UNIVERSITY OF CALIFORNIA HEALTH

# Artificial Intelligence in Health Care


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Chief Data Scientist, University of California Health (UC Health)

Priscilla Chan and Mark Zuckerberg Distinguished Professor

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# Conflicts of Interest

- Scientific founder
  - Personalis
  - NuMedii
  - Carmenta (Progenity)
  - Genstruct
- Honoraria for talks
  - Lilly
  - Pfizer
  - Siemens
  - Bristol Myers Squibb
  - AstraZeneca
  - Roche
  - Genentech
  - Warburg Pincus
  - CRG
  - AbbVie
  - Westat
- Past or present consultancy
  - Personalis
  - NuMedii
  - Lilly
  - Johnson and Johnson
  - Roche
  - Genstruct
  - Tercica
  - Ecoeos
  - Helix
  - Ansh Labs
  - uBiome
  - Prevendia
  - Samsung
  - Assay Depot
  - Regeneron
  - Verinata (Illumina)
  - Pathway Diagnostics
  - Geisinger Health
  - Covance
  - Wilson Sonsini Goodrich & Rosati
  - Orrick
  - 10X Genomics
  - GNS Healthcare
  - Gerson Lehman Group
  - Coatue Management
- Other corporate relationships
  - Northrop Grumman
  - Genentech
  - Johnson and Johnson
  - Optum
- Shares or Ownership
  - NuMedii (major)
  - Personalis (major)
  - Apple
  - Facebook
  - Alphabet (Google)
  - Microsoft
  - Amazon
  - Snap
  - 10x Genomics
  - Illumina
  - Nuna Health
  - Assay Depot (Scientist.com)
  - Vet24seven
  - Regeneron
  - Sanofi
  - Royalty Pharma
  - AstraZeneca
  - Moderna
  - Biogen
  - Paraxel
  - Sutro
- Speakers' bureau
  - None
- Companies started by students
  - Carmenta
  - Serendipity
  - Stimulomics
  - NunaHealth
  - Praedicat
  - MyTime
  - Flipora
  - Tumbl.in
  - Polyglot
  - Iota Health
  - Ongevity Health

nature
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46 The Big Idea
The True Measures Of Success
Michael J. Mauboussin
84 International Business
10 Rules for Managing Global Innovation
Keeley Wilson and Yves L. Doz
93 Leadership
What Ever Happened To Accountability?
Thomas E. Ricks
GETTING CONTROL OF
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PAGE 59
Wide Net For Exports
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Page 30
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Plus: Why the U.S. can't sit on the sidelines BY FAREED ZAKARIA
Household income: $100,000+
Age: 38-39
Likes: online news
Likes: Asian cuisine
Dislikes: cars
Likes: green living
Favorite celebrities
ZIP code: 10704
Wi-fi warrior
Sister is a lawyer
Job: medical professional
Likes: parenting
Spent $180 on intimate
Dislikes: autos & vehicles
Likes: movies
Smart-phone
Likes: coffee & tea
Has had LASIK surgery
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The world's most valuable resource
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# Artificial Intelligence and Machine Learning

- **Artificial Intelligence**: aspects of human intelligence modeled by computers
- **Machine Learning**: implementing aspects of AI through processing data
  - Supervised or unsupervised learning
- **Deep Learning**: one type of ML, modeling brain architecture with layers of individual classifiers, adding non-linearity

# 3 ways AI is already changing medicine

They might surprise you.

By Julia Belluz | @juliaoftoronto | julia.belluz@voxmedia.com | Mar 15, 2019, 12:40pm EDT

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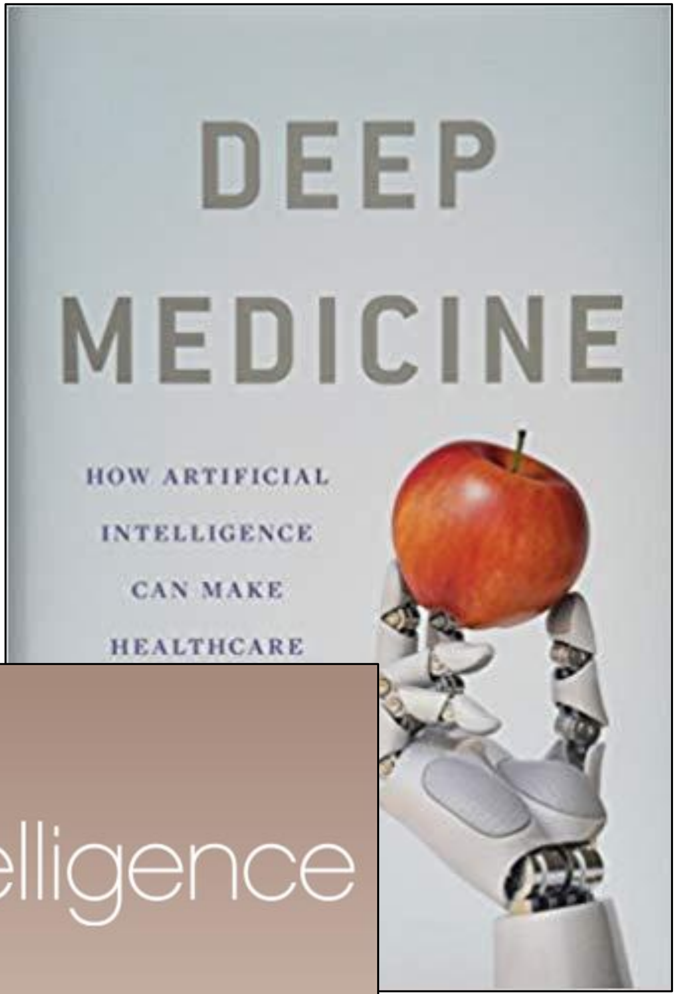


Radiology
Artificial Intelligence

JAMA Network | Open.

Editorial

## Advancing Health and Health Care Using Machine Learning
## *JAMA Network Open* Call for Papers

Frederick P. Rivara, MD, MPH; Stephan D. Fihn, MD, MPH; Roy H. Perlis, MD, MSc

The promise of machine learning to transform all aspects of medicine and health care has been r
celebrated, but to date this transformation remains largely aspirational.[1-5] Medicine poses uniqu
challenges compared with areas like recognizing images, driving autonomous vehicles, or gamin
which machine learning has had remarkable success. Obstacles to successful application of mac
learning in medicine include availability of large, high-quality databases to derive prediction mo
that are accurate and interpretable and deployment of these models in ways that improve, rath
than simply complicate, medical practice.

*JAMA Network Open*, a fully open access journal in the JAMA Network of journals with an
international audience of health care clinicians and policy makers, is pleased to announce a call
papers on "advancing health and health care using machine learning." We are interested in repor

PERSPECTIVE | FOCUS

nature medicine

https://doi.org/10.1038/s41591-018-0316-z

## A guide to deep learning in healthcare

Andre Esteva[1,3*], Alexandre Robicquet[1,3], Bharath Ramsundar[1], Volodymyr Kuleshov[1], Mark DePristo[2], Katherine Chou[2], Claire Cui[2], Greg Corrado[2], Sebastian Thrun[1] and Jeff Dean[2]

**Here we present deep-learning techniques for healthcare, centering our discussion on deep learning in computer vision, natural language processing, reinforcement learning, and generalized methods. We describe how these computational techniques can**

COMPUTERS AND BIOMEDICAL RESEARCH 6, 544–560 (1973)

# An Artificial Intelligence Program to Advise Physicians Regarding Antimicrobial Therapy*

EDWARD H. SHORTLIFFE†, STANTON G. AXLINE, BRUCE G. BUCHANAN, THOMAS C. MERIGAN, AND STANLEY N. COHEN

*Stanford University, Stanford, California 94305*



```
)
INSTRUCTIONS? (Y OR N)
**yes

     I AM HERE TO ADVISE YOU REGARDING AN APPROPRIATE CHOICE OF
     INFECTIOUS DISEASE THERAPY.  I UNDERSTAND THAT YOU HAVE A PATIENT
     FROM WHOM A POSSIBLY POSITIVE CULTURE (CALLED 'CULTURE-1') HAS
     BEEN OBTAINED.  PLEASE ANSWER THE FOLLOWING QUESTIONS,
     TERMINATING EACH RESPONSE WITH 'RETURN'.
     IF YOU ARE NOT CERTAIN OF YOUR ANSWER,  YOU MAY MODIFY THE
     RESPONSE BY INSERTING A CERTAINTY FACTOR (A NUMBER FROM 1 TO 10)
     IN PARENTHESES AFTER YOUR RESPONSE.  ABSOLUTE CERTAINTY (10) IS
     ASSUMED FOR EVERY UNMODIFIED ANSWER.
     NOTE THAT YOU MAY ALSO ENTER '?' IF YOU DO NOT KNOW THE ANSWER
     TO A QUESTION,  '??' IF YOU WOULD LIKE TO SEE A LIST OF
     RECOGNIZED RESPONSES, THE WORD 'WHY' IF YOU WOULD LIKE TO SEE THE
     DECISION RULE WHICH HAS GENERATED THE QUESTION, OR THE WORD
     'HELP' IF YOU ARE CONFUSED BY A QUESTION AND WOULD LIKE IT
     REPHRASED.  TOGETHER WE WILL TRY TO DETERMINE APPROPRIATE THERAPY
     FOR THIS PATIENT.
     SUMMARY:
      '?'    - ANSWER NOT KNOWN
      '??'   - REQUEST FOR RECOGNIZED RESPONSES
      'WHY'  - REQUEST FOR CURRENT DECISION RULE
      'HELP' - REQUEST FOR RESTATEMENT OF QUESTION
     SAMPLE RESPONSE:
       DID ORGANISM-1 GROW IN CLUMPS, CHAINS, OR PAIRS?
       **CHAINS (7) PAIRS (3)


" 2-MAY-73 14:42:55"

                         -----PATIENT-1-----
   PATIENT'S NAME:
   **J. Wilson
```



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## SPECIAL ARTICLE

## MEDICINE AND THE COMPUTER

### The Promise and Problems of Change

WILLIAM B. SCHWARTZ, M.D.*

**Abstract** Rapid advances in the information sciences, coupled with the political commitment to broad extensions of health care, promise to bring about basic changes in the structure of medical practice. Computing science will probably exert its major effects by augmenting and, in some cases, largely replac
physician. As
influences in
of both physi

care, it will also inevitably exact important social costs — psychologic, organizational, legal, economic and technical. Only through consideration of such potential costs will it be possible to introduce the new technology in an effective and acceptable manner. To accomplish this goal will require new

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Table 1. Example of an Actual Consultation in Which the Computer Assists the Physician in the Evaluation of a Complex Acid-Base Disturbance.*

| | |
|---|---|
| COMPUTER | WHAT IS THE PLASMA $CO_2$ CONTENT, PLEASE? |
| Physician: | 15 mMoles/L |
| COMPUTER: | AND THE PLASMA pH, PLEASE? |
| Physician: | 7.14 |
| COMPUTER: | THE FINDING OF A LOW $CO_2$ CONTENT, LOW pH AND NORMAL $Pco_2$ (CALCULATED TO BE 42 mmHg) INDICATES THE PRESENCE OF A MIXED RESPIRATORY AND METABOLIC ACIDOSIS, AND THE PATIENT SHOULD THEREFORE BE CHECKED FOR ANY SOURCE OF IMPAIRED VENTILATION. I WILL NOW BE GLAD TO ASSIST WITH THE DIAGNOSIS OF THE METABOLIC COMPONENT OF THIS PATIENT'S DISORDER. WHAT IS THE SERUM SODIUM CONCENTRATION PLEASE? |
| Physician: | 240 mEq/liter |
| COMPUTER: | IMPOSSIBLE VALUE! PLEASE CHECK AND RE-ENTER THE CORRECT SODIUM CONCENTRATION. |
| Physician: | 140 mEq/liter |
| COMPUTER: | WHAT IS THE CHLORIDE CONCENTRATION? |
| Physician: | 103 mEq/liter |
| COMPUTER: | THE CALCULATED "ANION GAP" IS 22 mEq/liter. METABOLIC ACIDOSIS WITH AN INCREASED "ANION GAP" IS SEEN IN<br>1. DIABETIC KETOACIDOSIS<br>2. SALICYLATE POISONING<br>3. ETHYLENE GLYCOL POISONING<br>4. METHYL ALCOHOL POISONING<br>5. PARALDEHYDE INGESTION (RARELY)<br>6. LACTIC ACIDOSIS<br>7. RENAL FAILURE |
| | 1. WHEN THE DISSOCIATED PRODUCTS OF THE ACID ARE $H^+$ AND AN ANION OTHER THAN CHLORIDE AS IN THE CASE OF:<br>A.—KETOACIDS (DIABETIC KETOACIDOSIS)<br>B.—LACTIC ACID (LACTIC ACIDOSIS)<br>C.—UNKNOWN ORGANIC ACIDS (AS SEEN IN SALICYLATE INTOXICATION OR POISONING WITH METHYL ALCOHOL, ETHYLENE GLYCOL, PARALDEHYDE).<br>2. WHEN (AS IN RENAL INSUFFICIENCY) THE REDUCTION IN PLASMA $HCO_3$ CONCENTRATION IS INDUCED BY DEFECTIVE EXCRETION OF HYDROGEN ION AND IS NOT ACCOMPANIED BY AN INCREASE IN CHLORIDE REABSORPTION. |
| COMPUTER: | IF YOU WOULD LIKE A MORE COMPLETE DISCUSSION OF THIS PROBLEM PLEASE SO INDICATE (BY TYPING *YES*) AND I CAN SUGGEST SEVERAL REFERENCES. [When requested, references are provided here.] |
| COMPUTER: | I AM NOW READY TO ASSIST IN NARROWING THE LIST OF POSSIBLE DIAGNOSES. WHAT IS THE BLOOD SUGAR PLEASE? |
| Physician: | 135 mg/100 ml |
| COMPUTER: | AND THE SERUM KETONE LEVEL, EXPRESSED IN TERMS OF DILUTED PLASMA? |
| Physician: | 1 to 2 |
| COMPUTER: | AND THE CREATININE CONCENTRATION? |
| Physician: | 2.1 mg per 100 ml |
| COMPUTER: | AND THE SALICYLATE CONCENTRATION PLEASE? |
| Physician: | 0 |

JAN 20, 2017 @ 02:11 AM 63,945

The Little Black Book of Billionaire Secrets

# First FDA Approval For Clinical Cloud-Based Deep Learning In Healthcare

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# Viz.ai Granted De Novo FDA Clearance for First Artificial Intelligence Triage Software

A new era of intelligent stroke care begins as regulatory approval is granted for the Viz.ai LVO Stroke Platform

iz.ai

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access to lif

NEWS PROVID
Viz.ai, Inc. →
Feb 15, 2018, 0

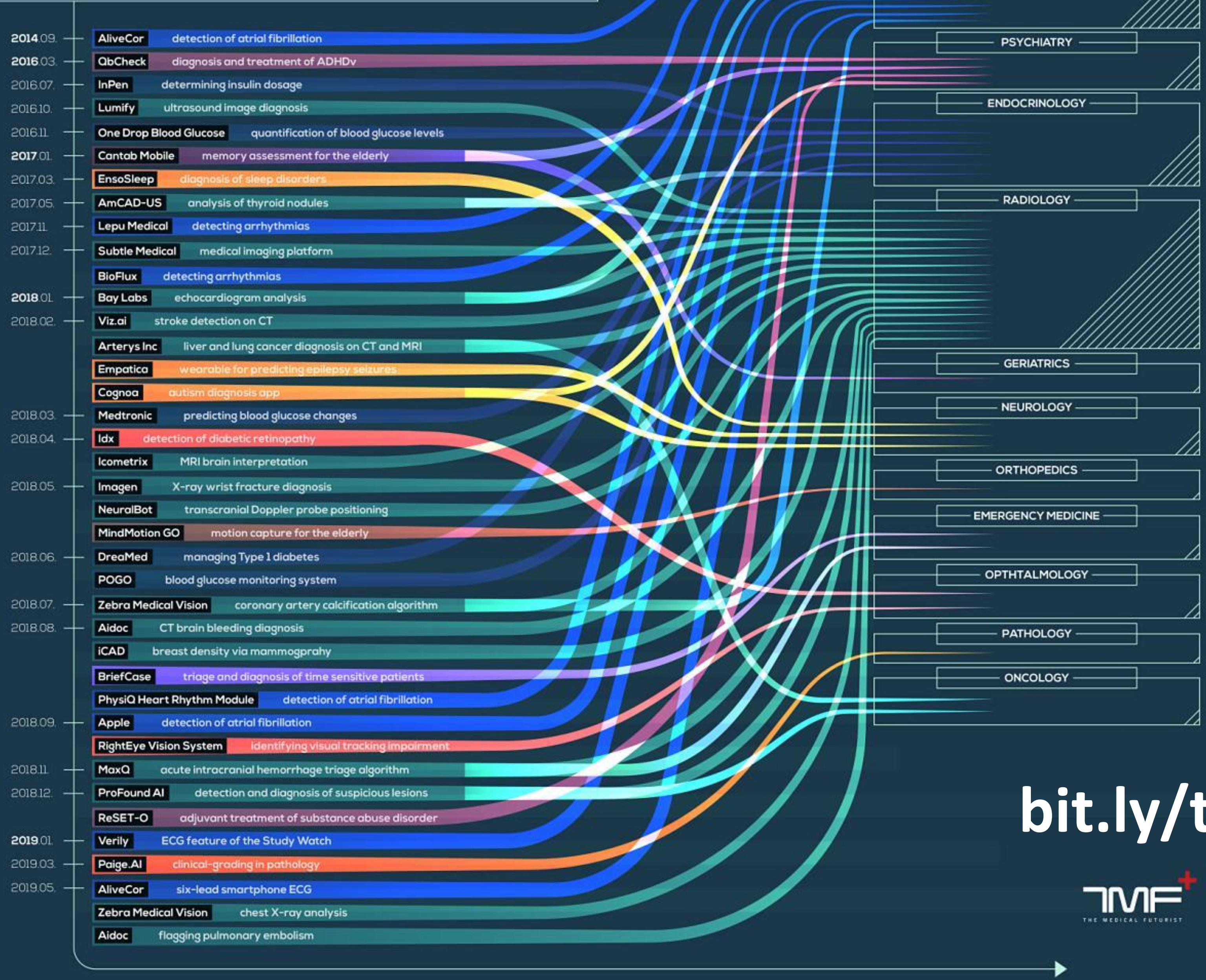
# FDA permits marketing of AI software autonomously detects diabetic retinop

