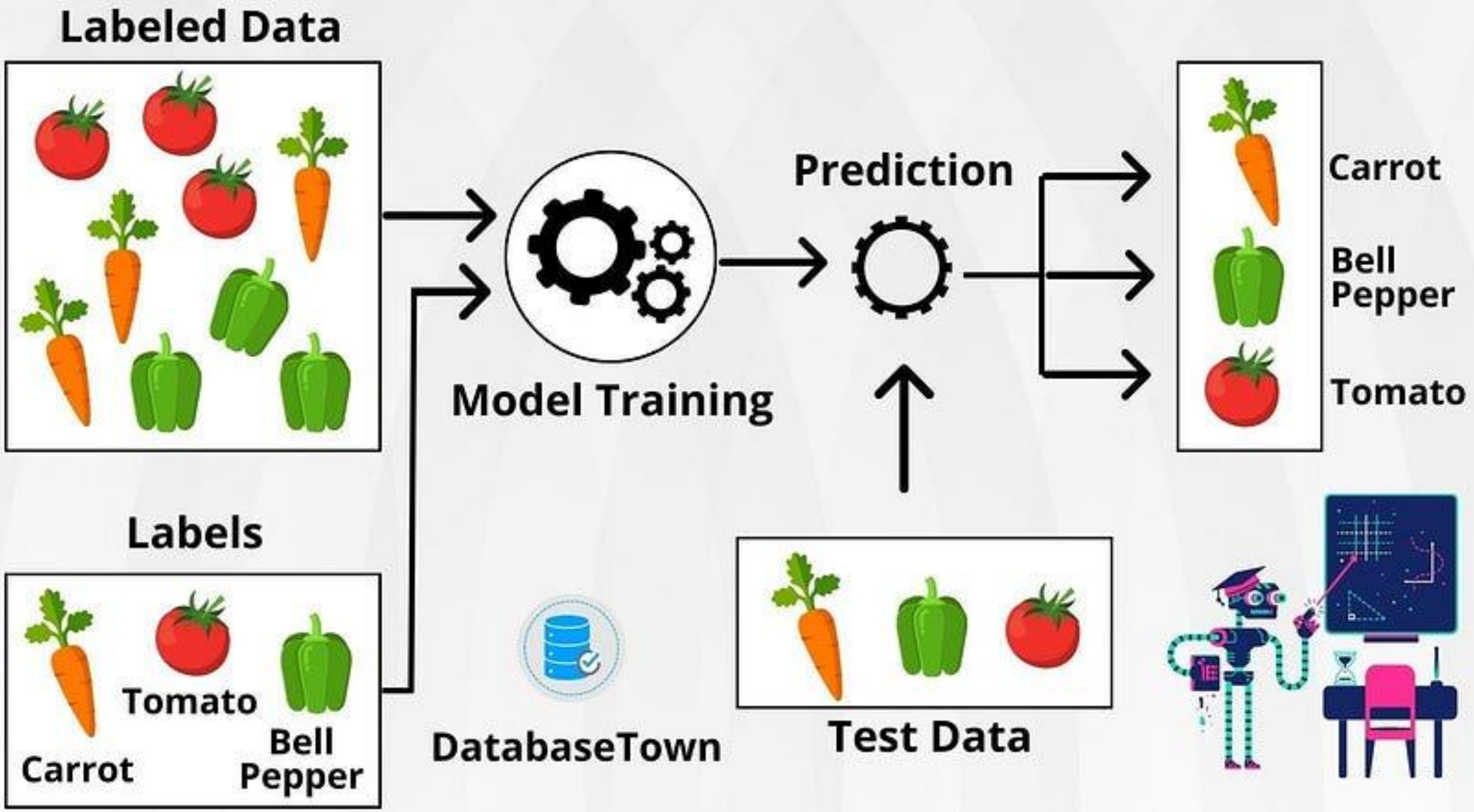


Basic Science



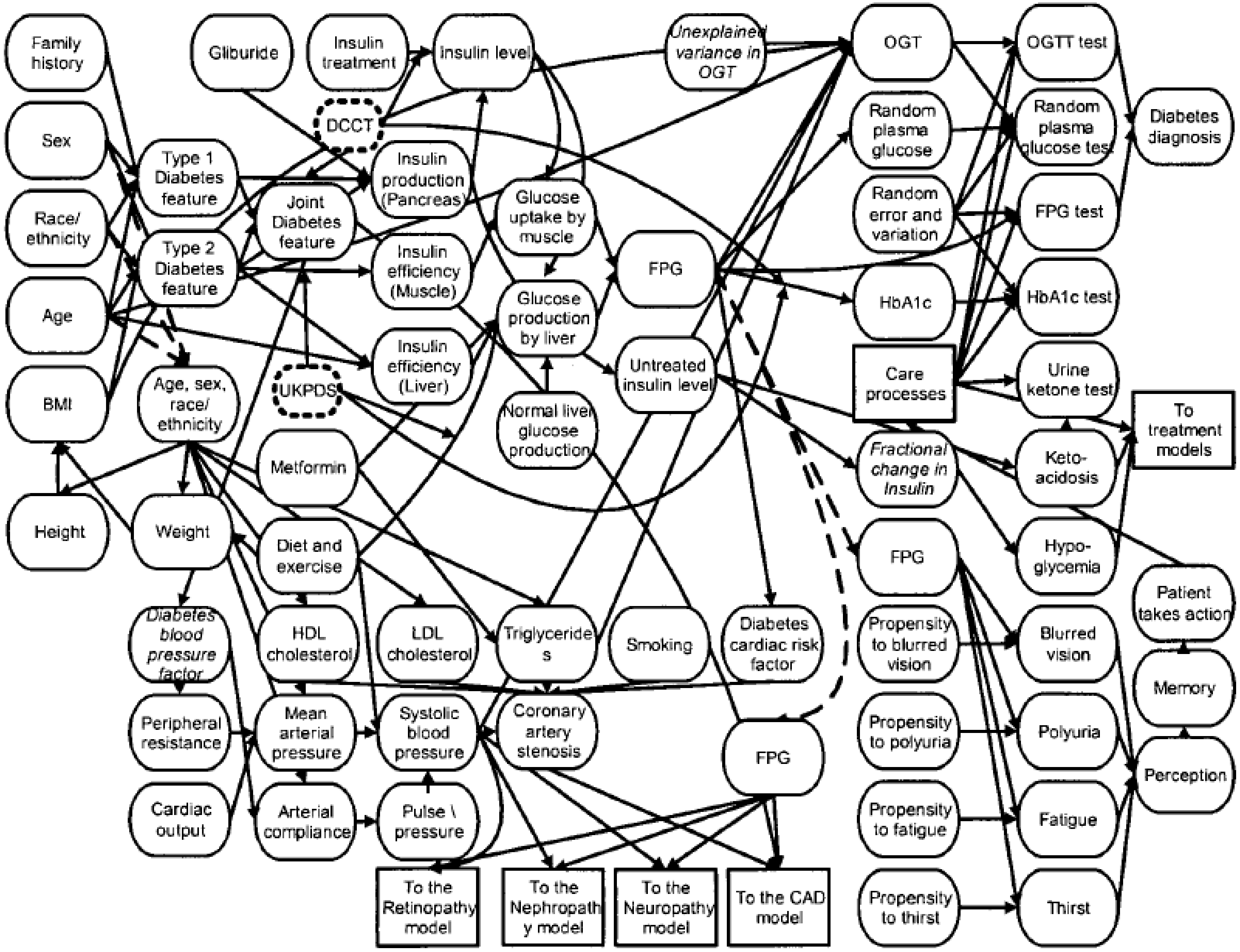
SUPERVISED LEARNING

Supervised machine learning is a branch of artificial intelligence that focuses on training models to make predictions or decisions based on labeled training data.



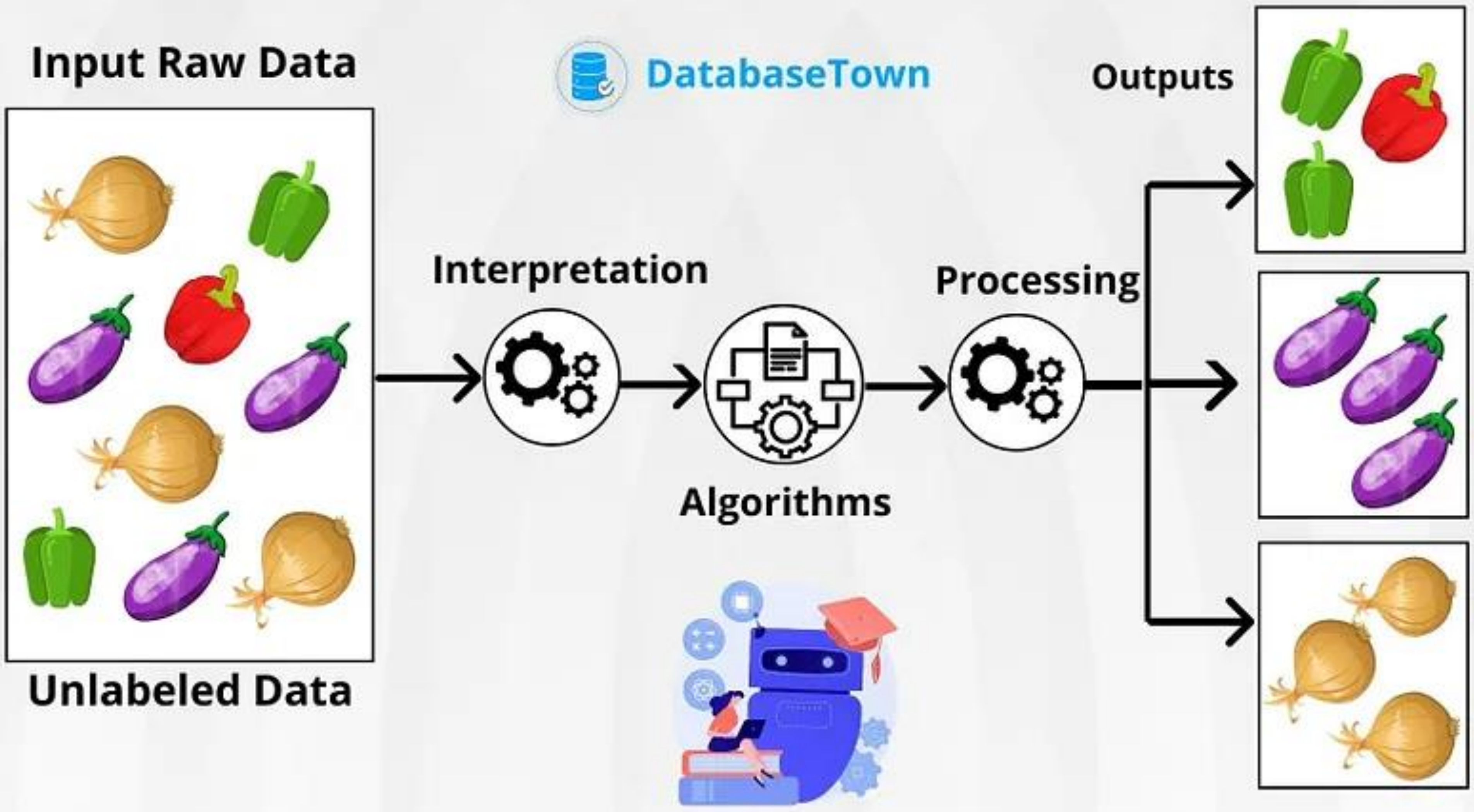
Archimedes model of diabetes

Eddy DM, Schlessinger L: Archimedes: a trial-validated model of diabetes. *Diabetes Care* 26:3093–3101, **2003**

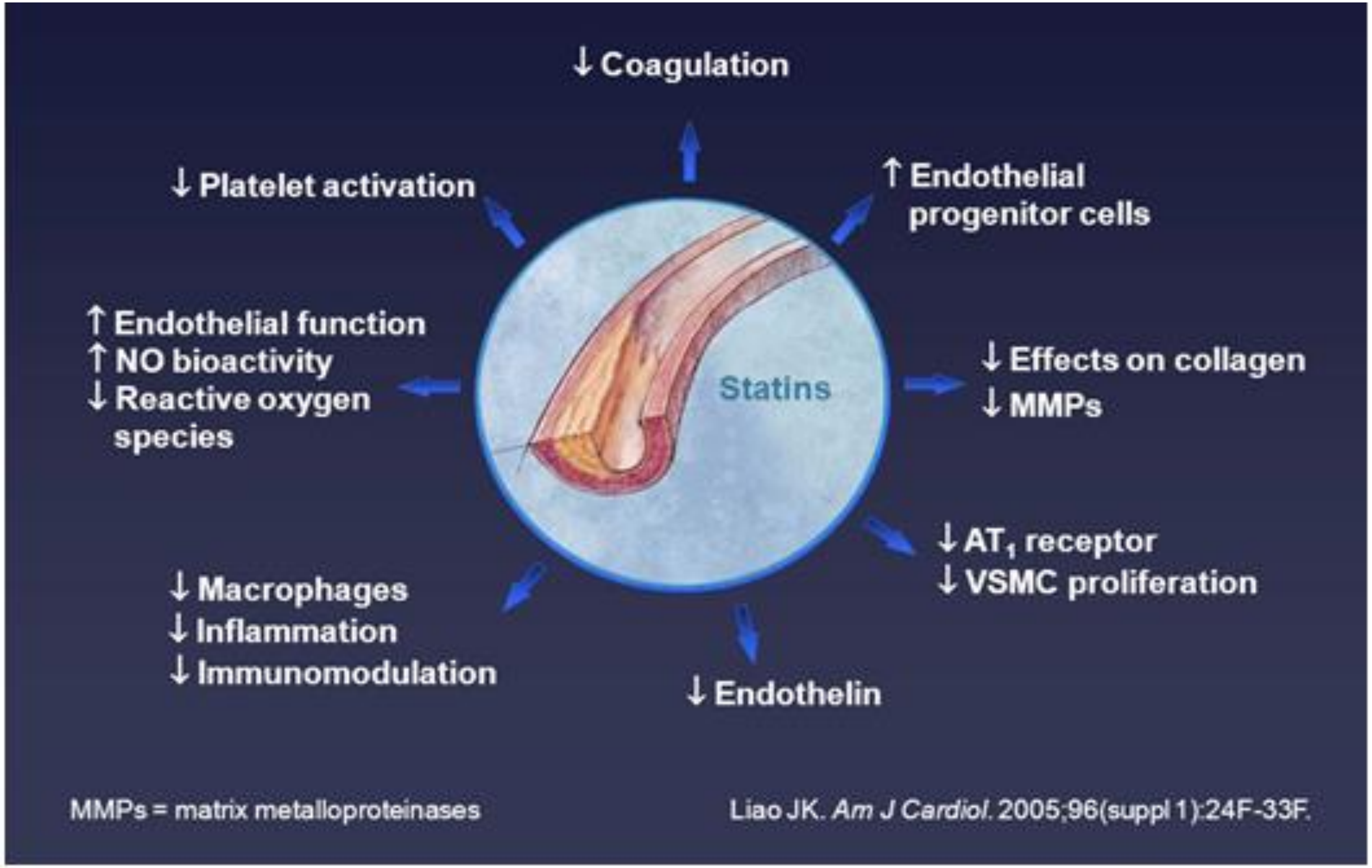


UNSUPERVISED LEARNING

Unsupervised learning is a type of machine learning where the algorithm learns from unlabeled data without any predefined outputs or target variables.

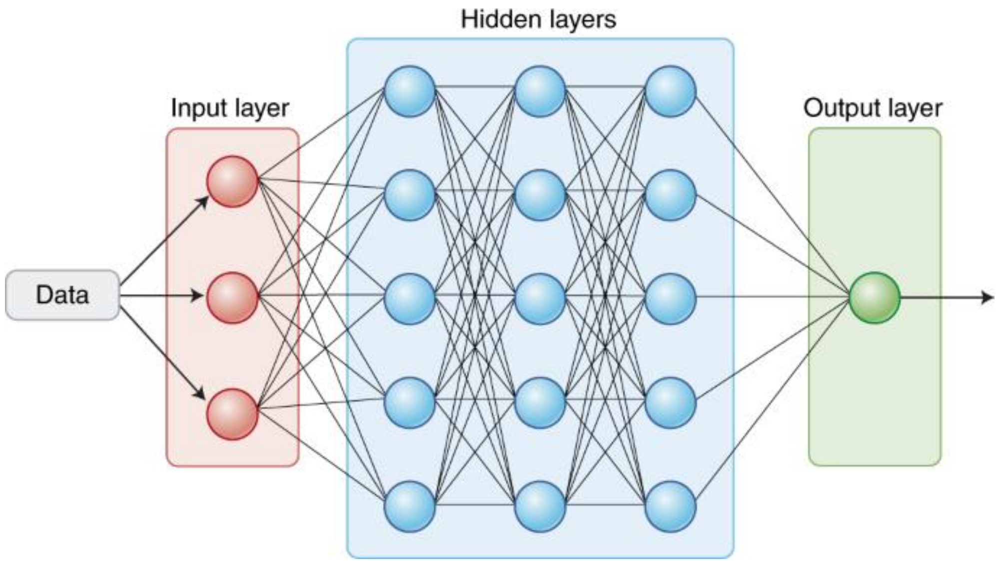


Pleiotropic effect of statins- beyond cholesterol

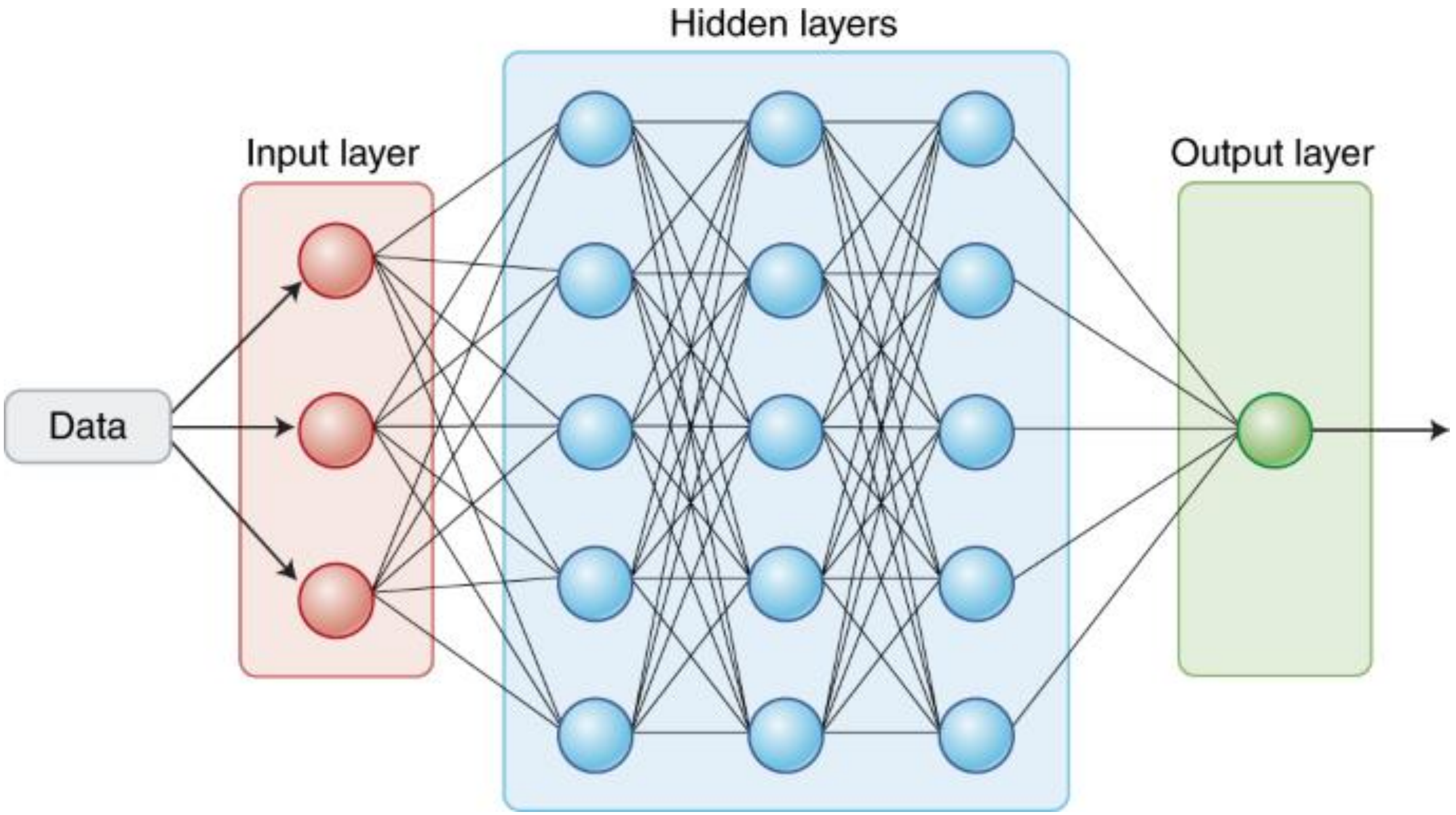


How do LLM’s work?

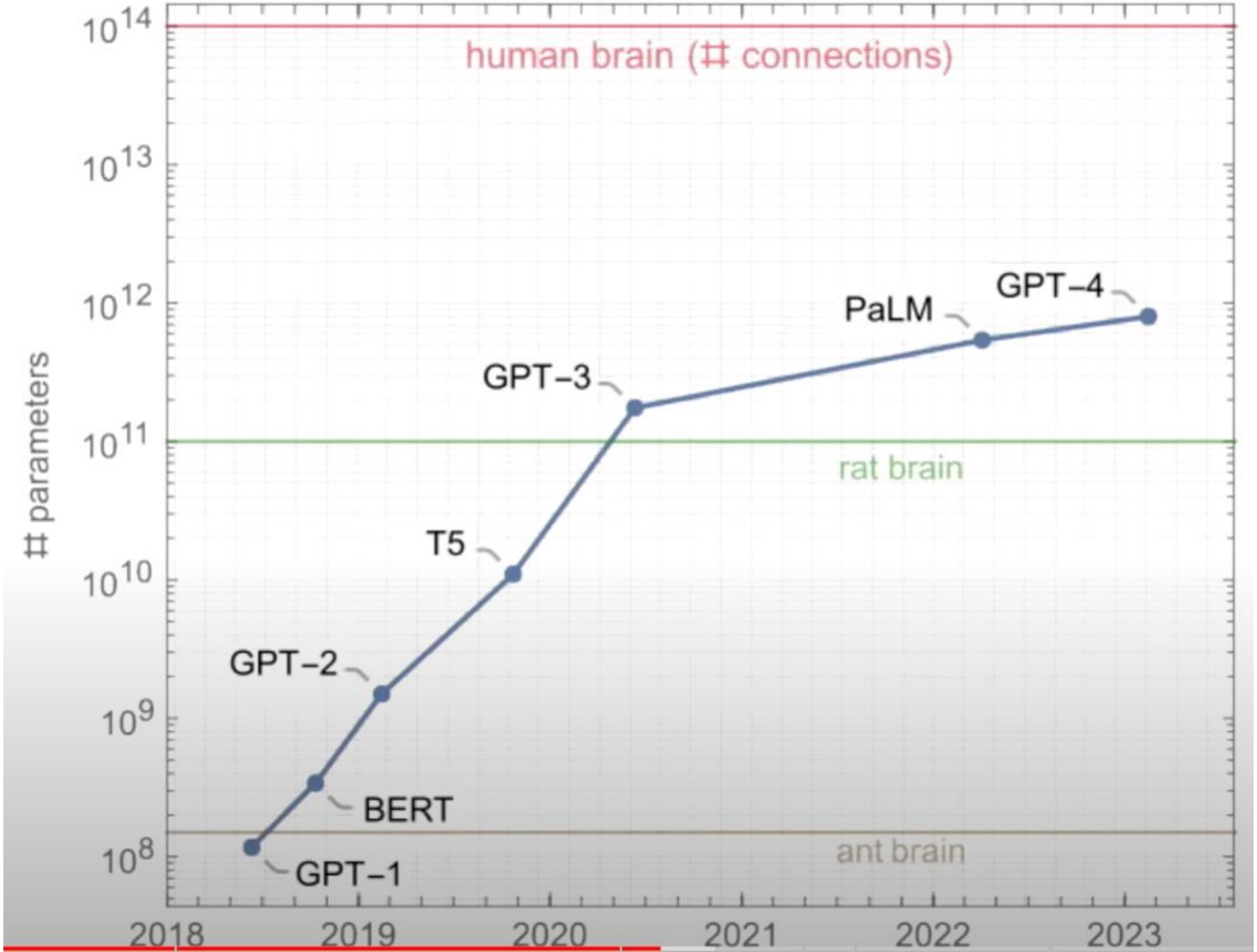
Tell me a story



Once . . .

