BIG DATA AND THE FUTURE OF CV MEDICINE

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Inova

April 27th, 2019

CONFLICTS OF INTEREST

- Employment
  - Duke University
  - Verily Life Sciences
- Corporate Board
  - Cytokinetics
- Consulting
  - Merck
  - Boeringer Ingelhheim
  - Amgen
  - Biogen
  - Genentech

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Alphabet

verily

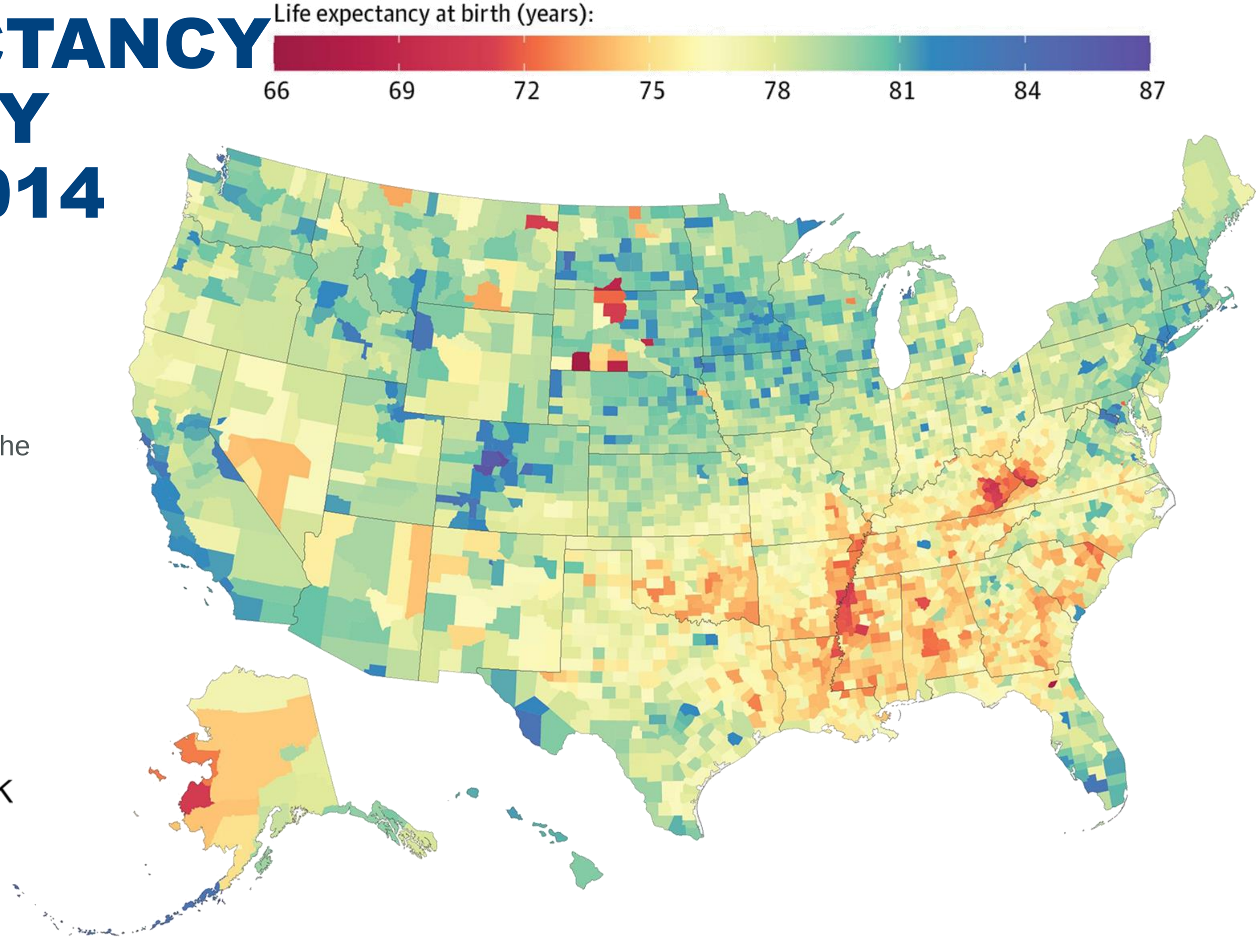
Verily partners closely with Google teams on commercial tools and applications across the healthcare vertical.

- User experience
- Science
- Holistic health platforms
- Tools and medical Devices
- Regulatory expertise
- Software and machine learning

Google

- Google Cloud Platform
- Search, Advertising & Maps
- DeepMind
- YouTube
- Research
- Android

LIFE EXPECTANCY AT BIRTH BY COUNTY, 2014



- Counties in South Dakota and North Dakota had the lowest life expectancy, and counties along the lower half of the Mississippi, in eastern Kentucky, and southwestern West Virginia also had very low life expectancy compared with the rest of the country. Counties in central Colorado had the highest life expectancies.

The JAMA Network

Dwyer-Lindgren L, et al. Inequalities in life expectancy among US counties, 1980 to 2014 - temporal trends and key drivers. JAMA Intern Med. 2017;177:1003-11. doi:10.1001/jamainternmed.2017.0918

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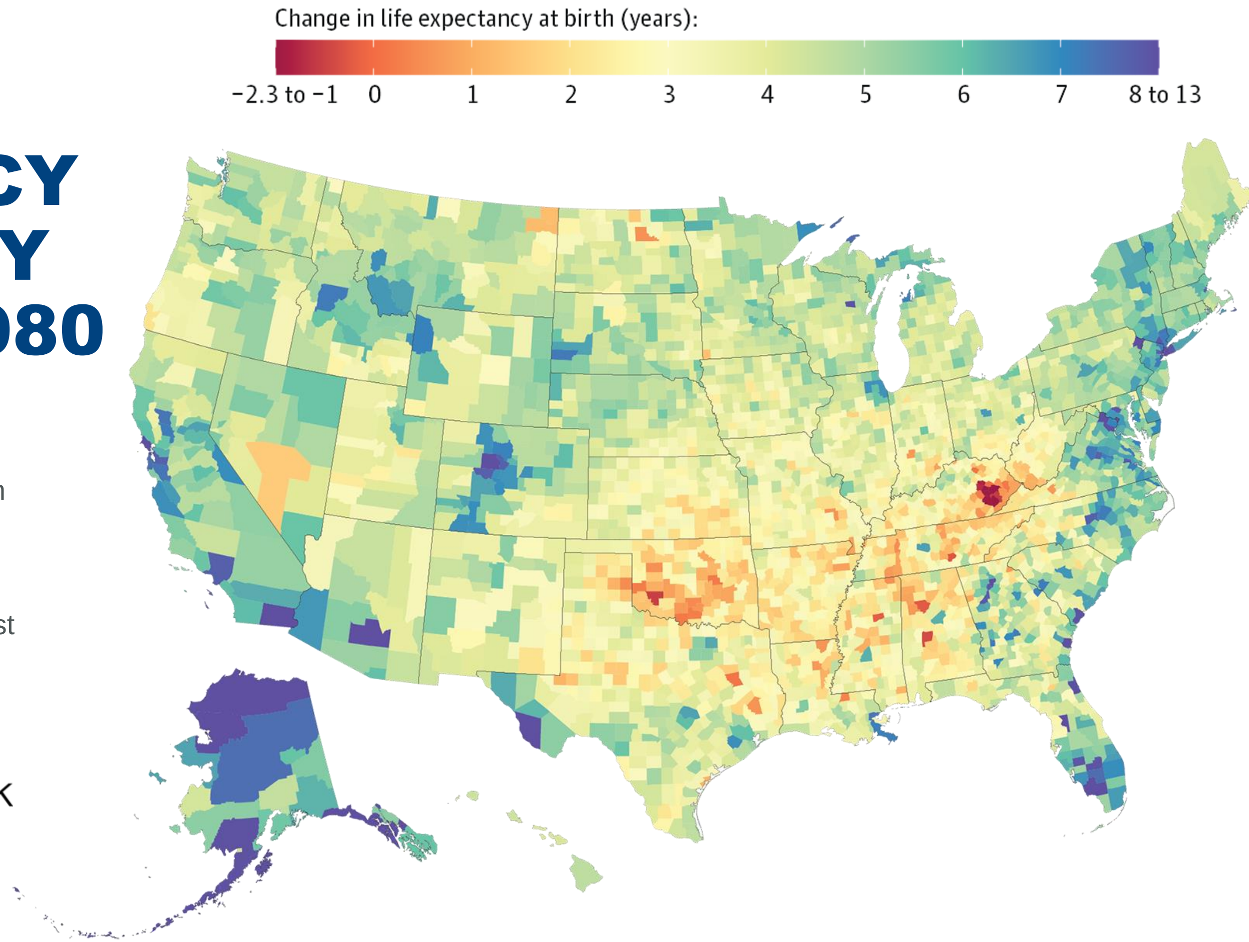
CHANGE IN LIFE EXPECTANCY AT BIRTH BY COUNTY, 1980 TO 2014

- Compared with the national average, counties in central Colorado, Alaska, and along both coasts experienced larger increases in life expectancy between 1980 and 2014, while some southern counties in states stretching from Oklahoma to West Virginia saw little, if any, improvement over this same period.

The JAMA Network



Dwyer-Lindgren L, et al. Inequalities in life expectancy among US counties, 1980 to 2014 - temporal trends and key drivers. JAMA Intern Med. 2017;177:1003-11. doi:10.1001/jamainternmed.2017.0918

From: **Inequalities in Life Expectancy Among US Counties, 1980 to 2014Temporal Trends and Key Drivers**

JAMA Intern Med. Published online May 08, 2017. doi:10.1001/jamainternmed.2017.0918

Table 1. Variables Included in the Regression Analysis With Summary Statistics and Bivariate Regression Results

Variable	Summary Statistics, Mean (SD) [Range]	Bivariate Regression Results	
		Coefficient (SE)	R^2
Socioeconomic and race/Ethnicity factors			
Population below the poverty line, %	16.3 (6.4) [3.1-62.0]	−0.24 (0.005)	0.47
Median household income, log $	10.6 (0.2) [9.8-11.6]	6.06 (0.130)	0.41
Graduates, age ≥25 y, %			
High school	83.7 (7.2) [46.3-98.6]	0.20 (0.004)	0.42
College	19.2 (8.6) [4.2-72.0]	0.15 (0.004)	0.34
Unemployment rate, age ≥16 y, %	9.1 (3.2) [2.1-27.4]	−0.29 (0.011)	0.18
Black population, %	9.4 (14.7) [0-85.8]	−0.07 (0.002)	0.24
American Indian, Native Alaskan, and Native Hawaiian population, %	2.3 (7.9) [0-97.2]	−0.06 (0.005)	0.04
Hispanic population, %	8.1 (13.1) [0-95.9]	0.02 (0.003)	0.01
Behavioral and metabolic risk factors, %			
Obesity prevalence, age ≥20 y	37.0 (4.3) [18.0-52.0]	−0.39 (0.006)	0.54
No leisure-time physical activity prevalence, age ≥20 y	27.0 (5.2) [11.7-47.2]	−0.34 (0.005)	0.62
Cigarette smoking prevalence, age ≥18 y	24.7 (4.1) [7.7-42.1]	−0.40 (0.007)	0.54
Hypertension prevalence, age ≥30 y	39.5 (3.6) [27.9-56.4]	−0.49 (0.007)	0.62
Diabetes prevalence, age ≥20 y	14.0 (2.4) [8.1-25.5]	−0.72 (0.011)	0.59
Health care factors			
Insured population, age <65 y, %	81.7 (5.7) [57.3-96.7]	0.15 (0.007)	0.14
Quality index	70.1 (11.5) [0-100]	0.10 (0.003)	0.28
Physicians per 1000 population, No.	1.1 (1.0) [0-4.4]	0.53 (0.039)	0.06

Abbreviation: SE, standard error.