By Dave Muoio | April 12, 2018

SH

The FDA has granted diagnostics company IDx's De Novo request

# FDA APPROVALS FOR ARTIFICIAL INTELLIGENCE-BASED ALGORITHMS IN MEDICINE




bit.ly/tmfFDA19

# Over 100 now approved just counting radiology!

## FDA Cleared AI Algorithms

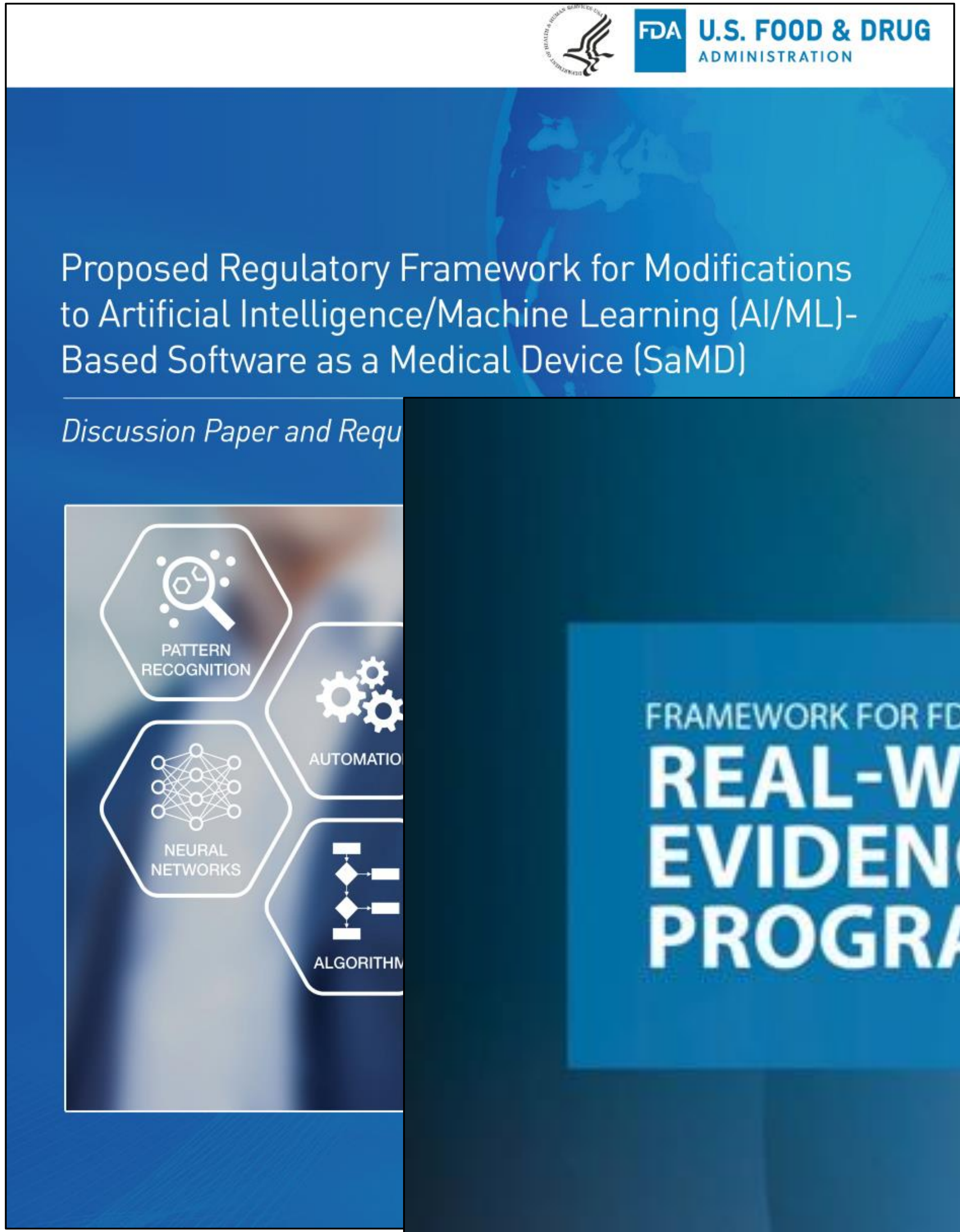
Our list of FDA cleared AI algorithms provides valuable details on each model, bringing all of the relevant information together for easy access. Convenient summaries for each algorithm include model manufacturer, FDA product code, body area, modality, predicate devices, evaluation related to product performance, and clinical validation. Our Define-AI use cases match many of the models and those are listed under Related Use Cases. For other details, clicking on the model will take you directly to the FDA summary.

Check back regularly to see which new algorithms are available and have been added to the list. Send information on AI algorithms that are not listed and report missing information to DSI@acr.org.

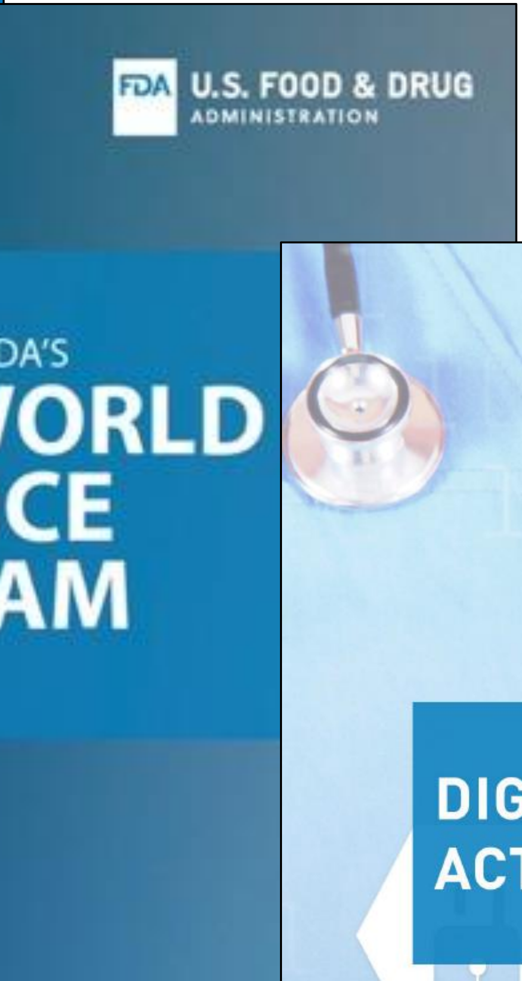
Search | Company | Subspeciality | Body Area | Modality | Date Cleared

| Product | Company | Subspeciality | Body Area | Modality | Date Cleared |
|---|---|---|---|---|---|
| qp-Prostate | Quibim | Abdominal Imaging | Prostate | MR | 02/04/2021 |
| Visage Breast Density | Visage Imaging GmbH | Women's Imaging | Breast | MAM | 01/29/2021 |
| uAI EasyTriage-Rib | Shanghai United Imaging Intelligence Co., Ltd. | Chest Imaging | Chest | CT | 01/15/2021 |
| BrainInsight | Hyperfine Research, Inc. | Neuroradiology | Brain | MR | 01/07/2021 |
| SQuEEZ Software | Cardiowise, Inc. | Cardiac Imaging | Heart | CT | 12/18/2020 |
| EchoGo Pro | Ultromics Ltd. | Cardiac Imaging | Heart | US | 12/18/2020 |
| HepaFat-AI | Resonance Health Analysis Service Pty Ltd. | Abdominal Imaging | Liver | MR | 12/07/2020 |
| HealthJOINT | Zebra Medical Vision Ltd. | Musculoskeletal Imaging | Knee | XRAY | 12/04/2020 |
| HALO | NiCo-Lab B.V. | Neuroradiology | Brain | CT | 11/20/2020 |
| Genius AI Detection | Hologic, Inc. | Women's Imaging | Breast | XRAY | 11/18/2020 |
| PROView | GE Medical Systems | Abdominal Imaging | Prostate | MR | 11/17/2020 |
| FastStroke, CT Perfusion 4D | GE Medical Systems | Neuroradiology | Brain | CT | 11/12/2020 |
| Neuro.AI Algorithm | TeraRecon, Inc. | Neuroradiology | Brain | CT,MR | 11/06/2020 |
| WRDensity | Whiterabbit.ai Inc. | Women's Imaging | Breast | MAM | 10/30/2020 |
| LSN | Imaging Biometrics, LLC | Abdominal Imaging | Liver | CT | 10/29/2020 |
| AVIEW LCS | Coreline Soft Co., Ltd | Chest Imaging | Lung | CT | 10/16/2020 |
| Syngo.CT Neuro Perfusion | Siemens Healthineers | Neuroradiology | Brain | CT | 10/11/2020 |
| Quantib Prostate | Quantib BV | Abdominal Imaging | Prostate | MR | [illegible] |
| Cleerly Labs V2.0 | Cleerly, Inc. | Cardiac Imaging | Coronary Arteries | CT,CTA | 10/02/2020 |

http://bit.ly/acr_ai




FDA U.S. FOOD & DRUG ADMINISTRATION




# Why is AI back in biomedicine?

- Great hardware from video gamers
- Software libraries with novel machine learning methods
- More big data sets to train with
  - Molecular data, genomics on more people, more cases
  - Electronic health records
- Hard unsolved questions need answers
  - Patient predictions
  - Efficient drug discovery
  - Population modeling


National Cancer Institute
The Cancer Genome Atlas
Understanding genomics to improve cancer care
ENCODE
HMP
NIH HUMAN MICROBIOME PROJECT
CCLE Cancer Cell Line Encyclopedia
HOME
BROWSE
ANALYSIS TOOLS
fitbit
All of Us
RESEARCH PROGRAM
BROAD INSTITUTE
Food and Drug Administration
MedWatch
Home > For the Scientific Community:Science > Projects > Connectivity Map > Connectivity Map
Connectivity Map
This research effort aims to generate a detailed map that links gene patterns associat
corresponding patterns produced by drug candidates and a variety of genetic manipula
HEP
Human Epigenome Project
NIH LINCS
PROGRAM
HOME
ABOUT
CENTERS
DATA
ASSAYS
UK 10K
National Cancer Institute
Surveillance Epidemiology and End Results
providing information on cancer statistics to help reduce the burden of these diseases on the U.S. pop
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Cancer Statistics
Datasets & Software
Publications
Connectivity Map Project Website
dbGaP
GENOTYPE and PHENOTYPE
PharmGKB
GO
Advanced search

# The United States is spending $billions on electronic health records, and too few are using any of this data

## Sutter's $1 Billion Boondoggle-New Electronic Records System Goes Dark

*California Nurses Association* Press Release, 8/27/13

Contact Information | Media Center

***Yet Another Ris***

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over 100 reports
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## Partners' $1.2b patient data system seen as key to future

Aims for one file per person, fewer errors

## How Kaiser bet $4 billion on electronic h records -- and won

Kaiser Permanente CIO Philip Fasano explains how electronic records have paid off and the health care giant's embrace of mobile technology

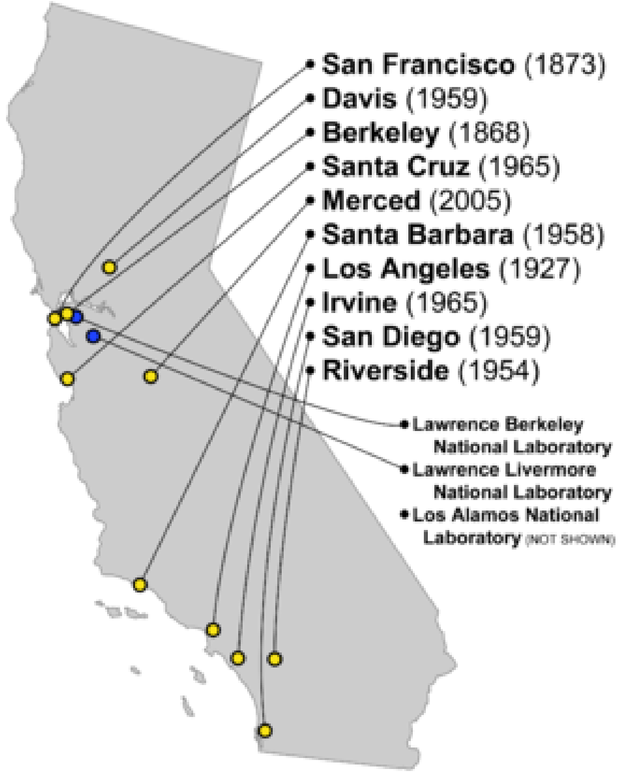
**University of California**

- 10 campuses and 3 national labs
- ~200,000 employees, ~250,000 students/yr

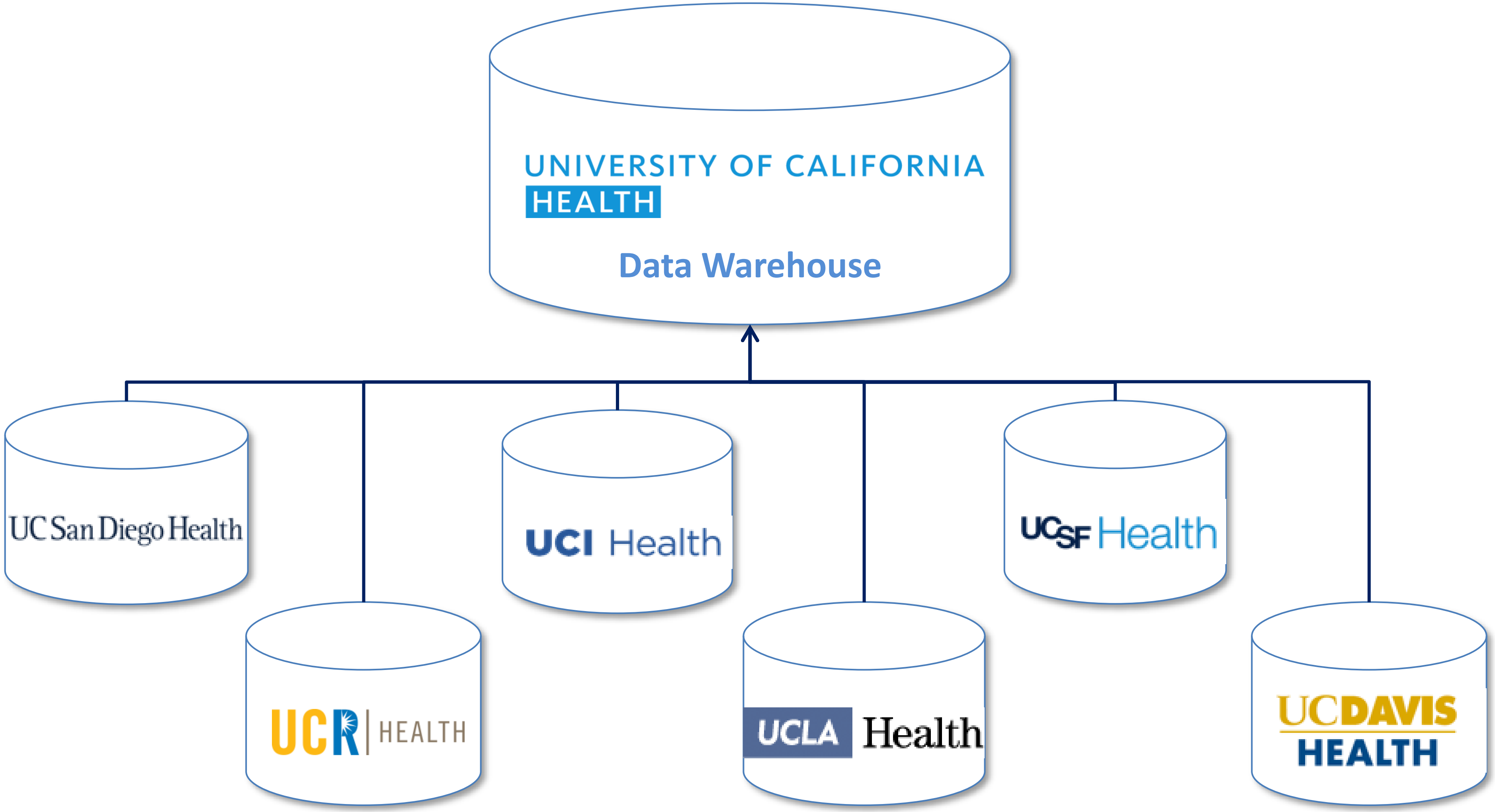
UNIVERSITY OF CALIFORNIA HEALTH

**UC Health**

- 20 health professional schools (6 med schools)
- Train half the medical students and residents in California
- ~$2 billion NIH funding
- $13+ billion clinical operating revenue
- 5000 faculty physicians, 12000 nurses
- UCSF and UCLA are in US News top 10
- 5 NCI Comprehensive Cancer Centers, 5 NIH CTSA
- IRB reliance, centralized contracting