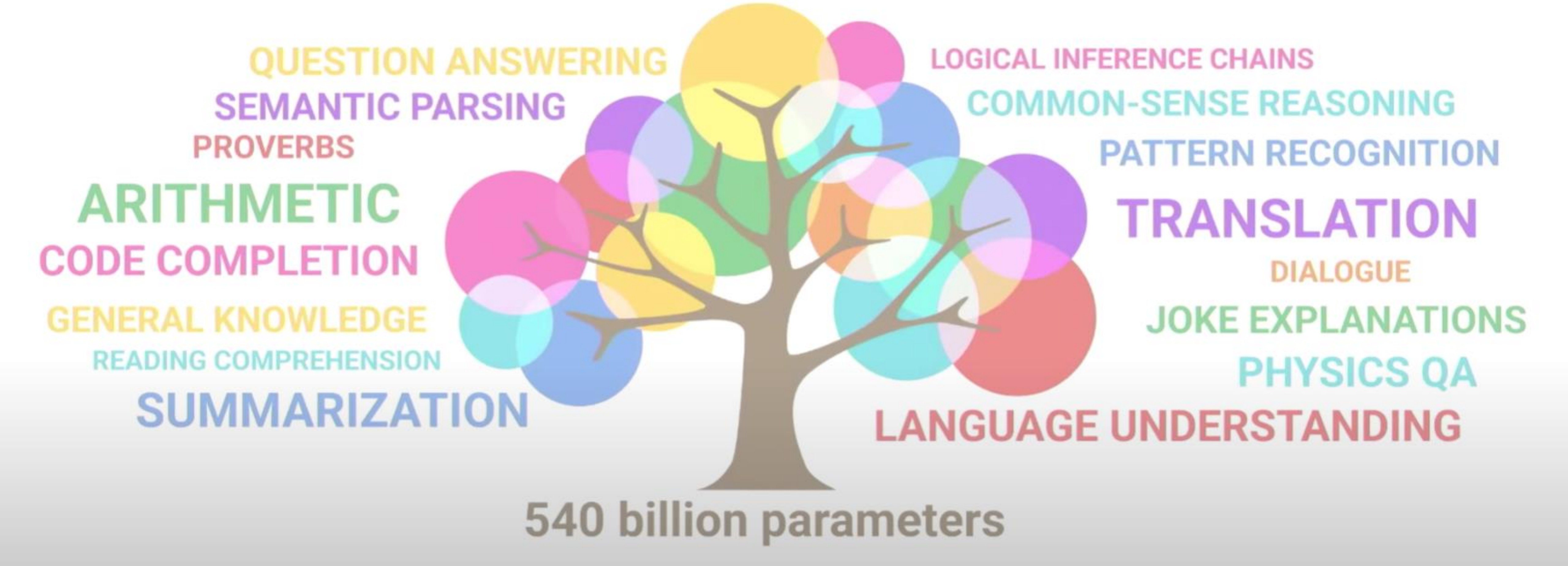


3x4+4 + 4x4+4 + 4x4+4 + 4x1+1 = **61**
trainable parameters

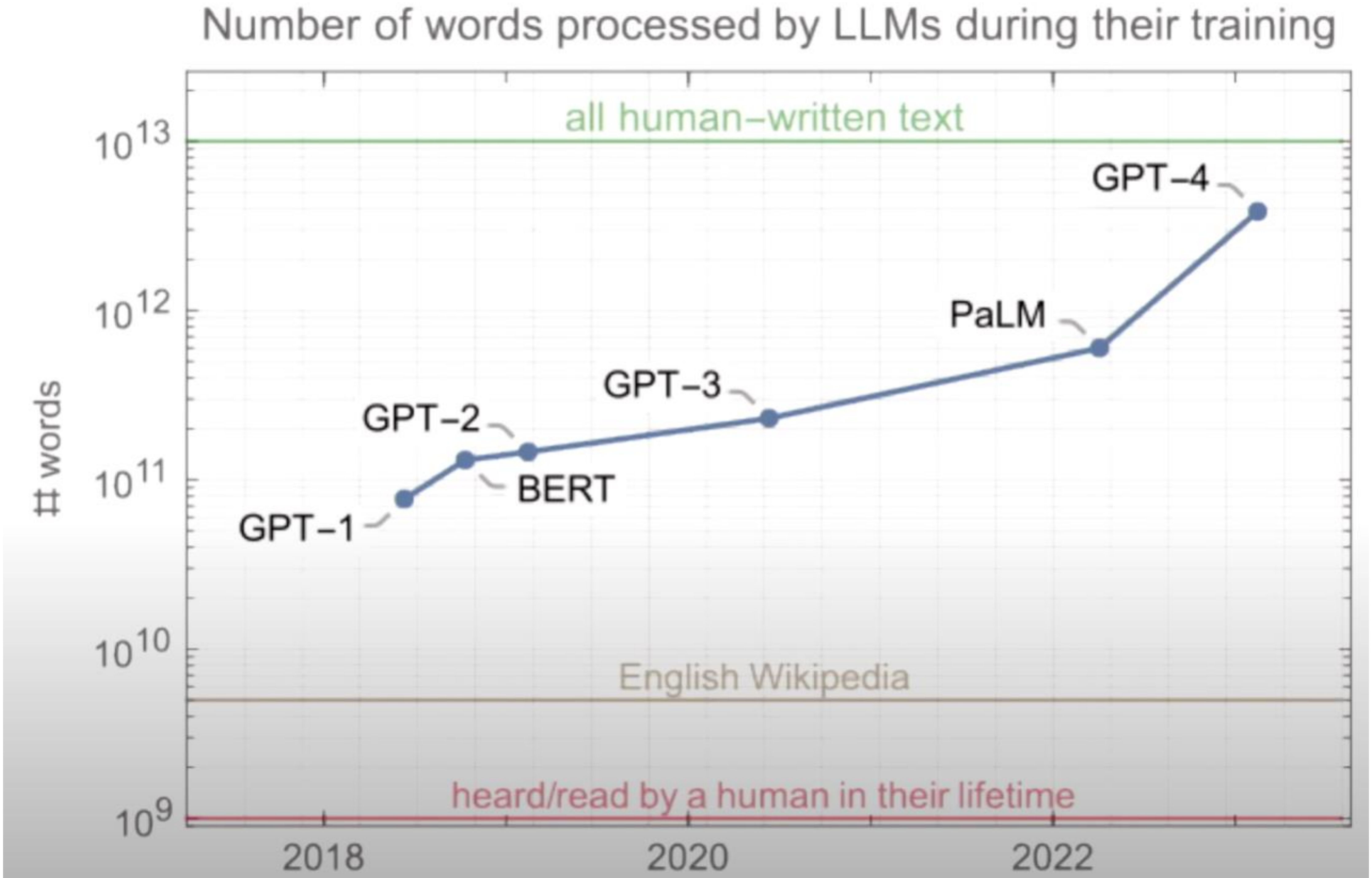


human brain (# connections)
rat brain
ant brain
parameters
10^{14}
10^{13}
10^{12}
10^{11}
10^{10}
10^{9}
10^{8}
GPT–4
PaLM
GPT–3
T5
GPT–2
BERT
GPT–1
2018
2019
2020
2021
2022
2023

Model Capabilities




LLM training prices (at the time of their creation)
Price, US$
10^8
10^7
10^6
10^5
10^4
1000
100
2018
2020
2022
GPT−1
BERT
GPT−2
GPT−3
PaLM
GPT−4



Number of words processed by LLMs during their training
all human–written text
GPT–4
PaLM
GPT–3
GPT–2
BERT
GPT–1
English Wikipedia
heard/read by a human in their lifetime
words
10^{13}
10^{12}
10^{11}
10^{10}
10^{9}
2018
2020
2022

Agentic AI & workflows

- Multiple AI models working together
- Each Agent has its own strengths (and limitations)
  - Text (LLM)
  - Math
  - Image interpretation
  - Empathy . . .
- Agents' efforts are orchestrated, perhaps by an Orchestration Agent (team leader)

Agent Hospital: A Simulacrum of Hospital with Evolvable Medical Agents

JUNKAI LI[†#], SIYU WANG[†], MENG ZHANG[†], WEITAO LI[†#], YUNGHWEI LAI[†], XINHUI KANG[†#], WEIZHI MA[†], and YANG LIU[#†]

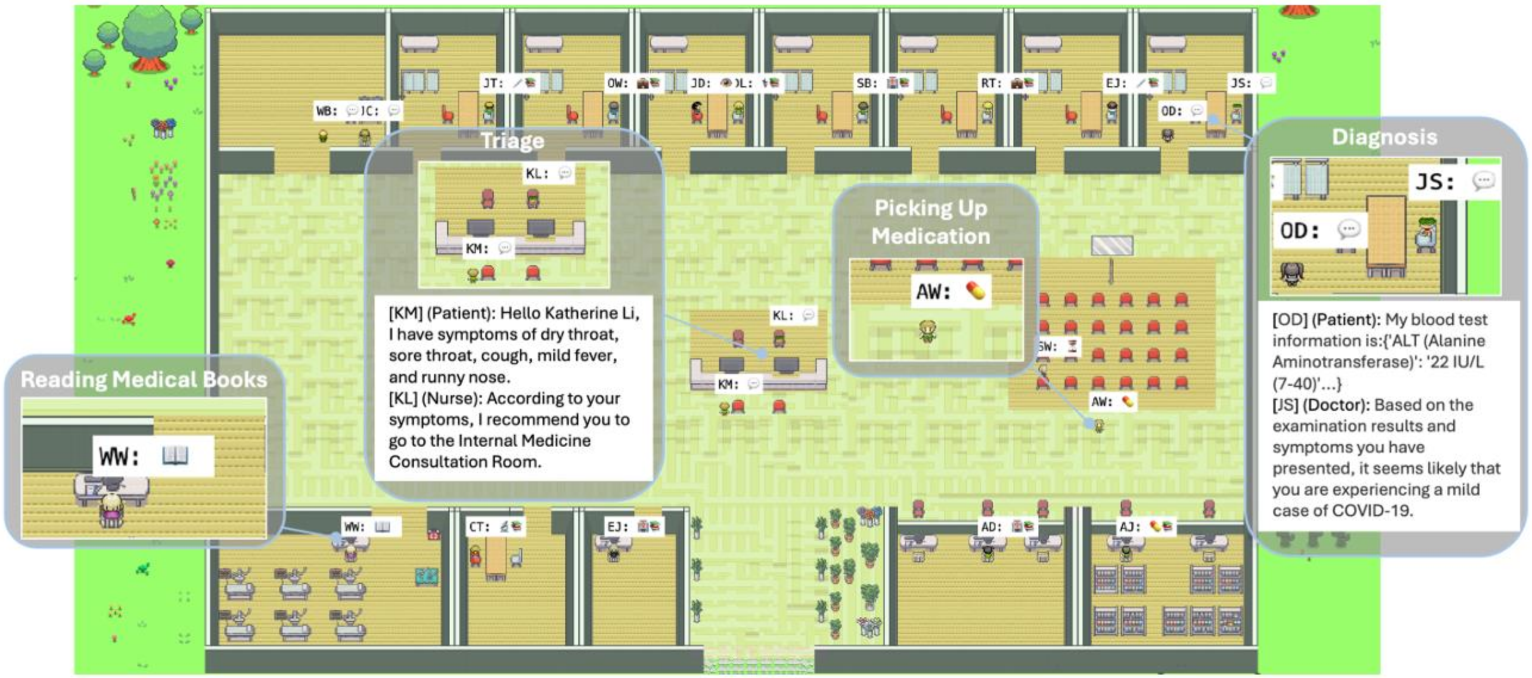


Fig. 1. An overview of `Agent Hospital`. It is a simulacrum of hospital in which patients, nurses, and doctors are autonomous agents powered by large language models. Agent Hospital simulates the whole closed cycle of treating a patient's illness: disease onset, triage, registration, consultation, medical examination, diagnosis, medicine dispensary, convalescence, and post-hospital follow-up visit. An interesting finding is that the doctor agents can keep improving treatment performance over time without manually labeled data, both in simulation and real-world evaluations.

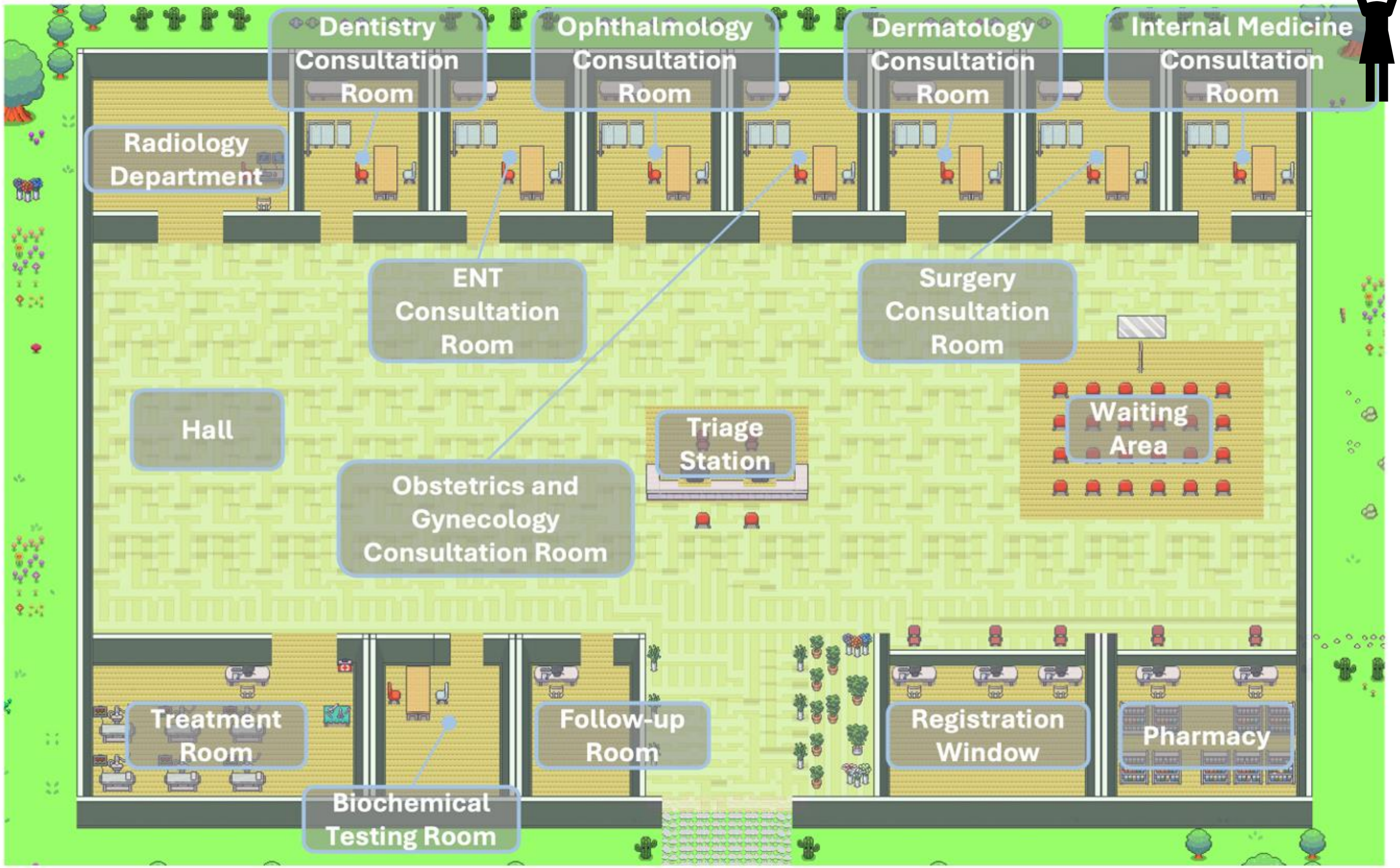
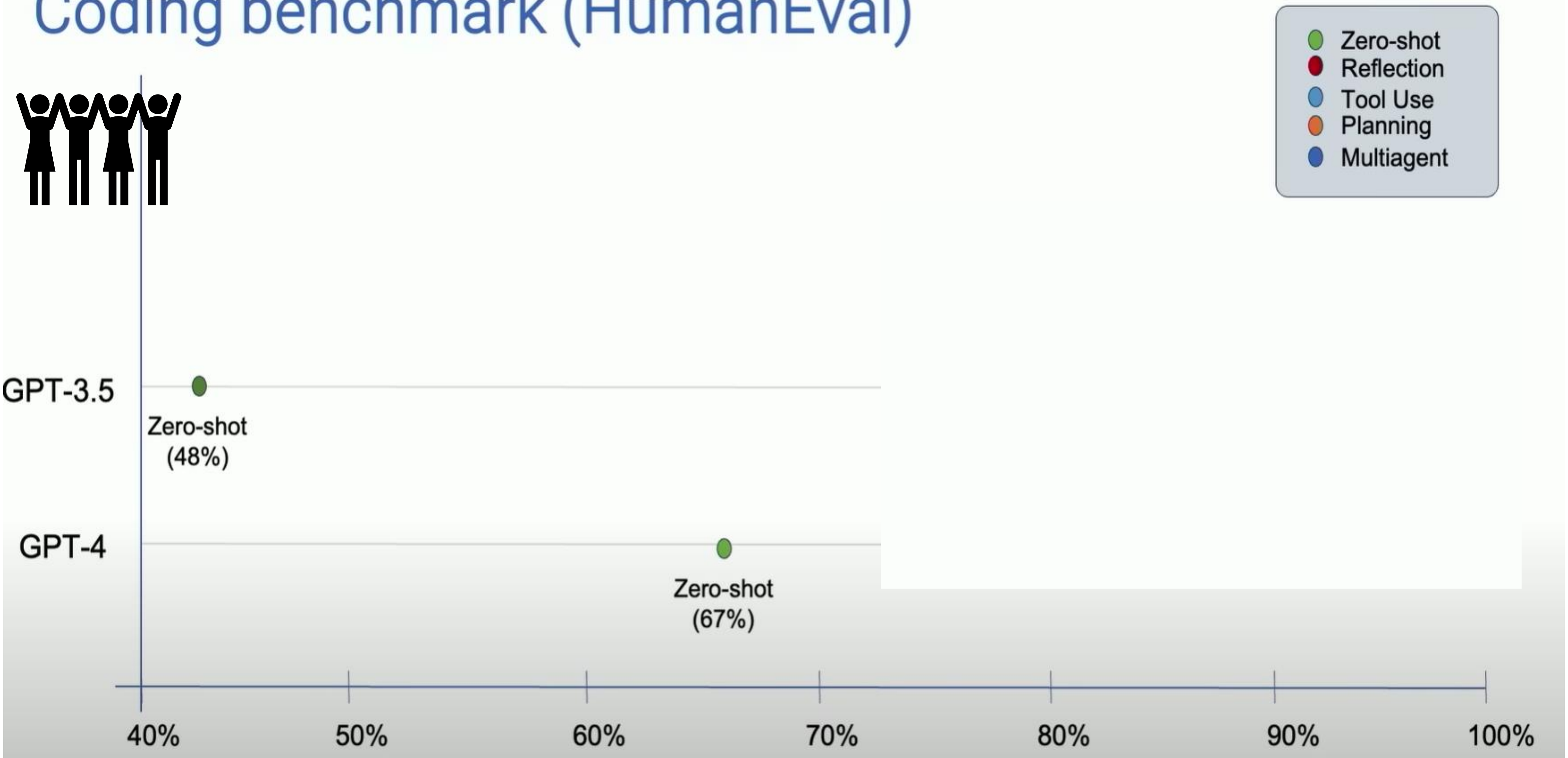


Fig. 2. The distribution of various areas within Agent Hospital.

Coding benchmark (HumanEval)



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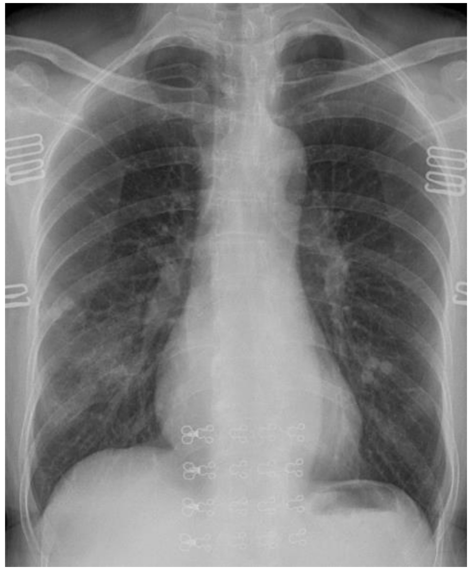
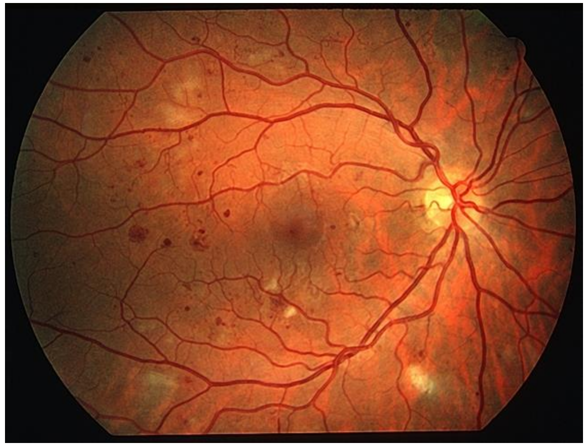
How can AI help me?