Table Title:

Variables Included in the Regression Analysis With Summary Statistics and Bivariate Regression Results

From: **Trends and Patterns of Geographic Variation in Cardiovascular Mortality Among US Counties, 1980-2014**

JAMA. 2017;317(19):1976-1992. doi:10.1001/jama.2017.4150

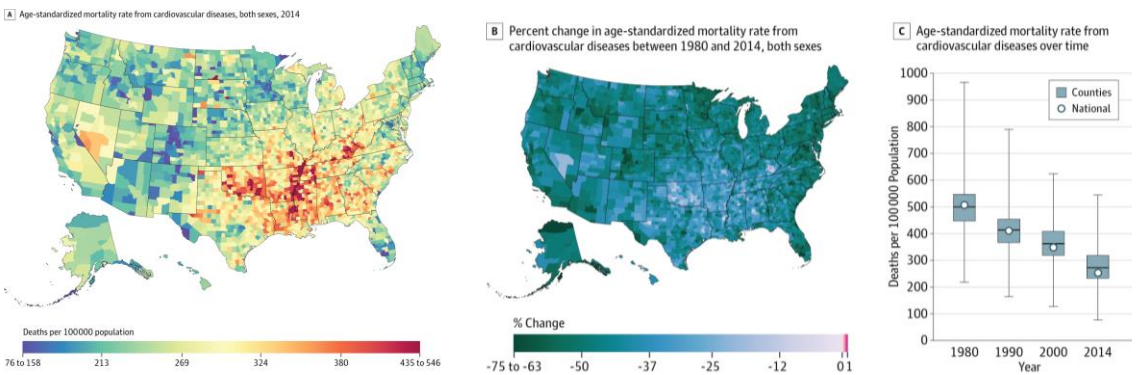


Figure Legend:

US County-Level Mortality From Cardiovascular DiseasesA, Age-standardized mortality rate for both sexes combined in 2014. B, Percent change in the age-standardized mortality rate for both sexes combined between 1980 and 2014. In panel A, the color scale is truncated at approximately the 1st and 99th percentiles as indicated by the range given on the scale. In panel B, the color scale is similarly truncated at the 1st percentile but not at the 99th percentile to avoid combining counties with decreases in the mortality rate and counties with increases in the mortality rate into a single group. C, Age-standardized mortality rate in 1980, 1990, 2000, and 2014. The bottom border, middle line, and top border of the boxes indicate the 25th, 50th, and 75th percentiles, respectively, across all counties; whiskers, the full range across counties; and circles, the national-level rate.

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Top 25 Causes of Disability-Adjusted Life-Years (DALYs) and % Change in Number of DALYs, All-Age DALYs, and Age-Standardized DALYs, 1990-2016

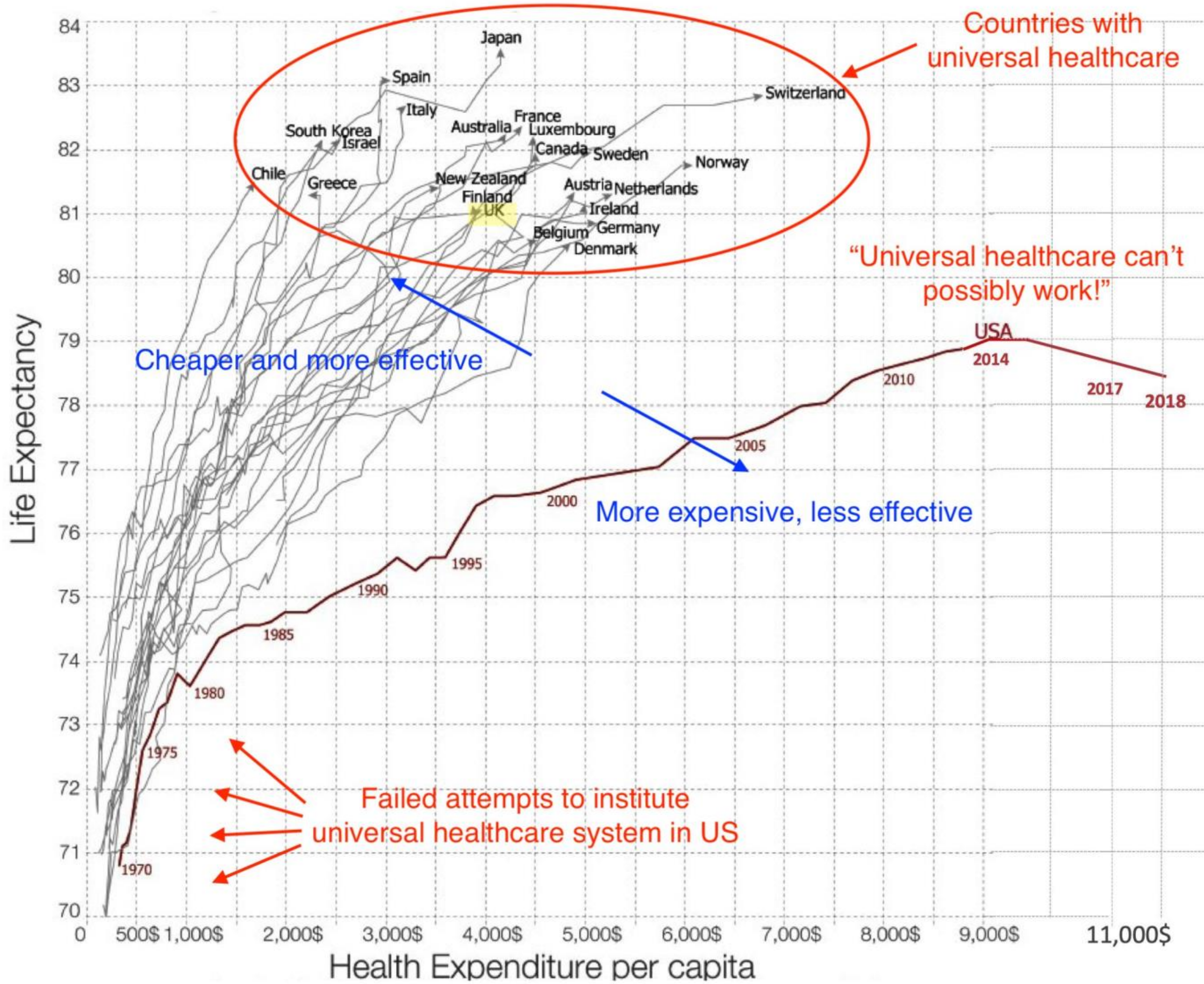
Dotted lines: leading cause decreased in rank between 1990-2016; solid lines: cause maintained/ascended to higher ranking.

Leading causes of DALYs, 1990	Leading causes of DALYs, 2016	Mean % Change (95% Uncertainty Interval), 1990-2016: No. of DALYs	All-Age DALY Rate	Age-Standardized DALY Rate
1 Ischemic heart disease	1 Ischemic heart disease	-18.3 (-20.5 to -16.1)	-36.7 (-38.4 to -35.0)	-49.7 (-51.1 to -48.3)
2 Lung cancer[a]	2 Lung cancer[a]	14.1 (10.7 to 17.7)	-11.6 (-14.2 to -8.8)	-32.5 (-34.5 to -30.4)
3 Low back pain	3 COPD	71.7 (66.2 to 78.7)	33.1 (28.8 to 38.5)	5.5 (2.2 to 9.7)
4 COPD	4 Diabetes	75.6 (67.1 to 83.9)	36.1 (29.5 to 42.5)	11.0 (5.7 to 16.2)
5 Motor vehicle road injury	5 Low back pain	25.1 (10.9 to 39.6)	-3.1 (-14.1 to 8.2)	-12.1 (-22.3 to -1.9)
6 Diabetes	6 Alzheimer disease	75.7 (63.4 to 88.2)	36.1 (26.6 to 45.8)	4.0 (-2.5 to 10.8)
7 Major depression	7 Opioid use disorders	74.5 (42.8 to 93.8)	35.2 (10.6 to 50.1)	47.9 (21.8 to 64.1)
8 Other musculoskeletal	8 Other musculoskeletal	32.2 (23.2 to 41.5)	2.4 (-4.6 to 9.6)	-2.6 (-9.0 to 3.6)
9 Migraine	9 Major depression	27.1 (21.6 to 32.7)	-1.5 (-5.8 to 2.8)	0.1 (-4.1 to 3.7)
10 Ischemic stroke	10 Migraine	27.2 (25.3 to 29.1)	-1.4 (-3.0 to 0.0)	-1.4 (-2.8 to -0.1)
11 Opioid use disorders	11 Neck pain	55.3 (39.2 to 73.3)	20.3 (7.8 to 34.2)	3.3 (-7.5 to 15.0)
12 Alzheimer disease	12 Ischemic stroke	26.3 (21.3 to 31.1)	-2.2 (-6.0 to 1.6)	-22.4 (-25.5 to -19.4)
13 HIV/AIDS other[b]	13 Falls	87.5 (68.4 to 97.5)	45.3 (30.5 to 53.0)	19.0 (8.5 to 24.5)
14 Anxiety disorders	14 Anxiety disorders	30.8 (25.7 to 36.0)	1.4 (-2.6 to 5.4)	0.6 (-3.2 to 4.5)
15 Neonatal preterm birth	15 Motor vehicle road injury	-16.5 (-20.3 to -12.2)	-35.3 (-38.3 to -31.9)	-35.0 (-37.7 to -31.8)
16 Colorectal cancer	16 Age-related hearing loss	72.5 (67.3 to 78.3)	33.6 (29.6 to 38.1)	9.8 (6.6 to 13.4)
17 Neck pain	17 Colorectal cancer	16.6 (12.4 to 20.9)	-9.7 (-12.9 to -6.3)	-27.4 (-29.9 to -24.7)
18 Breast cancer	18 Lower respiratory infection	27.7 (21.8 to 33.7)	-1.0 (-5.6 to 3.5)	-18.8 (-22.3 to -15.2)
19 Lower respiratory infection	19 Intracerebral hemorrhage	31.6 (26.1 to 36.4)	2.0 (-2.3 to 5.6)	-17.0 (-20.4 to -14.1)
20 Intracerebral hemorrhage	20 Breast cancer	6.1 (1.3 to 11.4)	-17.8 (-21.5 to -13.7)	-34.3 (-37.3 to -31.1)
21 Falls	21 Diabetes CKD[c]	127.6 (118.7 to 136.8)	76.3 (69.5 to 83.5)	44.3 (39.5 to 49.5)
22 Age-related hearing loss	22 Self-harm by other means	49.2 (23.3 to 58.9)	15.6 (-4.5 to 23.1)	20.3 (-0.5 to 28.0)
23 Acne vulgaris	23 Alcohol use disorders	30.8 (22.3 to 39.5)	1.3 (-5.2 to 8.1)	-0.2 (-5.8 to 5.7)
24 Self-harm by firearm	24 Osteoarthritis	75.3 (68.5 to 82.6)	35.8 (30.5 to 41.5)	8.0 (3.7 to 12.5)
25 Violence by firearm	25 Acne vulgaris	16.0 (14.3 to 17.8)	-10.1 (-11.4 to -8.7)	-1.5 (-3.0 to 0.2)
26 Alcohol use disorders	26 Neonatal preterm birth			
28 Self-harm by other means	28 Self-harm by firearm			
31 Osteoarthritis	37 Violence by firearm			
38 Diabetes CKD[c]	51 HIV/AIDS other[b]			

- Communicable, maternal, neonatal, and nutritional diseases
- Noncommunicable diseases
- Injuries

Life expectancy at birth (years) in 18 high income countries for women and men during 2010-16 and 1990-2015.