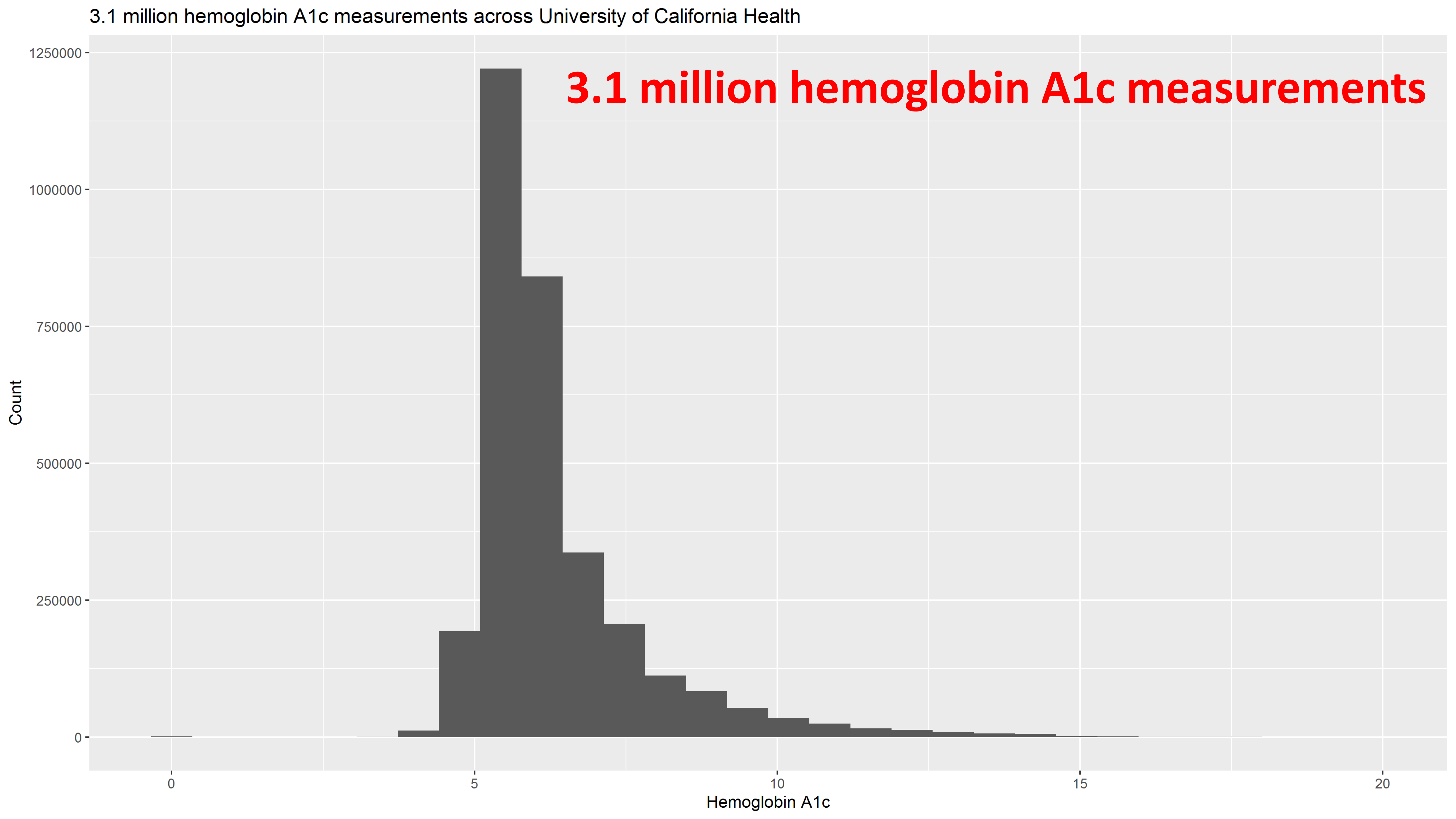
# *Combining healthcare data from across the six University of California medical schools and systems*




UC Health Data Analytics Platform

# The University of California has an incredible view of the medical system

- Combined EHR data from UCSF, UCLA, UC Irvine, UC Davis, UC San Diego, and UC Riverside
- Central database built using OMOP (not Epic) as a data backend
  - First Epic installation was January 2012
  - Structured data from 2012 to the present day
  - **7.0 million patients with “modern” data**
  - 220M encounters, 560M procedures, 798M med orders, 722M diagnosis codes, 2.1B lab tests and vital signs
  - “From Tylenol to CAR-T cells…”
  - California OSHPD data, pathology and radiology text elements, death index
  - Claims data from our self-funded plans now included
  - Continually harmonizing elements
- Quality and performance dashboards


3.1 million hemoglobin A1c measurements across University of California Health
3.1 million hemoglobin A1c measurements
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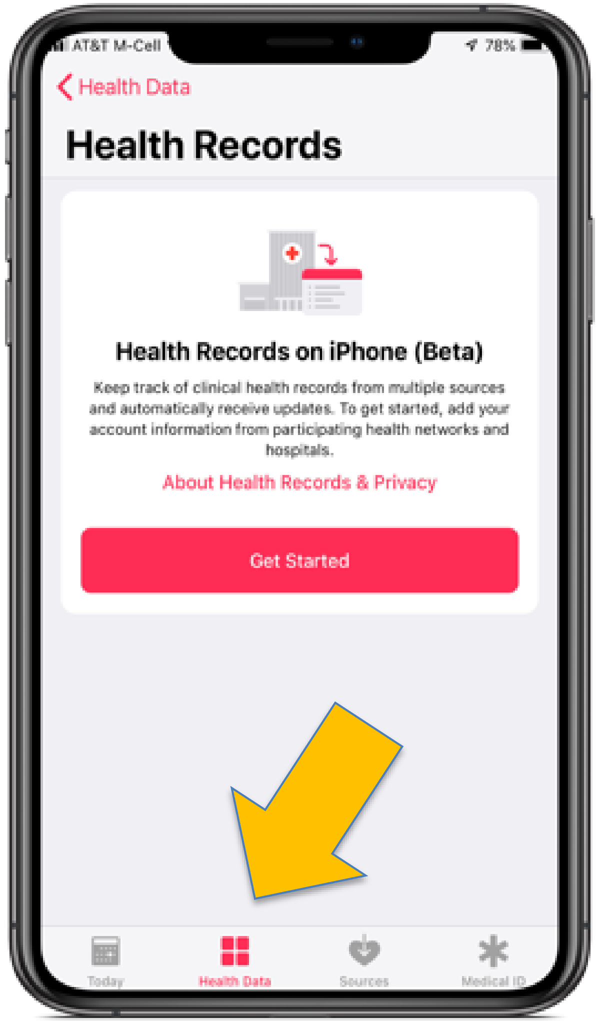
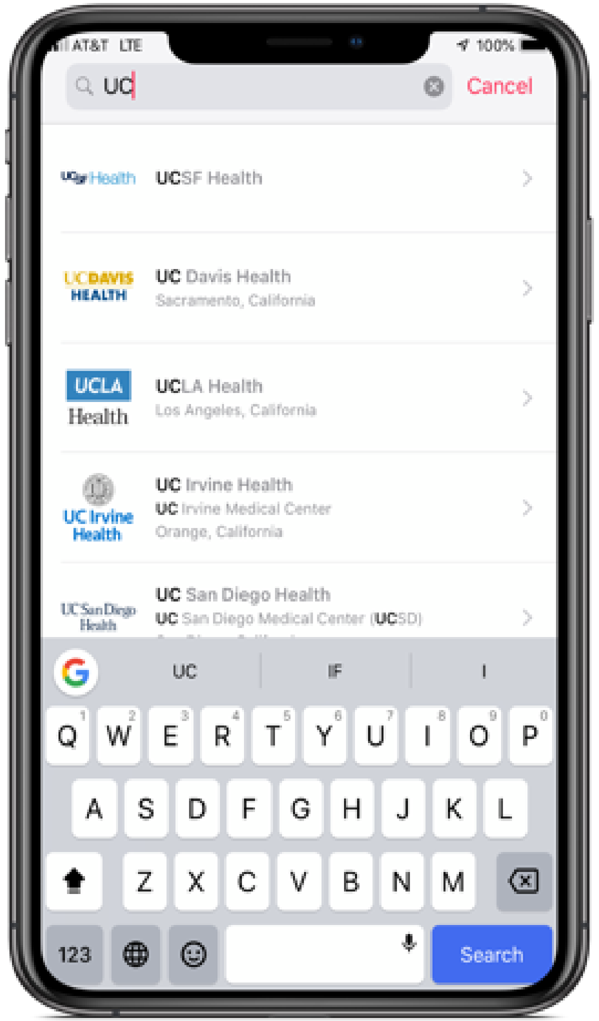
20
Hemoglobin A1c

# *All University of California academic medical centers provide health data to patients through FHIR (and Apple Health)*



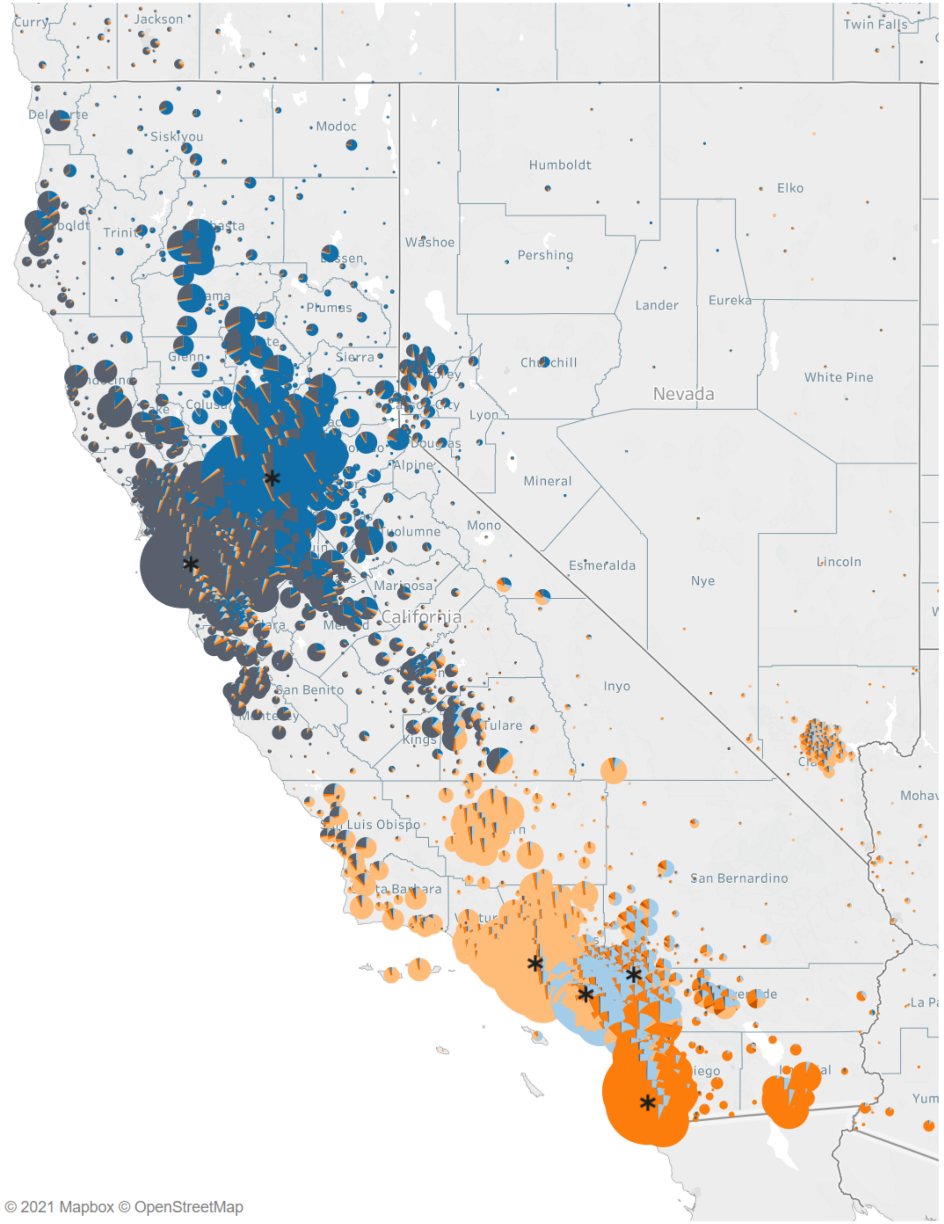

**bit.ly/ucappleh**

# UC Health Patients (since January 2012)

UNIVERSITY OF CALIFORNIA HEALTH

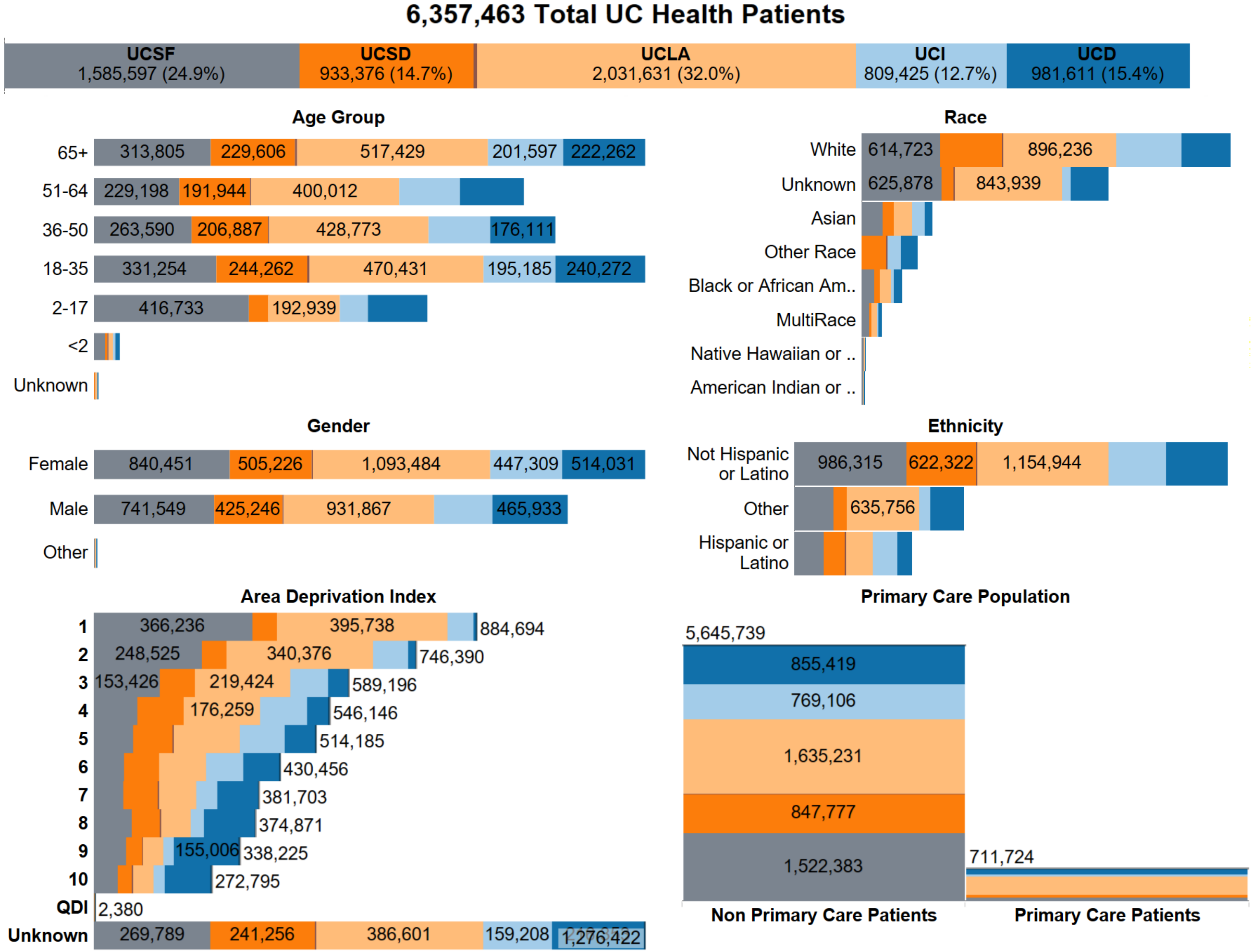
**Gender** All **ADI** All **Race** All **Age** All **Active?** All **PCP?** All **Ethnicity** All