- Documentation support
  - Prior authorizations
  - Dictations/Scribe
  - Patient messaging
  - Informed Consent
- Decision support
- Translation services

Predictive AI in Research



- Image interpretation (Rajpurkar, 2023)
  - Radiology: Chest X-rays for pneumonia, tuberculosis
  - Ophthalmology: diabetic retinopathy
  - Dermatology: skin cancer diagnosis
  - Pathology: breast cancer slides to predict mets



Predictive AI in research

- Adverse events during hospitalizations from EHR data (Rajkomar, 2018)
- Protein folding from amino acid sequences (Jumper, 2021)
- Predict future diagnoses based on past labs and diagnoses (Mukherjee, 2023)
- Semantic reconstruction of continuous language from fMRI brain recordings (Tang, 2023)
- Odor perception mapped to chemicals (Lee, 2023)
- Predict Alzheimer’s Disease from EHR data 7 years early (Tang, 2024)
- Voice as a biomarker of Parkinson’s, Alzheimer’s, cognitive impairment, COVID-19, etc. (Idrisoglu, 2023, Bensoussan, 2024)

AI exceeding human detection skills

- Retinal images
  - Age, biological sex, cardiovascular risk determination (Poplin, 2018)
  - Race (Coyner, 2023)
- Electrocardiograms
  - Age, biological sex (Attia, 2019)
  - Chronic kidney disease (Holmstrom, 2023)
- Chest x-rays
  - Race (Gichoya, 2022)
  - Cardiac function and valvular disease (Ueda, 2023)
  - Diabetes (Pyrros, 2023)
  - Correlation with chronological age in healthy cohorts and for chronic diseases, difference between estimated age and chronological age (Mitsuyama, 2023)
  - Cardiac risk prediction as accurately as ASCVD (Weiss, 2024)
- CT Scans
  - Detection of Pancreatic CA 475 days early with AUROC = 0.97 (Korfiatis, 2023)

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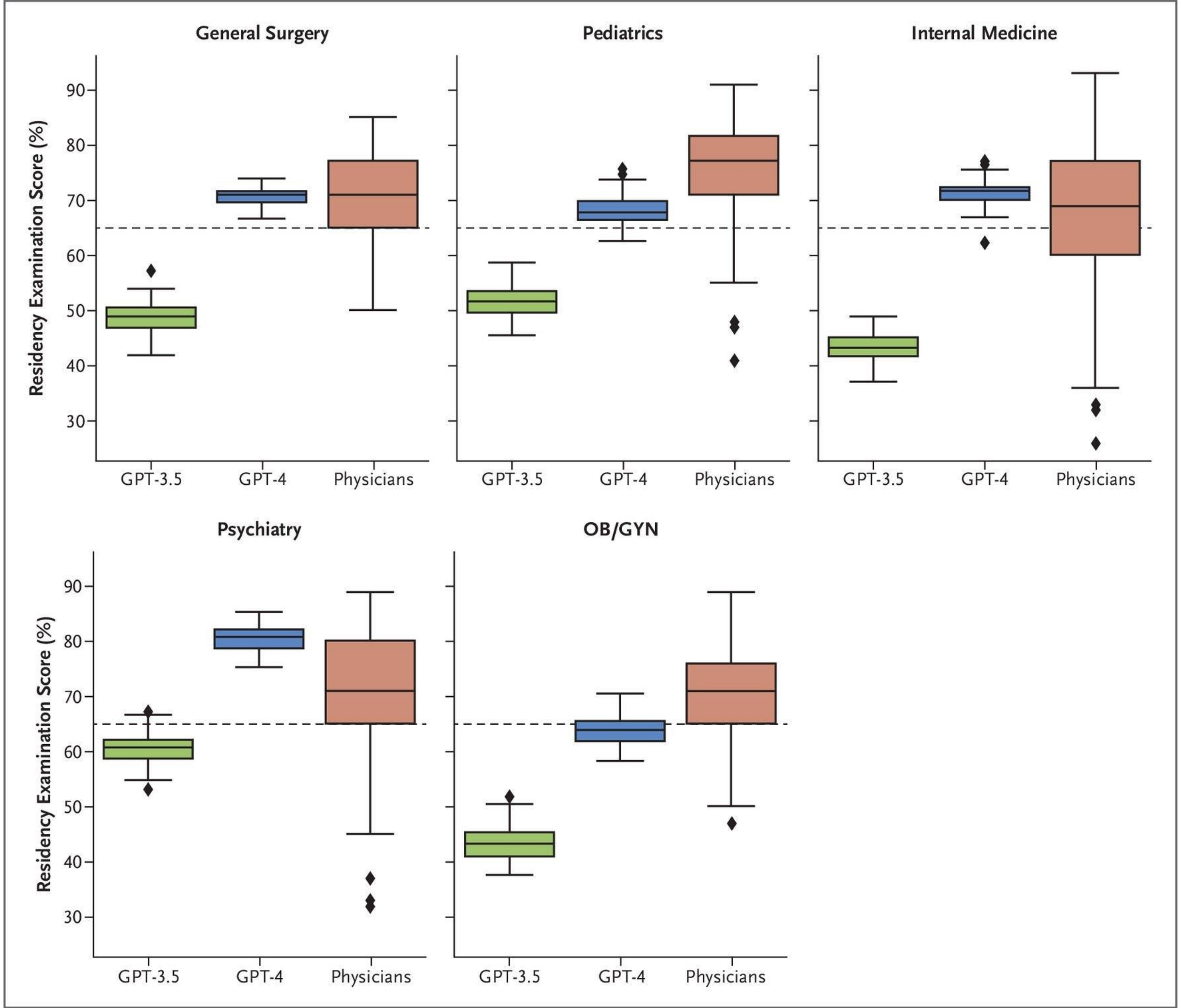
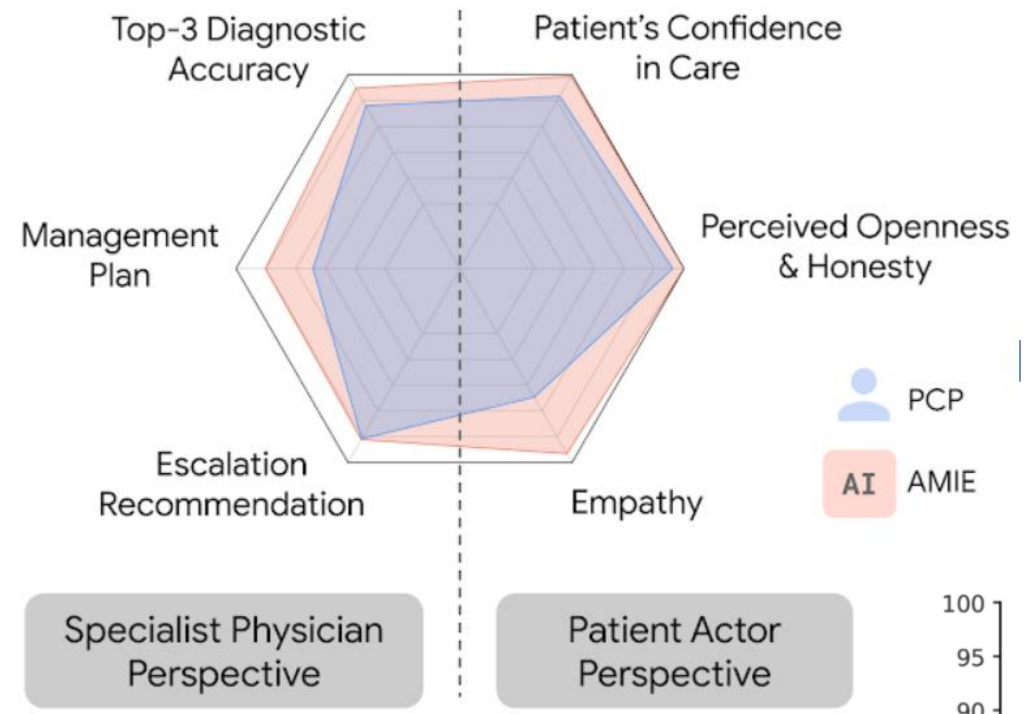
Will AI replace me?


General Surgery
Pediatrics
Internal Medicine
Psychiatry
OB/GYN
Residency Examination Score (%)
90
80
70
60
50
40
30
GPT-3.5
GPT-4
Physicians

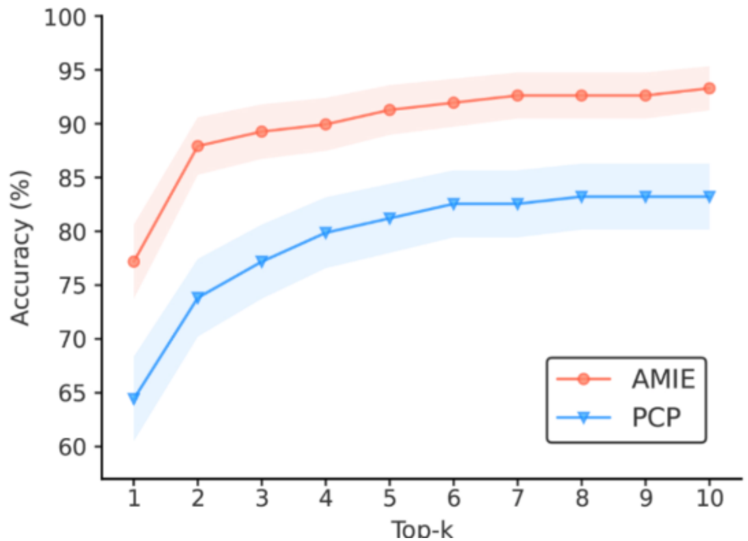
We’ll always have empathy, won’t we?

- Randomized, double-blind crossover study*
- Simulated patients with 149 case scenarios (OSCE format)
  - 20 PCPs vs.
  - LLM trained for diagnosis and conversation
- Blinded, chat-based
- Patients surveyed on performance

*not yet peer-reviewed

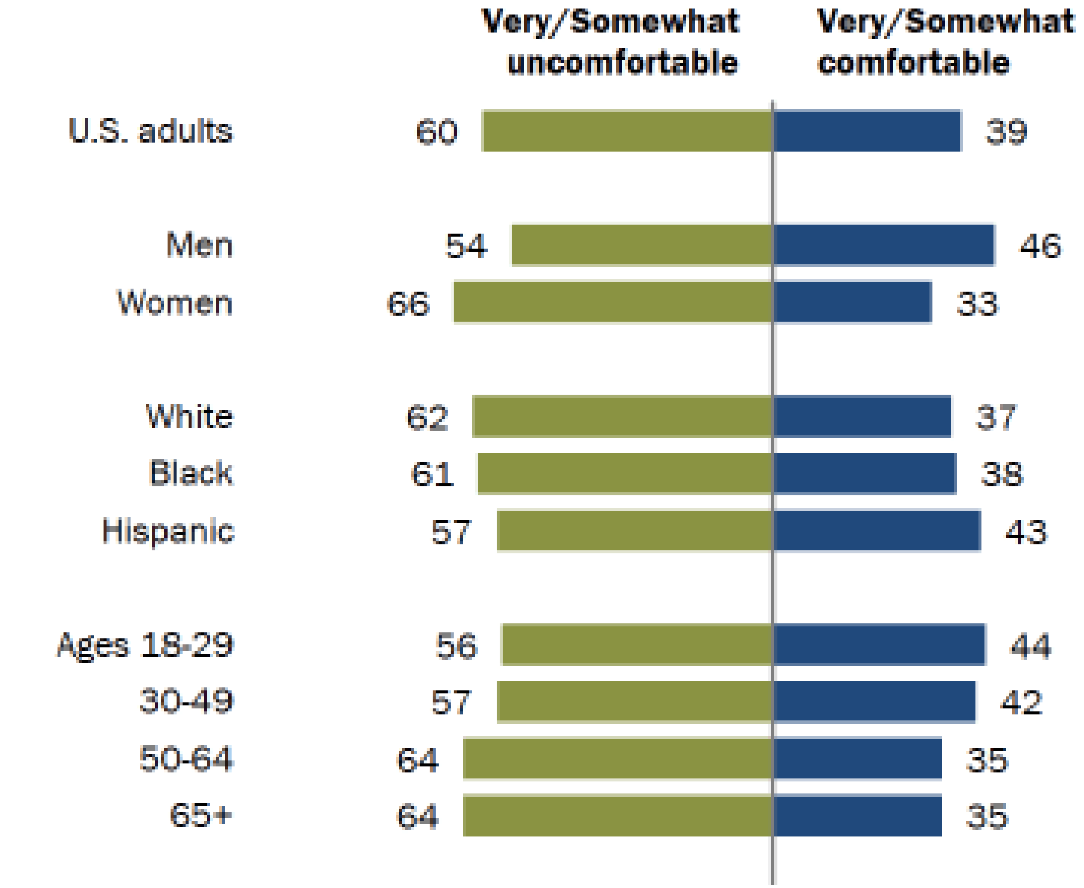


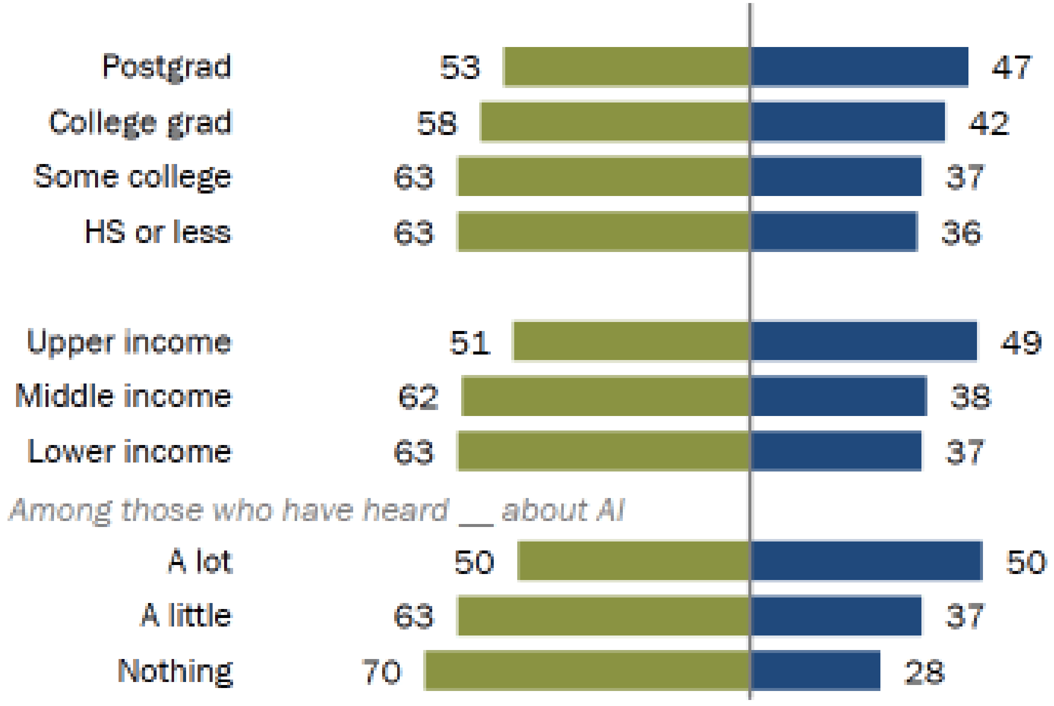
AMIE outperformed PCPs on multiple evaluation axes for diagnostic dialogue in our ev



Majority of U.S. adults would be uncomfortable if their health care provider relied on artificial intelligence

% of U.S. adults who say that they would feel __ if their health care provider relied on artificial intelligence to do things like diagnose disease and recommend treatments





Note: Respondents who did not give an answer are not shown. White and Black adults include those who report being only one race and are not Hispanic. Hispanics are of any race. Family income tiers are based on adjusted 2021 earnings.
Source: Survey conducted Dec. 12-18, 2022.
"60% of Americans Would Be Uncomfortable With Provider Relying on AI in Their Own Health Care"

PEW RESEARCH CENTER

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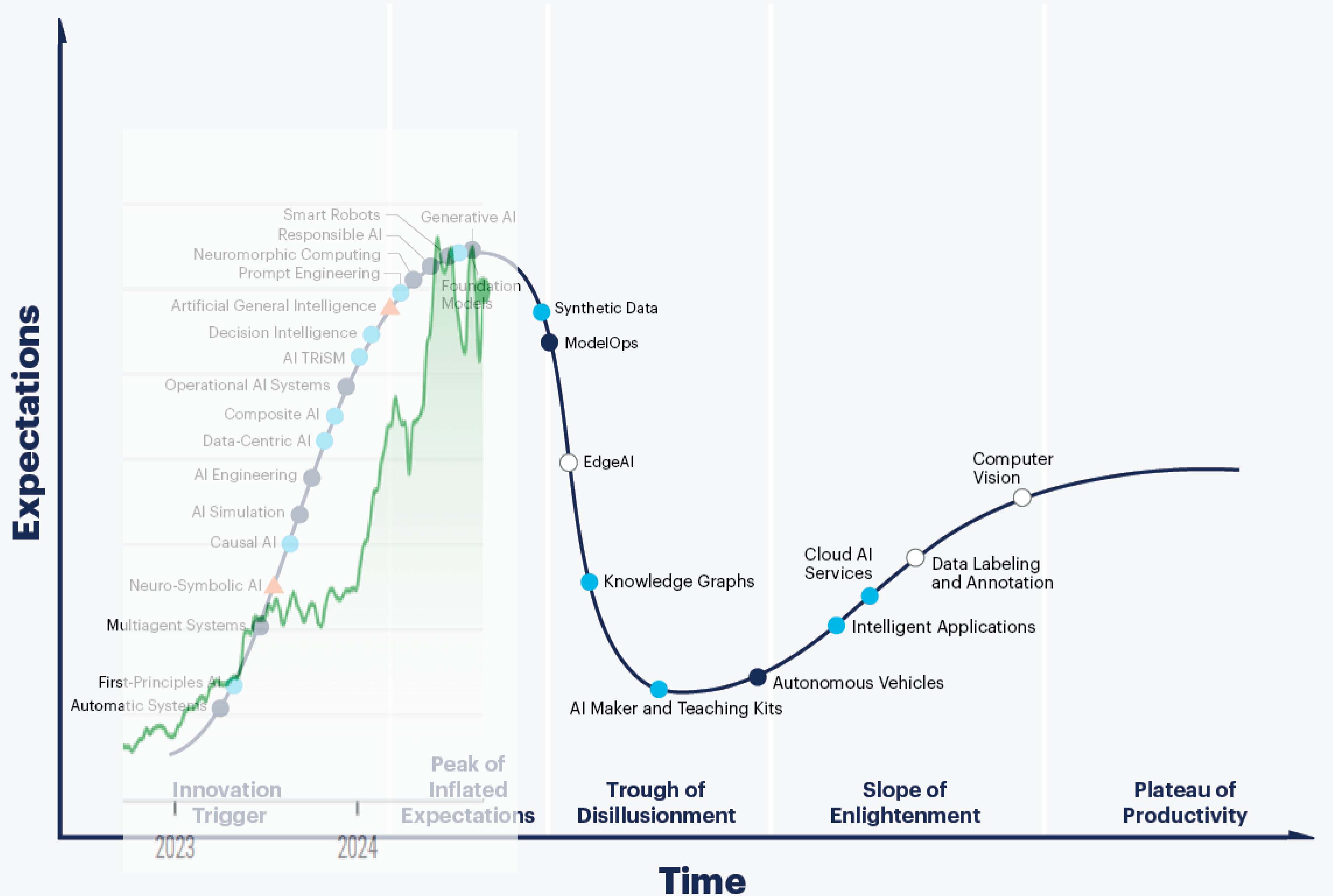
Hype Cycle for Artificial Intelligence, 2023



Plateau will be reached:

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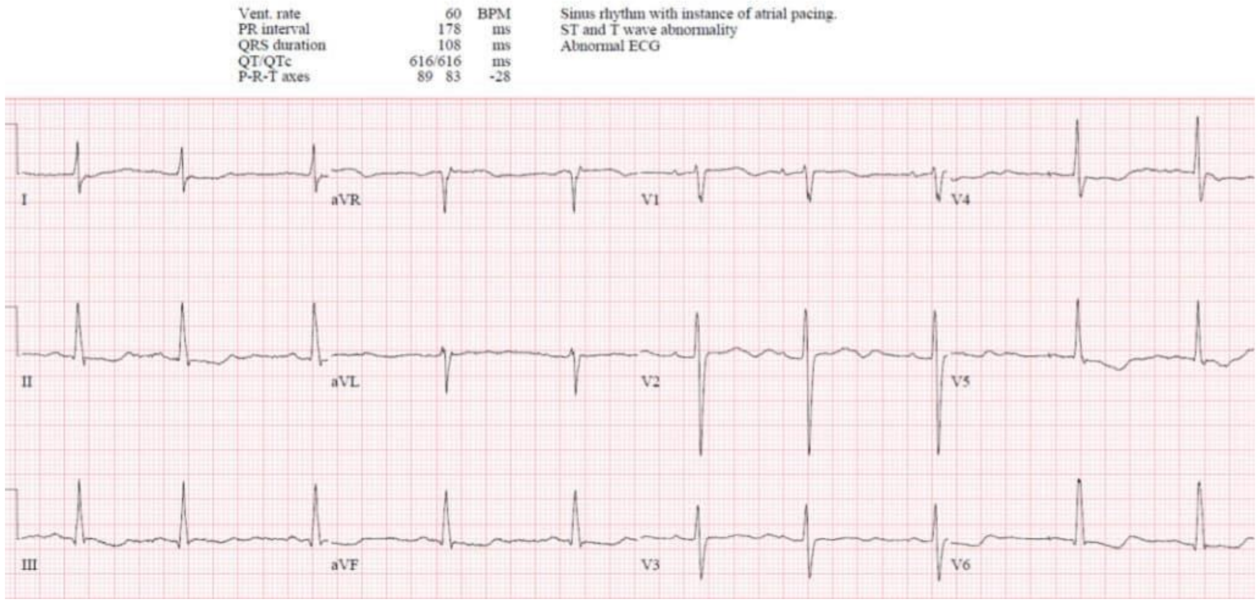
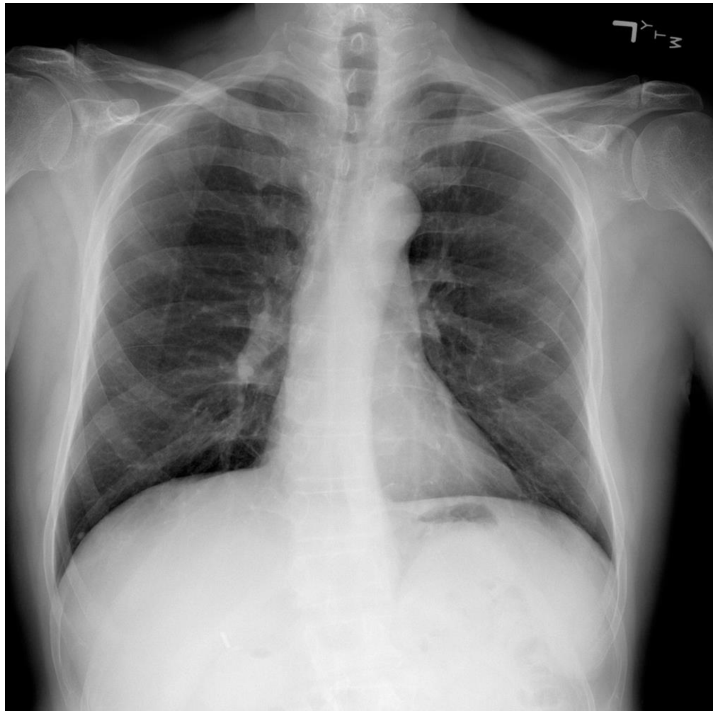
Risks of AI