Jessica Y Ho, and Arun S Hendi BMJ 2018;362:bmj.k2562

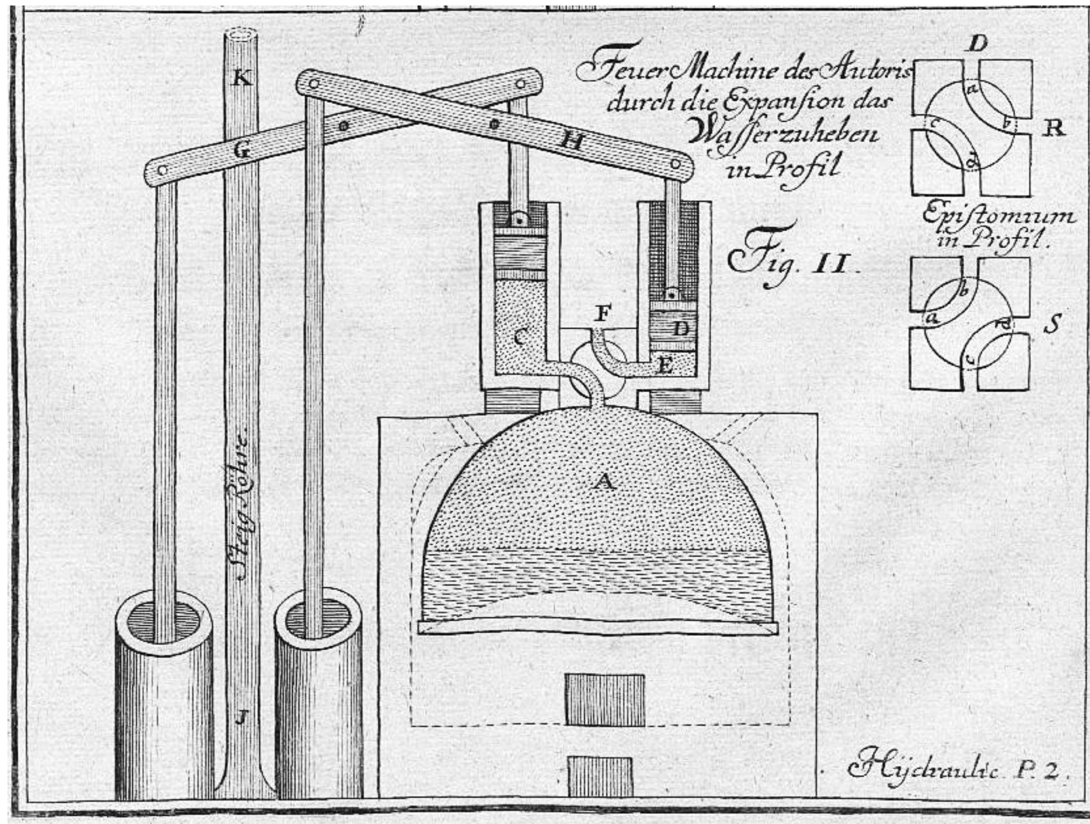


Countries with universal healthcare
Japan
Spain
Italy
Switzerland
South Korea
Israel
Australia
France
Luxembourg
Canada
Sweden
Norway
Chile
Greece
New Zealand
Finland
UK
Austria
Netherlands
Ireland
Germany
Belgium
Denmark
"Universal healthcare can't possibly work!"
USA
2014
2010
2017
2018
2005
2000
1995
1990
1985
1980
1975
1970
Cheaper and more effective
More expensive, less effective
Failed attempts to institute universal healthcare system in US
Life Expectancy
Health Expenditure per capita
84
83
82
81
80
79
78
77
76
75
74
73
72
71
70
0
500$
1,000$
2,000$
3,000$
4,000$
5,000$
6,000$
7,000$
8,000$
9,000$
11,000$

Four industrial revolutions

FIRST

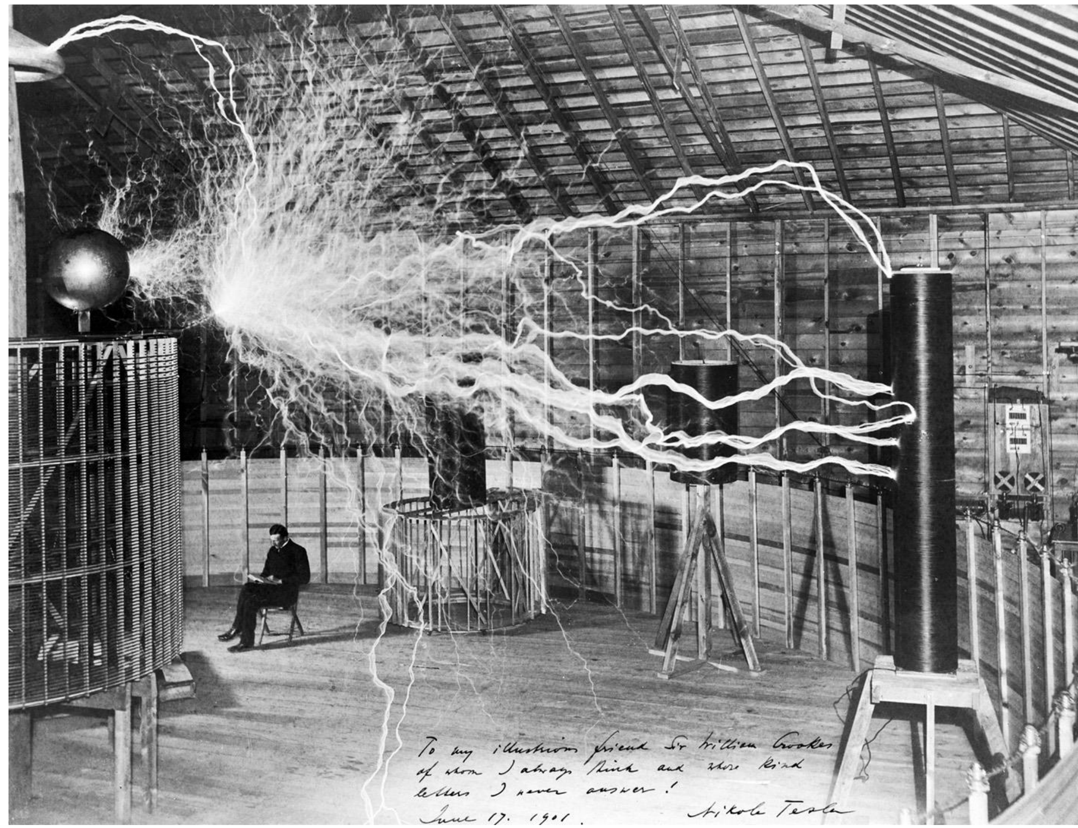
Water and steam power mechanize production.



Jacob Leupold, Steam Engine, in *Theatri Machinarum Hydraulicarum II* (1720)

Four industrial revolutions

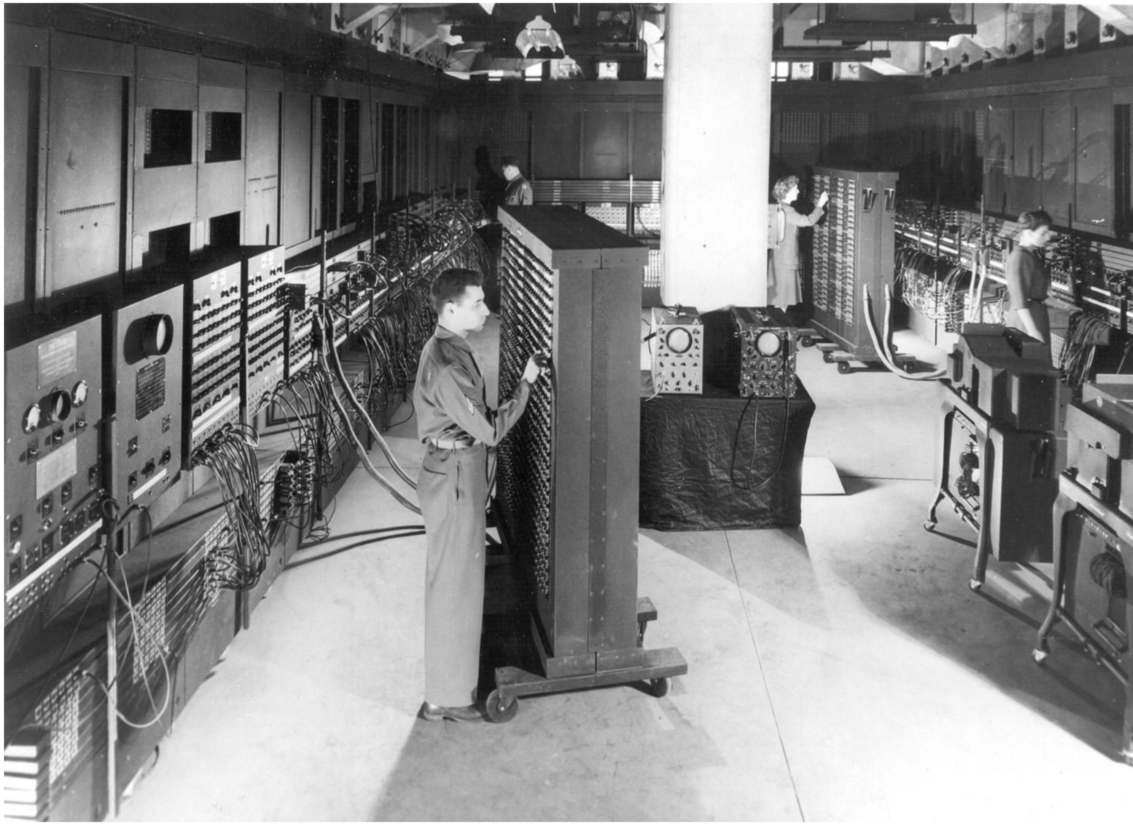
SECOND
Electric power creates mass production.



Four industrial revolutions

3

THIRD
Electronics and information technology automate production.