## Patient Volume by Home Zip Code

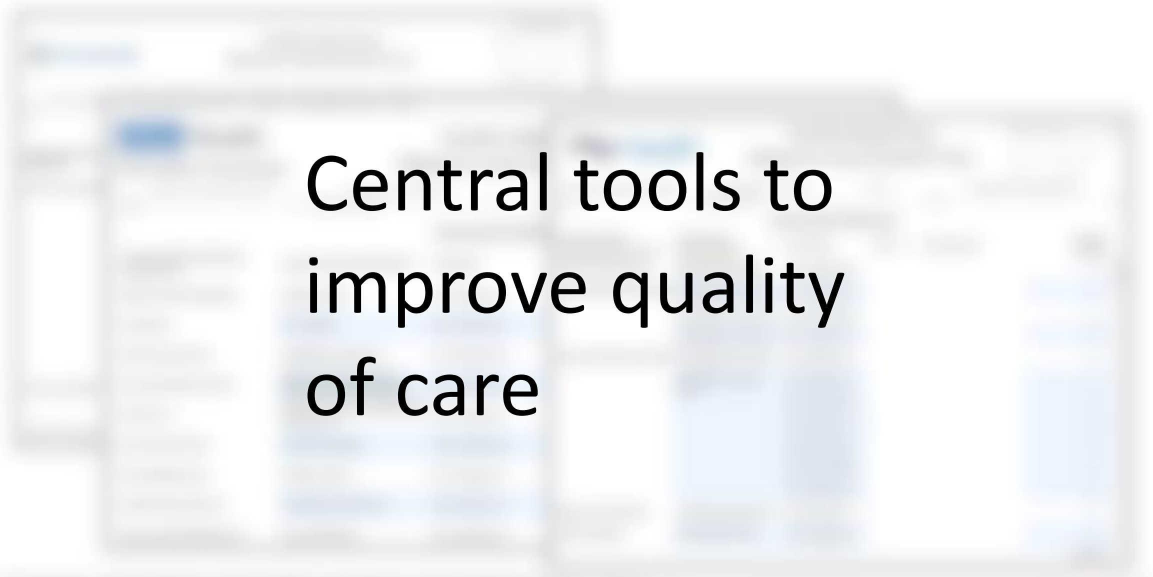



## Most Recent Visit Date Range

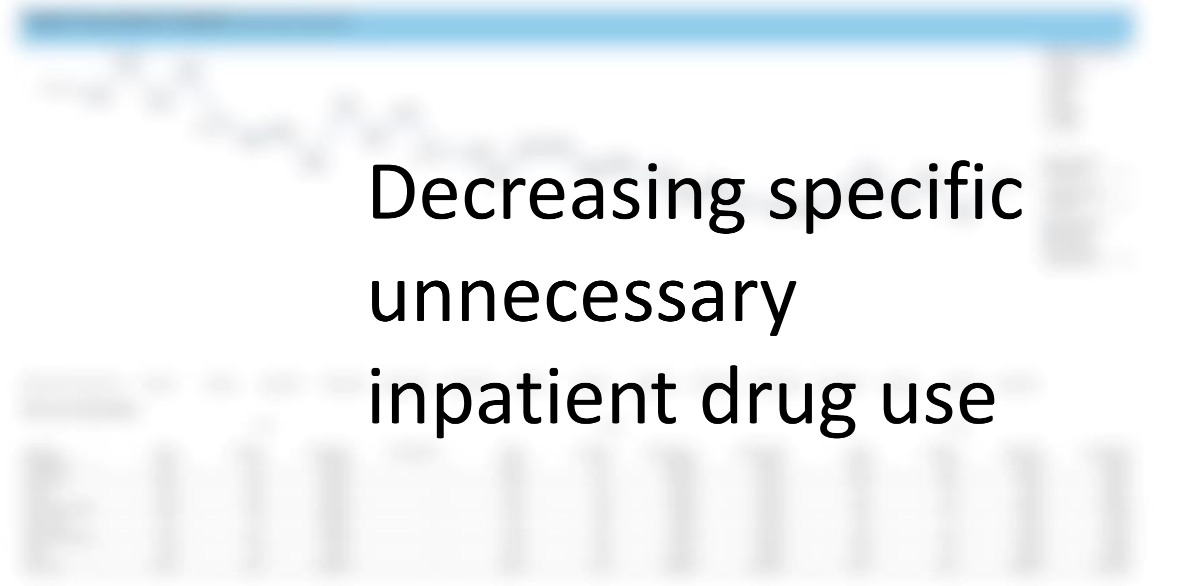
January 2012 to July 2021 and Null values



# Many operational teams within UC Health now using and benefitting from the UC Health Data Warehouse, saving $millions



Central tools to improve quality of care

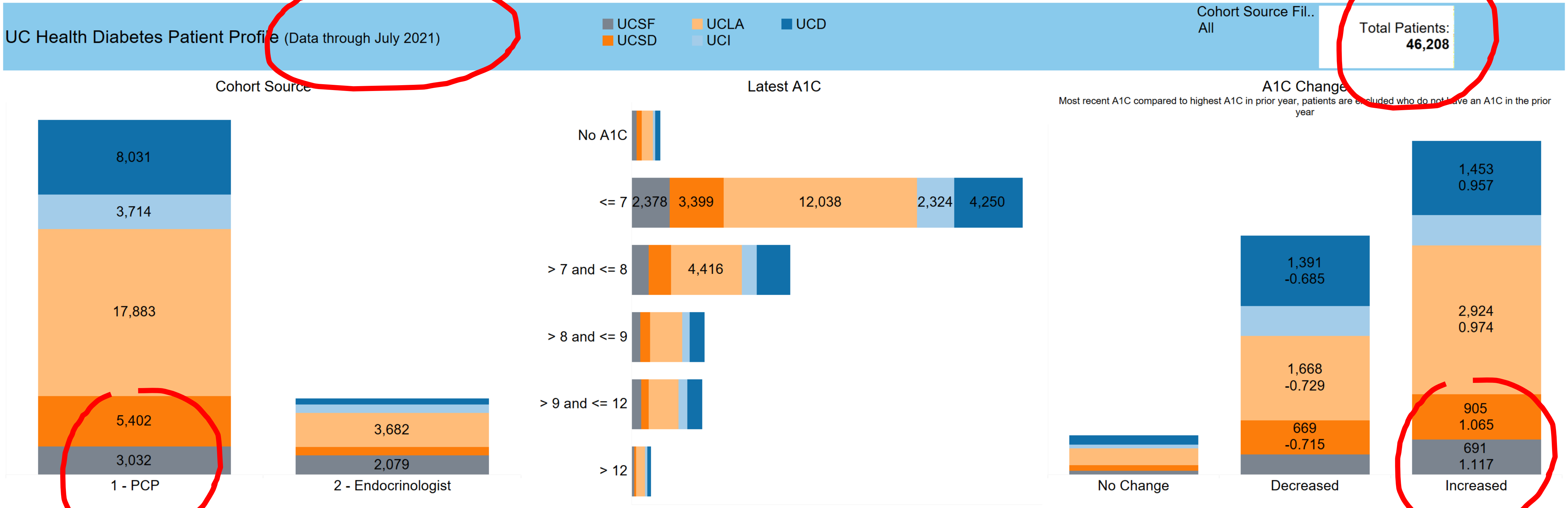


Decreasing specific unnecessary inpatient drug use

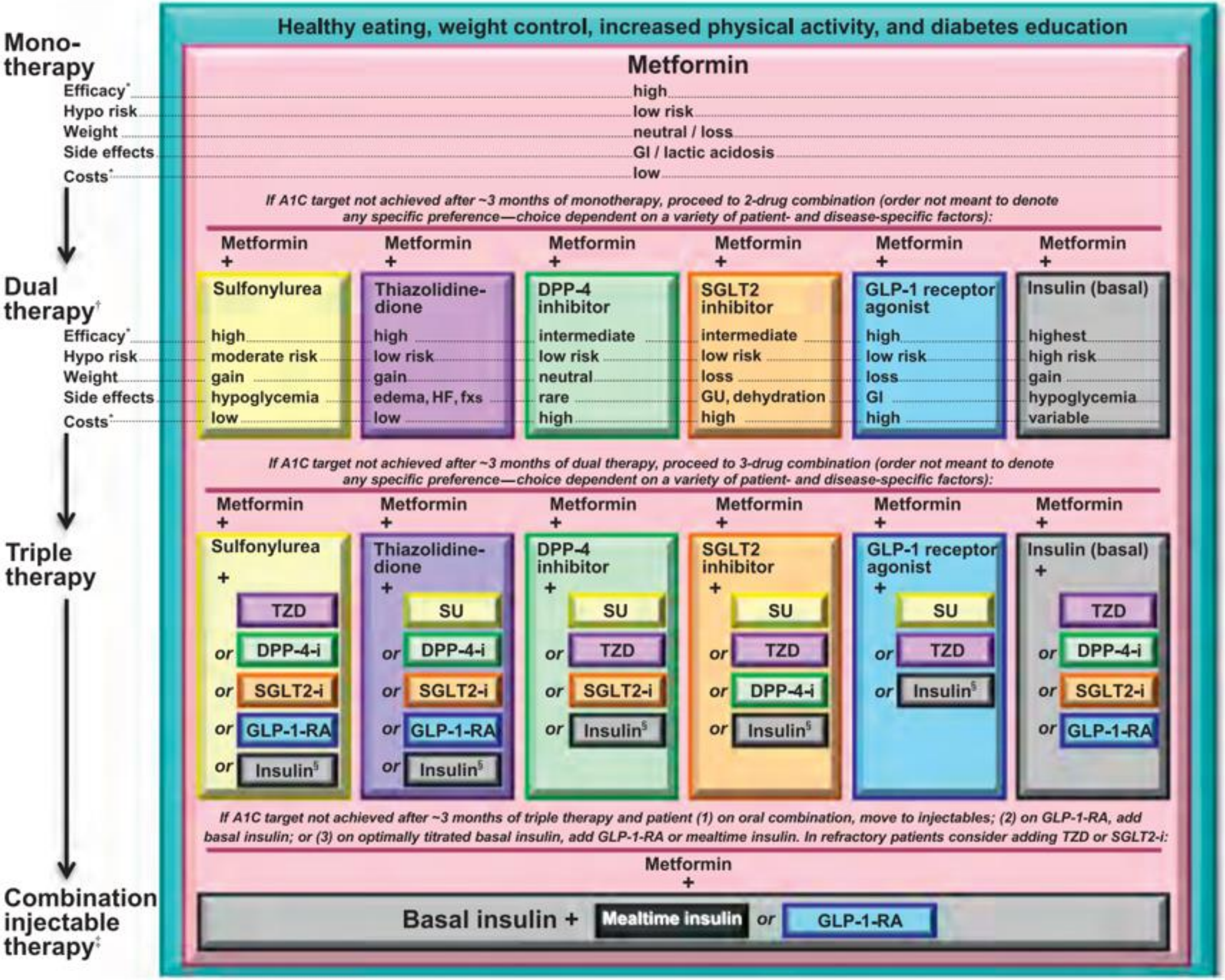
Managing costs in our self-funded health plans

Centralized population health management

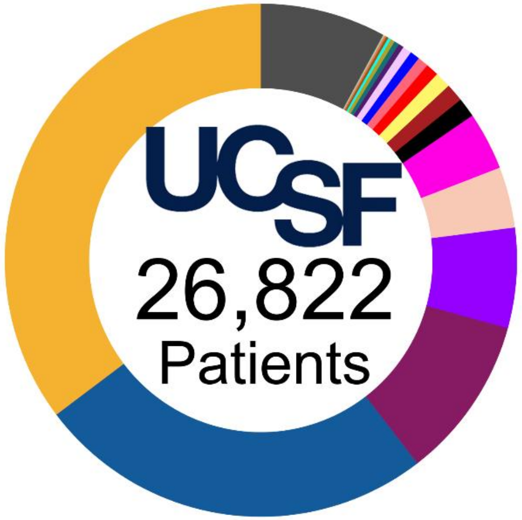
# One dashboard for primary care and specialists covers all 46+ thousand UC Health patients with type 2 diabetes




| Measure Name | 50% IHA Benchmark | UCD 1 - PCP | UCD 2 - Endocrinol.. | UCI 1 - PCP | UCI 2 - Endocrinol.. | UCLA 1 - PCP | UCLA 2 - Endocrinol.. | UCSD 1 - PCP | UCSD 2 - Endocrinol.. | UCSF 1 - PCP | UCSF 2 - Endocrinol.. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Optimal Diabetes Care (A1C control, BP control, Eye Exam, Nephropathy Attention) | 18.02% | 40.76% | 11.74% | 26.46% | 9.61% | 19.91% | 8.16% | 29.79% | 11.64% | 19.75% | 6.04% |
| A1C Control (A1C < 8.0%) | 61.07% | 66.57% | 31.14% | 63.61% | 53.18% | 66.77% | 58.32% | 67.66% | 42.11% | 59.92% | 44.96% |
| Blood Pressure Control (<140/90) | 56.86% | 73.25% | 73.35% | 65.31% | 57.18% | 63.34% | 60.27% | 66.65% | 46.98% | 57.07% | 36.94% |
| Eye Exam | 46.52% | 73.39% | 34.03% | 50.20% | 24.47% | 37.21% | 19.28% | 53.19% | 32.95% | 43.86% | 17.01% |
| Medical Attention for Nephropathy | 90.97% | 89.48% | 78.62% | 90.01% | 87.02% | 86.57% | 81.16% | 88.80% | 72.41% | 83.59% | 66.93% |
| Poor A1C Control (A1C > 9.0%) | 27.83% | 18.71% | 55.01% | 22.48% | 32.44% | 18.09% | 29.89% | 17.27% | 48.27% | 24.75% | 42.93% |



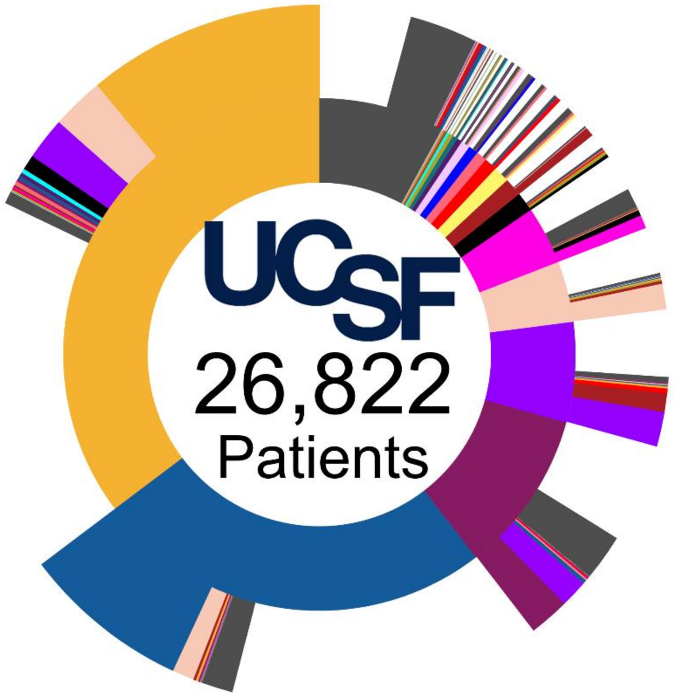

Source: American Diabetes Association Standards of Medical Care in Diabetes (2016)




26,822 Type 2 Diabetes Patients at UCSF since EHR Adoption in 2012

**Tom Peterson**

**bit.ly/uc_dc_5**




Monotherapies:
- Metformin (Met)
- Insulin
- Sulfonylurea (SU)
- Meglitinides
- DPP-4 Inhibitor (DPP-4)
- Thiazolidinedione (TZD)
- SGLT-2 Inhibitor (SGLT-2I)
- GLP-1 Agonist
- Alpha Alucosidase Inhibitor

- Other Combinations

Dual therapies:
- Met & SU
- Met & DPP-4
- Met & Insulin
- Met & GLP-1 Agonist
- Met & Meglitinides
- Met & TZD
- Met & SGLT-2I
- Met & Alpha Glucosidase Inhibitor