- Deskilling/Reskilling
- Automation Complacency

- GIGO: Bad/Incomplete data
  - Bias
  - Bad recommendations
  - Hallucinations





Demystifying the White House Executive Order on AI

What enterprise leaders need to know

Policy Impact of DSI Certification Criterion

Improve Transparency	Regarding how a Predictive DSI is designed, developed, trained, evaluated, and should be used
Enhance Trustworthiness	Through transparency on how certified health IT developers manage potential risks and govern predictive DSIs that are supplied by the health IT developer as part of its Health IT Module
Foster an information ecosystem	Necessary to help healthcare organizations and users of these tools better determine whether their Predictive DSIs are fair, appropriate, valid, effective, and safe (FAVES)
Advance Health Equity by Design	By addressing bias and health disparities, potentially propagated by predictive DSIs, to expand the use of these technologies in safer, more appropriate, and more equitable ways for patients and individuals

Table 1—*Comparison of model and trial results: trials that include people with diabetes*

						Result (%)	
Name of trial	Population	Outcome	Years	Initial size	Treatment group	Model	Trial
UKPDS	Newly diagnosed type 2 diabetes	Myocardial infarction	12	1,138	Conventional	19.6	19
				2,729	Intensive*	15.4	16
		Albuminuria	12	1,138	Conventional	33.8	34
				2,729	Intensive	21.3	23
		Proteinuria	12	1,138	Conventional	9.8	10.3
				2,729	Intensive	7.6	6.8
		Retinopathy	12	1,138	Conventional	50	49
				2,729	Intensive	39	39
DPP†	Impaired glucose tolerance, Impaired fasting glucose and Overweight	Progression to diabetes	4	1,082	Control	38	37
				1,073	Metformin	31	28
				1,079	Lifestyle	21	20
HPS†	High risk for CAD events‡	Major coronary events	5	10,267	Placebo	11.7	11.8
				10,269	Simvastatin	8	8.8
		CHD death	5	10,267	Placebo	6.2	6.9
				10,269	Simvastatin	5	5.5
HOPE	High CAD risk§	Myocardial infarction	4.5	4,652	Placebo	11.3	11.3
				4,645	Ramipril	8.9	9
MICRO-HOPE†	High CAD risk, type 2 diabetes	Myocardial infarction	4	1,808	Placebo	13	12.9
				1,769	Ramipril	9	10.2
CARE‖	Recent myocardial infarction, average cholesterol	Myocardial infarction	5	2,078	Placebo	12.3	13.2
				2,081	Simvastatin	9.3	10.2
		CHD death	5	2,078	Placebo	6.2	5.7
				2,081	Simvastatin	4.4	4.6
Lewis	Type 1 diabetes, nephropathy	Doubling of creatinine	4	202	Placebo	37	33
				207	Captopril	19	22
IRMA-2	Type 2 diabetes, micro-albuminurea	Nephropathy	1.8	201	Placebo	17.4	15
				195	Irbesartan 150	9.5	9
				194	Irbesartan 300	5.3	4.5
DCCT primary	Type 1 diabetes without retinopathy	Retinopathy	8	378	Loose control	34	38
				348	Tight control	9.3	10
		Albuminuria	8	378	Loose control	29	28
				348	Tight control	17	15
		Proteinuria	9	378	Loose control	32	25
				348	Tight control	15	18
DCCT secondary	Type 1 diabetes with retinopathy	Retinopathy	8	352	Loose control	52	48
				363	Tight control	22	21
		Albuminuria	8	352	Loose control	33	35
				363	Tight control	22	22
		Proteinuria	9	352	Loose control	9	11
				363	Tight control	5	6
IDNT	Type 2 diabetes, nephropathy	Doubling of creatinine	4	579	Placebo	35	37
				569	Irbesartan	26	28

*Sulphonylurea, Metformin, or insulin; †not used to build physiology model; ‡CAD, occlusive arterial disease or diabetes; §CAD or diabetes plus at least one CVD risk factor; ‖eight additional validation exercises were done for the under-60 and over-60 age-groups. No model results were significantly different from trial results.

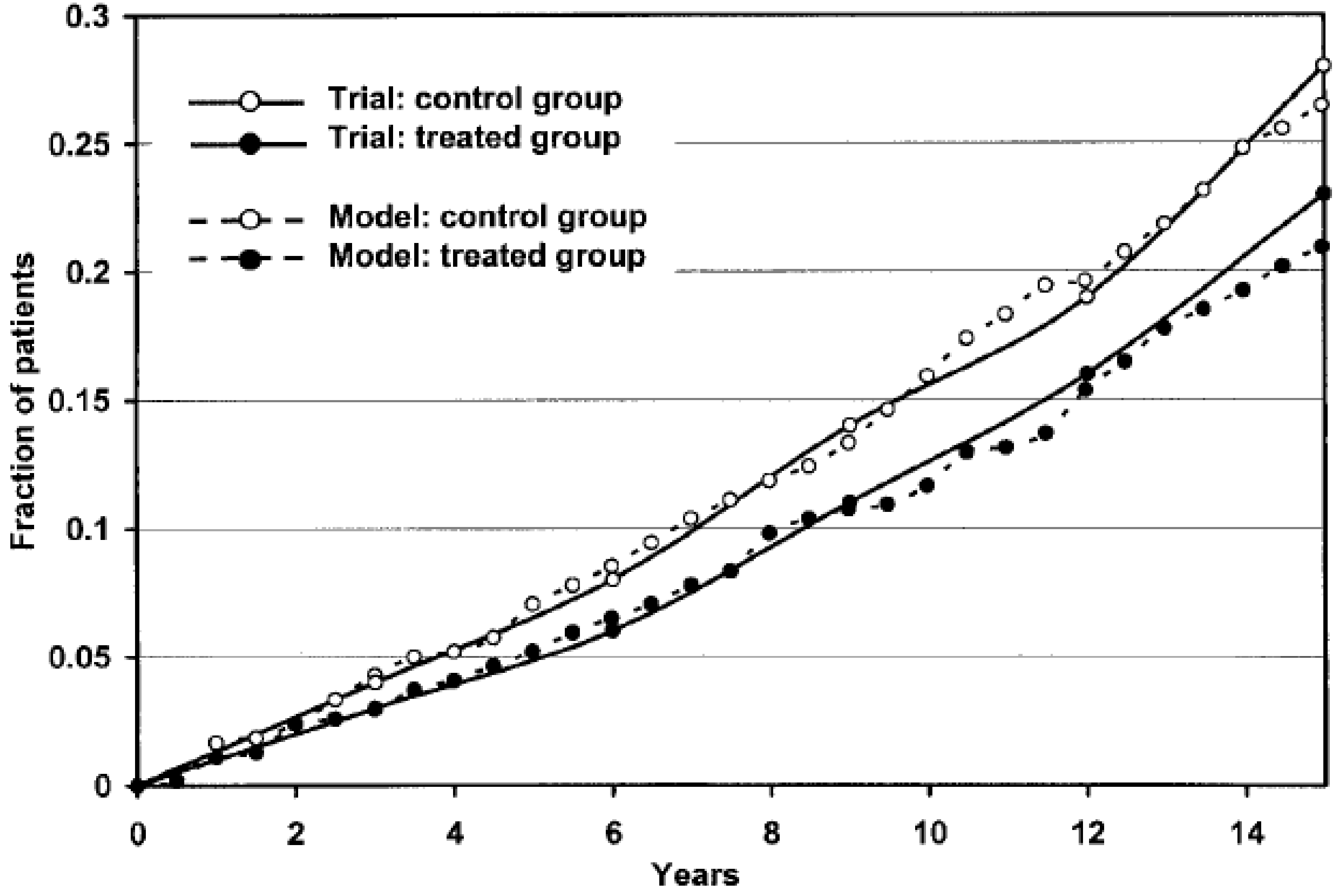


Figure 1—*Comparison of model and trial: fraction of patients having myocardial infarctions in the UKPDS.*

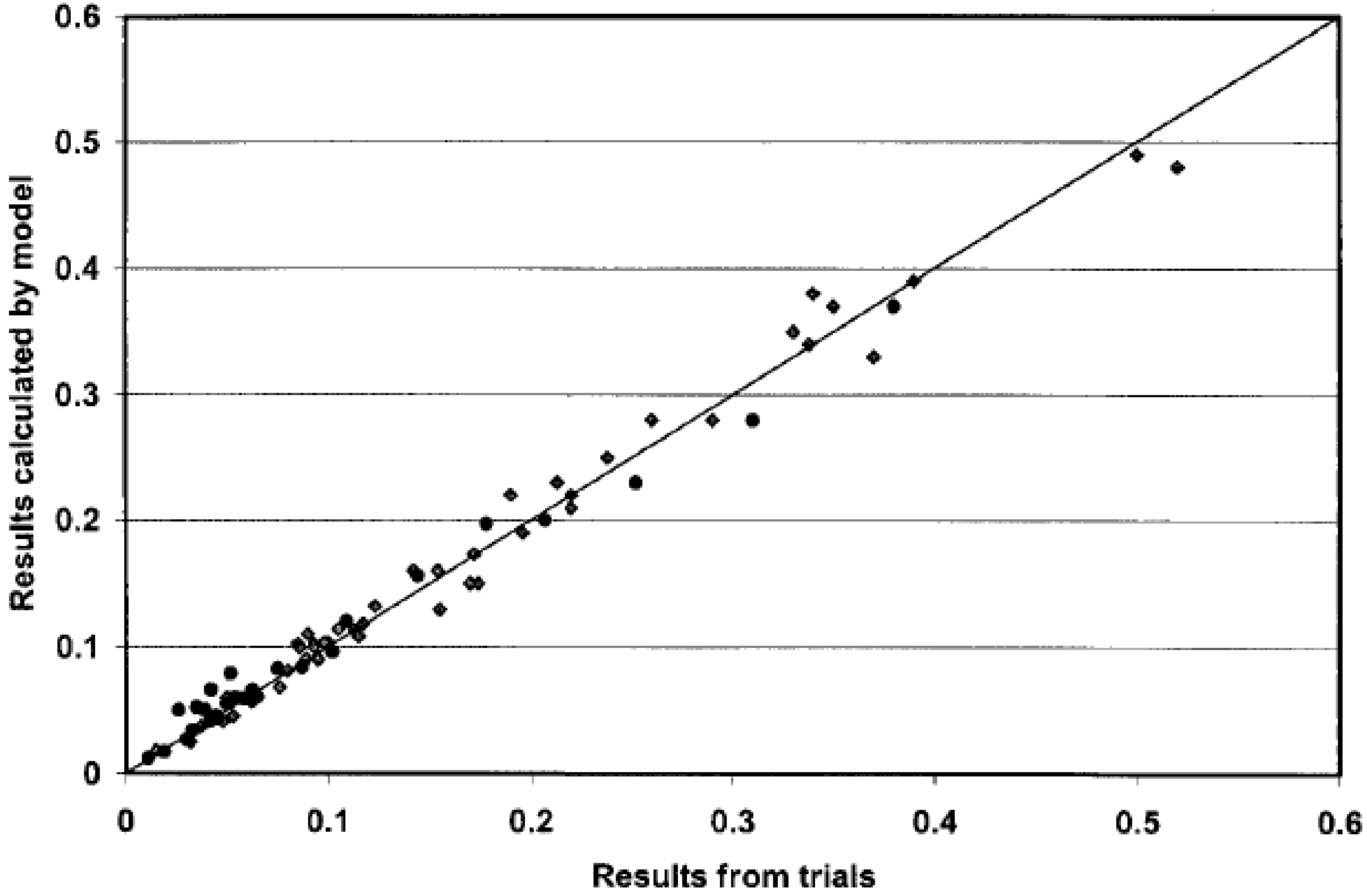
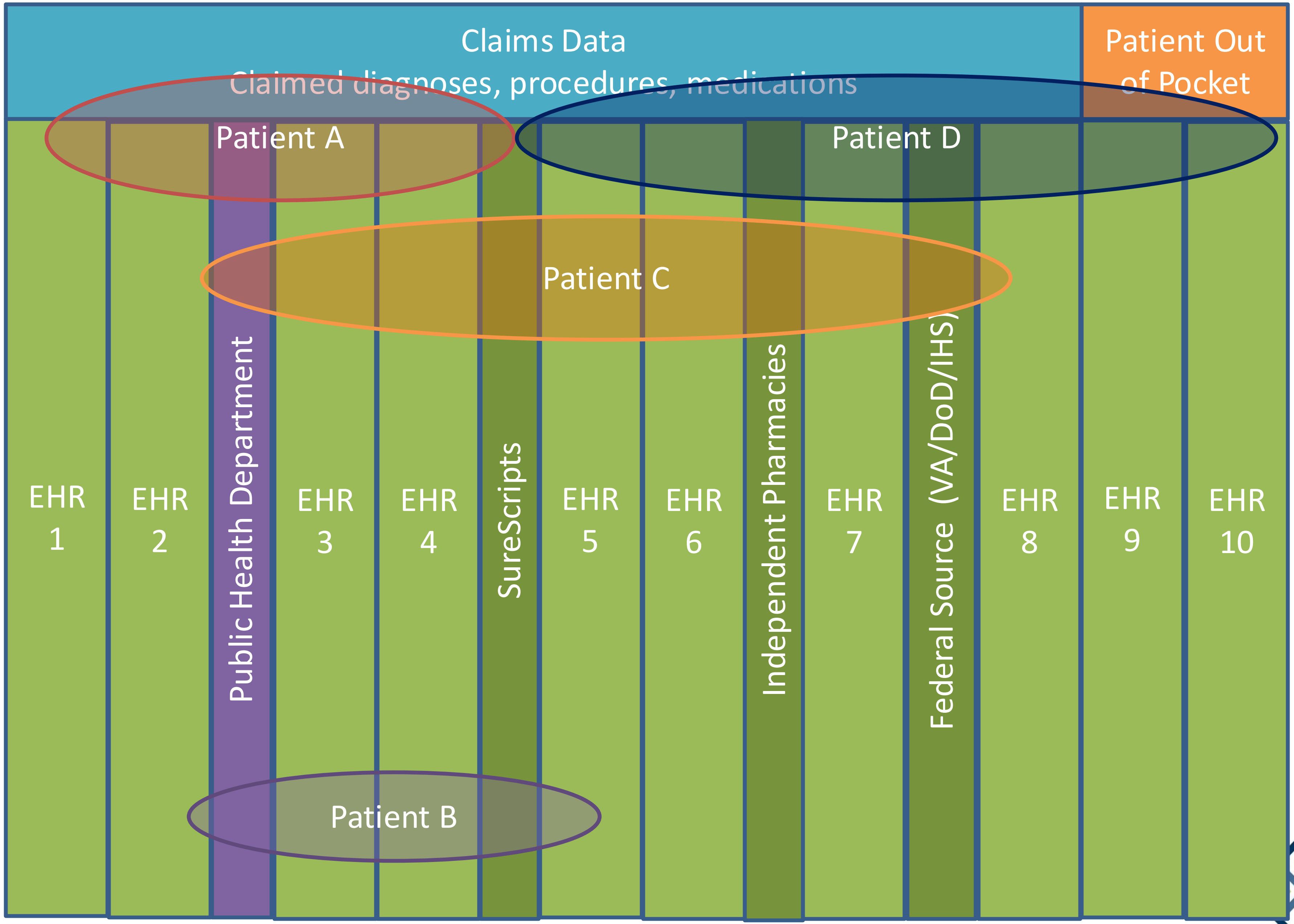
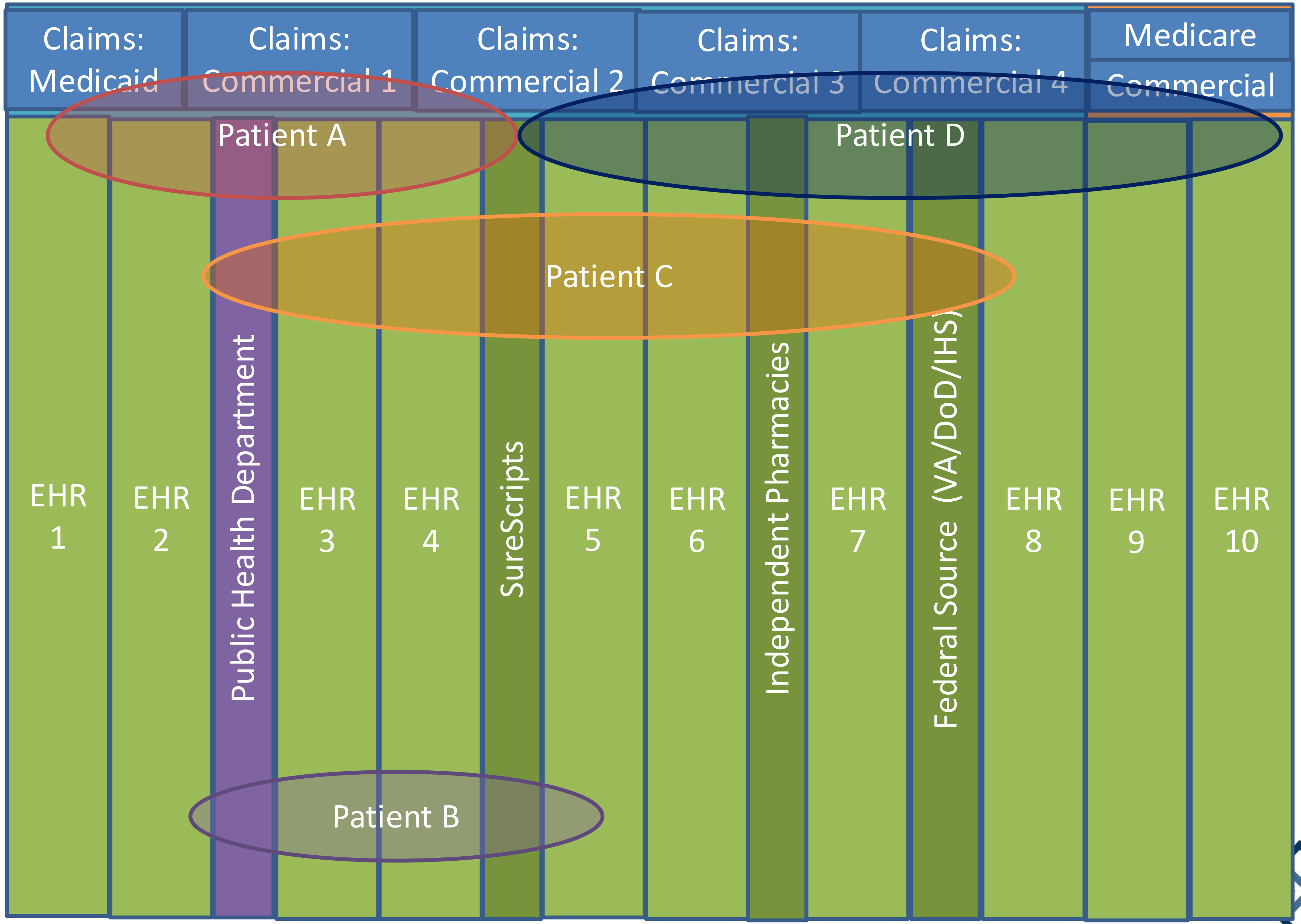


Figure 3—*Comparison of the results calculated by model with the results of the actual trials for 74 validation exercises. Filled circles compare the results calculated by the trials (x-axis) and the results calculated by the model (y-axis) for independent or external validation exercises. Gray diamonds compare the results for dependent or internal validation exercises. The 45° line indicates perfect accuracy. The results will deviate from this line due to random factors as well as any inaccuracies in the model.*

