AMERICA'S PHYSICIAN GROUPS

Data Analytics:

Lessons from the Frontier

MyHealtheData Initiative

Speech: Remarks by CMS Administrator Seema Verma at the HIMSS18 Conference

Mar 06, 2018 | Data, eHealth

Administrator Seema Verma
@SeemaCMS
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If you need help finding a plan that works best for your #healthcare needs, but don't have a enough time for all the tedious research, don't worry- @CMSGov's #BlueButton 2.0 apps can help. Take a look to see what apps could help you: medicare.gov/manage-your-he …

8:38 AM - 3 May 2019

Administrator Seema Verma
@SeemaCMS

"By unleashing data, the Trump Administration is establishing an environment of shared learning and opportunity for federal and state partners to continue to realize values from best practices..."
cms.gov/newsroom/press...

PHYSICIAN GROUPS

Democratizing Insights

in 2015

$11,117,003 Total payments | Ophthalmology

Provider's Services at a Glance, 2015

Types of services provided by

Category	Total reimbursed by Medicare	Percent of total reimbursements by Medicare
Drugs	$9,058,512	81.5%
Surgeries and procedures	$968,328	8.7%
Exams and medical services	$883,228	7.9%
Evaluation and management	$141,303	1.3%
Other	$23,153	0.2%
Imaging tests	$2,930	<0.1%

Note: Category totals may not add up to a provider's total payments because information about a provider's specific services to fewer than 11 Medicare patients is suppressed by Medicare.

Provider's Services in Detail, 2015

Services performed on more than 10 patients:

Procedure	Number performed	Number of Medicare patients	Average Medicare reimbursement per procedure	Total Medicare payments for procedure
Injection, ranibizumab, 0.1 mg Drugs CODE: J2778-O	28,760 Top 20% nationally	722	$307.90	$8,855,204
Injection of drug into eye Surgeries and procedures CODE: 67028-O	5,880 Top 20% nationally	924	$89.81	$528,083

HCC Prevalence Rates, 2014 - 2015		MA "Switchers"		
		2014 HCCs	2015 HCCs Incl Chart Review	2015 HCCs Excl Chart Review
Avg. HCC Score		0.97	1.09	1.04
Vascular Heirarchy	HCC 107 (Vascular Disease with Complications)	1.36%	1.41%	1.36%
	HCC 108 (Vascular Disease)	11.05%	13.82%	12.62%
Kidney Heirarchy	HCC 134 (Dialysis Status)	0.01%	0.01%	0.00%
	HCC 135 (Acute Renal Failure)	2.41%	2.83%	2.76%
	HCC 136 (CKD, Stage 5)	0.16%	0.16%	0.15%
	HCC 137 (CKD, Stage 4)	0.26%	0.38%	0.36%
Diabetes Heirarchy	HCC 17 (Diabetes with Acute Complications)	0.19%	0.18%	0.17%
	HCC 18 (Diabetes with Chronic Complications)	9.74%	13.13%	12.36%
	HCC 19 (Diabetes Without Complication)	17.72%	14.55%	14.61%
	HCC 22 (Morbid Obesity)	3.33%	6.42%	4.67%
Substance Abuse Heirarchy	HCC 54 (Drug/Alcohol Psychosis)	0.25%	0.21%	0.20%
	HCC 55 (Drug/Alcohol Dependence)	1.22%	1.94%	1.74%
	HCC 84 (Cardiorespiratory Failure and Shock)	1.54%	1.89%	1.84%
	HCC 85 (Congestive Heart Failure)	8.83%	10.67%	9.67%
Cardiac Arrest Heirarchy	HCC 86 (Acute Myocardial Infarction)	0.48%	0.57%	0.56%
	HCC 87 (Unstable Angina and Other Acute Ischemic Heart Disease)	1.20%	1.06%	1.02%
	HCC 88 (Angina Pectoris)	1.43%	2.16%	1.87%
	HCC 96 (Speciifed Heart Arrhythmias)	10.09%	11.07%	10.67%