Triple therapies:
- Met, SU, & DPP-4
- Met, SU, & Insulin
- Met, DPP-4, & Insulin
- Met, SGLT-2I, & Insulin

26,822 Type 2 Diabetes Patients at UCSF since EHR Adoption in 2012

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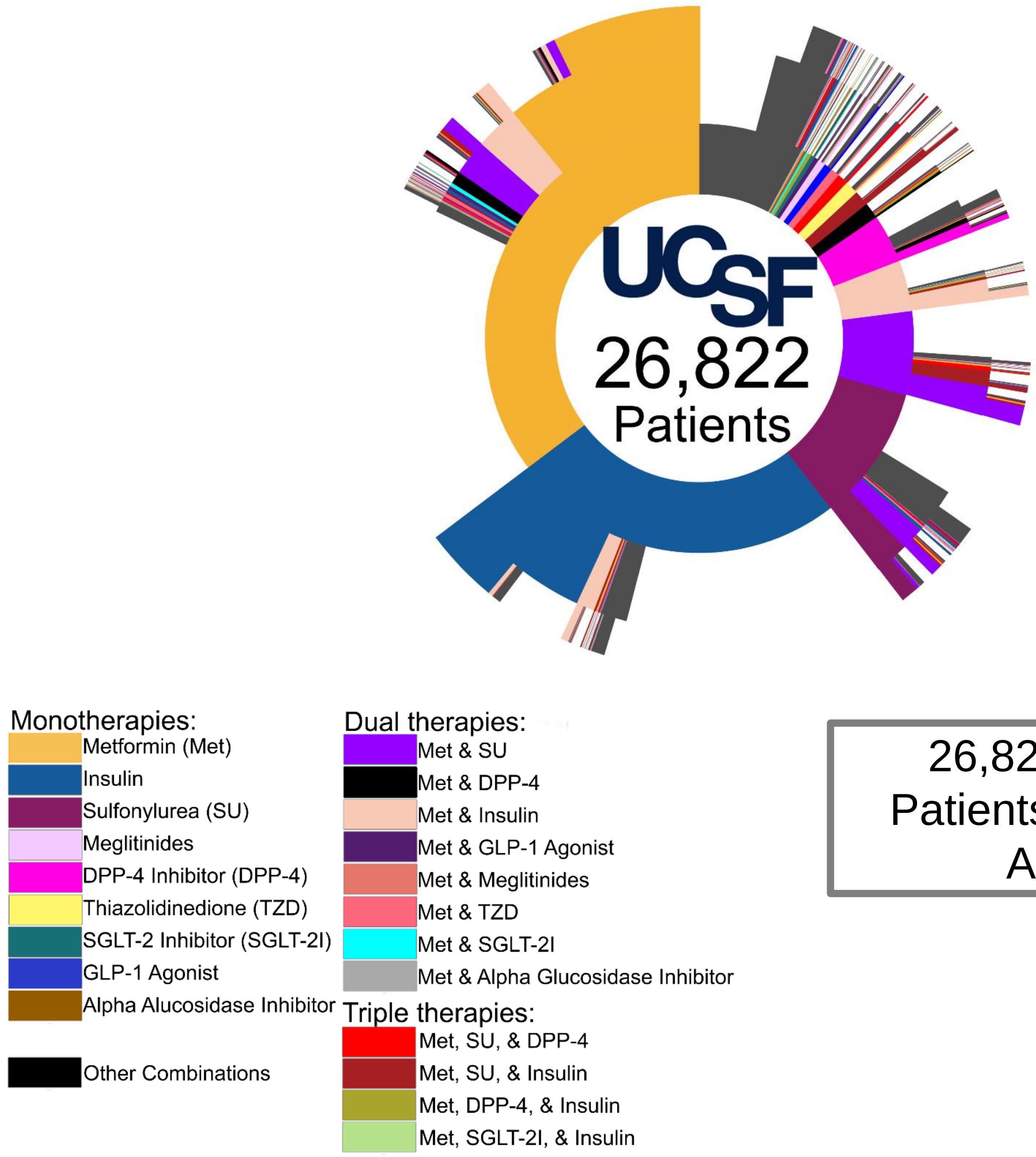


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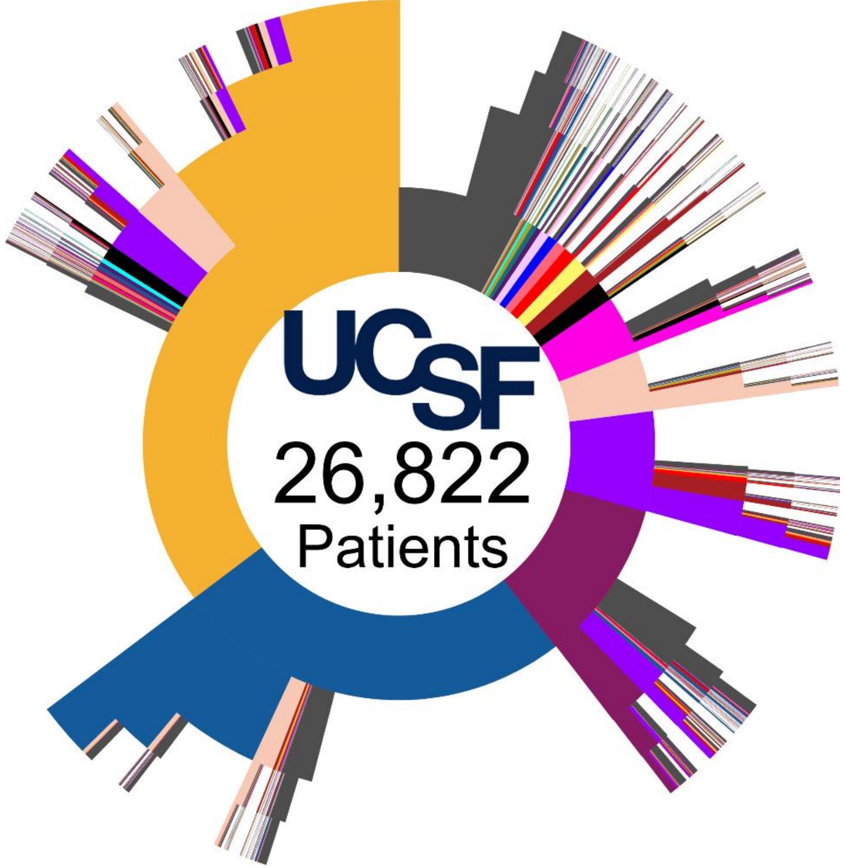


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26,822 Type 2 Diabetes Patients at UCSF since EHR Adoption in 2012

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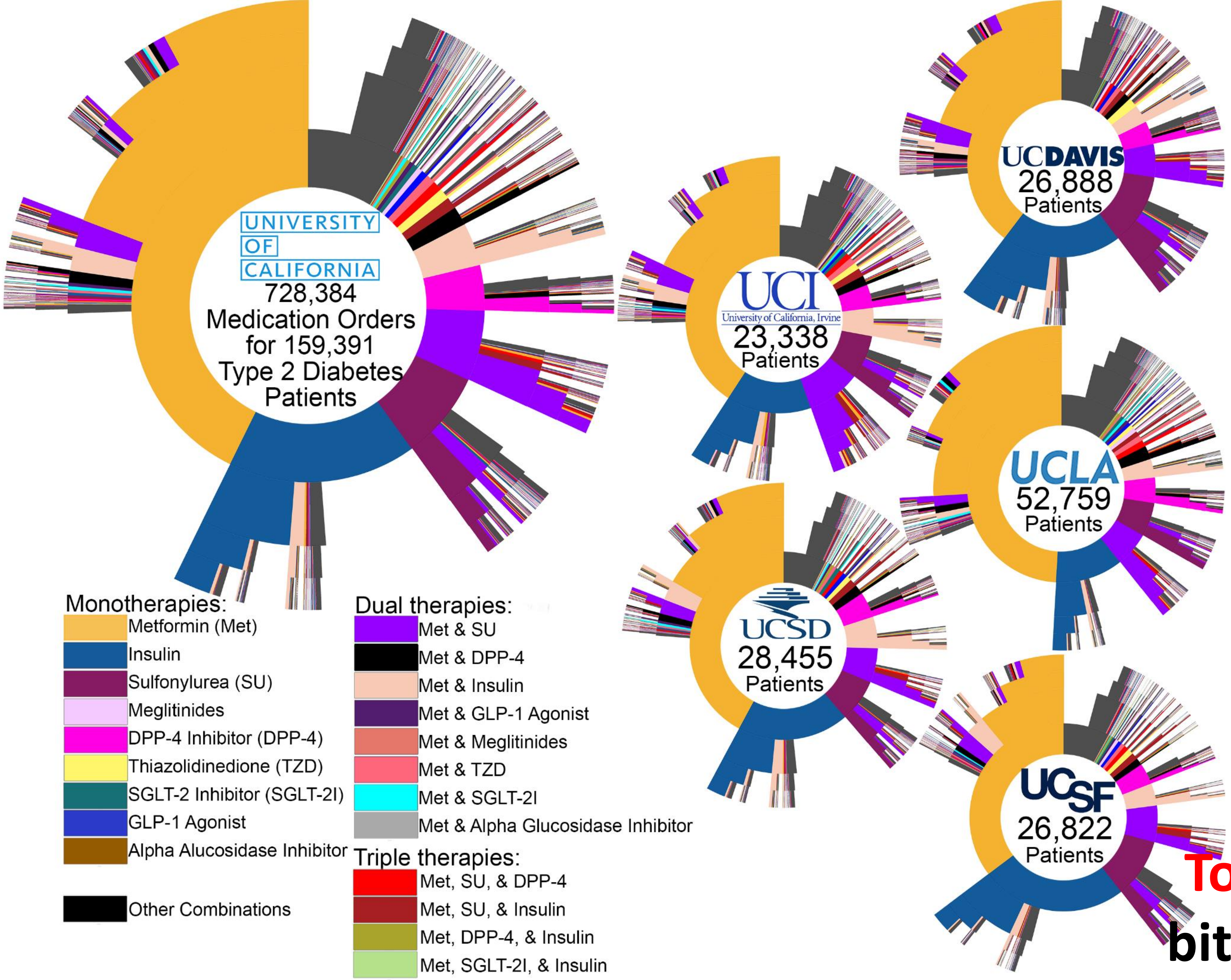


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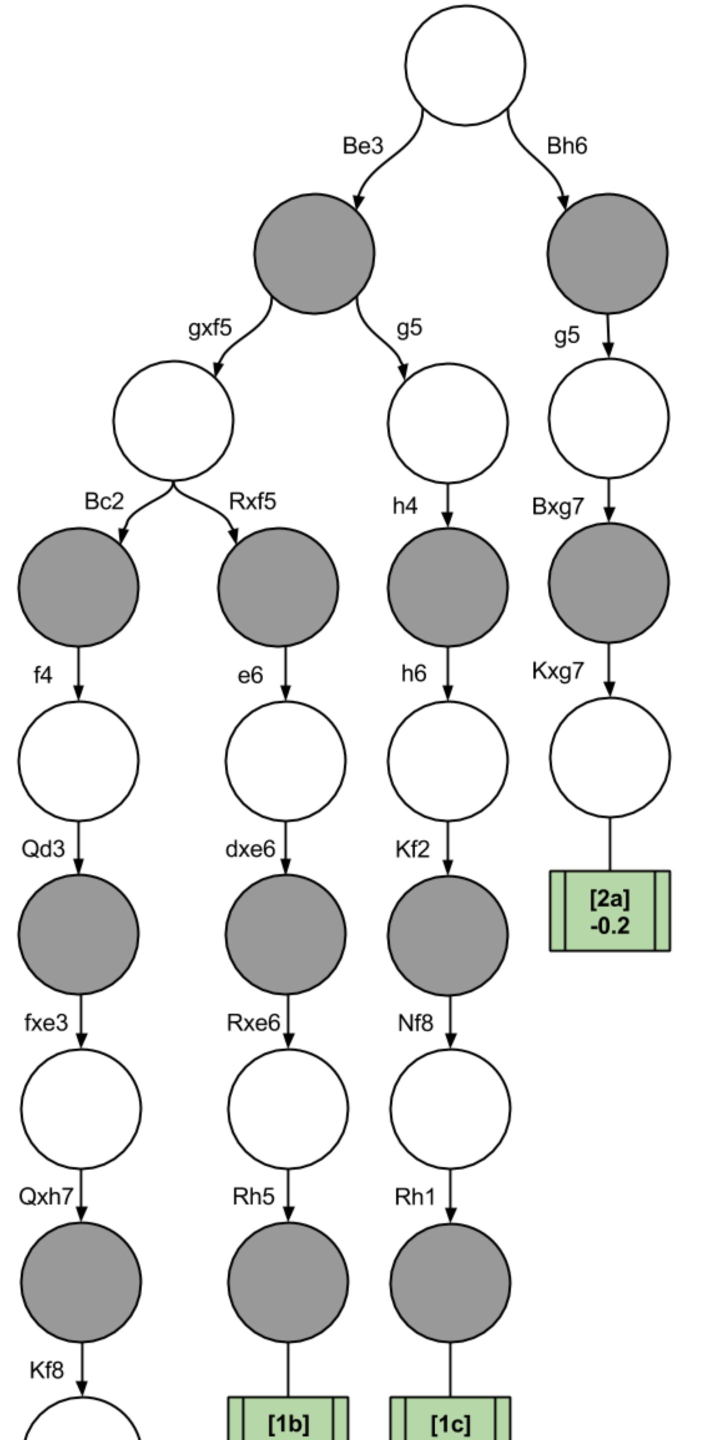
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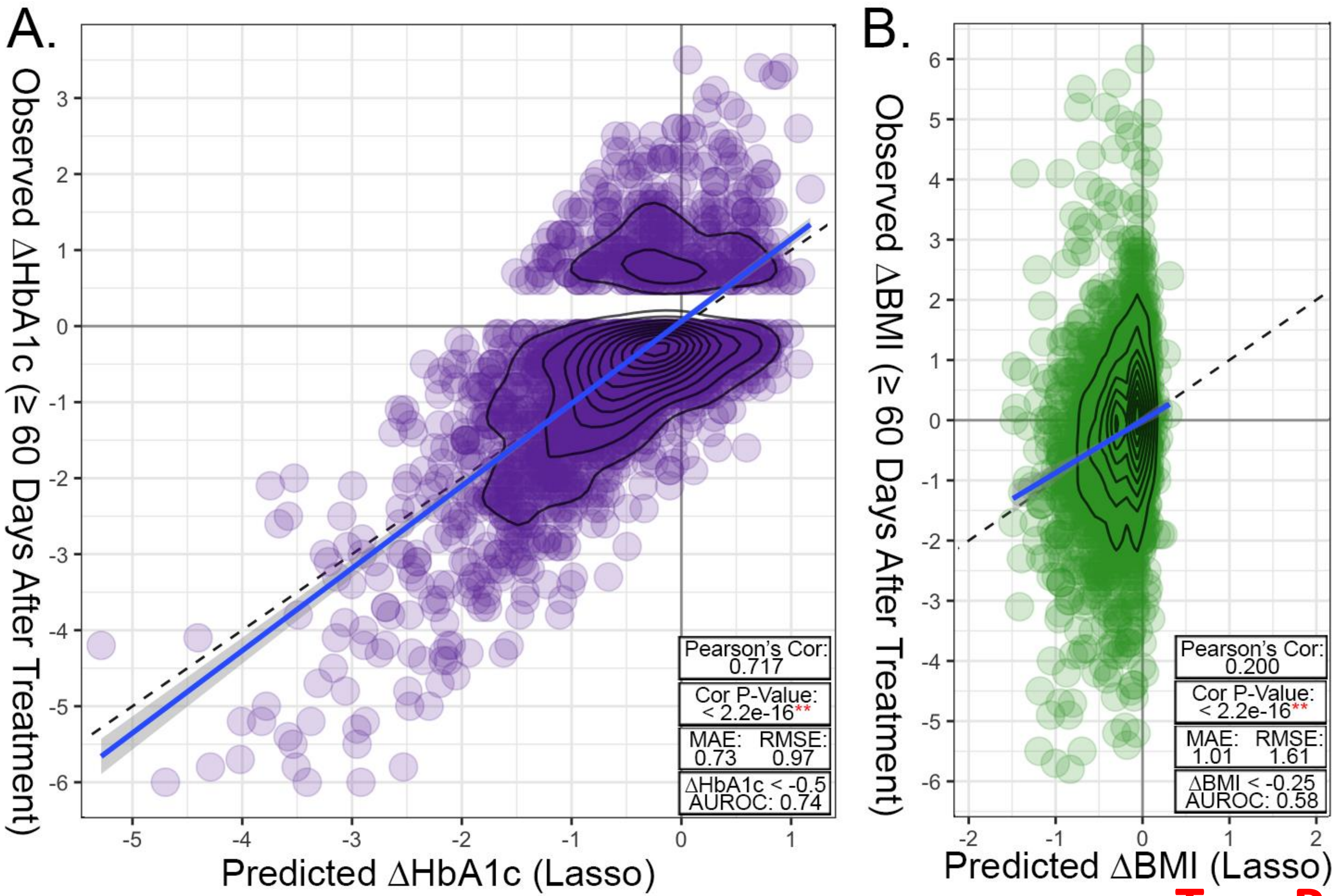
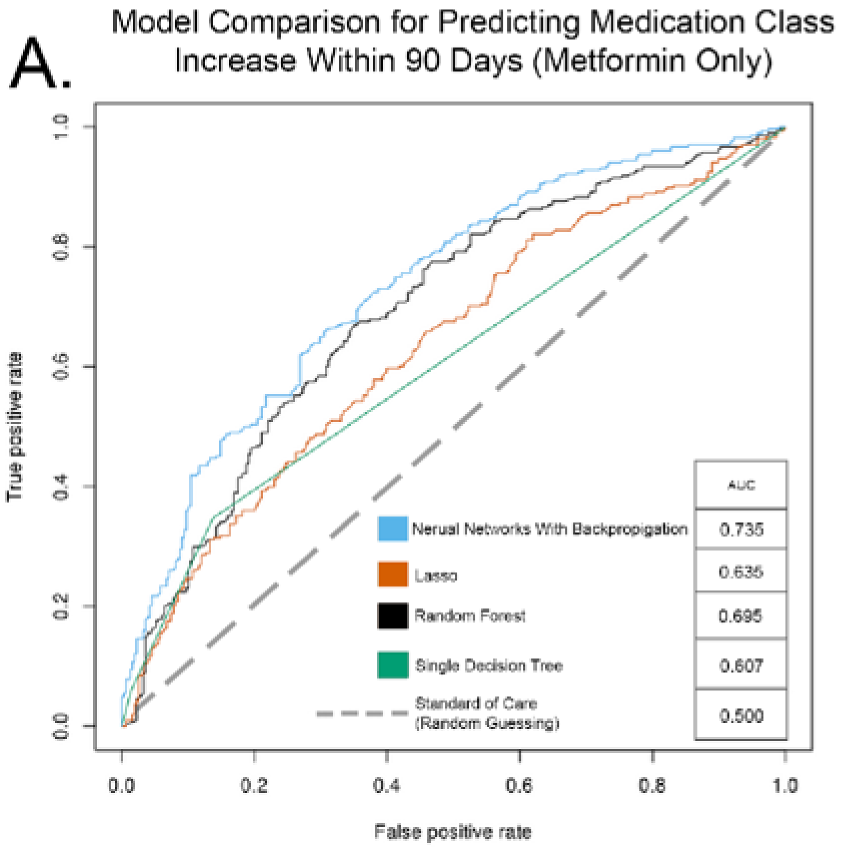
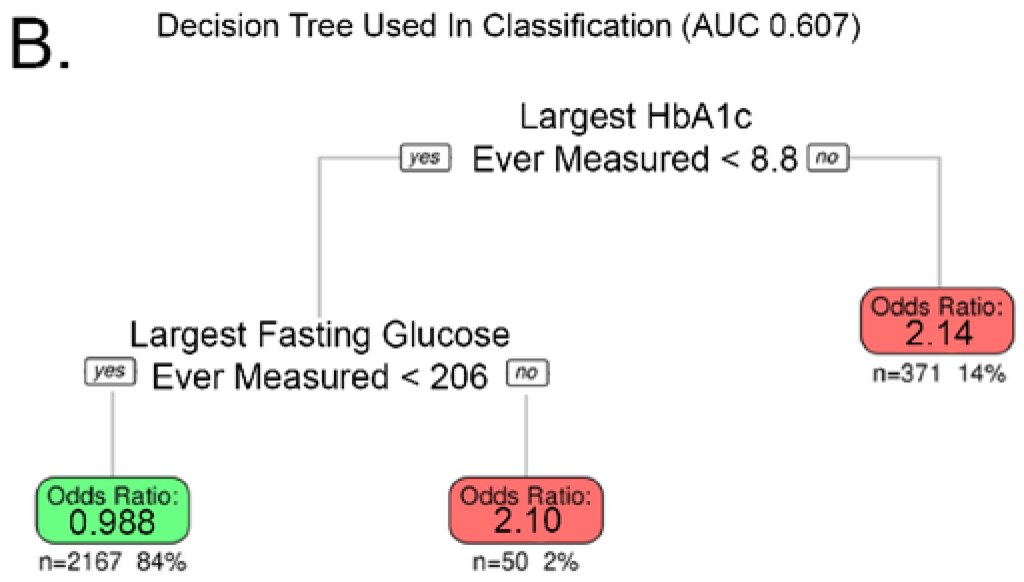
[1c]