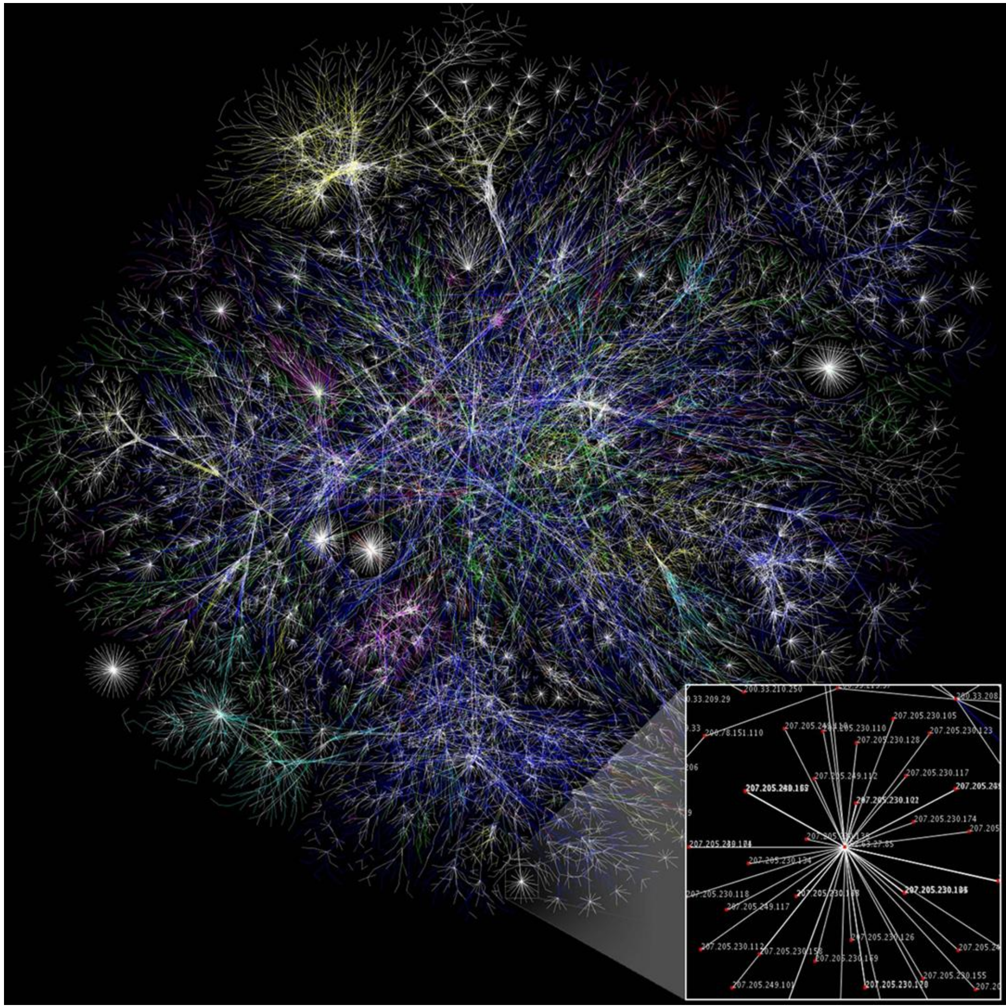


ENIAC digital computer. Unidentified U.S. Army photographer. Public Domain, https://commons.wikimedia.org/w/index.php?curid=978770

Four industrial revolutions

FOURTH

The digital revolution—characterized by a fusion of technologies—blurs the lines between physical, digital, and biological spheres.



Opte Project. Internet map. https://commons.wikimedia.org/wiki/File:Internet_map_1024.jpg

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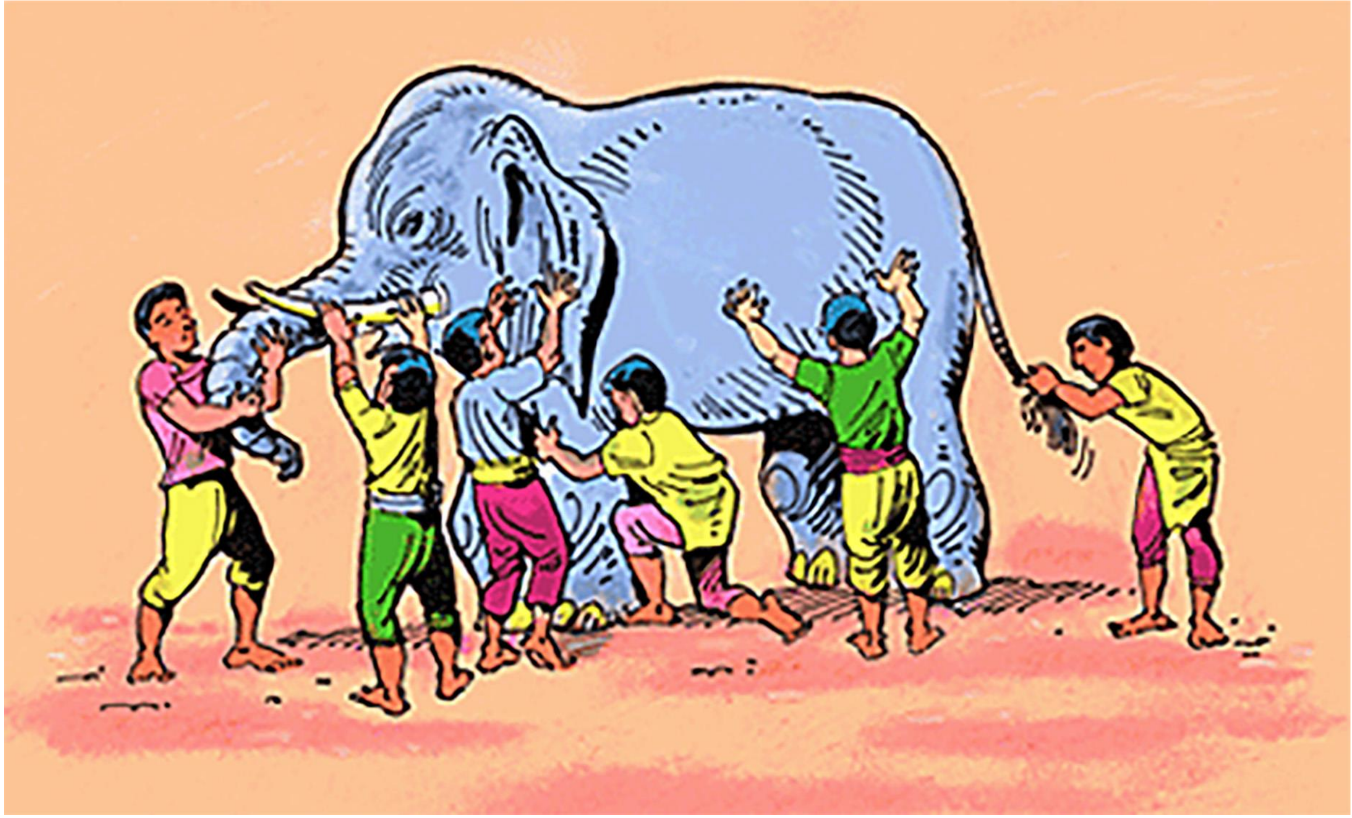
HISTORY OF DIGITAL DISRUPTION

Company /Industry	Core Business	Transformational Change	Digital Disruption Enhance Existing Income Model?	Successful Internal Transformation?	Digital Disrupter
Kodak	Photographic Film & Paper	Digital Photography	**NO**	**X**	SAMSUNG MOTOROLA SHARP SONY
BARNES & NOBLE	Selling Books from Stores	Online Book Orders	**NO**	**X**	amazon.com
CHEMICAL BANK	Lending Money	ATMs and Online Banking	**YES**	✓	All Modern Banks
BLOCKBUSTER VIDEO	Video Rental	Digital Streaming	**NO**	**X**	NETFLIX
	Fee-for-Service Health Care	Value-based, Digitally Enabled Medicine	**NO**	**?**	**?**
	Sell more drugs at higher prices	Value based reimbursement	**NO**	**?**	**?**

Qualities of the New Data Environment

- **Volume**
  - New methods of data storage allow access to huge amounts of data
- **Ubiquity/Liquidity**
  - Data are available anywhere across geography, social and economic classes
- **Latency**
  - There is no delay in access to data inherent in the technology
- **Analysis**
  - Data, information, knowledge, wisdom continuum is being shifted to the right




"To learn the truth, we must put all the parts together."

16.3M results

in 0.57 second

The cost of a smartphone in 1985: $32M

today
$250
(with contract)

Mobile Phone $9,000 (DynaTAC)	**Text Messaging** $1,105 (fax machine)	**GPS** $6,630 (Magellan GPS)	**Voice Recorder** $110 (Realistic CTA)
Digital Watch $45 (Casio DBC)	**Music Player** $400 (Sony Discman)	**Video Camera** $3,745 (Sony V8)	**Video Player** $1,105 (Sony VCR)
Encyclopedia $2,200 (Encyclopedia)	**Processor** $32M (Cray)	**Portable TV** $665 (Casio Mini TV)	**Video Conference** $110,520 (Future Sys)

Project Baseline

WE'VE MAPPED THE WORLD. NOW LET'S MAP HUMAN HEALTH.

www.projectbaseline.com

verily

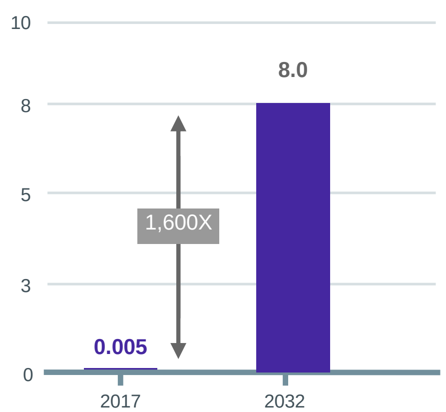
Duke University School of Medicine

Stanford MEDICINE

Google

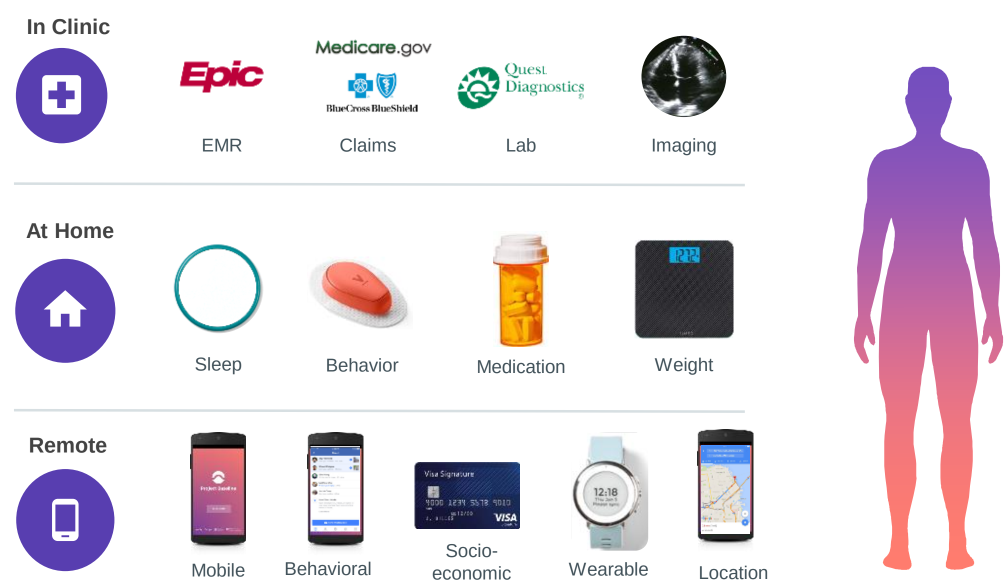
Collecting comprehensive health data

Generate tools and technologies to collect diverse, comprehensive health data in-clinic, at-home, and remotely.