Source: https://graphics.wsj.com/medicare-billing/; CareJourney analysis of VRDC

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Challenge: Scaling What Works

Calling All Innovators – Health Care Innovation Challenge Open for Great Ideas

Performance Goal	Performance Payment Per Beneficiary: With required minimum weight loss	Performance Payment Per Beneficiary: Without required minimum weight loss
First core session attended	$25	$25
Four total core sessions attended	$50	$50
Nine total core sessions attended	$90	$90
Two sessions attended in first core maintenance session interval (months 7-9 of the MDPP core services period)	$60	$15
Two sessions attended in second core maintenance session interval (months 10-12 of the MDPP core services period)	$60	$15
5% weight loss achieved	$160	$0
9% weight loss achieved	$25	$0
Two sessions attended in ongoing maintenance session interval (four consecutive 3-month intervals over months 13-24 of the MDPP ongoing services period)	$50	$0
Total performance payment	**$670**	**$195**

"For the impact on total cost of care, RTI…showed statistically significant gross savings…totaling $2,650." - CMS Actuary on a CMMI-funded ~5,600 beneficiary trial

Medicare diabetes prevention program helps a few hundred instead of hundreds of thousands

POLITICO

Code	2018	Q1 2019
G9890	124	15
G9891	220	363
G9873	38	127
G9874	32	73
G9878	28	14
G9879	27	-
G9875	21	219
G9880	-	43
G9876	-	15
G9881	-	21
Patients Treated:	202	396

Source: https://www.cms.gov/Research-Statistics-Data-and-Systems/Research/ActuarialStudies/Downloads/Diabetes-Prevention-Recertification-2017-11-01.pdf; https://www.cms.gov/Research-Statistics-Data-and-Systems/Research/ActuarialStudies/Downloads/Diabetes-Prevention-Certification-2016-03-14.pdf; CareJourney analysis of VRDC

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#1) CMS Claims Data API Portfolio

Blue Button

- For Medicare beneficiaries
- Single data call

Beneficiary Claims Data

- For Accountable Care Organizations (ACO)
- Bulk data calls

Data at the Point of Care

- For Providers
- Bulk data calls

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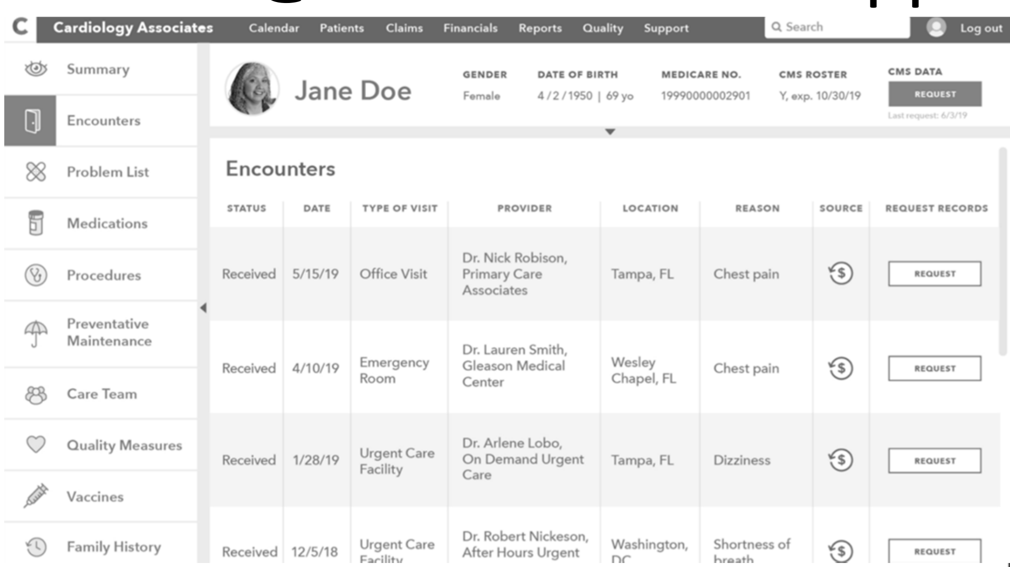
Data @ POC "SMART" App