Tom Peterson

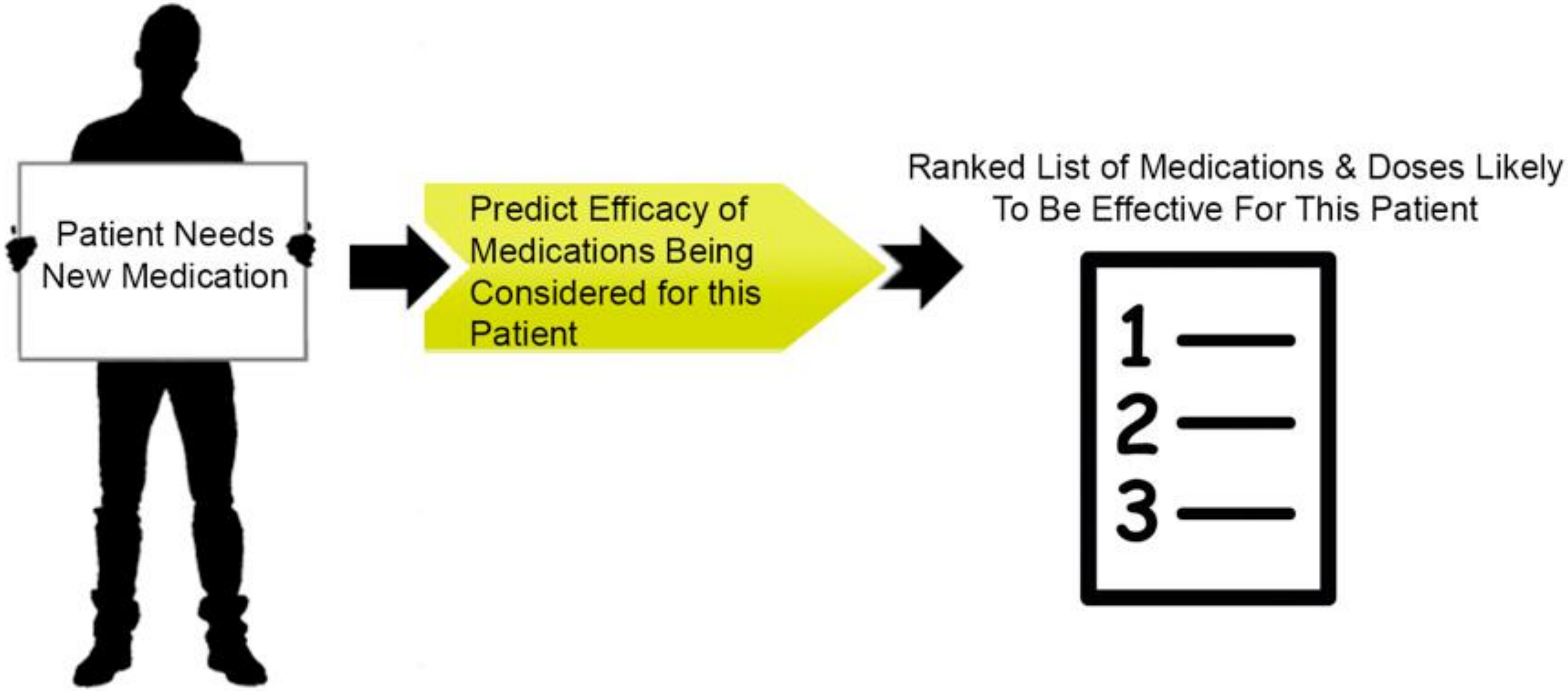
# Can we predict who will do well with metformin?



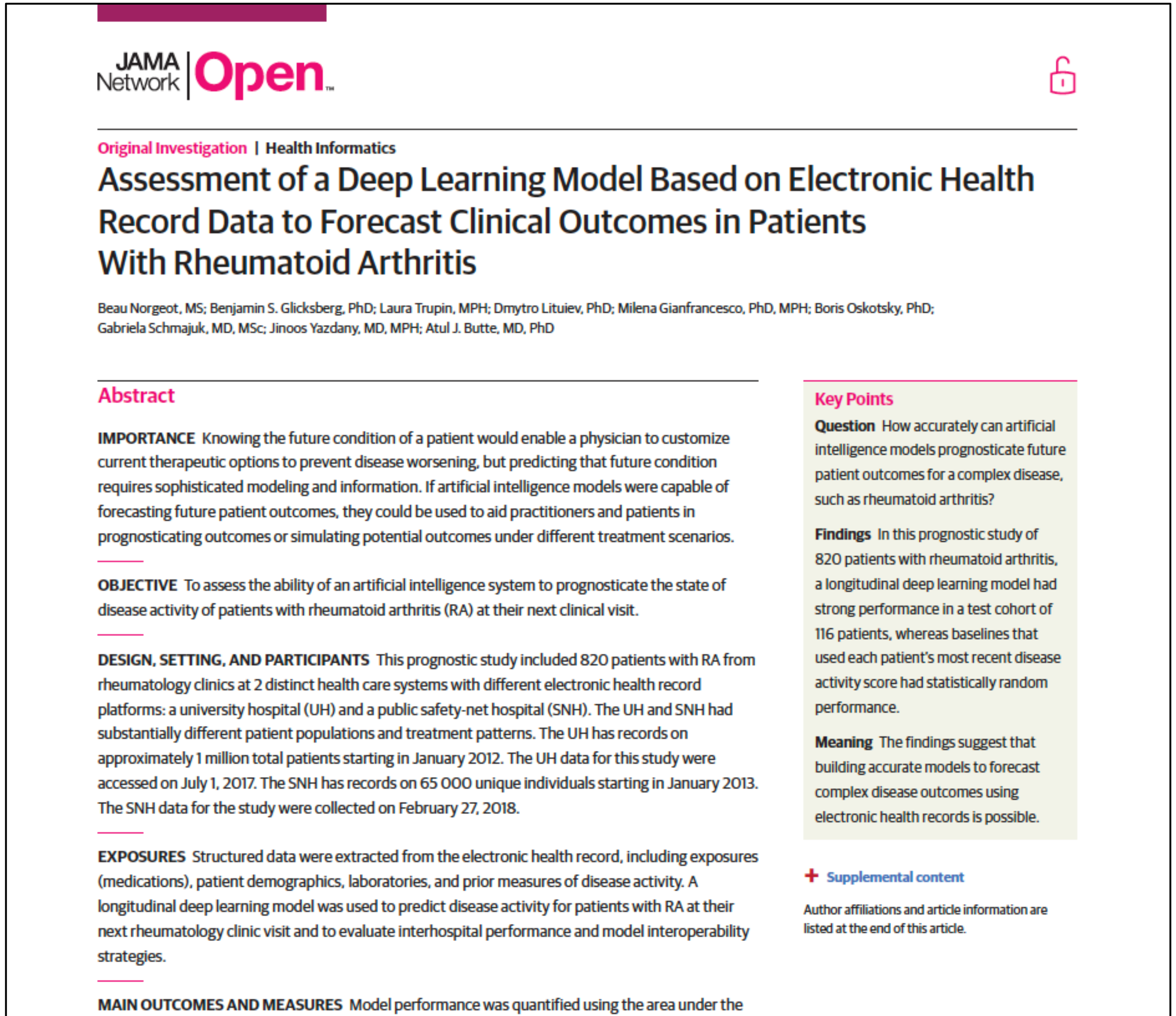

Tom Peterson

# Precision Medicine In Practice




Tom Peterson

# Predicting the future state of a patient with Rheumatoid Arthritis



JAMA Network Open

Original Investigation | Health Informatics

## Assessment of a Deep Learning Model Based on Electronic Health Record Data to Forecast Clinical Outcomes in Patients With Rheumatoid Arthritis

Beau Norgeot, MS; Benjamin S. Glicksberg, PhD; Laura Trupin, MPH; Dmytro Lituiev, PhD; Milena Gianfrancesco, PhD, MPH; Boris Oskotsky, PhD; Gabriela Schmajuk, MD, MSc; Jinoos Yazdany, MD, MPH; Atul J. Butte, MD, PhD

### Abstract

**IMPORTANCE** Knowing the future condition of a patient would enable a physician to customize current therapeutic options to prevent disease worsening, but predicting that future condition requires sophisticated modeling and information. If artificial intelligence models were capable of forecasting future patient outcomes, they could be used to aid practitioners and patients in prognosticating outcomes or simulating potential outcomes under different treatment scenarios.

**OBJECTIVE** To assess the ability of an artificial intelligence system to prognosticate the state of disease activity of patients with rheumatoid arthritis (RA) at their next clinical visit.

**DESIGN, SETTING, AND PARTICIPANTS** This prognostic study included 820 patients with RA from rheumatology clinics at 2 distinct health care systems with different electronic health record platforms: a university hospital (UH) and a public safety-net hospital (SNH). The UH and SNH had substantially different patient populations and treatment patterns. The UH has records on approximately 1 million total patients starting in January 2012. The UH data for this study were accessed on July 1, 2017. The SNH has records on 65 000 unique individuals starting in January 2013. The SNH data for the study were collected on February 27, 2018.

**EXPOSURES** Structured data were extracted from the electronic health record, including exposures (medications), patient demographics, laboratories, and prior measures of disease activity. A longitudinal deep learning model was used to predict disease activity for patients with RA at their next rheumatology clinic visit and to evaluate interhospital performance and model interoperability strategies.

**MAIN OUTCOMES AND MEASURES** Model performance was quantified using the area under the

**Key Points**

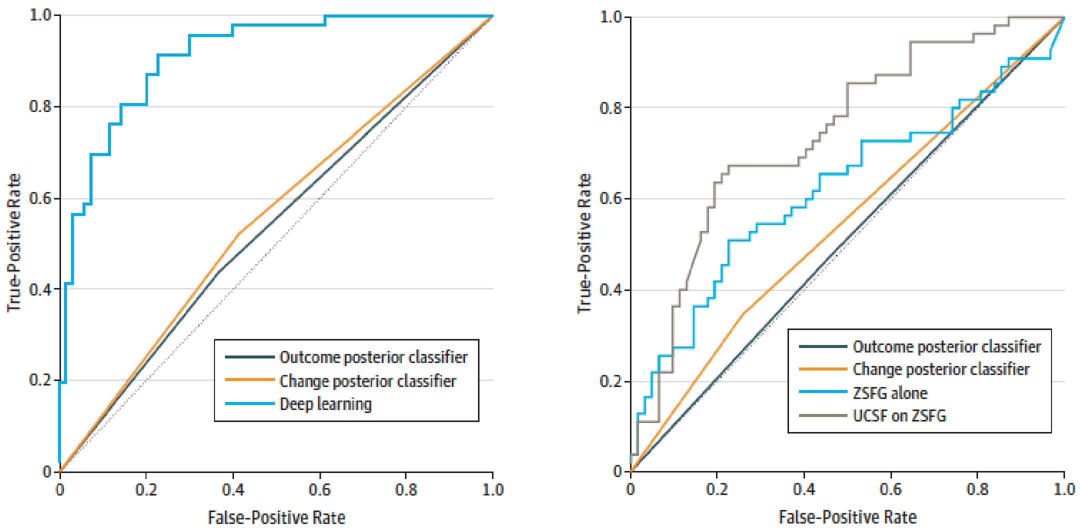
**Question** How accurately can artificial intelligence models prognosticate future patient outcomes for a complex disease, such as rheumatoid arthritis?

**Findings** In this prognostic study of 820 patients with rheumatoid arthritis, a longitudinal deep learning model had strong performance in a test cohort of 116 patients, whereas baselines that used each patient's most recent disease activity score had statistically random performance.

**Meaning** The findings suggest that building accurate models to forecast complex disease outcomes using electronic health records is possible.

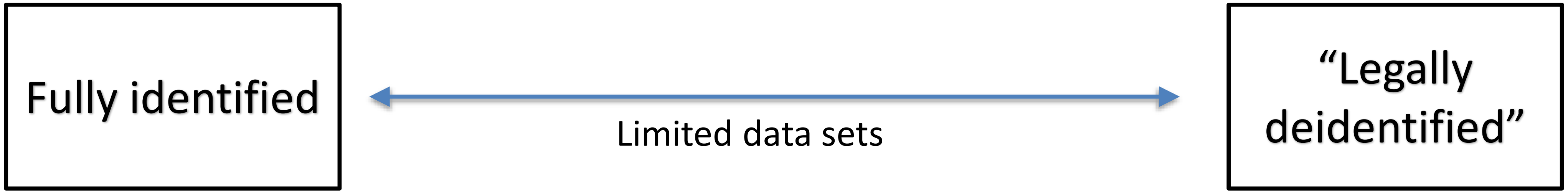
+ Supplemental content

Author affiliations and article information are listed at the end of this article.