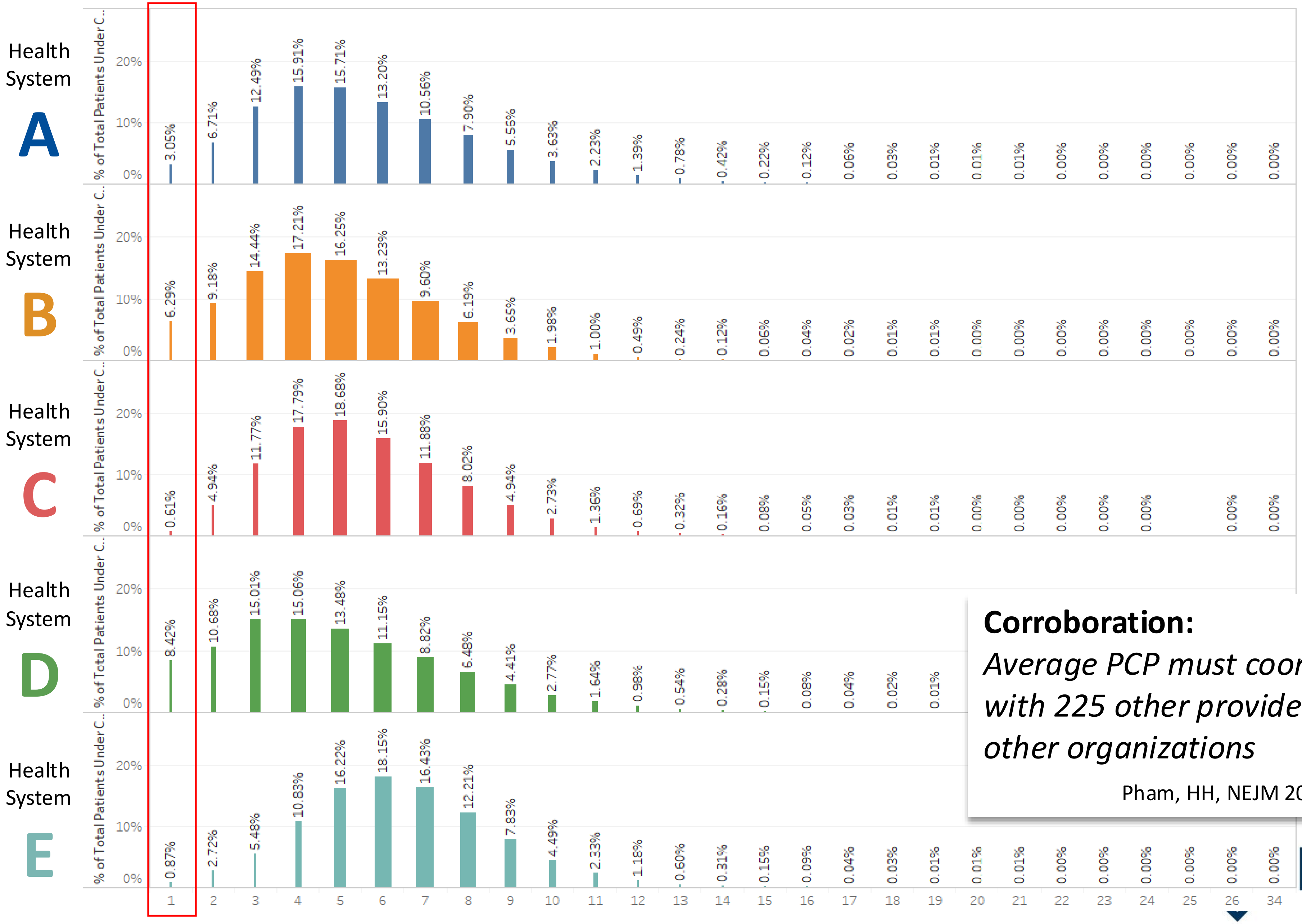


MyHealth ACCESS NETWORK



MyHealth ACCESS NETWORK

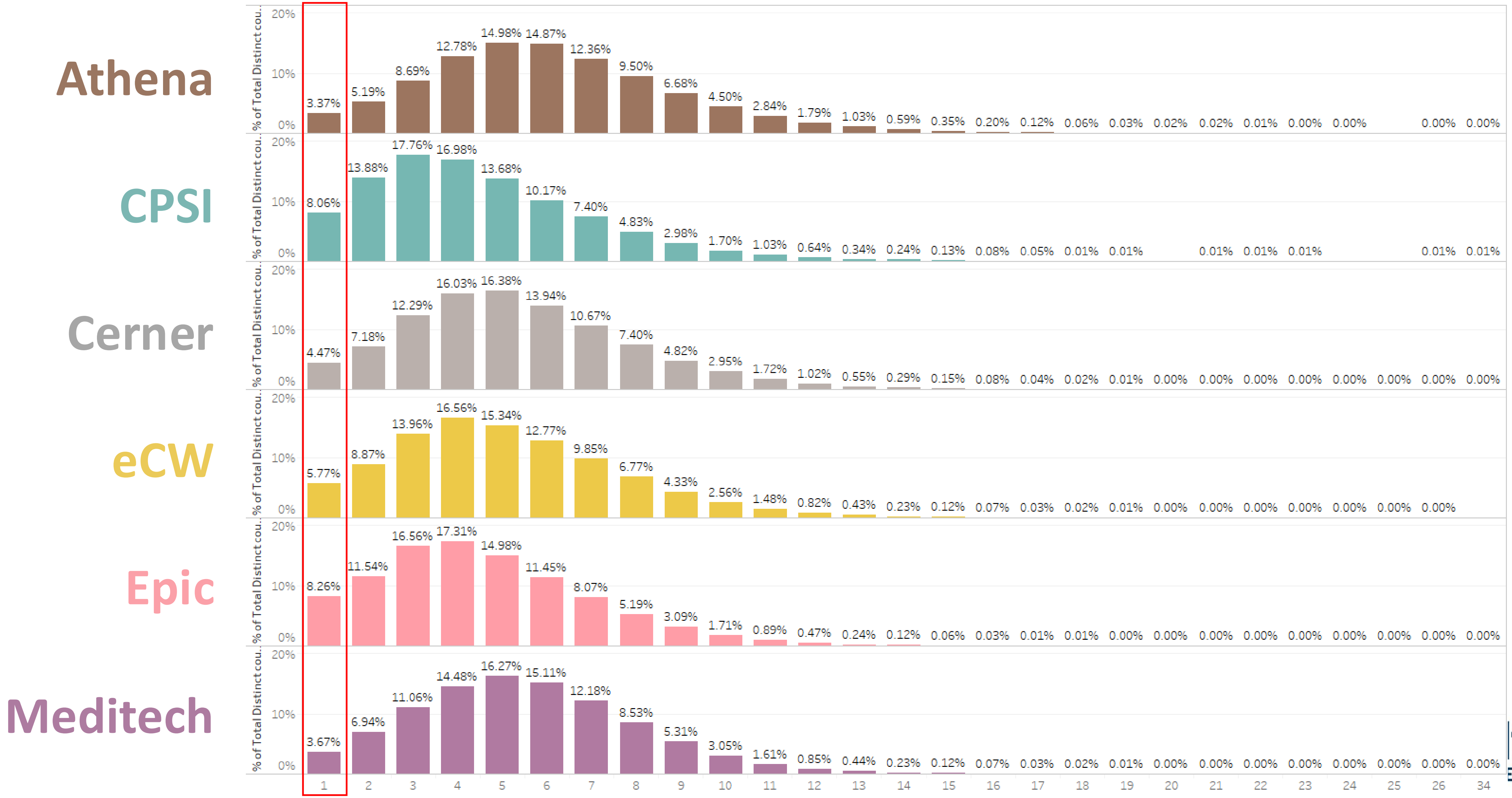
Data fragmentation by health system



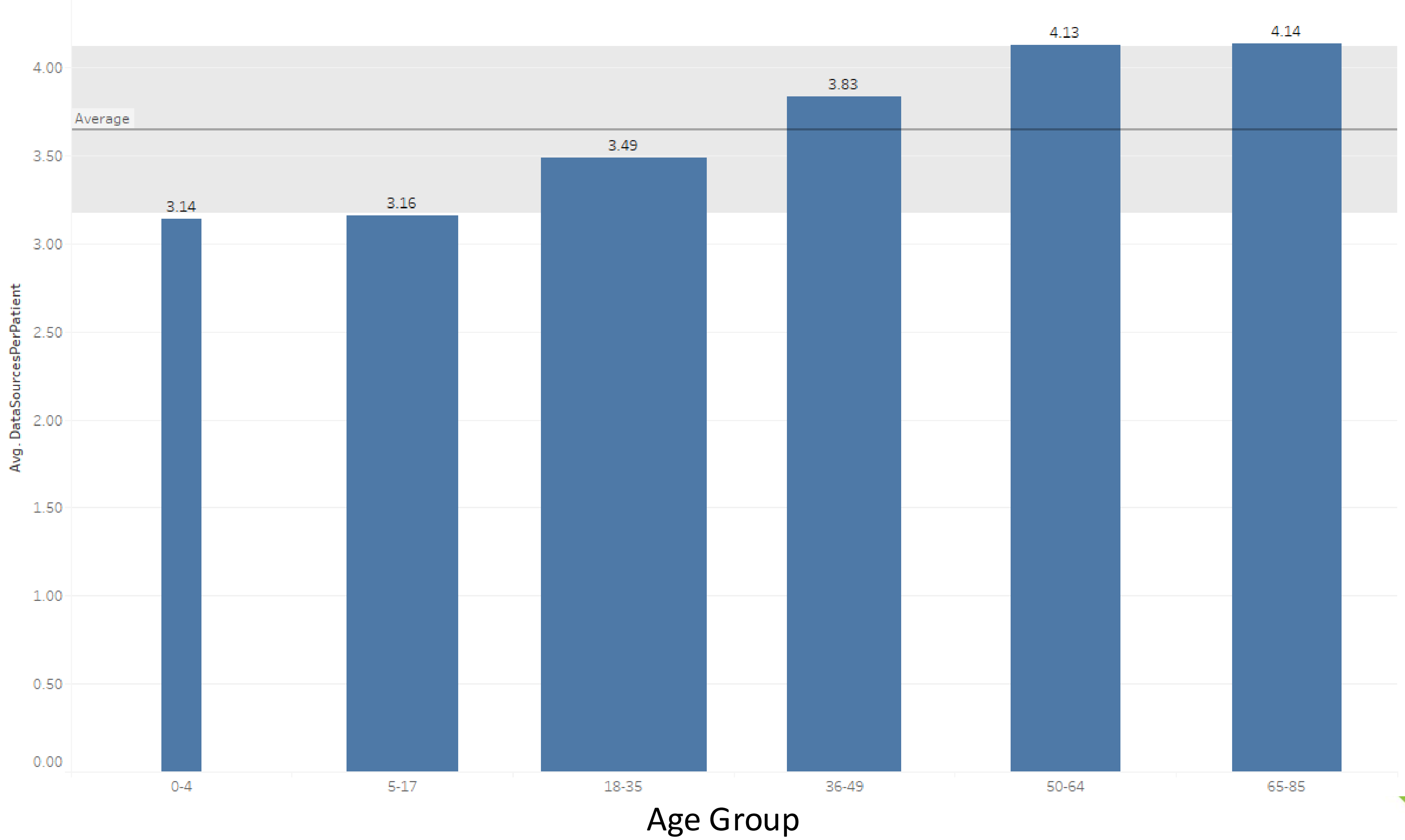
Corroboration:
Average PCP must coordinate care with 225 other providers in 117 other organizations

Pham, HH, NEJM 2007; 356: 1130-1139

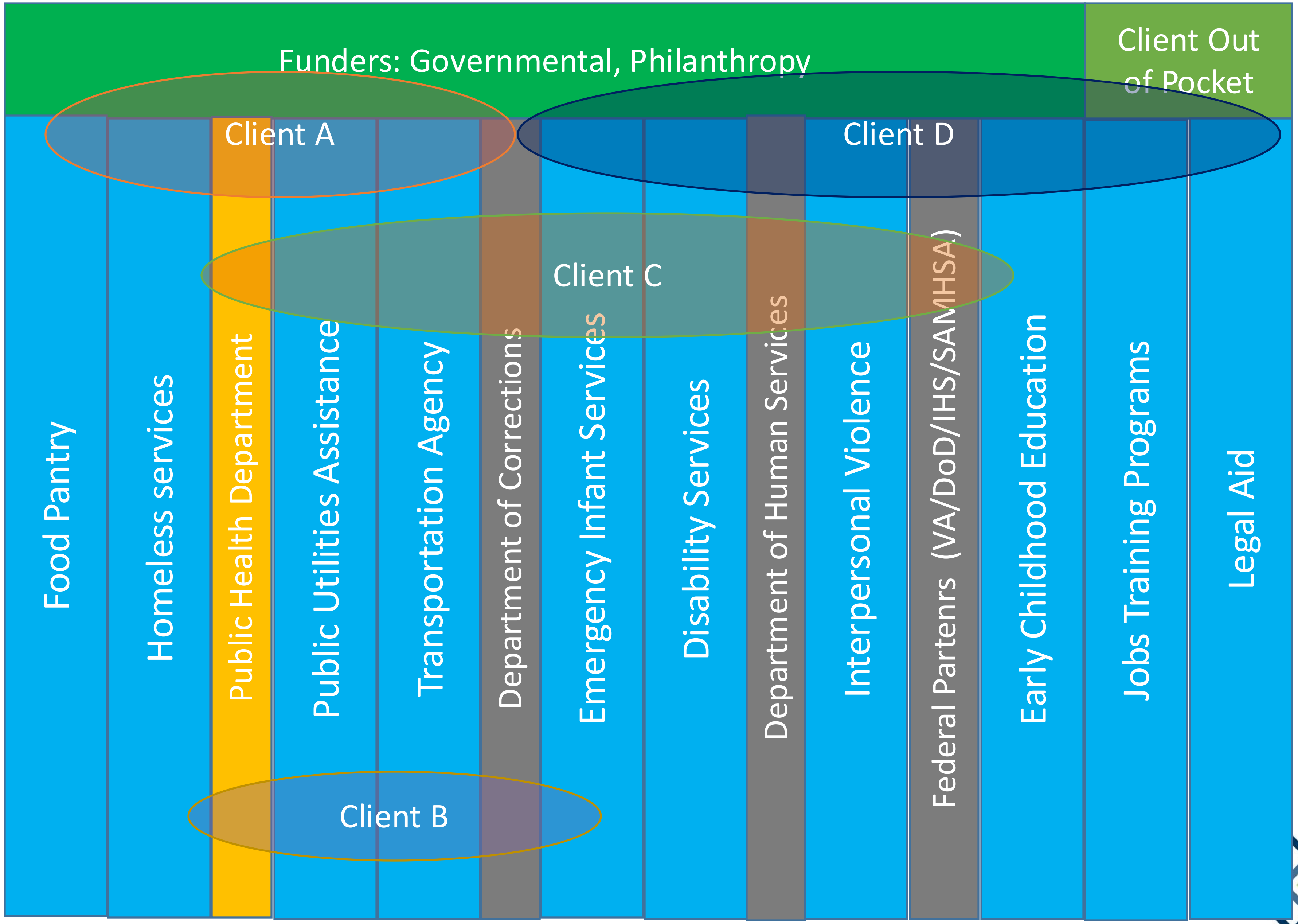
Fragmentation by EHR Vendor



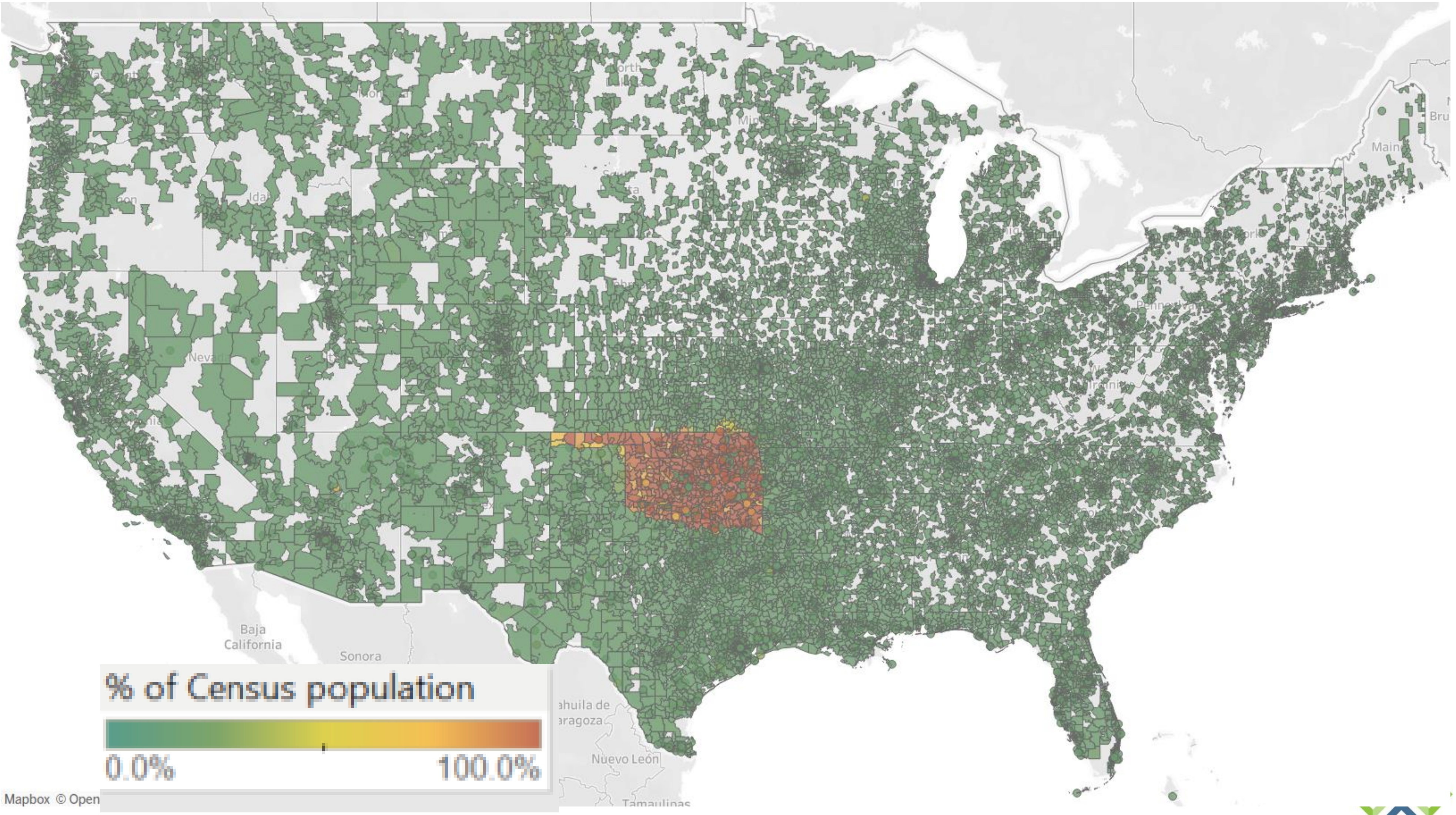
Number of Data Sources by Age Grouping



Social Determinants of Health



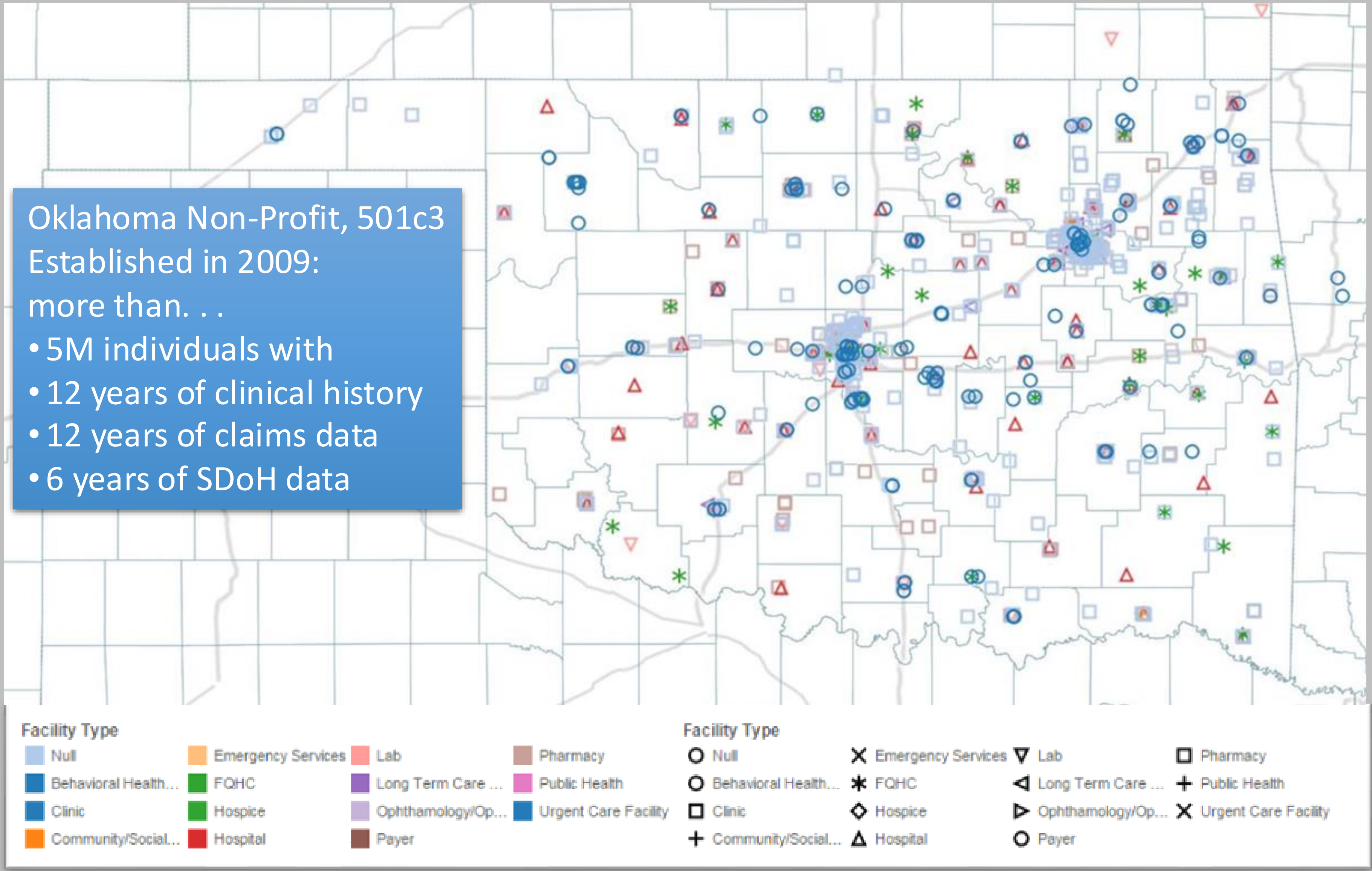
MyHealth Patient Population



>2200 locations serving >130,000 patients daily

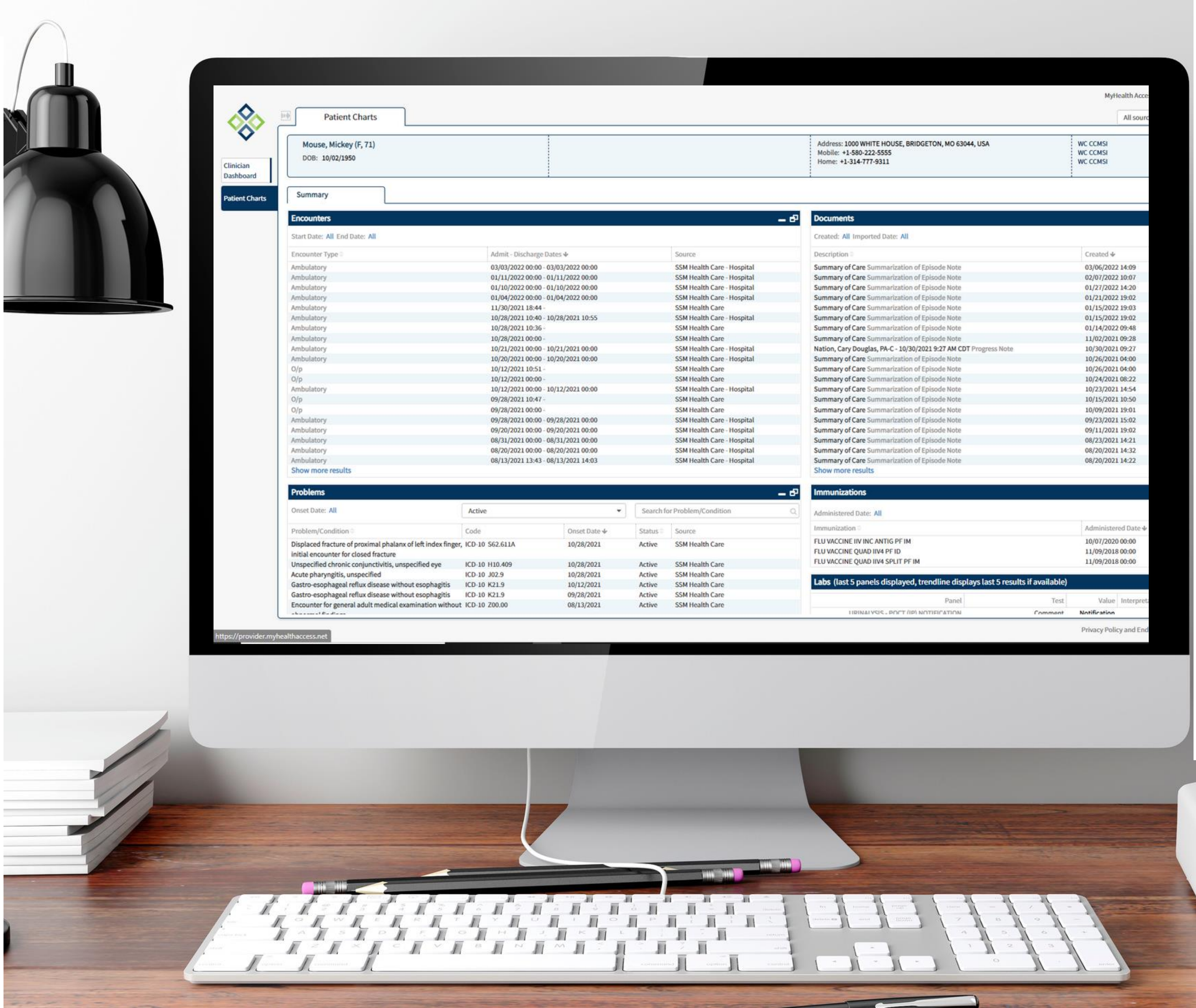
Oklahoma Non-Profit, 501c3
Established in 2009:
more than. . .