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Accessing CMS Data

Standards-Based (FHIR) Claims APIs

Who: Beneficiaries, Clinicians, ACOs, PDP Sponsors

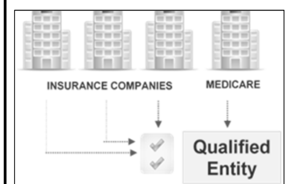
Access Fee?: No

Virtual Research Data Center (VRDC)

Who: Researchers (academic, non-profit, for profit)

Access Fee?: Yes

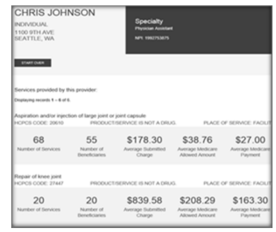
Qualified Entity Program



Who: Organizations with claims from other sources

Access Fee?: Yes

Public Use Files & Tools



Who: Anyone

Access Fee?: No

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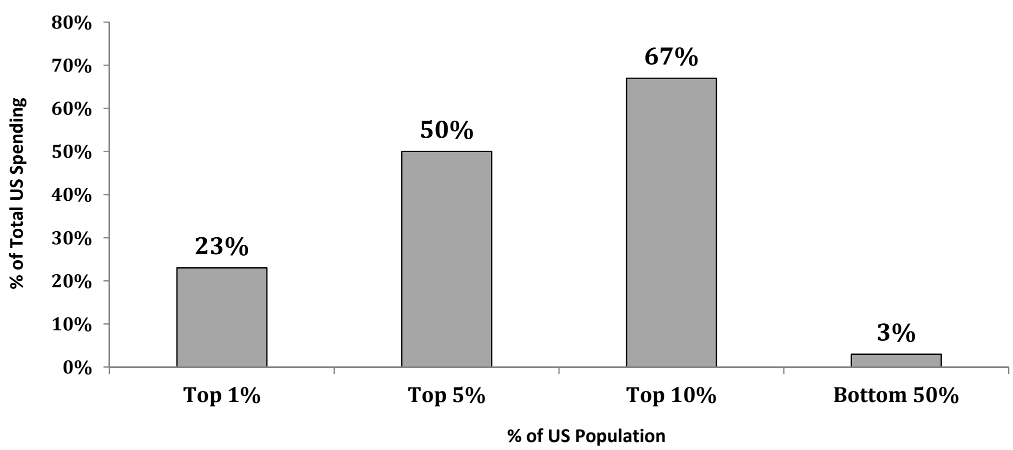
2) Focus on "High-Need/High-Cost" Patients



Ref: MEPS Data

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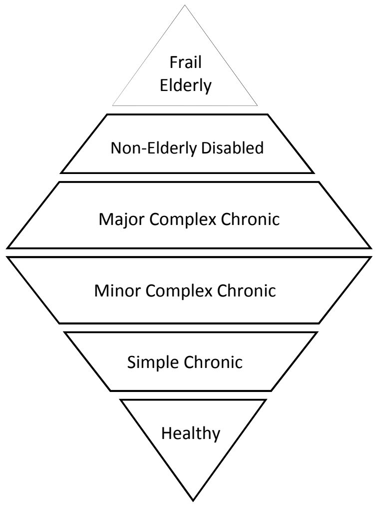
Segmentation Framework for HN/HC Patients

Clinically-Relevant Population Segments

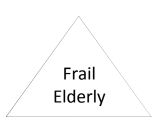


1. **Help identify patients who will be high-cost (and why)**
2. **Help determine if programs/interventions work for complex, high-need patients**
3. **Identify "high-performing" healthcare providers caring for complex, high-need patients**

Use segmentation to help predict who will become high-cost

Clinically-Relevant Population Segments

Sub-segmentation



40%

of frail elders will be "high cost" (top 10% most expensive)

<u>**Subpopulation #1:**</u>
Functional limitations only
(65%)

<u>**Subpopulation #2:**</u>
Functional +
cognitive limitations
(35%)

52%

Top 10% most expensive

81%

Top 25% most expensive

Figueroa et al., Submission pending.