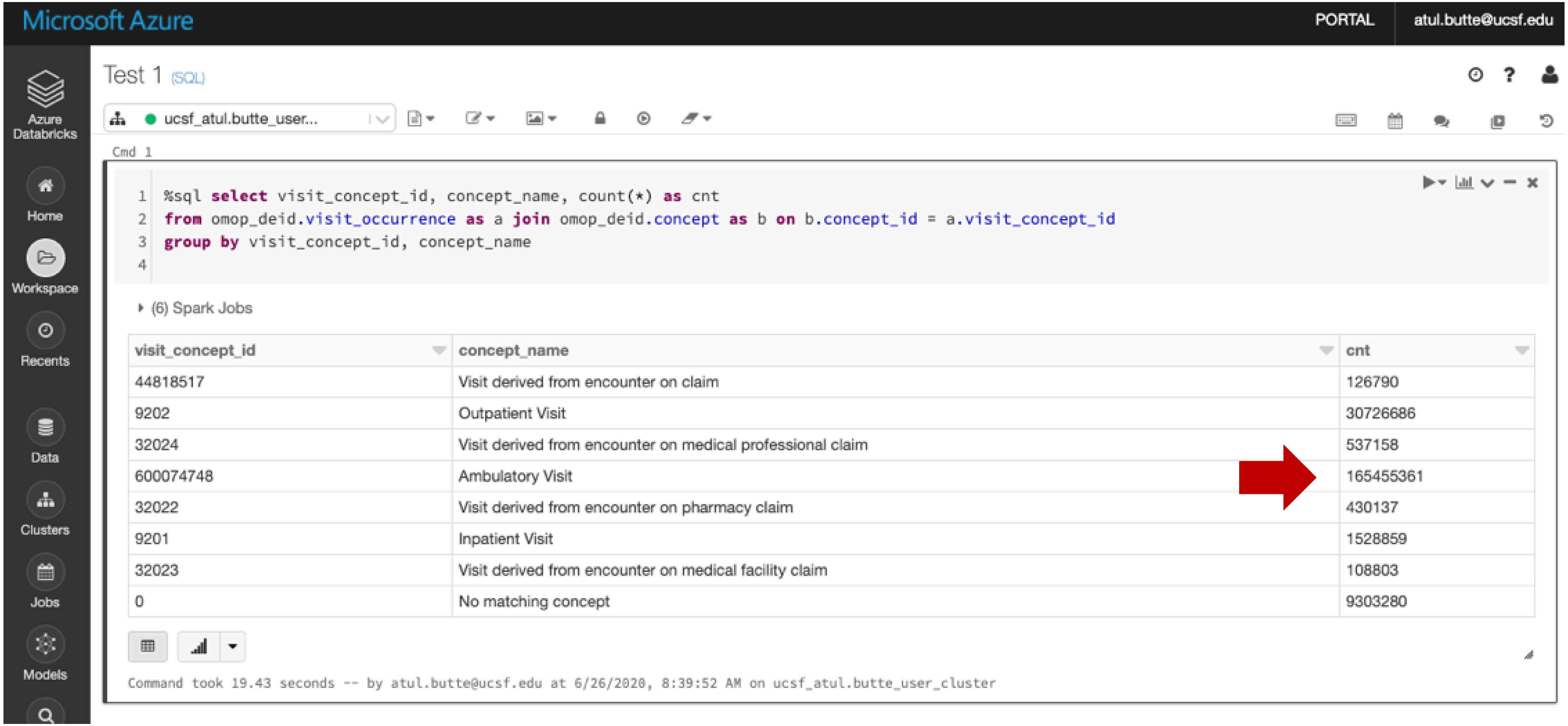

**Beau Norgeot**
**bit.ly/jamaRA**

# How will research access work?




- Researchers should first write and optimize OMOP SQL queries locally, on their own campuses
- When ready to scale (and authorized), we spin up a virtual machine for the researcher, populated with common tools
  - Electronically sign a UC Health data use agreement
  - R, Tableau, Jupyter Notebooks, Julia, SQL, Windows or Linux available
- Upload your scripts and run, but cannot download data
- Safe, respectful, regulated research use of clinical data

# Safe, Respectful access to Deidentified Data now available through Azure Databricks, single sign on




```sql
%sql select visit_concept_id, concept_name, count(*) as cnt
from omop_deid.visit_occurrence as a join omop_deid.concept as b on b.concept_id = a.visit_concept_id
group by visit_concept_id, concept_name
```

| visit_concept_id | concept_name | cnt |
|---|---|---|
| 44818517 | Visit derived from encounter on claim | 126790 |
| 9202 | Outpatient Visit | 30726686 |
| 32024 | Visit derived from encounter on medical professional claim | 537158 |
| 600074748 | Ambulatory Visit | 165455361 |
| 32022 | Visit derived from encounter on pharmacy claim | 430137 |
| 9201 | Inpatient Visit | 1528859 |
| 32023 | Visit derived from encounter on medical facility claim | 108803 |
| 0 | No matching concept | 9303280 |

Command took 19.43 seconds -- by atul.butte@ucsf.edu at 6/26/2020, 8:39:52 AM on ucsf_atul.butte_user_cluster


- 500 registered attendees, 90 posters
- All UC Campuses represented, and two of our national labs
- Sessions rated highly across the board
- Leadership session outcome:
  - ➢ Planning for a Multi-campus Research Unit
  - ➢ Annual meeting



# Enabling UC researchers and patients to go beyond… machine learning in a safe, respectful, fair, equitable way in medicine

npj | Digital Me

ARTICLE OPEN

Scalable and
records

Alvin Rajkomar[1,2], Eyal Oren[1], Kai Chen[1], Andrew M. Dai[1], Nissan Hajaj[1], Michaela Hardt[1], Peter J. Liu[1], Xiaobing Liu[1], Jake Marcus[1], Mimi Sun[1], Patrik Sundberg[1], Hector Yee[1], Kun Zhang[1], Yi Zhang[1], Gerardo Flores[1], Gavin E. Duggan[1], Jamie Irvine[1], Quoc Le[1], Kurt Litsch[1], Alexander Mossin[1], Justin Tansuwan[1], De Wang[1], James Wexler[1], Jimbo Wilson[1], Dana Ludwig[2], Samuel L. Volchenboum Katherine Chou[1], Michael Pearson[1], Srinivasan Madabushi[1], Nigam H. Shah[4], Atul J. Butte[2], Michael D. Howell[1], Claire Cui[1], Greg S. Corrado[1] and Jeffrey Dean[1]

Predictive modeling with electronic health record (EHR) data is anticipated to drive personalized medicine and improve healthcare quality. Constructing predictive statistical models typically requires extraction of curated predictor variables from normalized EHR data, a labor-intensive process that discards the vast majority of information in each patient's record. We propose a representation of patients' entire raw EHR records based on the Fast Healthcare Interoperability Resources (FHIR) format. We demonstrate that deep learning methods using this representation are capable of accurately predicting multiple medical events from multiple centers without site-specific data harmonization. We validated our approach using de-identified EHR data from two US academic medical centers with 216,221 adult patients hospitalized for at least 24 h. In the sequential format we propose, this volume of EHR data unrolled into a total of 46,864,534,945 data points, including clinical notes. Deep learning models achieved high accuracy for tasks such as predicting: in-hospital mortality (area under the receiver operator curve [AUROC] across sites 0.93–0.94), 30-day unplanned readmission (AUROC 0.75–0.76), prolonged length of stay (AUROC 0.85–0.86), and all of a patient's final discharge diagnoses (frequency-weighted AUROC 0.90). These models outperformed traditional, clinically-used predictive models in all cases. We believe that this approach can be used to create accurate and scalable predictions for a variety of clinical scenarios. In a case study of a particular prediction, we demonstrate that neural networks can be used to identify relevant information from the patient's chart.

*npj Digital Medicine* (2018)1:18 ; doi:10.1038/s41746-018-0029-1

INTRODUCTION

The promise of digital medicine stems in part from the hope that, by digitizing health data, we might more easily leverage computer information systems to understand and improve care. In fact, routinely collected patient healthcare data are now approaching the genomic scale in volume and complexity.[1] Unfortunately, most of this information is not yet used in the sorts of predictive statistical models clinicians might use to improve care delivery. It is widely suspected that use of such efforts, if successful, could provide major benefits not only for patient safety and quality but also in reducing healthcare costs.[2–6]

In spite of the richness and potential of available data, scaling the development of predictive models is difficult because, for traditional predictive modeling techniques, each outcome to be predicted requires the creation of a custom dataset with specific variables.[7] It is widely held that 80% of the effort in an analytic model is preprocessing, merging, customizing, and cleaning datasets,[8,9] not analyzing them for insights. This profoundly limits the scalability of predictive models.

Another challenge is that the number of potential predictor variables in the electronic health record (EHR) may easily number in the thousands, particularly if free-text notes from doctors,

nurses, and other providers are included. Traditional modelin
approaches have dealt with this complexity simply by choosing
very limited number of commonly collected variables to conside
This is problematic because the resulting models may produ
imprecise predictions: false-positive predictions can overwhel
physicians, nurses, and other providers with false alarms ar
concomitant alert fatigue,[10] which the Joint Commission identifie
as a national patient safety priority in 2014.[11] False-negativ
predictions can miss significant numbers of clinically importa
events, leading to poor clinical outcomes.[11,12] Incorporating th
entire EHR, including clinicians' free-text notes, offers some hop
of overcoming these shortcomings but is unwieldy for mo
predictive modeling techniques.

Recent developments in deep learning and artificial neur
networks may allow us to address many of these challenges ar
unlock the information in the EHR. Deep learning emerged as th
preferred machine learning approach in machine percepti
problems ranging from computer vision to speech recognitio
but has more recently proven useful in natural languag
processing, sequence prediction, and mixed modality da
settings.[13–17] These systems are known for their ability to hand
large volumes of relatively messy data, including errors in labe

[1]Google Inc, Mountain View, CA, USA; [2]University of California, San Francisco, San Francisco, CA, USA; [3]University of Chicago Medicine, Chicago, IL, USA and [4]Stanford Univers Stanford, CA, USA
Correspondence: Alvin Rajkomar (alvinrajkomar@google.com)
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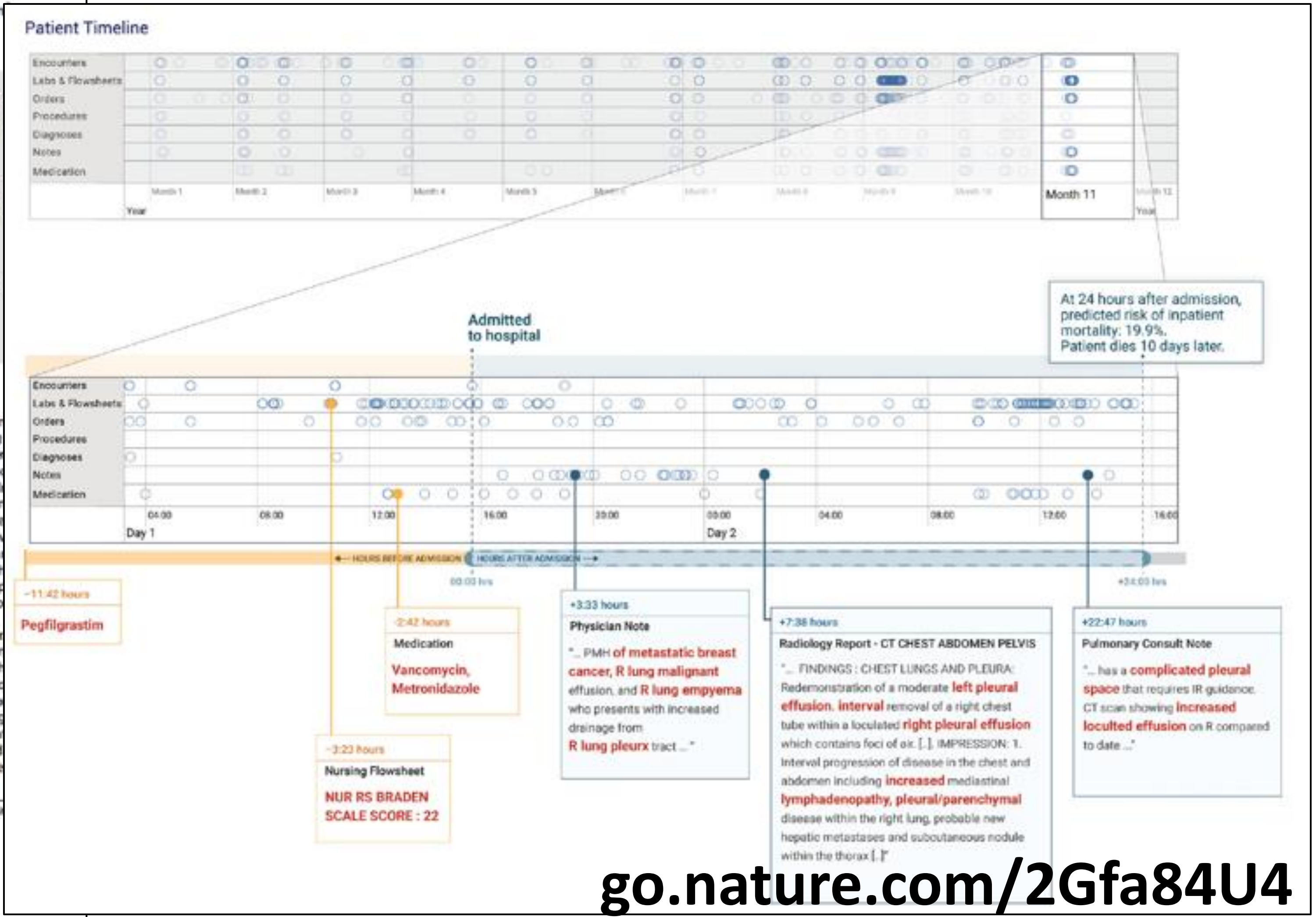
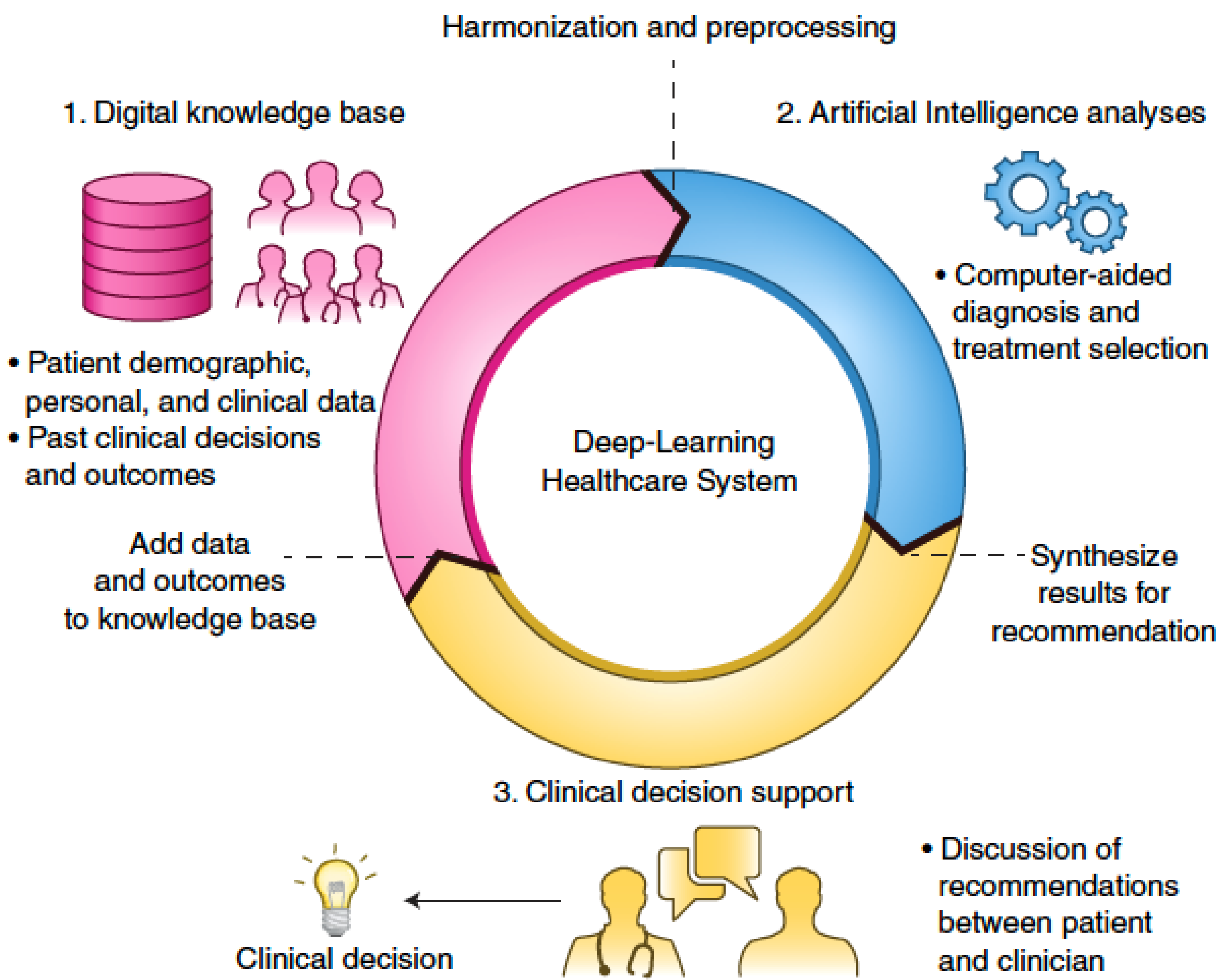



go.nature.com/2Gfa84U4

# A New Deep Learning Healthcare System




**Beau Norgeot**

bit.ly/DLHCare

# Must be aware of biases in training data and methods

MIT Technology Review

Artificial intelligence Oct 25

**A biased medical algorithm favored**
**people for health-care programs**

A study has highlighted the risks inherent in using historical dat
learning algorithms to make predictions.