- 5M individuals with
- 12 years of clinical history
- 12 years of claims data
- 6 years of SDoH data



MyHealth ACCESS NETWORK

PROVIDER PORTAL



Value Proposition:

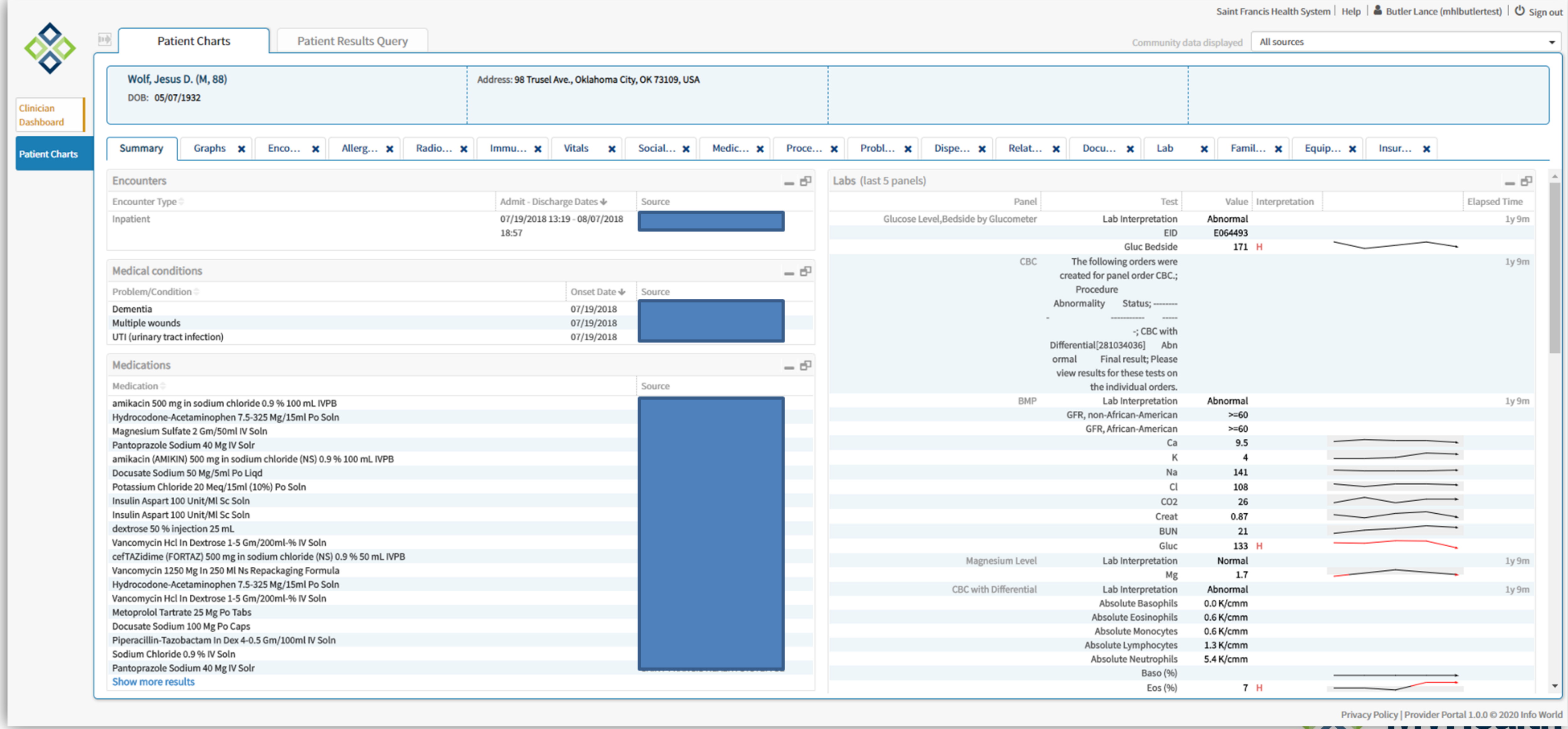
- Find the most complete records immediately.
- No need to read separate documents from every org.
- Close loops on referrals.

MyHealth® ACCESS NETWORK

Health Data Utility: Rich Clinical, Claims, NMDoH Data

- Diagnoses
- Medications
- Allergies
- Vital signs
- Clinical documents
  - H&P
  - D/C summary
  - Operative/Procedure notes
  - Progress notes
  - POLST/MOLST
  - Advanced Directives/Powers of Atty
- Labs/Observations/Assessments
- Insurance
- Dispensed Medications
- Equipment Devices
- Related Persons
- Social History
- Family History
- Radiology
- Care Team
- Goals of treatment

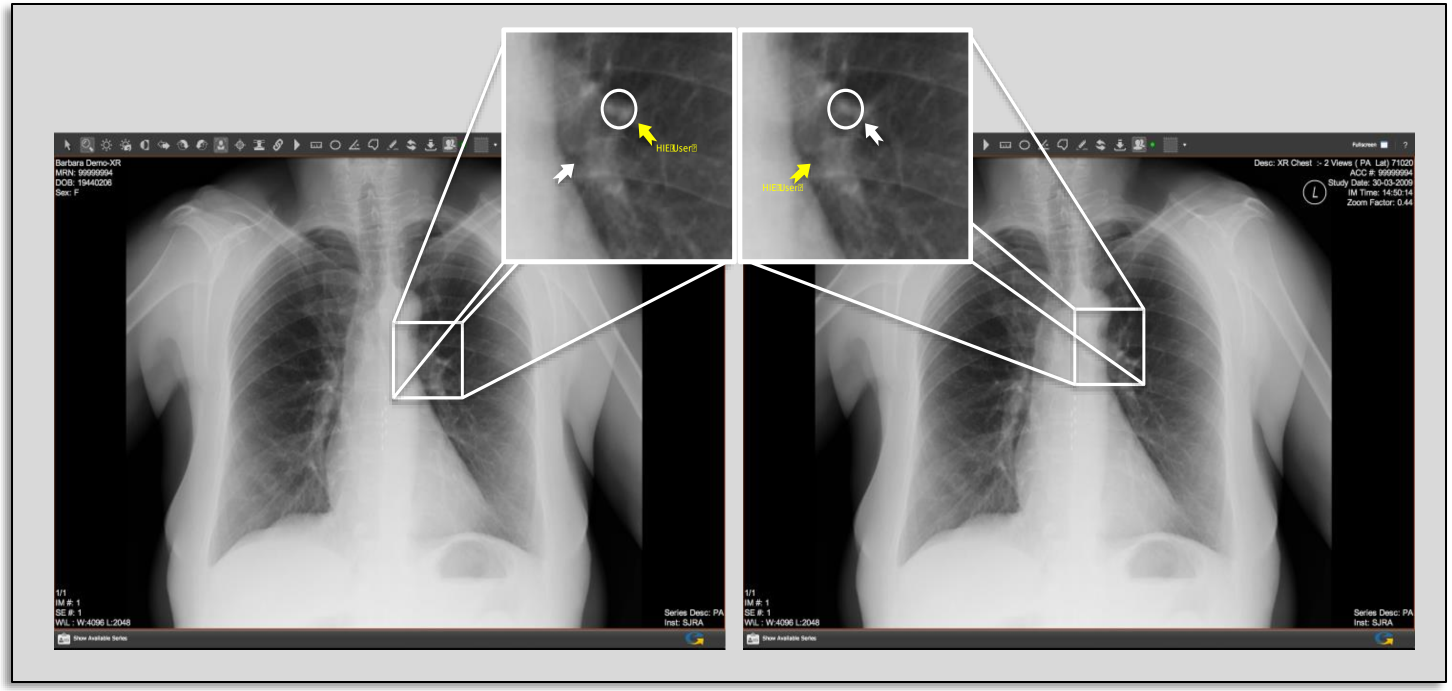
MyHealth Provider Portal + FHIR API

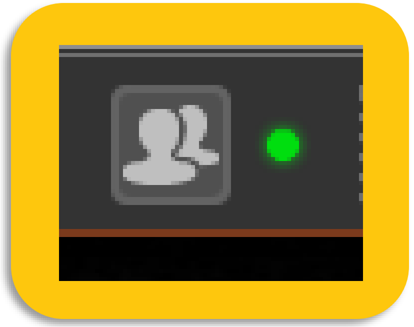


ACCESS NETWORK

Proposed: Real-Time Image Exchange & Collaboration

- Immediate consultations with any caregiver in the HIE community
- One-click to initiate a collaboration session
- Full access to real-time image manipulation for all collaborators
- Standard feature is accessible for all eHealthViewer® ZF users





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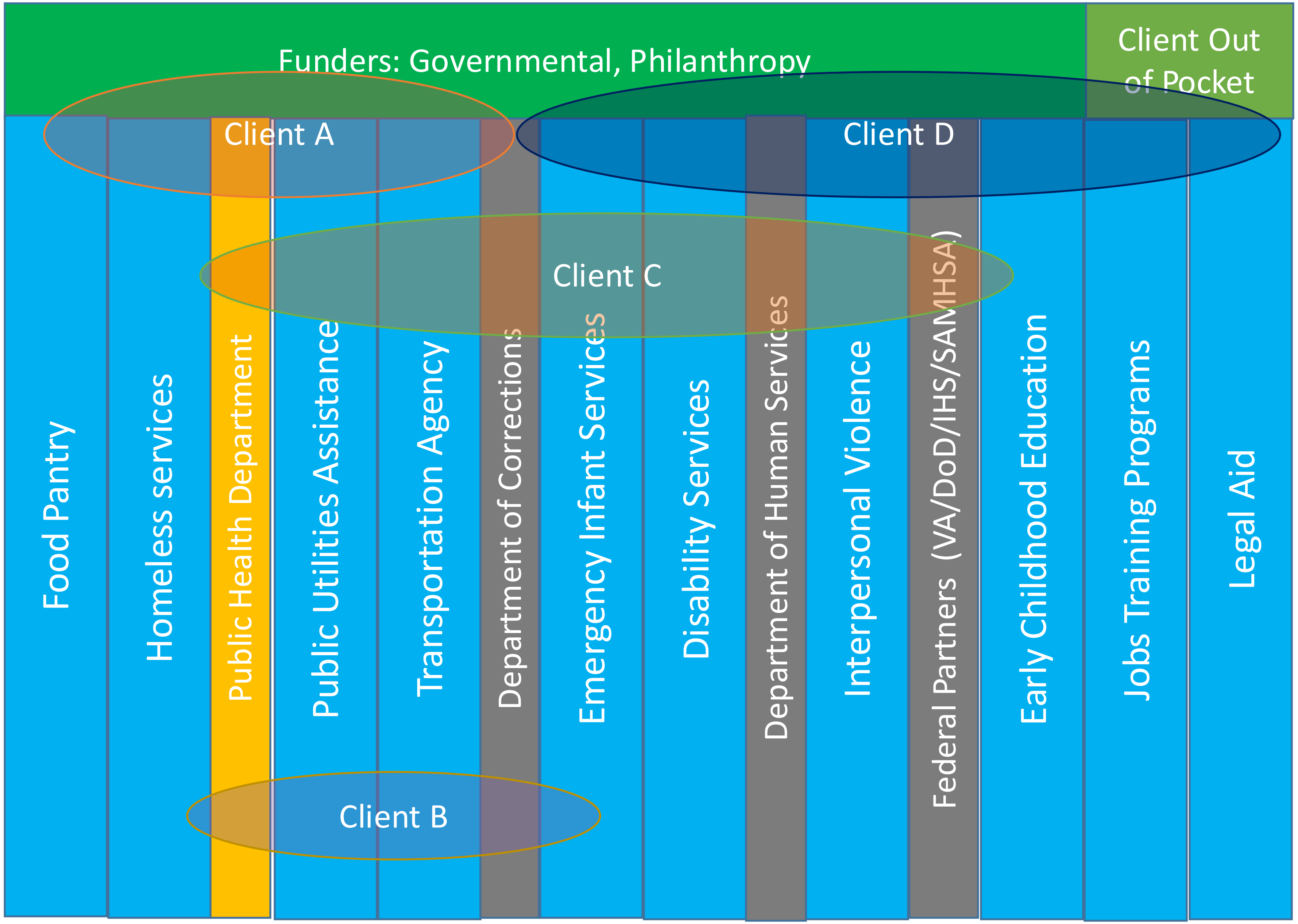
MyHealth now working with social needs and early childhood programs, where data is even more fragmented…



SDOH Mobile Screening & Referral

1
Clinical Encounter

Patient checks into clinic.

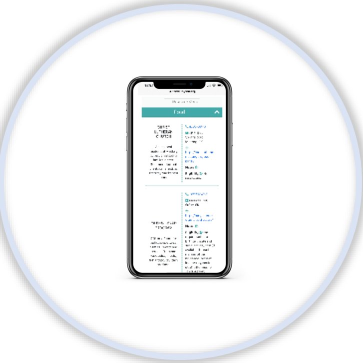
2
SDoH Screening

SDoH Screening text from MyHealth is triggered to patient's cell phone while they are in the waiting room.

3
Process Results

MyHealth processes the results to determine social needs reported.

4
CRS Returned



If a need is reported, a community resource summary is returned via text with information for 3 resources per need identified.

5
Closed Loop Referral Partner

Referral sent to partner for closed loop coordination.

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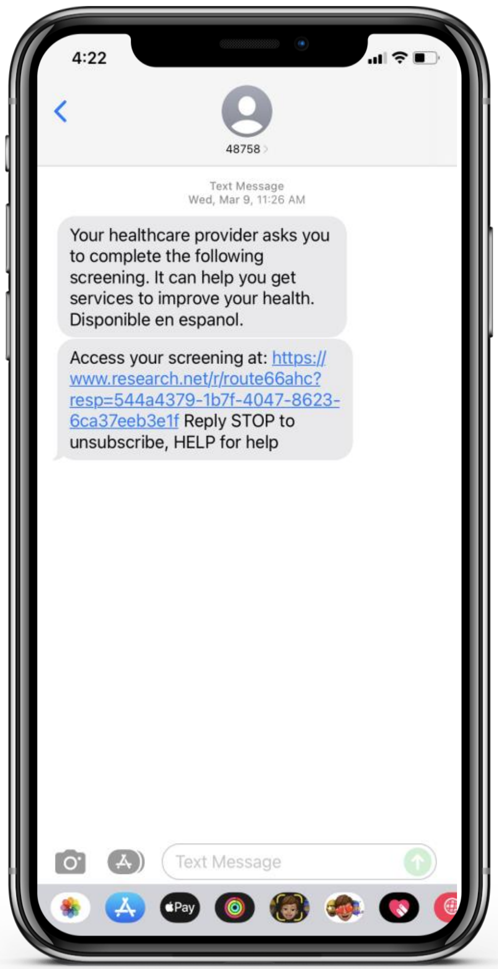
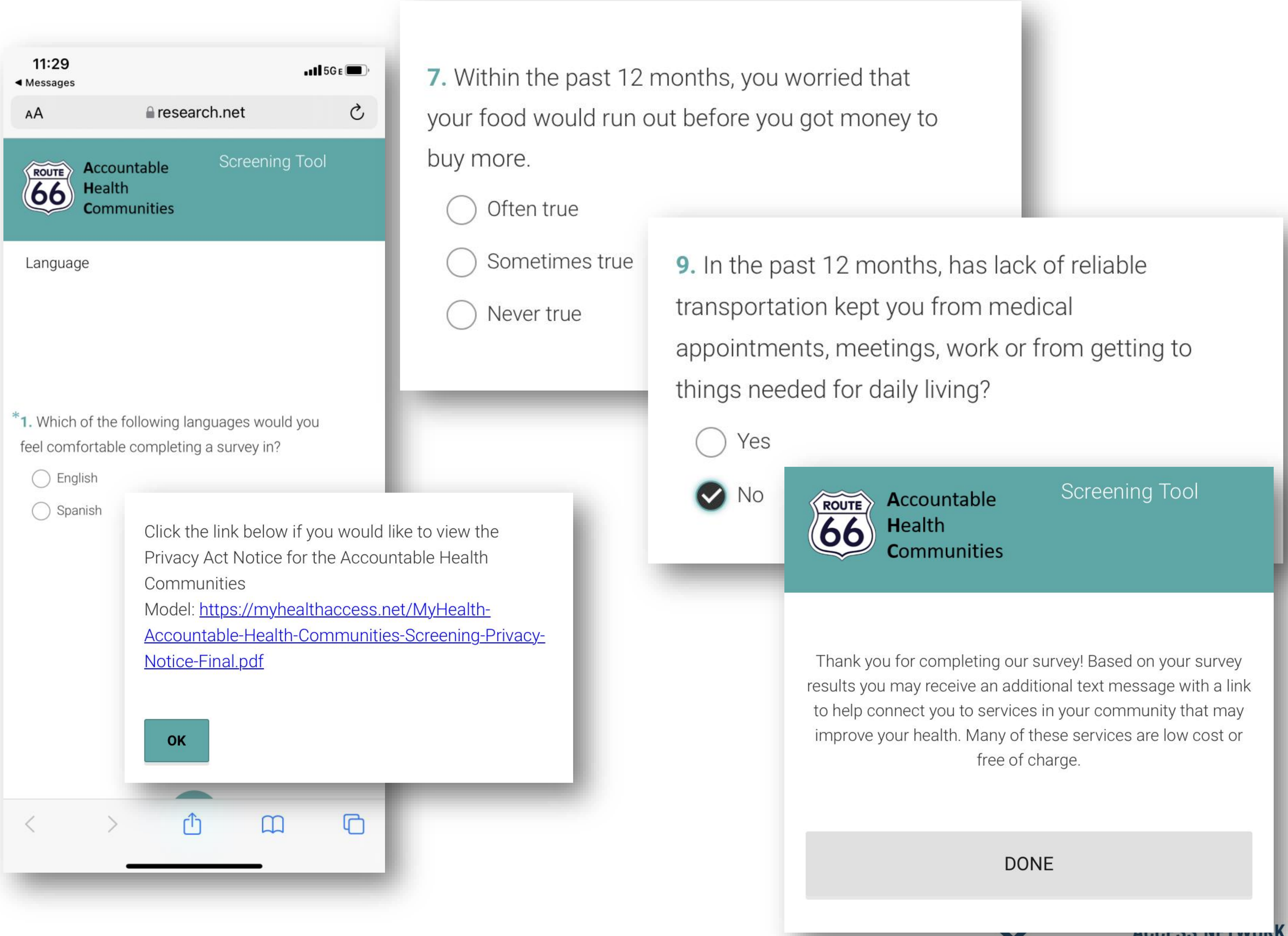
Mobile Screening





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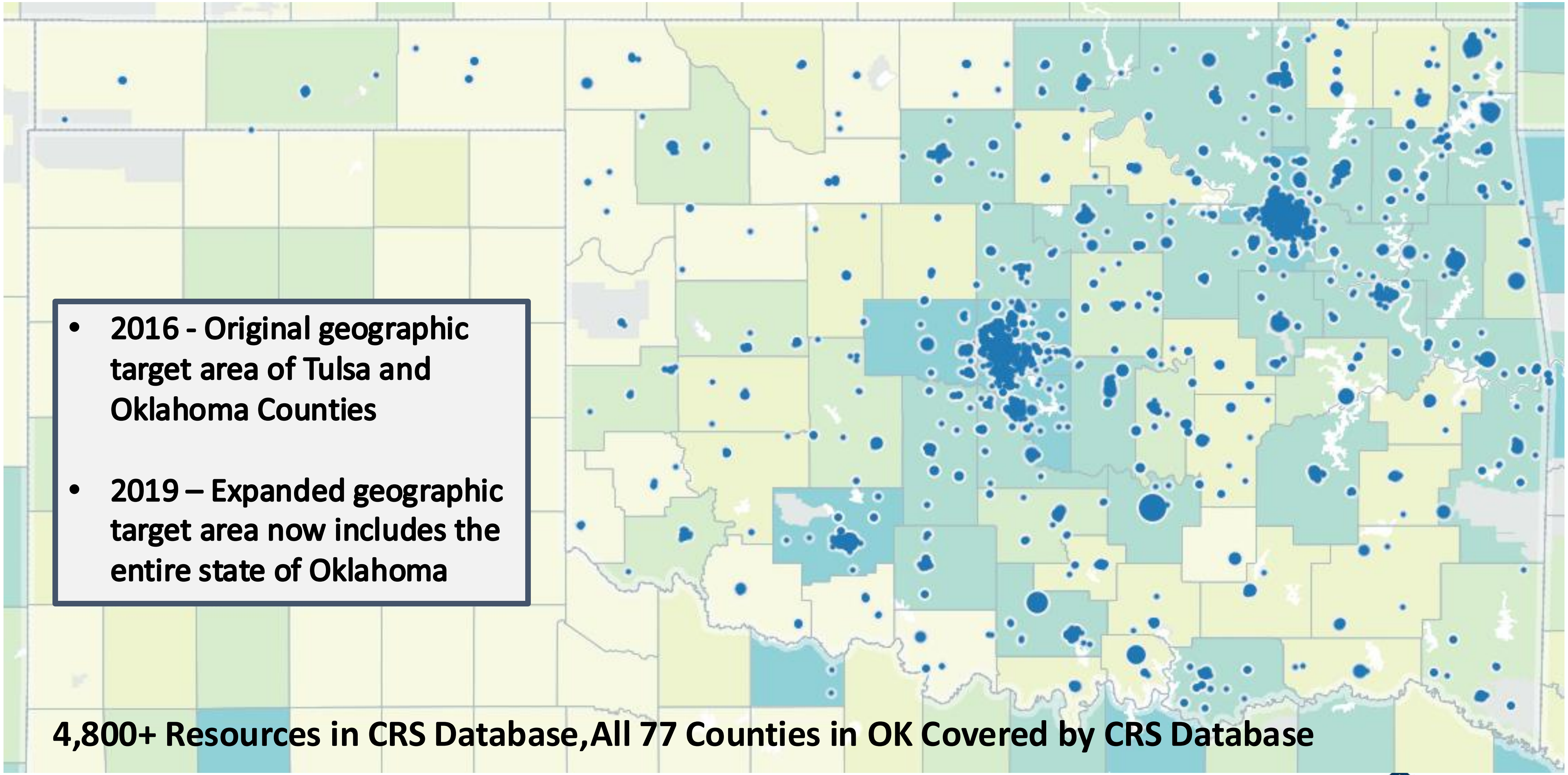
Community Resources in Oklahoma



- 2016 - Original geographic target area of Tulsa and Oklahoma Counties
- 2019 – Expanded geographic target area now includes the entire state of Oklahoma

4,800+ Resources in CRS Database,All 77 Counties in OK Covered by CRS Database

Community Resource Inventory

MyHealth ACCESS NETWORK

Route 66 Accountable Health Communities

Hello mhcholley!