Use segmentation to assess whether programs work for complex, high-need patients (ACOs)

Frail Elderly

Medicare ACO (MSSP) practices

Non-ACO control practices

2011 **2016**

Difference-in-difference study

ACOs are associated with <u>3% net savings</u> for frail elders

Figueroa et al., Submission pending.

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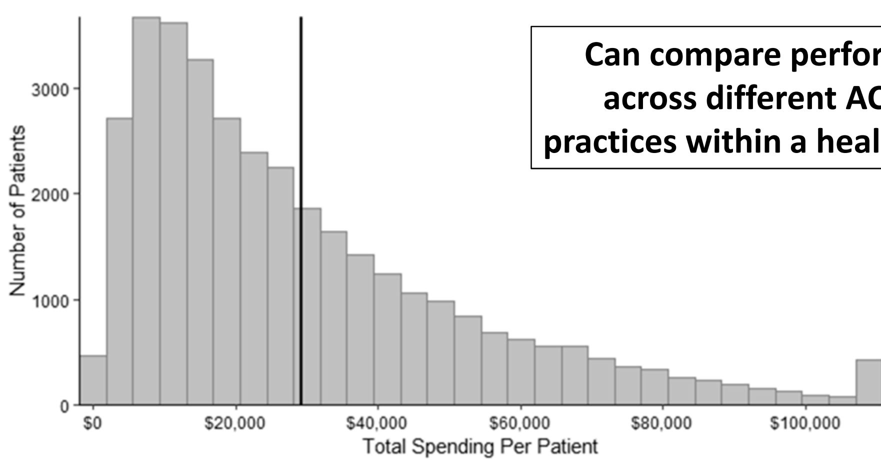
Spending varies substantially across frail elders with functional + cognitive impairment



Can compare performance across different ACOs or practices within a health system

Figueroa et al., Submission pending.

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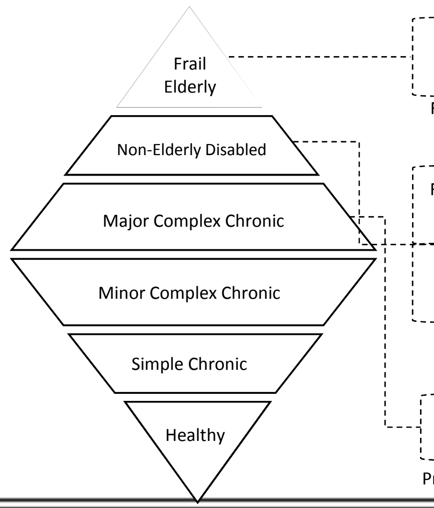
Segmenting "High-Need/High-Cost" Populations

Clinically-Relevant Population Segments

Sub-Populations



Subpopulation #1:
Functional limitations only

Subpopulation #2:
Functional/cognitive limitations

Subpopulation #1:
Functionally impaired disabled

Subpopulation #2:
Cognitively impaired disabled

Subpopulation #3:
"Drug dominant" disabled

Subpopulation #1:
No serious mental illness

Subpopulation #2:
Presence of serious mental illness

Note: Algorithms to segment and sub-segment will be publicly available

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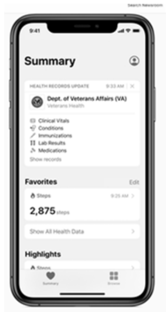
#3) Leveraging Cognitive Services APIs