**The news:** An algorithm that many US health providers use to
will most need extra medical care privileged white patients ove
according to researchers at UC Berkeley, whose study was pu
Effectively, it bumped whites up the queue for special treatments for complex
conditions like kidney problems or diabetes.

**The study:** The researchers dug through almost 50,000 records from a large,
undisclosed academic hospital. They found that white patients were given hig

## How Biased is GPT-3?

Despite its impressive performance, the world's newest language model reflects societal biases in gender, race, and religion

Catherine Yeo Follow
Jun 3 · 4 min read ★

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Its release w
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NEWS · 24 JANUARY 2020

## The battle for ethical AI at the world's biggest machine-learning conference

Bias and the prospect of societal harm increasingly plague artificial-intelligence research – but it's not clear who should be on the lookout for these problems.

Elizabeth Gibney

PDF version

RELATED ARTICLES

How one conference embraced diversity

Can a major AI conference shed its reputation for hosting sexist behaviour?

Bias detectives: the researchers striving to make

# We need more transparency in developed and published models

Check for updates

# Minimum information about clinical artificial intelligence modeling: the MI-CLAIM checklist

Here we present the MI-CLAIM checklist, a tool intended to improve transparent reporting of AI algorithms in medicine.

Beau Norgeot, Giorgio Quer, Brett K. Beaulieu-Jones, Ali Torkamani, Raquel Dias, Milena Gianfrancesco, Rima Arnaout, Isaac S. Kohane, Suchi Saria, Eric Topol, Ziad Obermeyer, Bin Yu and Atul J. Butte

The application of artificial intelligence (AI) in medicine is an old idea[1–3], but methods for this in the past involved programming computers with patterns or rules ascertained from human experts, which resulted in deterministic, rules-based systems. The study of AI in medicine has grown tremendously in the past few years due to increasingly available datasets from medical practice, including clinical images, genetics, and electronic health records, as well as the maturity of methods that use data to teach computers[4–6]. The use of data labeled by clinical experts to train machine, probabilistic, and statistical models is called 'supervised machine learning'. Successful uses of these new machine-learning approaches include targeted real-time early-warning systems for adverse events[7], the detection of diabetic retinopathy[8], the classification of pathology and other images, the prediction of the near-term future state of patients with rheumatoid arthritis[9], patient discharge disposition[10], and more.



Beau Norgeot

go.nature.com/36Y8bGW

| Before paper submission | | |
|---|---|---|
| **Study design (Part 1)** | **Completed: page number** | **Notes if not completed** |
| The clinical problem in which the model will be employed is clearly detailed in the paper. | ☐ | |
| The research question is clearly stated. | ☐ | |
| The characteristics of the cohorts (training and test sets) are detailed in the text. | ☐ | |
| The cohorts (training and test sets) are shown to be representative of real-world clinical settings. | ☐ | |
| The state-of-the-art solution used as a baseline for comparison has been identified and detailed. | ☐ | |
| **Data and optimization (Parts 2, 3)** | **Completed: page number** | **Notes if not completed** |
| The origin of the data is described and the original format is detailed in the paper. | ☐ | |
| Transformations of the data before it is applied to the proposed model are described. | ☐ | |
| The independence between training and test sets has been proven in the paper. | ☐ | |
| Details on the models that were evaluated and the code developed to select the best model are provided. | ☐ | |
| Is the input data type structured or unstructured? | ☐ Structured ☐ Unstructured | |
| **Model performance (Part 4)** | **Completed: page number** | **Notes if not completed** |
| The primary metric selected to evaluate algorithm performance (e.g., AUC, F-score, etc.), including the justification for selection, has been clearly stated. | ☐ | |
| The primary metric selected to evaluate the clinical utility of the model (e.g., PPV, NNT, etc.), including the justification for selection, has been clearly stated. | ☐ | |
| The performance comparison between baseline and proposed model is presented with the appropriate statistical significance. | ☐ | |
| **Model examination (Part 5)** | **Completed: page number** | **Notes if not completed** |
| Examination technique 1[a] | ☐ | |
| Examination technique 2[a] | ☐ | |
| A discussion of the relevance of the examination results with respect to model/algorithm performance is presented. | ☐ | |
| A discussion of the feasibility and significance of model interpretability at the case level if examination methods are uninterpretable is presented. | ☐ | |
| A discussion of the reliability and robustness of the model as the underlying data distribution shifts is included. | ☐ | |
| **Reproducibility (Part 6): choose appropriate tier of transparency** | | **Notes** |
| Tier 1: complete sharing of the code | ☐ | |
| Tier 2: allow a third party to evaluate the code for accuracy/fairness; share the results of this evaluation | ☐ | |
| Tier 3: release of a virtual machine (binary) for running the code on new data without sharing its details | ☐ | |
| Tier 4: no sharing | ☐ | |

PPV, positive predictive value; NNT, numbers needed to treat.

[a]Common examination approaches based on study type: for studies involving exclusively structured data, coefficients and sensitivity analysis are often appropriate; for studies involving unstructured data in the domains of image analysis or natural language processing, saliency maps (or equivalents) and sensitivity analyses are often appropriate.

**Beau Norgeot**

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VIEWPOINT

# The Case for Algorithmic Stewardship for Artificial Intelligence and Machine Learning Technologies

**Stephanie Eaneff, MSP**
Berkeley Institute for Data Science, University of California, Berkeley; and Bakar Computational Health Sciences Institute, University of California, San Francisco.

**Ziad Obermeyer, MD**
University of California, Berkeley School of Public Health.

**Atul J. Butte, MD, PhD**
Bakar Computational Health Sciences Institute, University of California, San Francisco; and Center for Data-Driven Insights and Innovation, University of California Health, Oakland.

The first manual on hospital administration, published in 1808, described a hospital steward as "an individual who [is] honest and above reproach," with duties including the purchasing and management of hospital materials.[1] Today, a steward's job can be seen as ensuring the safe and effective use of clinical resources. The Joint Commission, for instance, requires antimicrobial stewardship programs to support appropriate antimicrobial use, including by monitoring antibiotic prescribing and resistance patterns.

A similar approach to "algorithmic stewardship" is now warranted. Algorithms, or computer-implementable instructions to perform specific tasks, are available for clinical use, including complex artificial intelligence (AI) and machine learning (ML) algorithms and simple rule-based algorithms. More than 50 AI/ML algorithms have been cleared by the US Food and Drug Administration[2] for uses that include identifying intracranial hemorrhage from brain computed tomographic scans[3] and detecting seizures in real time.[4] Algorithms are also used to inform clinical operations, such as predicting which patients will health systems must also develop oversight frameworks to ensure that algorithms are used safely, effectively, and fairly. Such efforts should focus particularly on complex and predictive algorithms that necessitate additional layers of quality control. Health systems that use predictive algorithms to provide clinical care or support operations should designate a person or group responsible for algorithmic stewardship. This group should be advised by clinicians who are familiar with the language of data, patients, bioethicists, scientists, and safety and regulatory organizations. In this Viewpoint, drawing from best practices from other areas of clinical practice, several key considerations for emerging algorithmic stewardship programs are identified.

## Create and Maintain an Algorithm Inventory

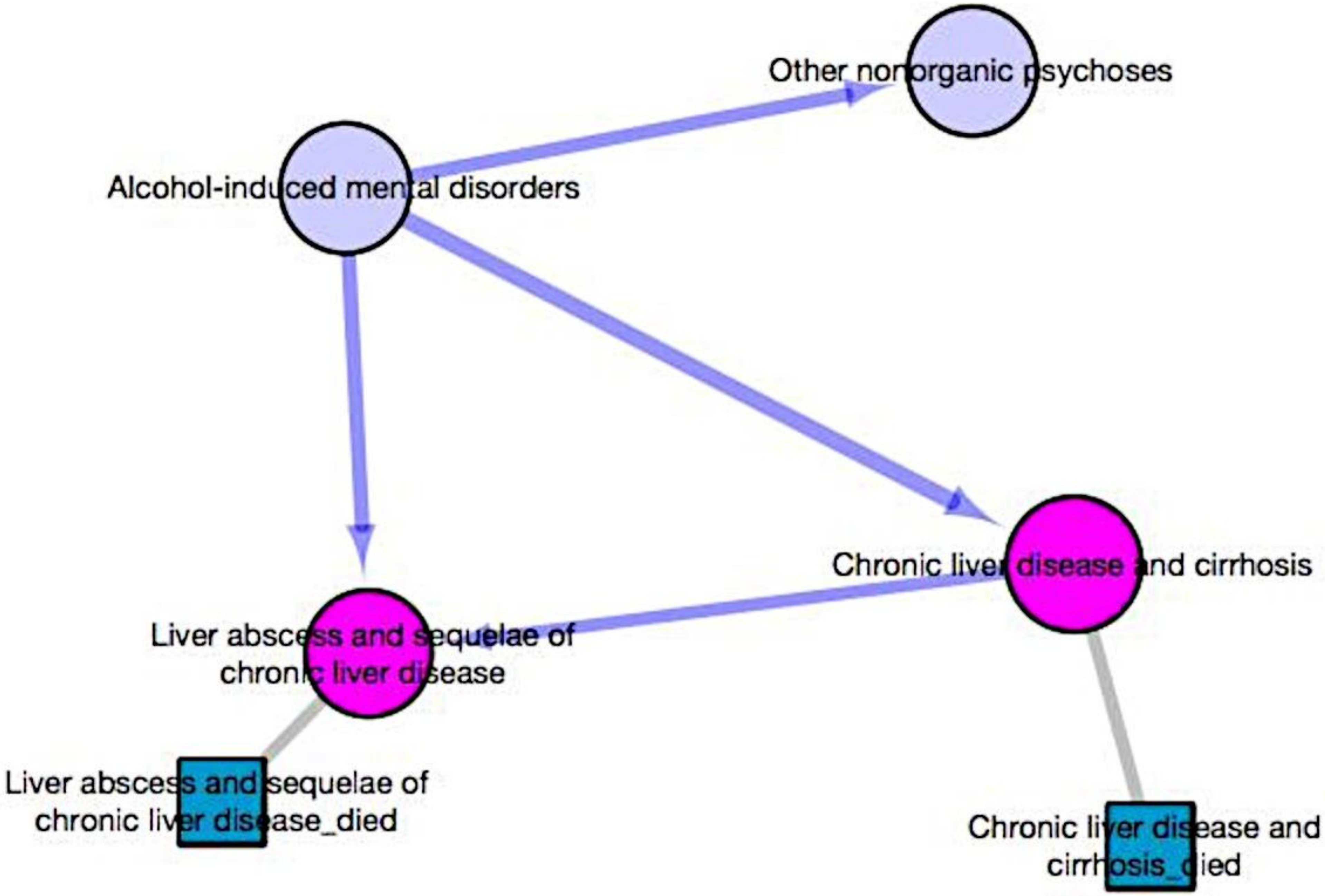
Health systems should inventory all predictive algorithms currently in use, with a particular emphasis on understanding the exact outcome being predicted and the decisions made on the basis of those predictions. This is particularly important because recent work has shown that algorithms can reach enormous scale

**Stephanie Eaneff**
**bit.ly/algostew**

## Figure. Existing and Proposed Processes and Tools to Ensure Appropriate Use of Drugs for Algorithmic Stewardship Efforts

| | Existing processes and tools | Proposed processes and tools for algorithmic stewardship |
|---|---|---|
| 1 Clinical trials | Phase 1, 2, and 3 trials | Assess safety, efficacy, and fairness (potentially via clinical trials) |
| 2 Scale-up and early adoption | Hospital formulary | Algorithm inventory |
| 3 Postmarket use and evaluation | Medication use evaluations | Algorithm use evaluations |
| 4 Ongoing oversight | Antimicrobial steward role | Algorithmic steward role |

Stephanie Eaneff
bit.ly/algostew

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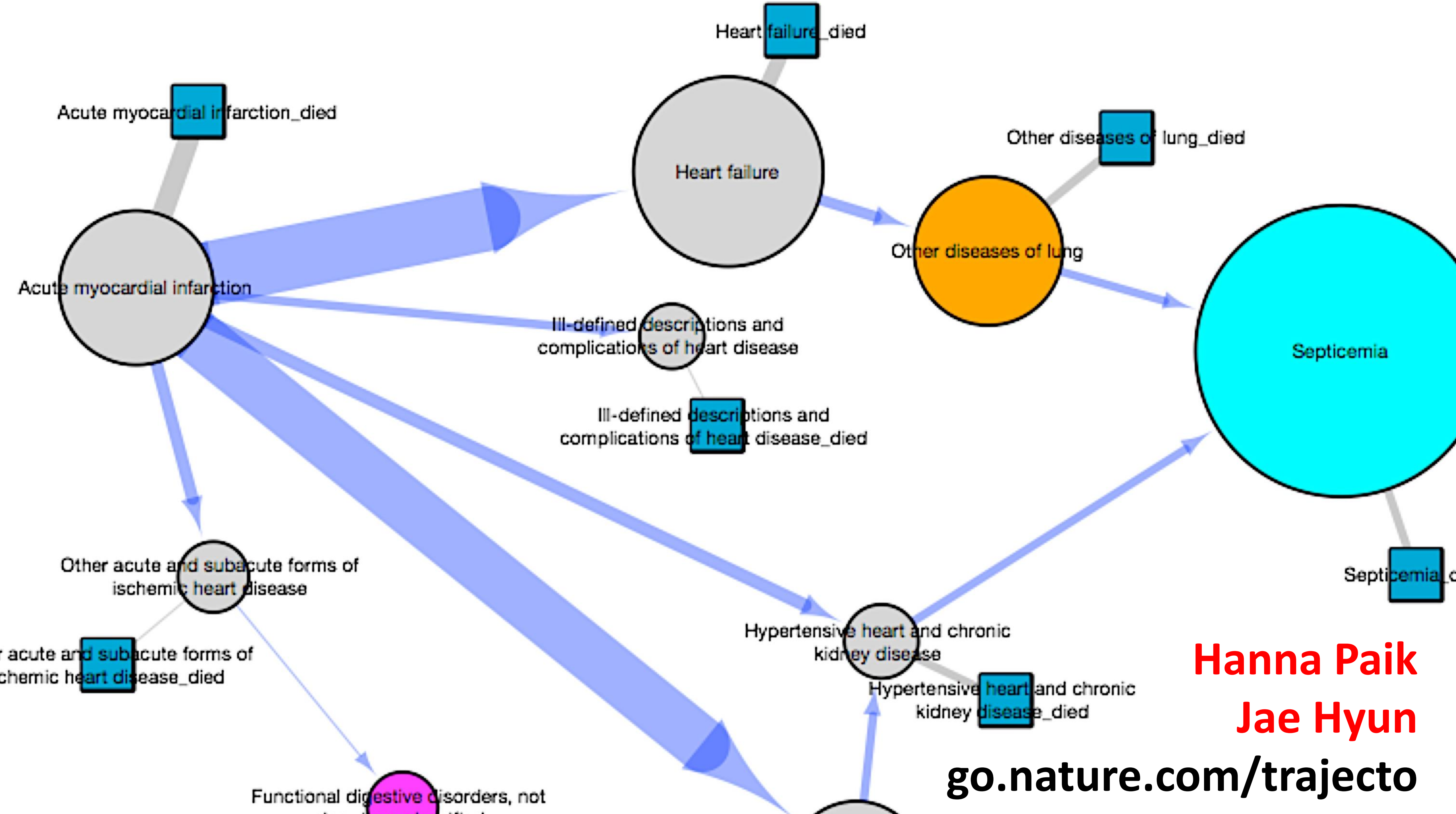


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Mean Age = 48

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