Terabytes of health data per patient

6 TB of collected data on each Project Baseline participant per year



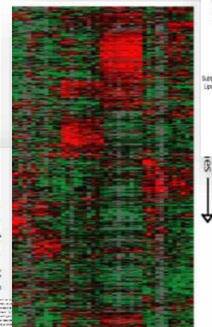
Creating a ‘stack’ of novel personal phenotypes

Exposome

Genome

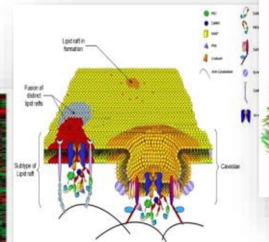
10^9

Transcriptome



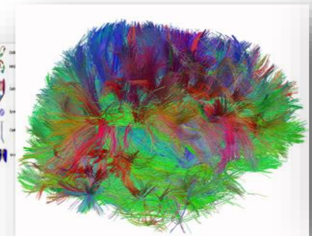
10^{16}

Proteome



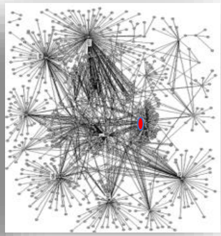
10^{20}

Cellular
Connectome



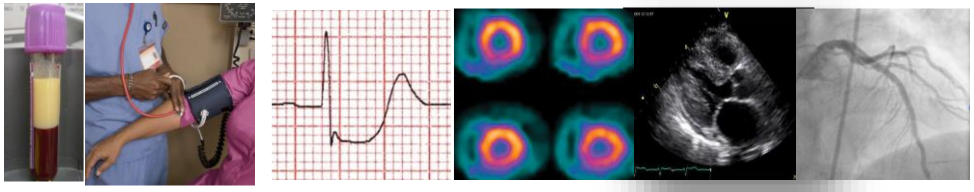
10^{69}

Physiome

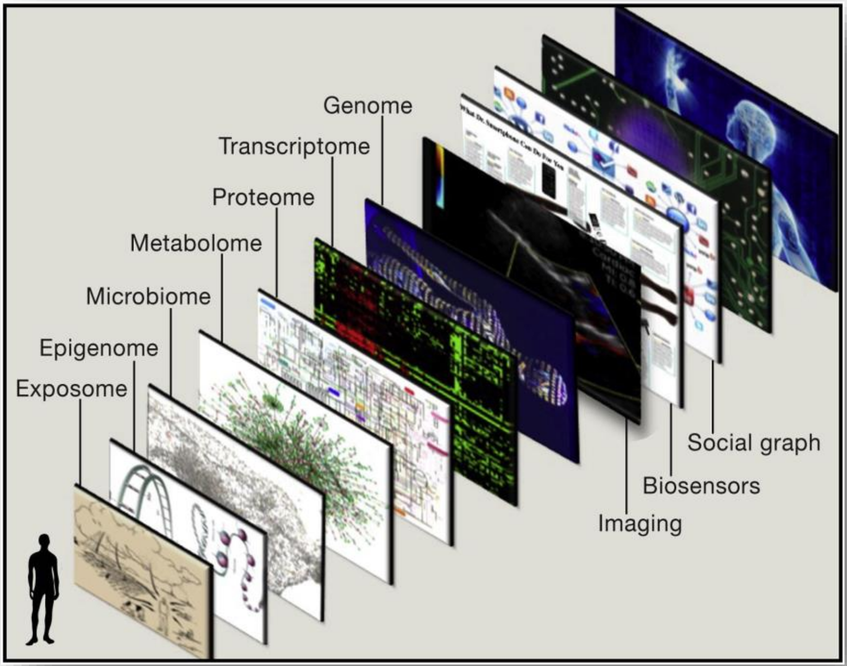


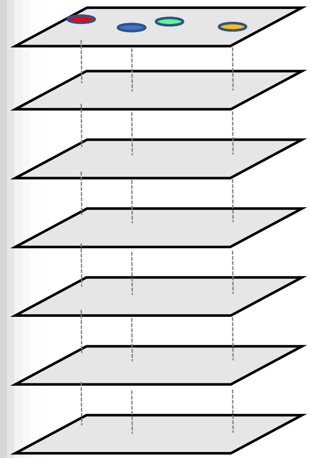
Timescale
Dependent

All clinical phenotypes 10^4



Phenotype stack





- Integration across scales requires new data, new tools, new taxonomy
- Unifying metadata: **small molecules, biophysical stimuli**
- Breadth vs Depth
- Co-clinical modeling

ONE BRAVE IDEA™

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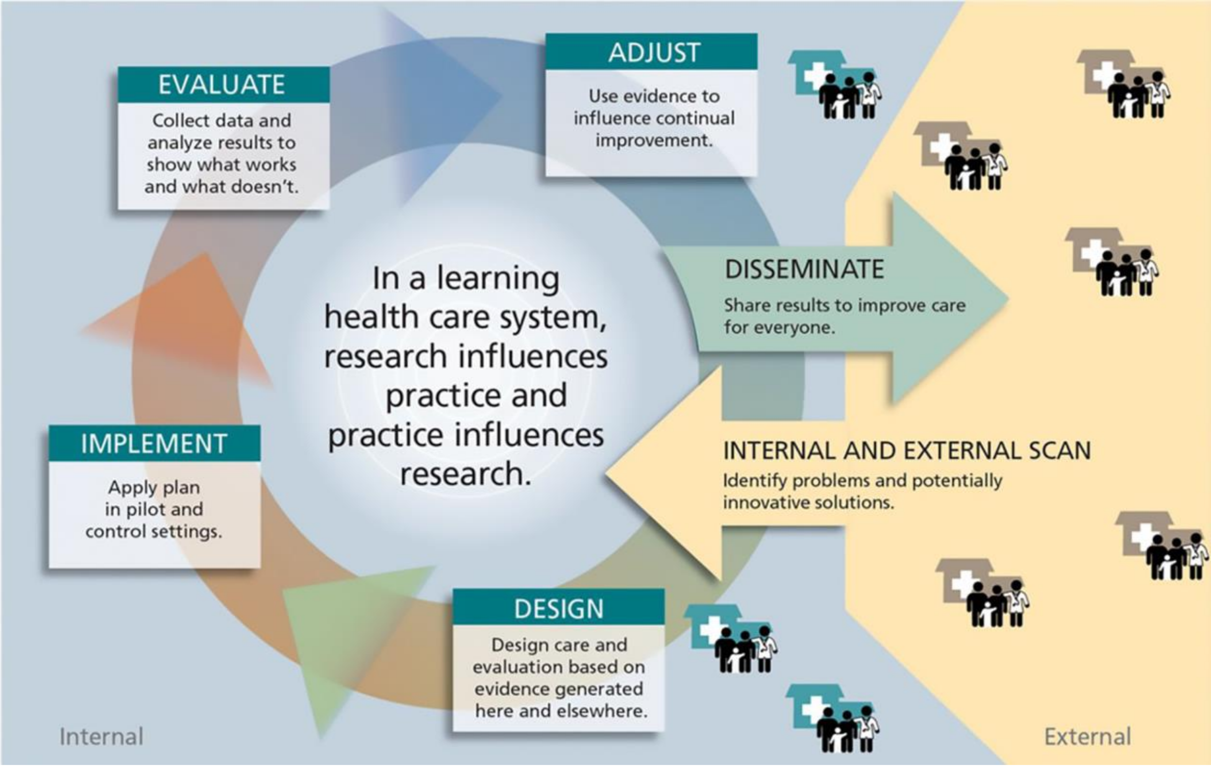
Learning health care systems



www.fda.gov

PCORnet® embodies a "network of networks" that harnesses the power of partnerships

pcornet®

9
Clinical Research Networks (**CRNs**) + 2
Health Plan Research Networks (**HPRNs**) + Patient Partners + 1
Coordinating Center = A national infrastructure for people-centered clinical research

CRNs

ADVANCE

[Accelerating Data Value Across a National Community Health Center Network (ADVANCE)]
Oregon Community Health Information Network (OCHIN)

CAPriCORN

[Chicago Area Patient Centered Outcomes Research Network (CAPriCORN)]
The Chicago Community Trust

GPC
Greater Plains Collaborative

[Greater Plains Collaborative (GPC)]
University of Kansas Medical Center

REACHnet
Research Action for Health Network

[Research Action for Health Network (REACHnet)]
Louisiana Public Health Institute (LPHI)

mid-south clinical data research network
NETWORK OF HOSPITALS AND CLINICAL PRACTICES THROUGHOUT THE SOUTHEAST AND THE NATION

[Mid-South CDRN]
Vanderbilt University

PEDSnet
A Pediatric Learning Health System

[National PEDSnet: A Pediatric Learning Health System]
The Children's Hospital of Philadelphia

NYC-CDRN
New York City Clinical Data Research Network

[New York City Clinical Data Research Network (NYC-CDRN)]
Weill Medical College of Cornell University