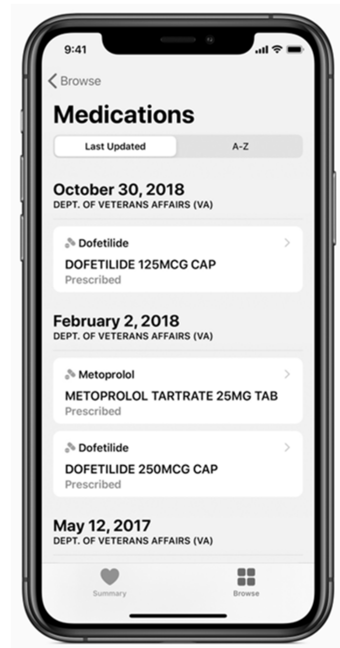
Give your apps a human side

Vision	Speech	Language	Knowledge	Search	Labs
Computer Vision	Bing Speech	Bing Spell Check	Academic Knowledge	Bing Autosuggest	Project Prague (gesture)
Content Moderator	Custom Speech Service	Language Understanding	Entity Linking	Bing Image Search	Cuzco (events)
Emotion	Speaker Recognition	Linguistic Analysis	Knowledge Exploration	Bing News Search	Johannesburg (routing)
Face		Translator Text & Speech	Recommendations	Bing Video Search	Nanjing (Isochrones)
Video		Web Language Model	QnA Maker	Bing Web Search	Abu Dhabi (distance matrix)
Video Indexer		Text Analytics	Custom Decision Service	Bing Custom Search	Wollongong (location)
Custom Vision Service					

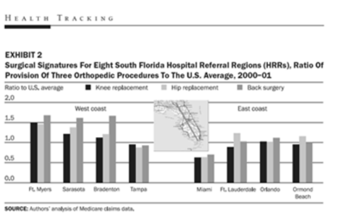


UPDATE
November 6, 2019

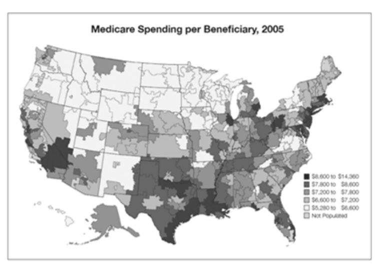
Health Records on iPhone now available to veterans across the US



https://www.apple.com/newsroom/2019/11/health-records-on-iphone-now-available-to-veterans-across-the-us/

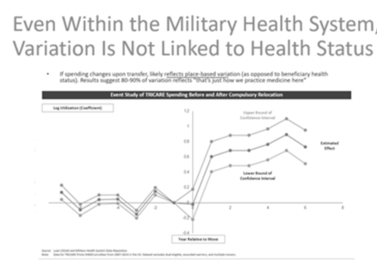


Improving Quality and Curbing Health Care Spending: Opportunities for the Congress and the Obama Administration



A Dartmouth Atlas White Paper

This Dartmouth Atlas White Paper was written by John E. Wennberg, Shannon Brownlee, Elliott S. Fisher, Jonathan S. Skinner and James N. Weinstein.
December 2008