Logout

Community Resources

Organization	Location City	Location Zip	Services Available	Areas Served	Actions
Search Organization	Search Location City	Search Location Zip	Choose a service	Search Areas Served	Reset Filters
2-1-1 HELPLINE DISASTER RESOURCES			Utilities		
2-1-1 HELPLINE DISASTER RESOURCES			Family Community Support, Utilities		
AARP OKLAHOMA	Ponca City	74601			
AARP OKLAHOMA	Oklahoma City	73132			
AARP OKLAHOMA	Oklahoma City	73120			
AARP OKLAHOMA	Oklahoma City	73139			
AARP OKLAHOMA	Oklahoma City	73111			
AARP OKLAHOMA	Oklahoma City	73142			

Showing 1 to 9 of 4,965 entries

Location Details

Food - FOOD RESOURCE CENTER

Food - PRIME TIMERS

Social Need:	Food
Description:	Provides free breakfast, lunch, and social activities to senior citizens 55 years and older.
App Process:	Walk-ins accepted
Eligibility:	Must be 55 years of age or older.
Phones:	Type: voice Number: 4056322644 Extension: None Department: None Note: None
Email:	dingraham@skylineurbanministry.org
Website:	-
Service Areas:	Oklahoma county
Fees:	None
Hours:	Mon, Wed, Fri 9am-11:30am; Breakfast at 9:00am; Lunch at 11:00am.
Documents:	None

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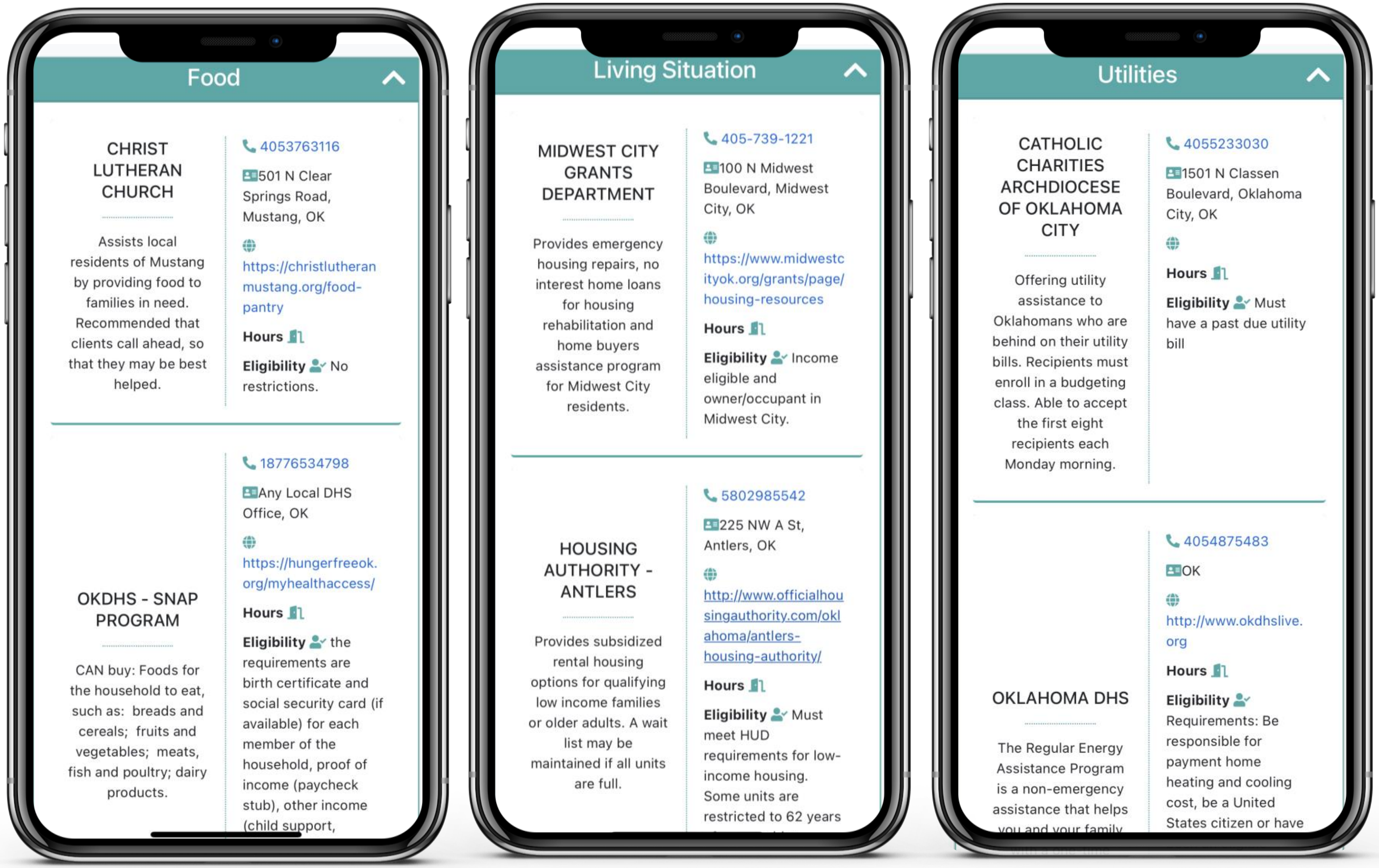
Community Resource Summary

Texted back to patient after completion of the screening



Every community resource summary includes information for 211

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SDOH Program Metrics

August 2018– May 30, 2024

By the numbers:

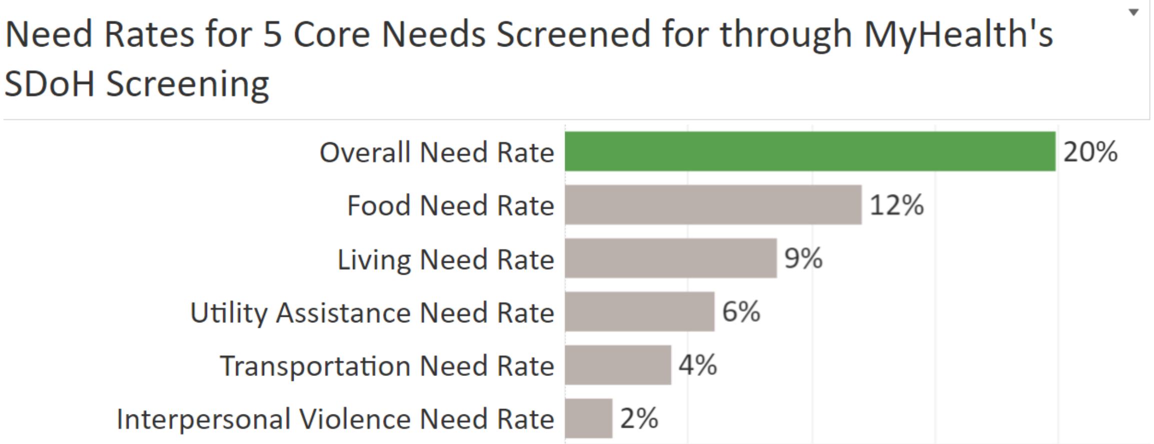
- ✓ **4.6+** million offers to screen
- ✓ **900,000+** responses
- ✓ **300,000+** responses with needs
- ✓ **400,000+** individual needs reported & addressed

Screening Delivery Rate

83%

Screening Response Rate

21%



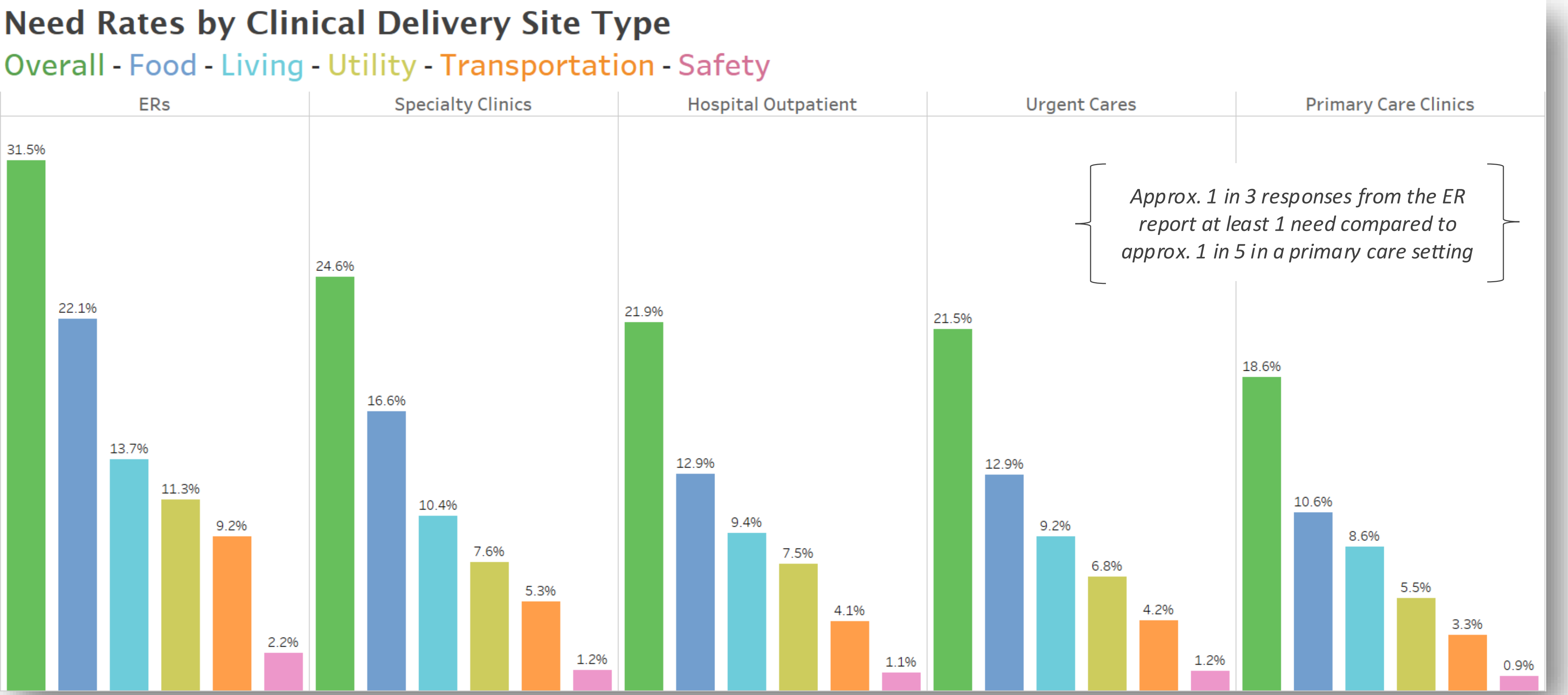
24% of responses report 2+ needs

average of **1.7** needs are reported per need positive screening

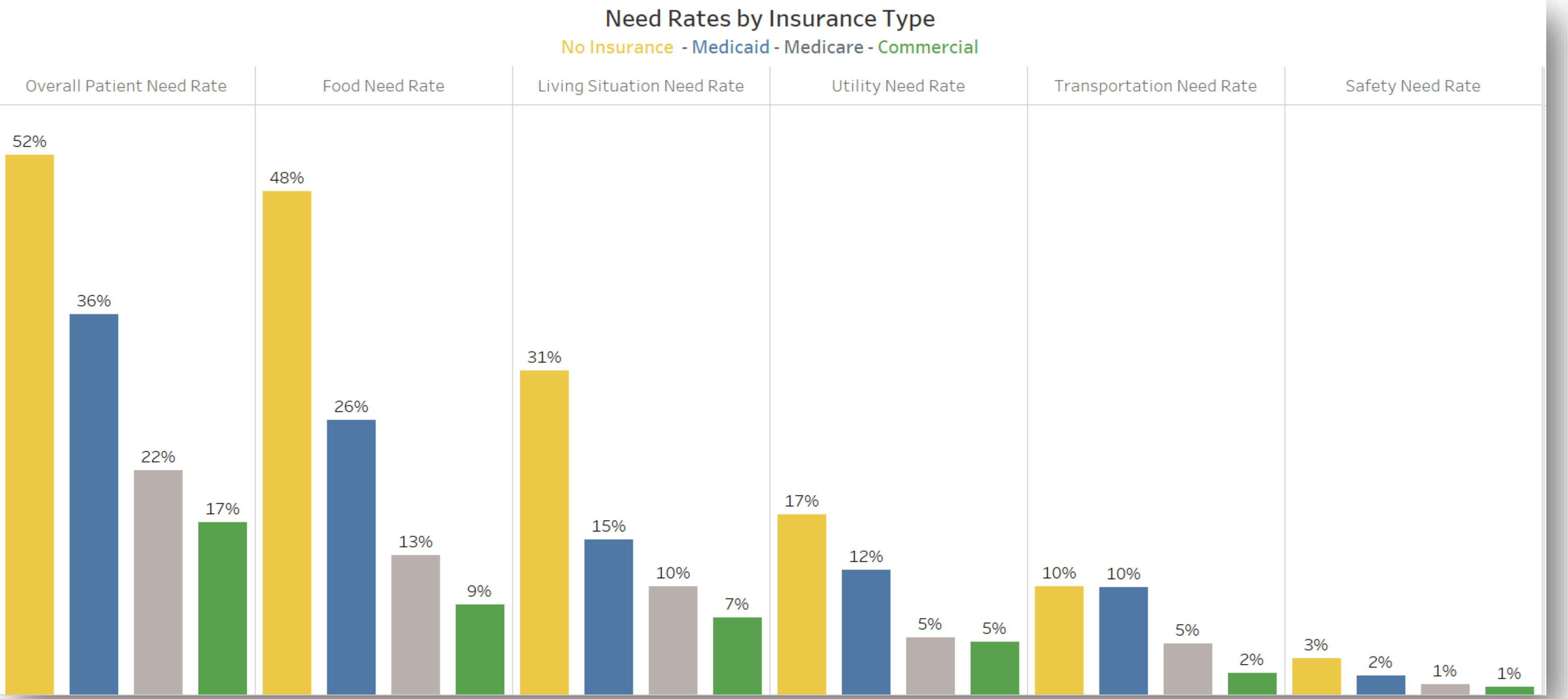
85% of responses with a living need is due to living conditions* rather having a place to stay

*Living condition issues include lack of heating, lead paint or pipes, mold, oven or stove not working, pests, missing or not working smoke detectors, and water leaks

MyHealth AHC Need Rates by Clinical Site Type



MyHealth AHC Need Rates by Insurance Type



PRELIMINARY AHC OUTCOMES

Outcomes reported by CMS evaluation team

Medicaid Beneficiaries

Medicare Beneficiaries

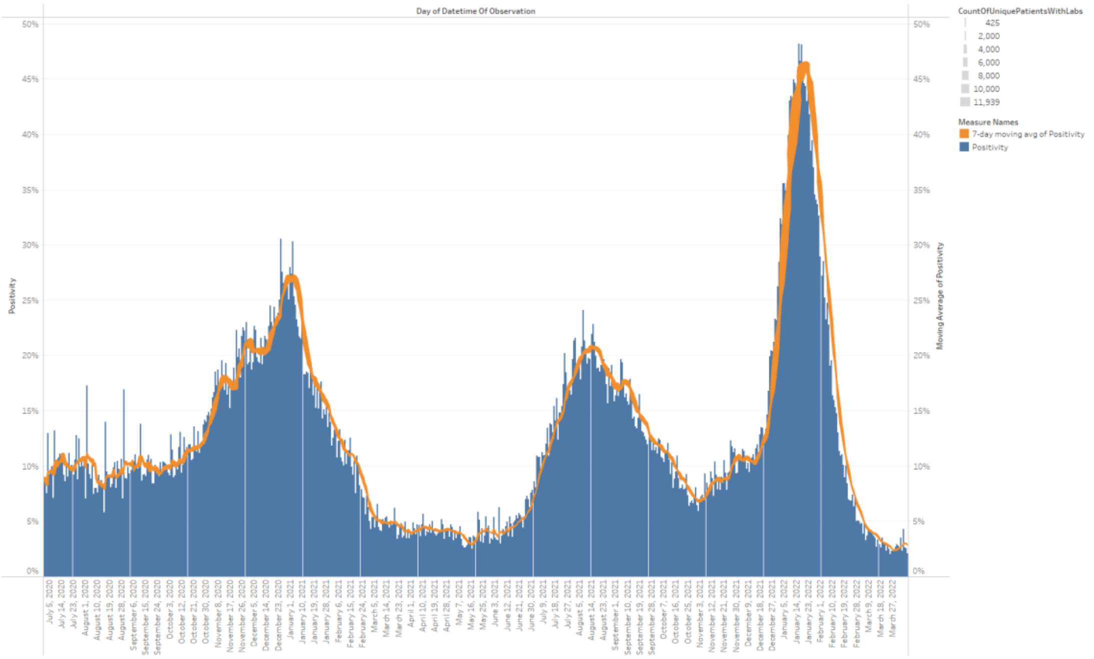
TOTAL EXPENDITURE

INPATIENT ADMISSIONS

READMISSIONS

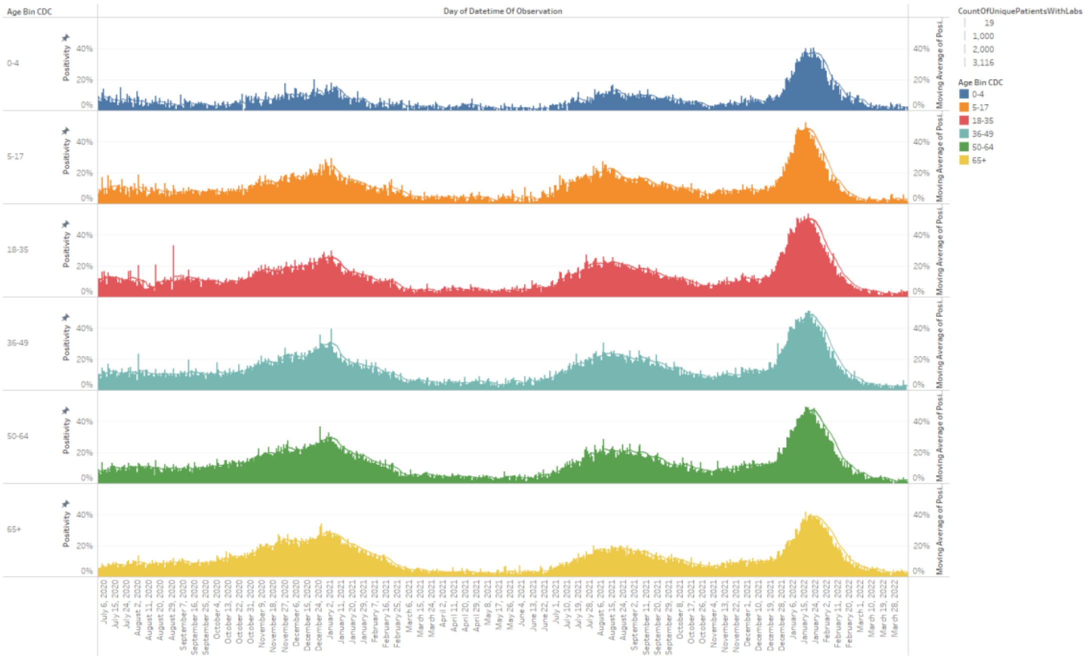
ED VISITS

Positivity



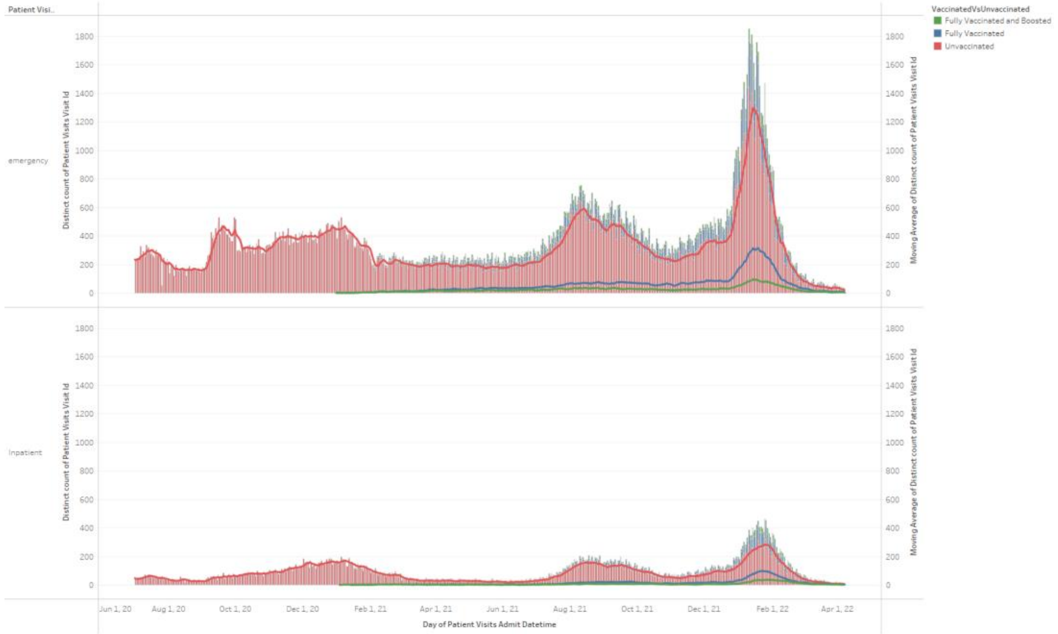
The trends of Positivity and 7-day moving avg of Positivity for Datetime Of Observation Day. Color shows details about Positivity and 7-day moving avg of Positivity. Size shows CountOfUniquePatientsWithLabs. The data is filtered on Lab Codes Clean, Lab Results Clean, Datetime Of Observation, City and County Names All. The Lab Codes Clean filter keeps COVID-19 Test. The Lab Results Clean filter keeps Negative and Positive. The Datetime Of Observation filter includes the last 22 months. The filter associated with this field ranges from 7/1/2020 to 4/30/2022. The City filter keeps 18,668 of 18,668 members. The County Names All filter keeps 8,938 of 8,938 members.