OneFlorida
Clinical Research Consortium

[OneFlorida Clinical Data Research Network]
University of Florida

PaTH Network
patient empowered research

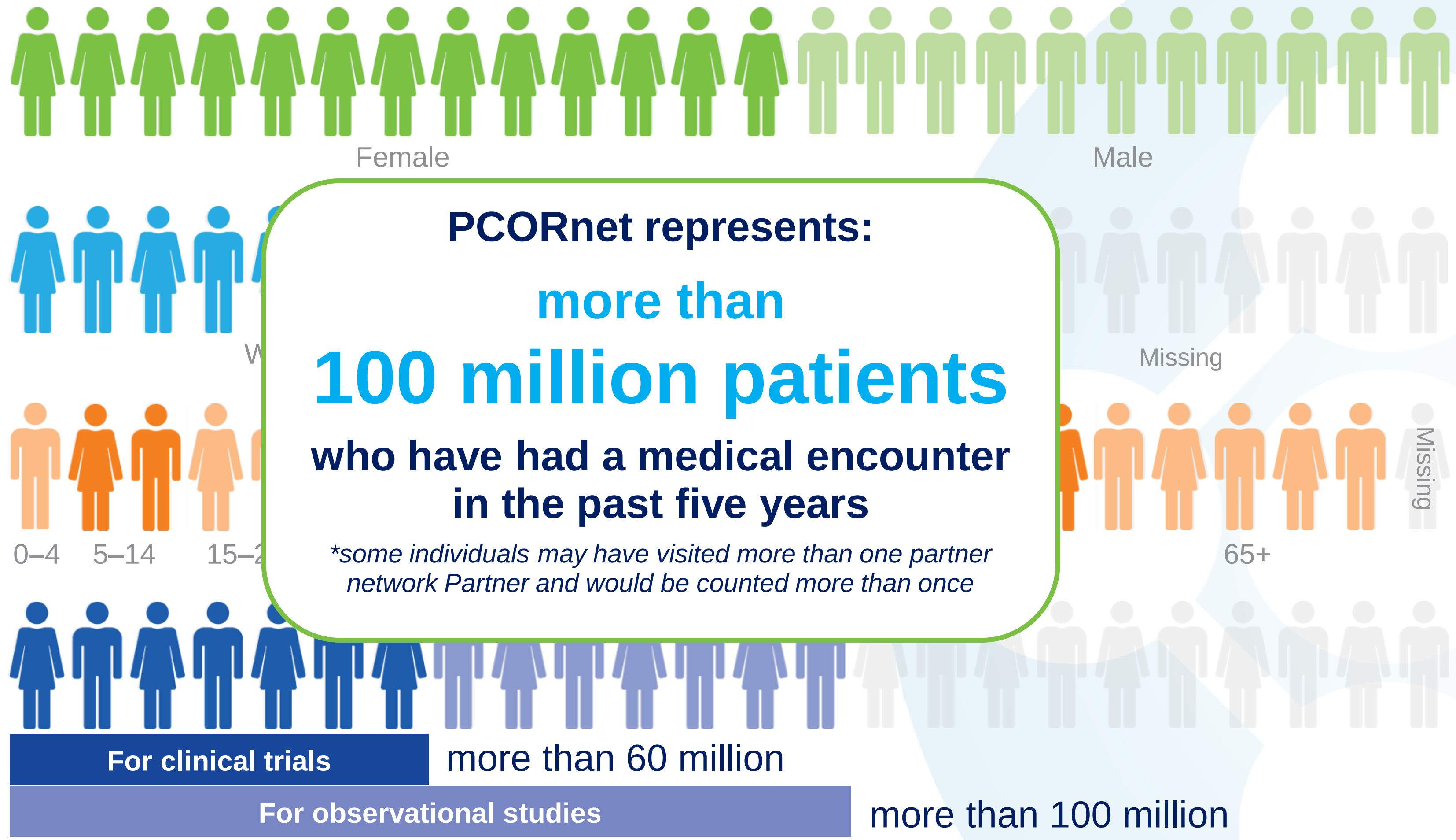
[PaTH: Towards a Learning Health System]
University of Pittsburgh

HPRNs

HealthCore (a subsidiary of Anthem)

Humana – Comprehensive Health Insights (CHI; a subsidiary of Humana Pharmacy Solutions)

Resulting in a national evidence system with unparalleled research readiness



PCORnet represents:

more than

100 million patients

who have had a medical encounter in the past five years

**some individuals may have visited more than one partner network Partner and would be counted more than once*

pcornet®

ADAPTABLE Study Design

15,000 patients with known ASCVD + ≥ 1 "enrichment factor"

Patients identified by research networks through EHR searches
Computable phenotype identifies pts via inclusion/exclusion criteria

Patients able to learn, provide e-consent, and self randomize on a web portal
Treatment assignment provided directly to patient

ASA 81 mg QD

RANDOMIZATION

ASA 325 mg QD

Electronic patient follow-up: Every 3 or 6 months
Supplemented with EHR, health plans, Medicare

Primary endpoint:
Composite of all-cause mortality, hospitalization for MI, or hospitalization for stroke
Primary safety endpoint:
Hospitalization for major bleeding

- To develop and refine the infrastructure for PCORnet to conduct multiple comparative effectiveness trials in the future

ClinicalTrials.gov: NCT02697916

Site Approach and Enrollment

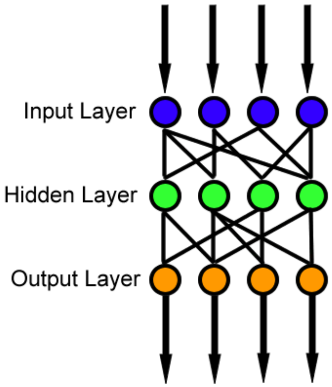
CDRN	Total Number Eligible	Total Number Approached	% of Eligible Approached	Golden Tickets Entered	% Golden Tickets entered per Approached	Total Enrolled	# Non-internet Enrolled	% Enrolled Per Approached	% Enrolled Per Golden Ticket Entered
CAPriCORN	18,389	12,251	**67%**	821	**7%**	516	203	**4%**	**63%**
GPC	92,053	62,365	**68%**	3594	**6%**	1690	119	**3%**	**47%**
HPRN	160,914	160,914	**100%**	1,551	**1%**	358	2	0%	**23%**
LHSNet	128,981	35,342	**27%**	1493	**4%**	865	115	**2%**	**58%**
Mid-South	92,714	43,629	**47%**	7,283	**17%**	3942	491	**9%**	**54%**
NYC-CDRN	22,141	6,575	**30%**	1339	**20%**	710	253	**11%**	**53%**
OneFlorida	59,373	5,220	**9%**	749	**14%**	593	154	**11%**	**79%**
PaTH	47,594	41,187	**87%**	3682	**9%**	1279	58	**3%**	**35%**
pScanner	15,669	6,855	**44%**	253	**4%**	131	8	**2%**	**52%**
REACHnet	33,299	20,583	**62%**	1801	**9%**	773	240	**4%**	**43%**
TOTAL	**671,133**	**394,921**	**59%**	**22,566**	**6%**	**10,857**	**1,643**	**3%**	**48%**

What if a choice made over the counter prevented…

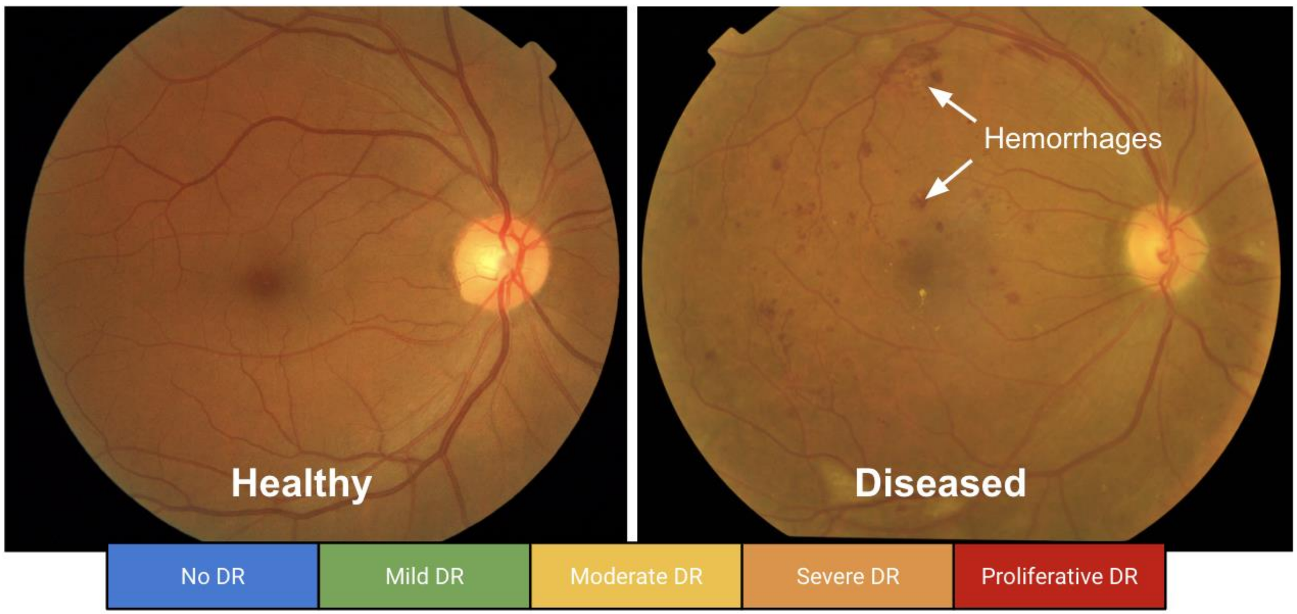
19,000 Deaths/Heart Attacks
Or
Thousands of Bleeds
Annually in the United States

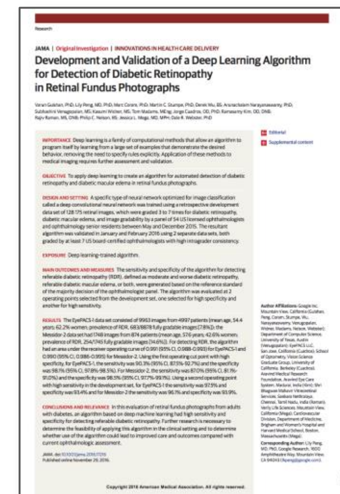
definitions

- Machine learning is a subset of artificial intelligence in the field of computer science that often uses statistical techniques to give computers the ability to "learn" (i.e., **progressively improve performance) on a specific task) with data, without being explicitly programmed.**
- Artificial neural networks (ANNs) or connectionist systems are computing systems vaguely inspired by the biological neural networks that constitute animal brains. Such systems **"learn" to perform tasks by considering examples,** generally without being programmed with any task-specific rules.
- Natural language processing (NLP) is an area of computer science and artificial intelligence concerned with the **interactions between computers and human (natural) languages**, in particular how to program computers to process and analyze large amounts of natural language data.

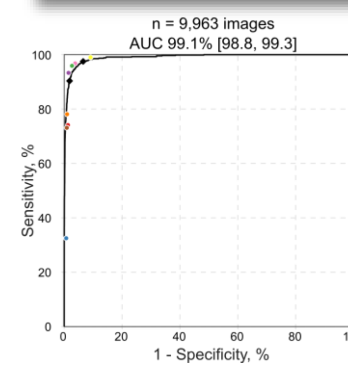


Innovations jointly deployed by Google + Verily

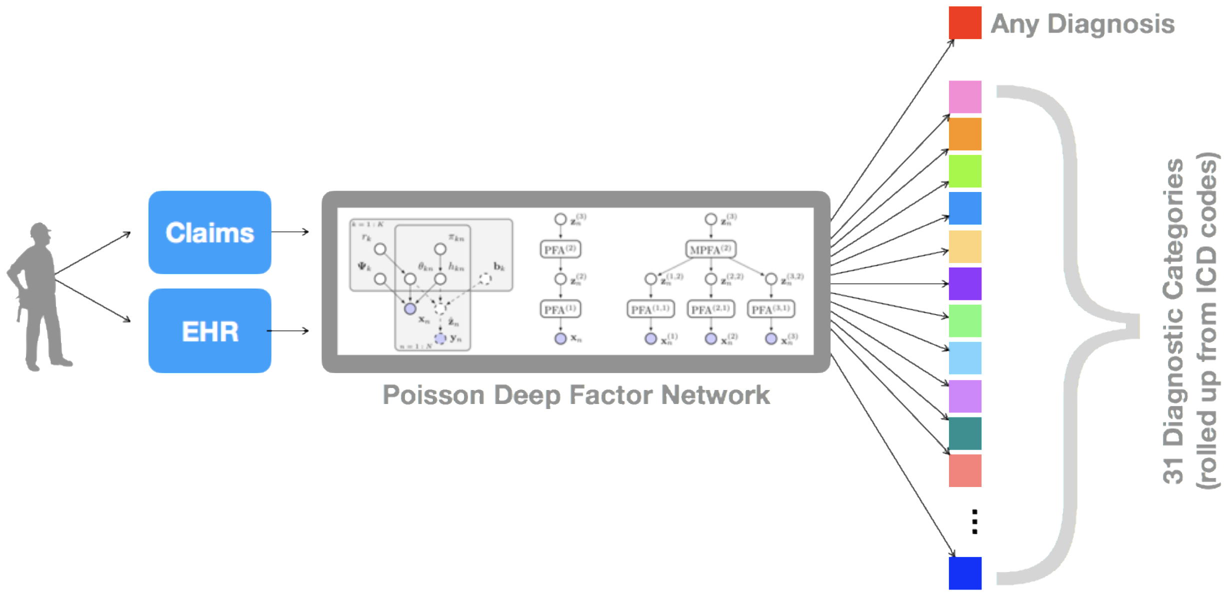



JAMA | Original Investigation | INNOVATIONS IN HEALTH CARE DELIVERY

Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

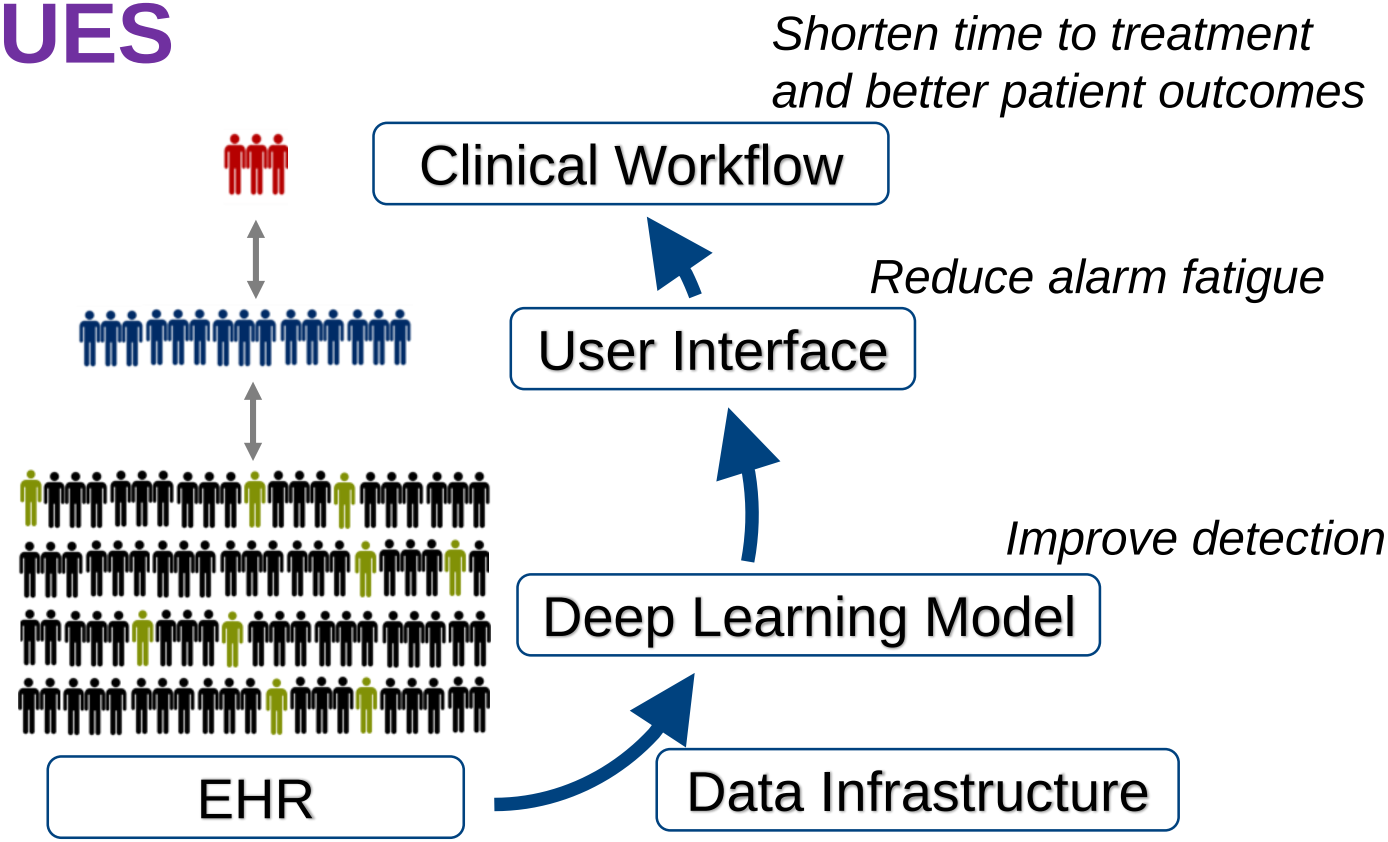


Admission Risk Prediction Model



Expressed as absolute 6-month probability and percentile risk (e.g. 73% and 87th %-ile)

FLAGGING ACUTE INPATIENT ISSUES



“The Boeing 737 Max and the Problems Autopilot Can’t Solve”
- New York Times

“Trump Laments Modern Airplanes as ‘Too Complex to Fly' in Wake of Deadly Crashes” - *Chicago Tribune*

1 in 20

Google searches are health related

Duke | FORGE
HEALTH DATA IN ACTION

WHY DEPRESSION?

DEPRESSION IS HIGHLY PREVALENT

300 M

people suffer from depression globally, WHO has declared it a leading cause of disability [WHO]

MANY PEOPLE DON'T GET TREATMENT

50%

of people with depression in the US did not get any treatment [JAMA]

TREATMENT IS OFTEN DELAYED

7 YRS

average time from onset to treatment in the US [JAMA]

TREATMENT IS EFFECTIVE

70%

of patients can improve, often in a matter of weeks [NIMH]

Google has the reach, scale and technology to help

PRODUCT OVERVIEW: What is PHQ-9?

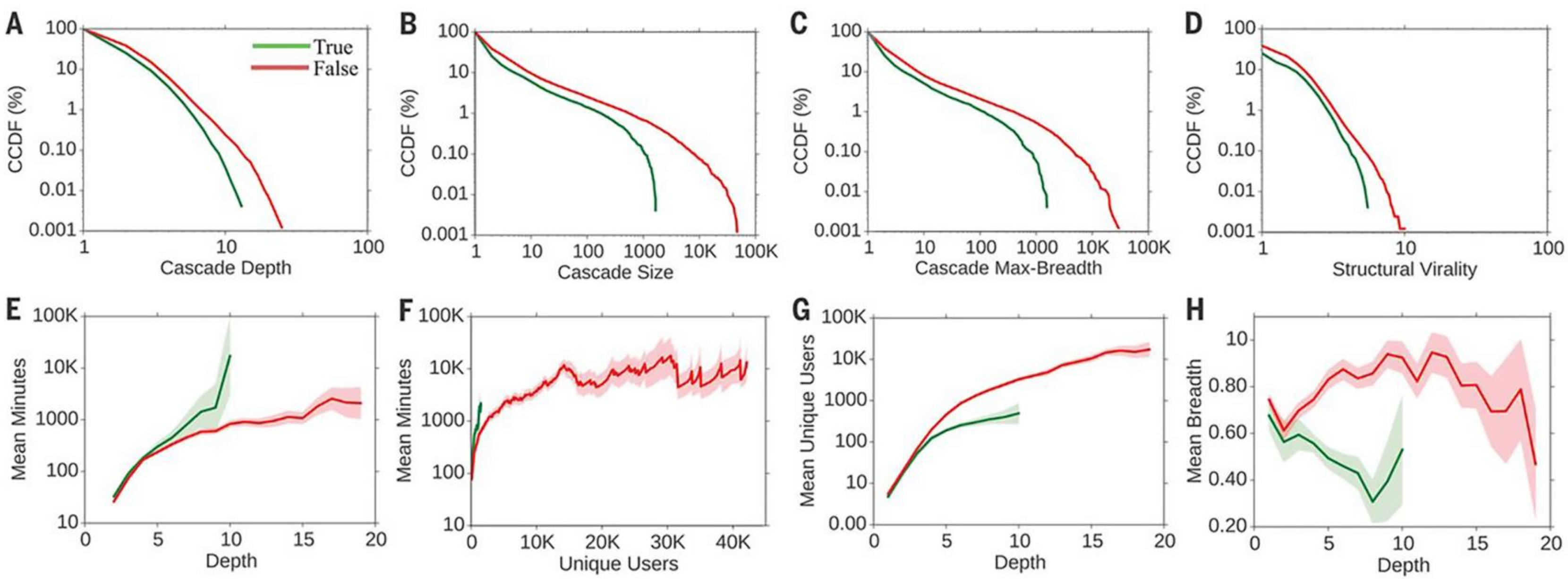
PHQ-9 is a Patient Health Questionnaire, with 9 questions, that is used to measure depression severity

PATIENT HEALTH QUESTIONNAIRE-9

Over the last 2 weeks, how often have you been bothered by any of the following problems?	Not at all	Several days	More than half the days	Nearly every day
1. Little interest or pleasure in doing things	0	1	2	3
2. Feeling down, depressed, or hopeless	0	1	2	3
3. Trouble falling or staying asleep, or sleeping too much	0	1	2	3
4. Feeling tired or having little energy	0	1	2	3
5. Poor appetite or overeating	0	1	2	3
6. Feeling bad about yourself — or that you are a failure or have let yourself or your family down	0	1	2	3
7. Trouble concentrating on things, such as reading the newspaper or watching television	0	1	2	3
8. Moving or speaking so slowly that other people could have noticed? Or the opposite — being so fidgety or restless that you have been moving around a lot more than usual	0	1	2	3
9. Thoughts that you would be better off dead or of hurting yourself in some way	0	1	2	3

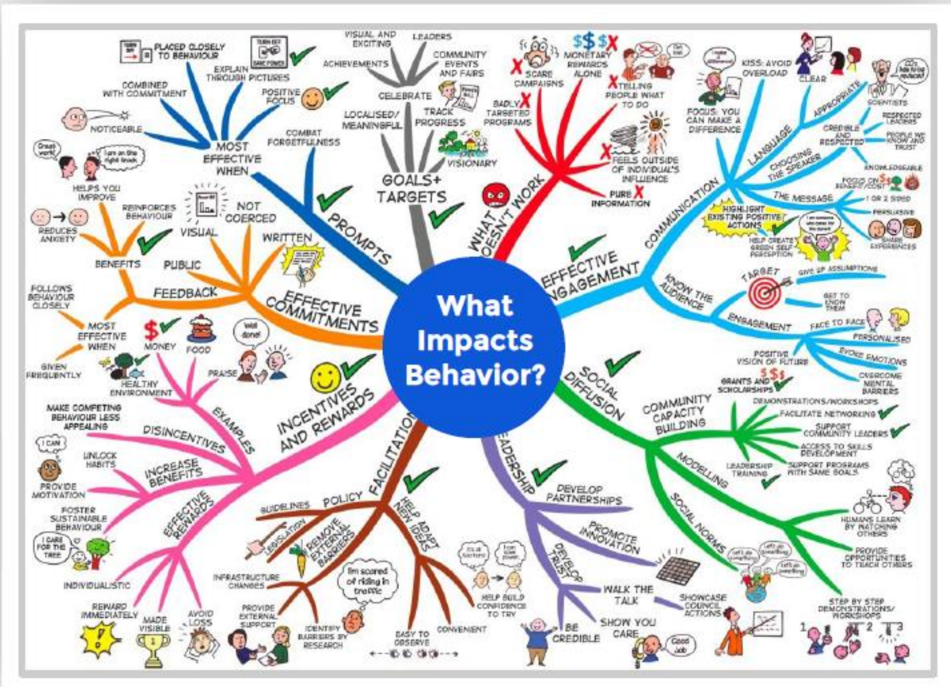
Krista Kennell / Stone / Catwalker / Shutterstock / The Atlantic
https://www.theatlantic.com/technology/archive/2018/03/largest-study-ever-fake-news-mit-twitter/555104/

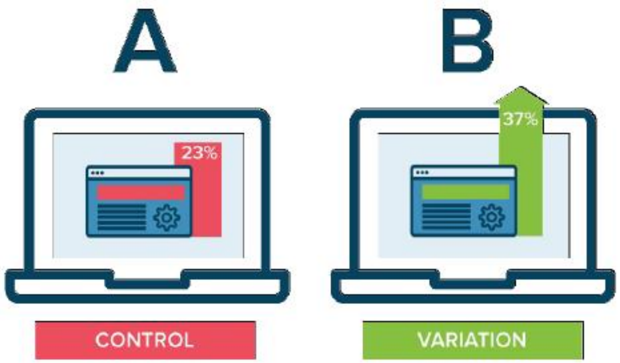
Complementary cumulative distribution functions (CCDFs) of true and false rumor cascades



Vosoughi S, et al. Science. 2018;359:1146-51.