PositivityByAge



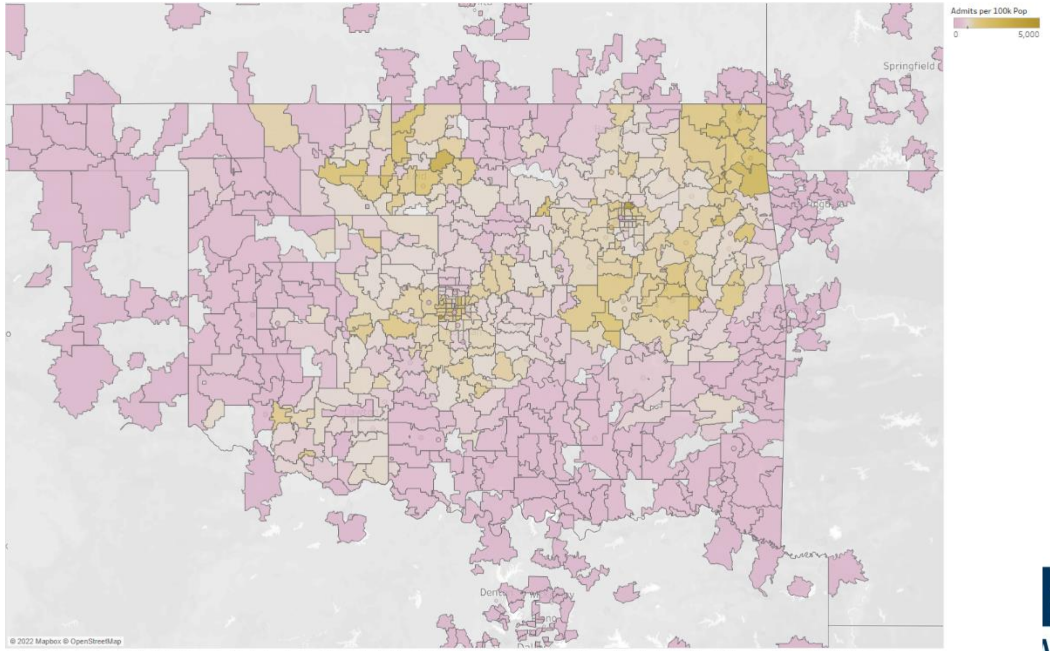
The trends of Positivity and Moving Average of Positivity for Datetime Of Observation Day broken down by Age Bin CDC. Color shows details about Age Bin CDC. Size shows CountOfUniquePatientsWithLabs. The data is filtered on Lab Codes Clean, Lab Results Clean and Datetime Of Observation. The Lab Codes Clean filter keeps COVID-19 Test. The Lab Results Clean filter keeps Negative and Positive. The Datetime Of Observation filter includes the last 22 months. The filter associated with this field ranges from 7/1/2020 to 4/30/2022.

AdmissionsByVaccineStatus2



The trends of distinct count of Patient Visits Visit Id and Moving Average of Distinct count of Patient Visits Visit Id for Patient Visits Admit Datetime Day broken down by Patient Visits Patient Class. Color shows details about VaccinatedVsUnvaccinated. The data is filtered on Lab Codes Clean, Lab Results Clean, Patient Visits Admit Datetime, ConditionRelatedAdmission, VaccinePriorToAdmission and MaxVaccineDoseCategories. The Lab Codes Clean filter keeps COVID-19 Test. The Lab Results Clean filter keeps Positive. The Patient Visits Admit Datetime filter includes the last 22 months. The filter associated with this field ranges from 7/1/2020 to 4/30/2022. The ConditionRelatedAdmission filter keeps Condition Related. The VaccinePriorToAdmission filter keeps No Vaccine and Vaccine Before Admission. The MaxVaccineDoseCategories filter keeps 0-None, 1-One Dose, 2-Two Doses and 3-Booster. The view is filtered on Patient Visits Patient Class and Patient Visits Admit Datetime Day. The Patient Visits Patient Class filter keeps emergency and inpatient. The Patient Visits Admit Datetime Day filter ranges from April 1, 2020 to April 7, 2022.

AdmissionsPer100KAllTime



Map based on Longitude (generated) and Latitude (generated). Color shows InpatientAdmissionsPer100KPop. Details are shown for Lab_zip5. The data is filtered on Lab Codes Clean, Datetime Of Observation, Patient Visits Admit Datetime Year, Lab Results Clean and ConditionRelatedAdmission. The Lab Codes Clean filter keeps COVID-19 Test. The Datetime Of Observation filter ranges from 4/1/2020 12:00:00 AM to 4/7/2022 5:35:00 PM. The Patient Visits Admit Datetime Year filter keeps 2021 and 2022. The Lab Results Clean filter keeps Positive. The ConditionRelatedAdmission filter keeps Condition Related. The view is filtered on CountInpatientAdmissions, which ranges from 1 to 1,451.

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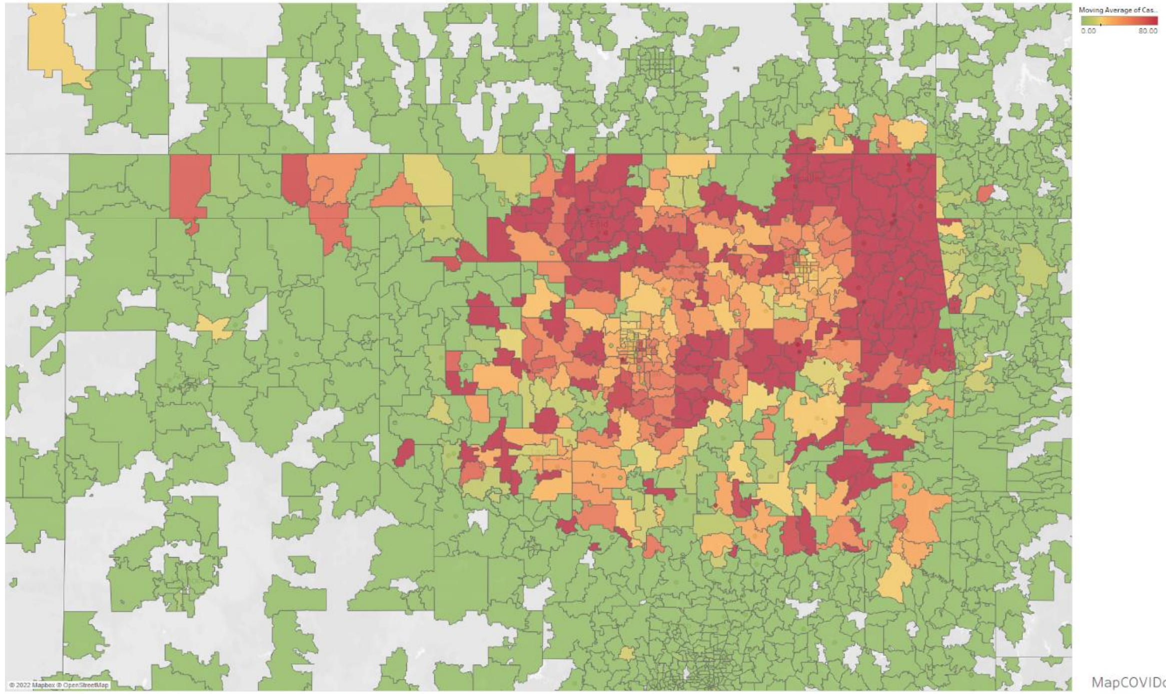
MapCOVIDcasesPer100Kpop - January 26, 2022

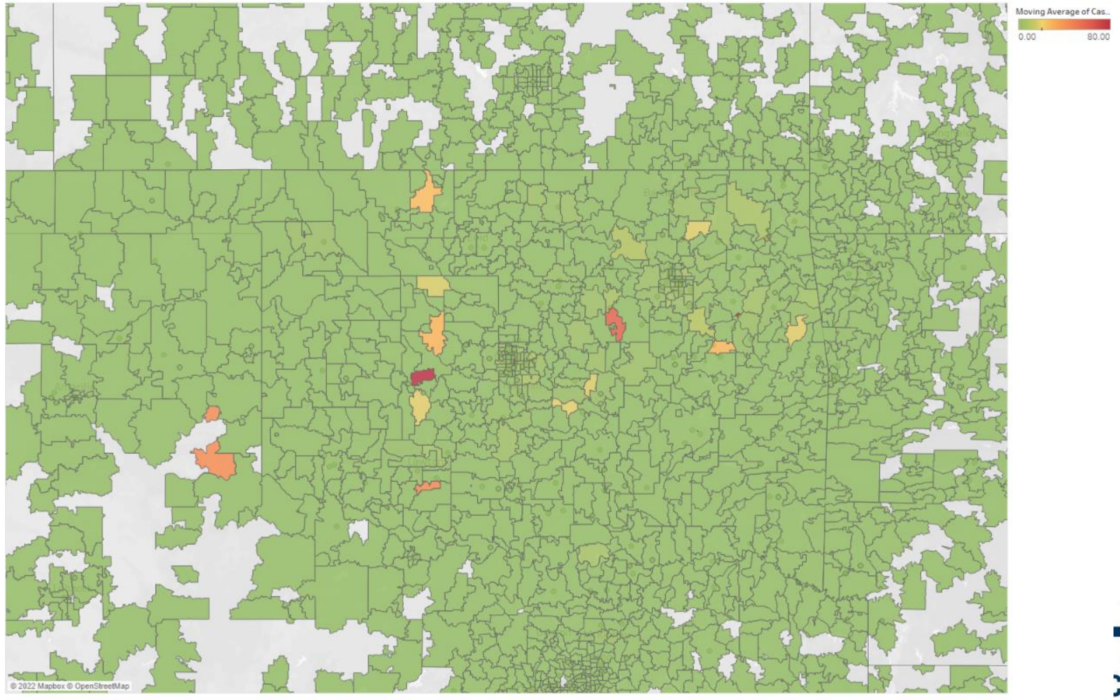


Map based on Longitude (generated) and Latitude (generated). Color shows Moving Average of CasesPer100kPop. Details are shown for Lab_zip5. The data is filtered on Lab Codes Clean and Datetime Of Observation. The Lab Codes Clean filter keeps COVID-19 Test. The Datetime Of Observation filter ranges from 4/1/2020 12:00:00 AM to 1/31/2022 5:35:00 PM.

January, 2022

April, 2022

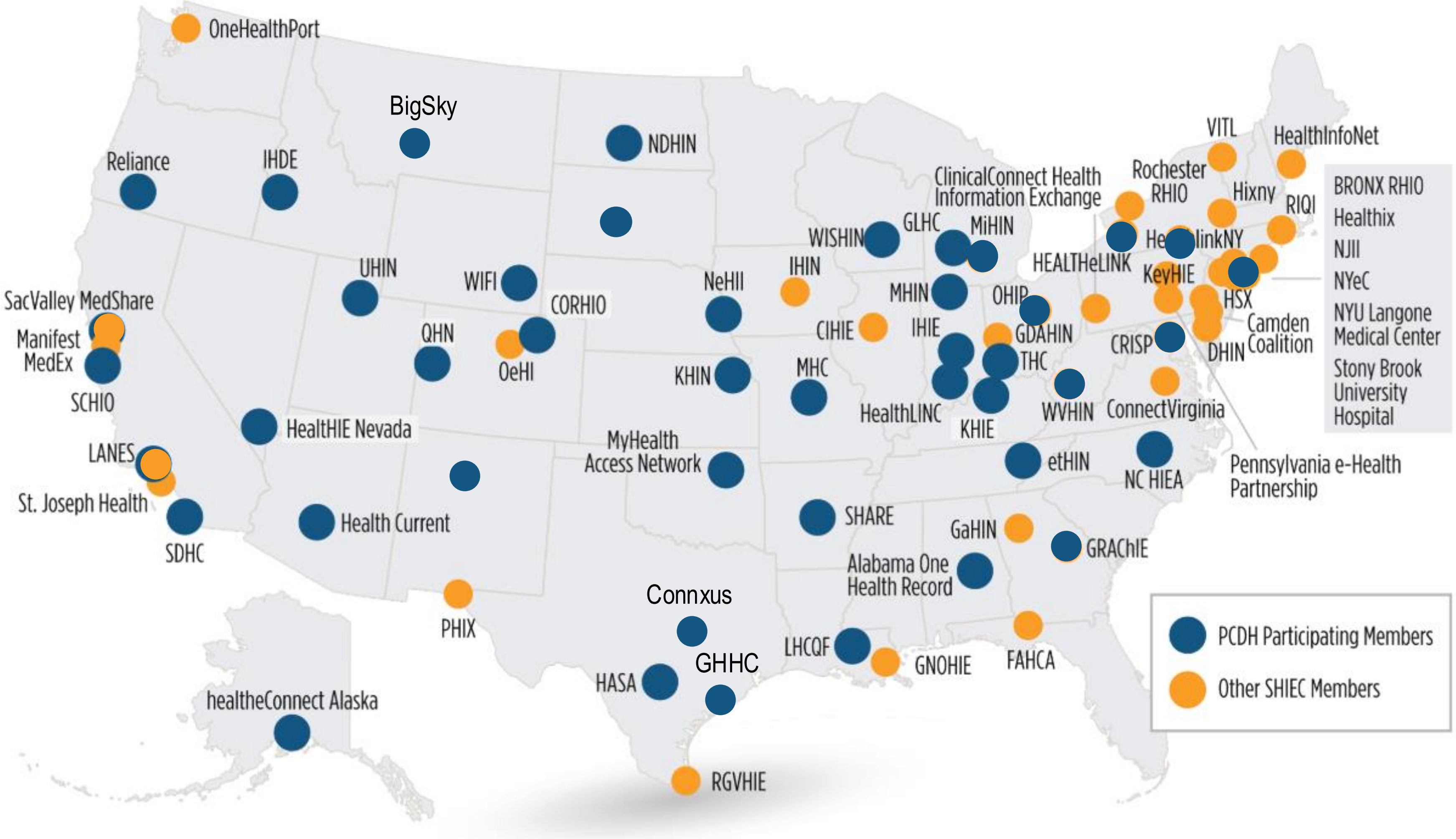
MapCOVIDcasesPer100Kpop - April 5, 2022



Map based on Longitude (generated) and Latitude (generated). Color shows Moving Average of CasesPer100kPop. Details are shown for Lab_zip5. The data is filtered on Lab Codes Clean and Datetime Of Observation. The Lab Codes Clean filter keeps COVID-19 Test. The Datetime Of Observation filter ranges from 4/1/2020 12:00:00 AM to 4/7/2022 5:35:00 PM.

Health ACCESS NETWORK

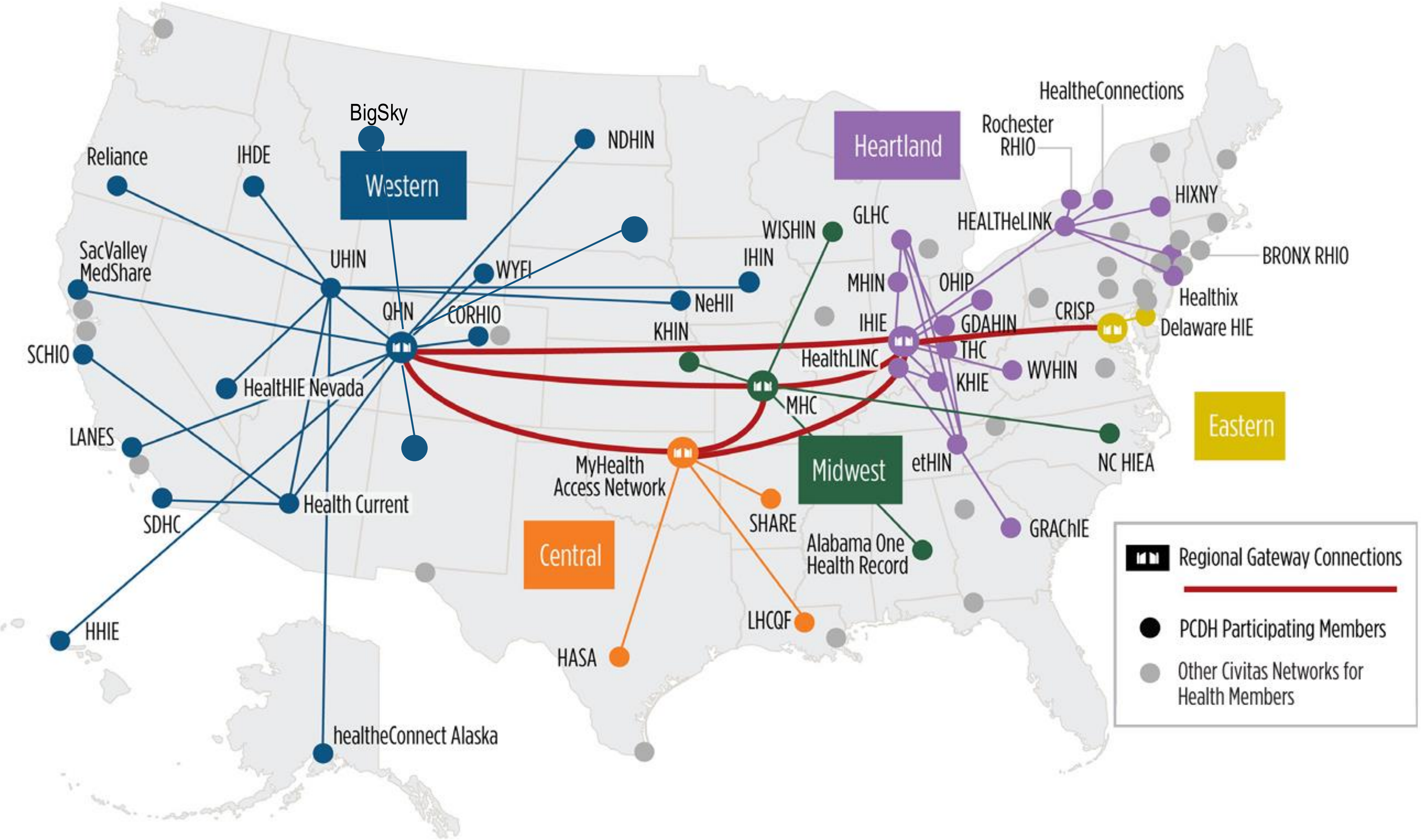
CIVITAS
Networks for Health



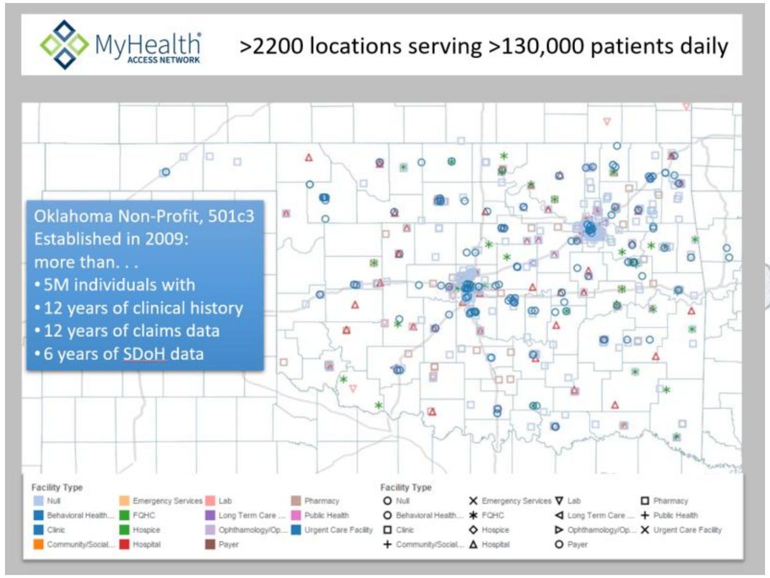
How does this model scale nationwide?

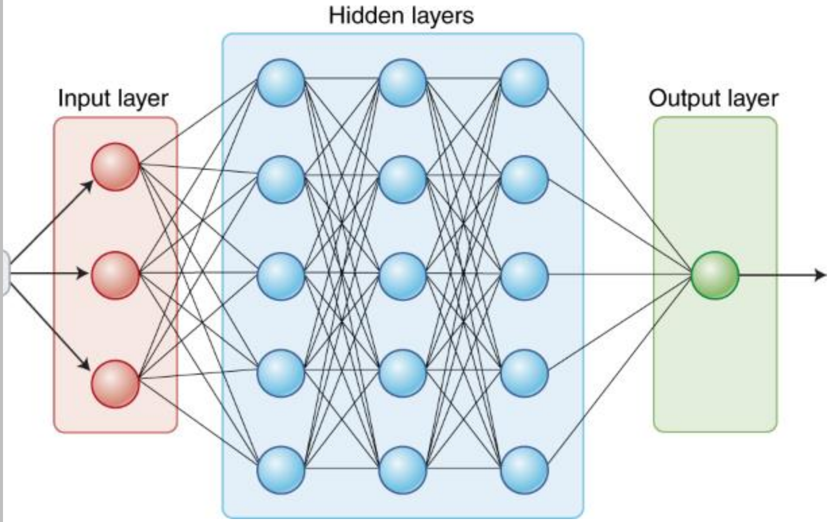
CIVITAS
Networks for Health

Patient Centered Data Home™ rapid growth



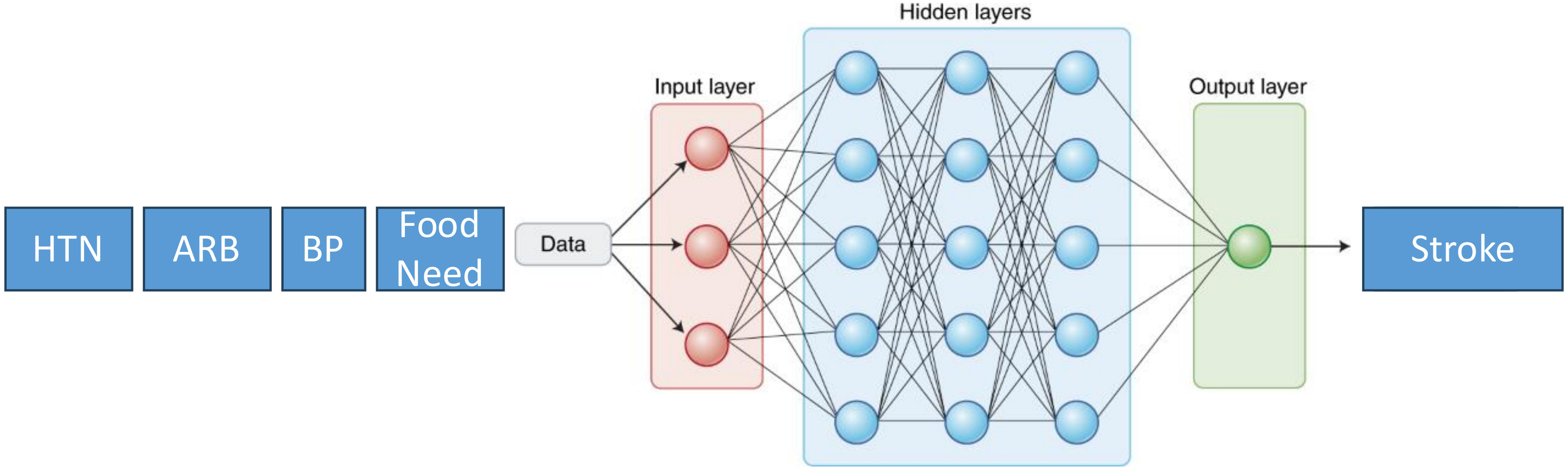
Our Opportunity





- Earlier and more accurate detection of disease
  - Cancer, CV, complex diseases as yet unknown
- Earlier and more accurate detection of dis-ease
  - Mental health, social needs, human interactions
- Better treatments
  - Effective, fewer side effects, cost effective
- Reductions in the cost of care and services & Improvement in Access
  - Democratization not just of information but of interpretation of information
- Reductions in provider burden
  - Documentation, proving performance, coordination and communication
- Improve policy-making and policy-un-making
  - Evidence-based policy-making

Training on an entire population's data



Questions & Discussion

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MyHealth ACCESS NETWORK