Data Activation and Testing Outcomes





Verily |

Digital transformation

2010

Mapping Human Health

2020

Individual Productivity and IT Silos

- Data on premise, hard to access, analyze and use
- Productivity tools built for individual, local usage
- IT focusing on **where** it computes

Collective Intelligence and Distributed Computing

- Data stored in cloud, simple to query
- Collaborative, cloud based productivity
- Machine learning drives deep, actionable insights
- IT changing **how** it computes

CONCRETE CHANGES DUE TO THE 4TH INDUSTRIAL REVOLUTION

1. **”Home inversion”—prevention and chronic care will move to the home, school, workplace and neighborhood**
2. Health care team—function will be optimized to enable members to function at the top of their capability with task shifting to community health workers and nurses for many activities in the home
3. Clinic visit preparation—will set up using interactive system at home using sensors, cell phones and chatbots
4. **Clinic visits—will be virtual in many cases, but when human interaction useful, clinician and patient will talk and interact physically (clinic notes done using NLP and AI)**
5. Post-clinic visit-–information will be available on an as-needed basis, tailored to the needs, health literacy and numeracy of the patient

CONCRETE CHANGES DUE TO THE 4TH INDUSTRIAL REVOLUTION

6. **Behavior change—will be reinforced by the digital environment**

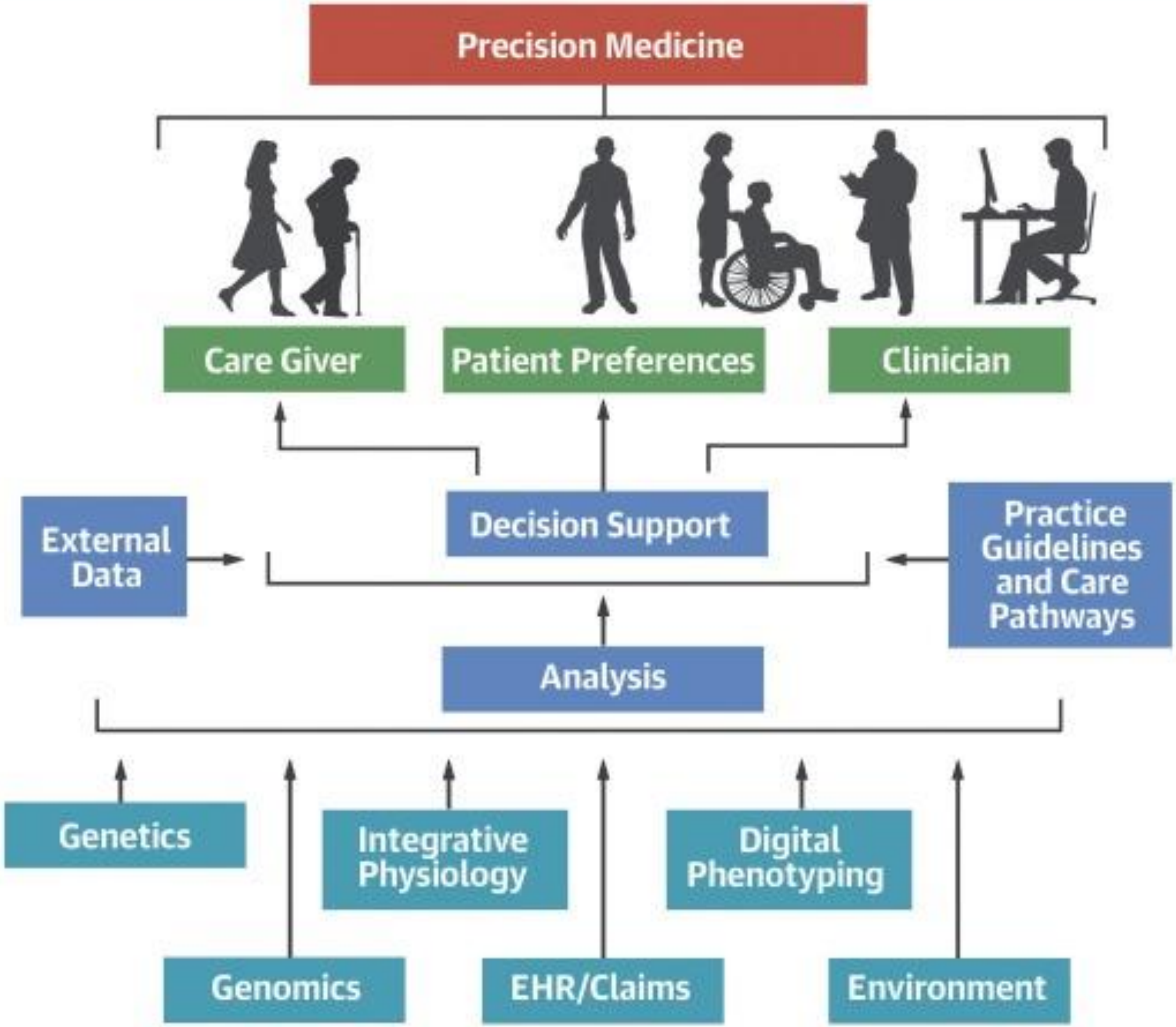
7. Procedures and surgeries—will be monitored by a digital environment in which ML will be used to guide procedures;

8. Ingestion of data across the spectrum of biology, clinical, imaging, sensors, behavior, social interactions and environment will be routine

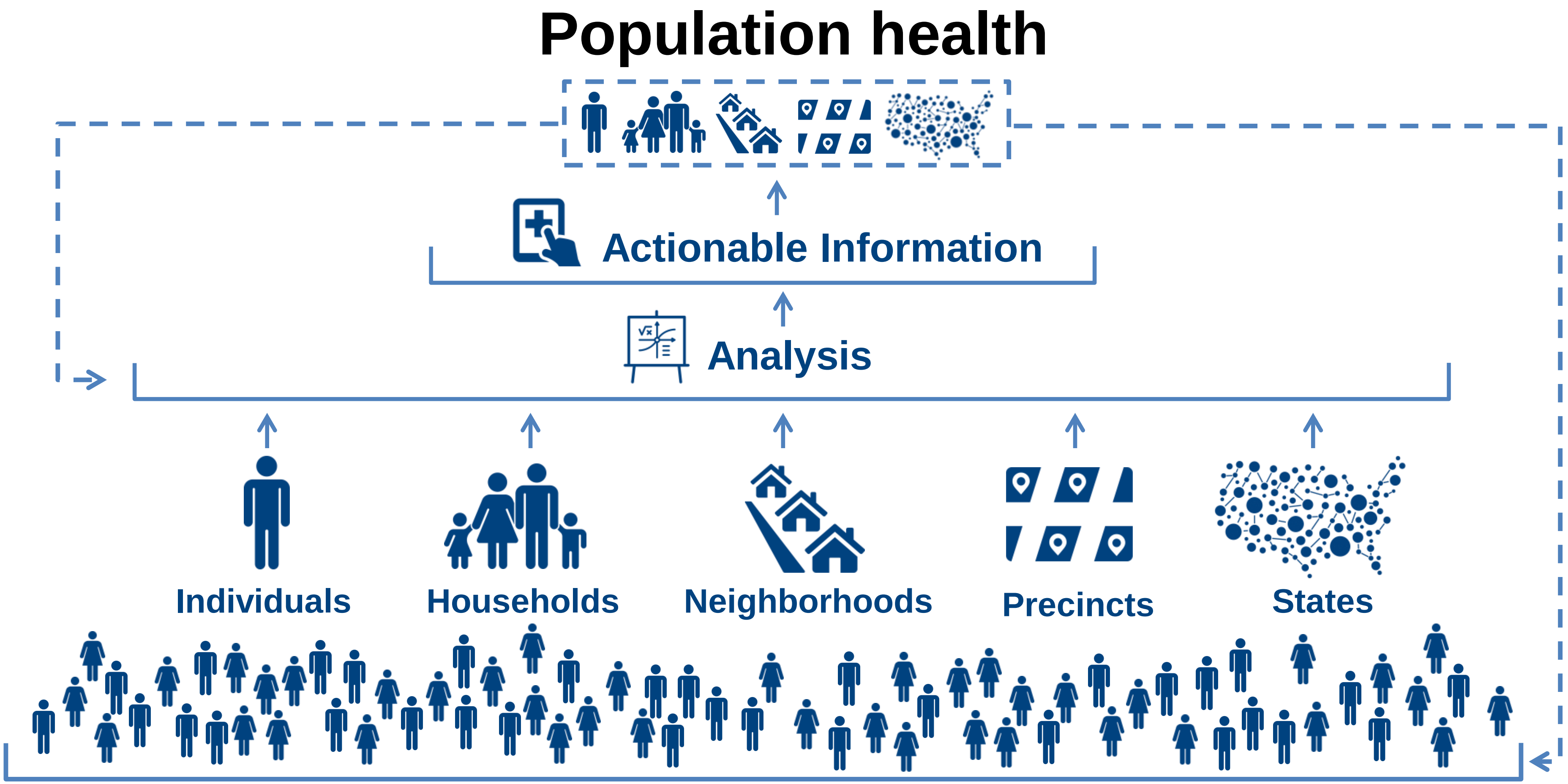
9. **Precision medicine will stratify people based on risk and knowledge of effective interventions, and personalized medicine will tailor actions to the needs and values of people and families**

10. **Population health will use the same information aggregated at the level of families, neighborhoods, precincts, towns, counties, states and regions**

CENTRAL ILLUSTRATION: Precision Medicine



Califf, R.M. J Am Coll Cardiol. 2018;72(25):3301–9.


Population health
Actionable Information
Analysis
Individuals
Households
Neighborhoods
Precincts
States