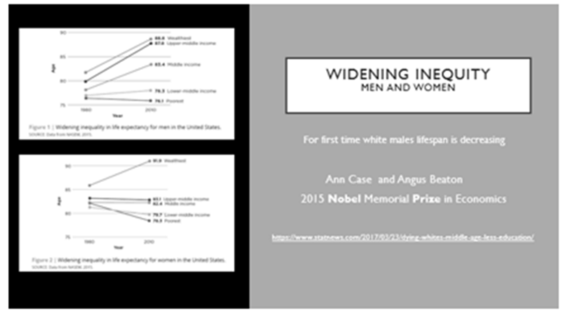


Variation

Outcomes

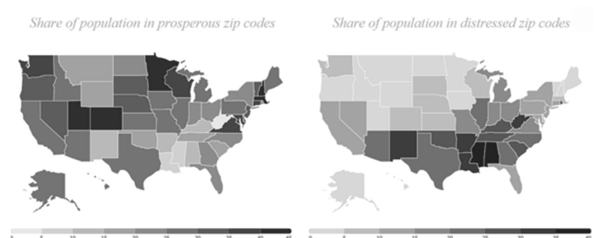
Cost

Mission: America's Physician Groups is to assist accountable physician groups to improve the quality and value of healthcare provided to patients.

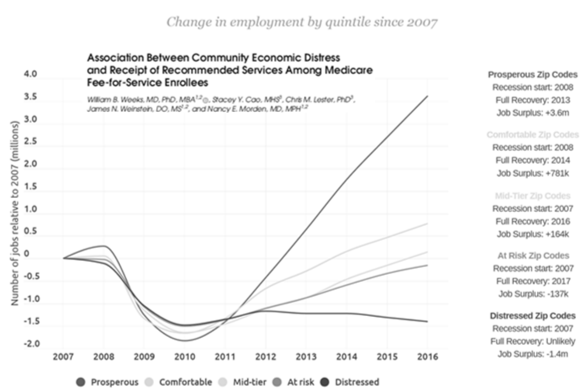


Health Inequities

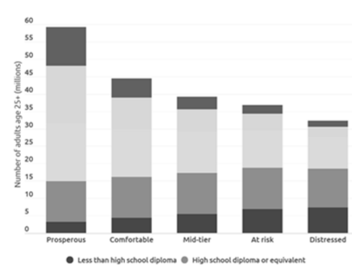
What about us ?



One-third or more of the population resides in a distressed zip code

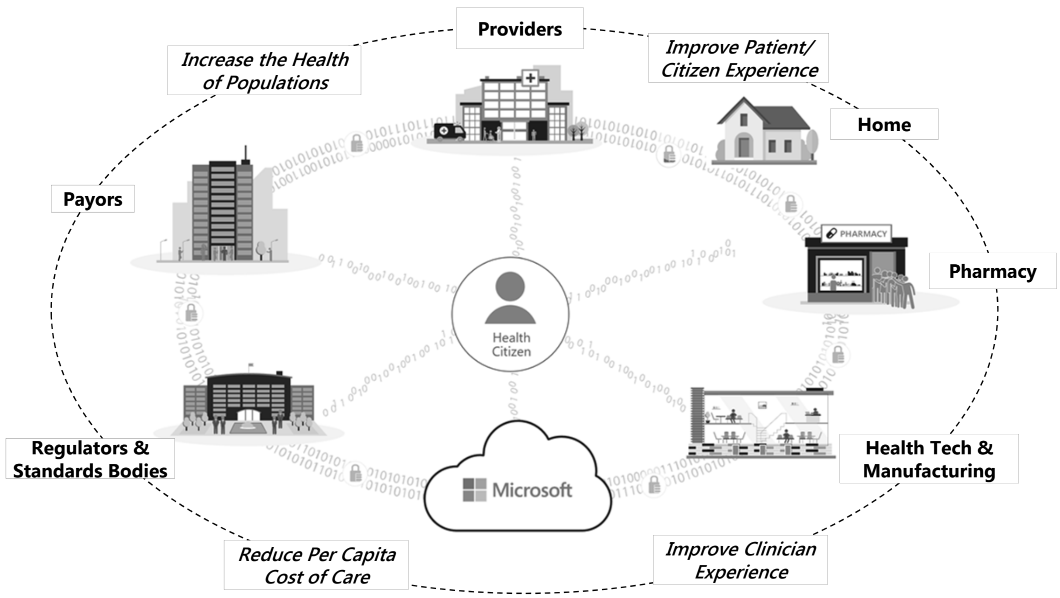


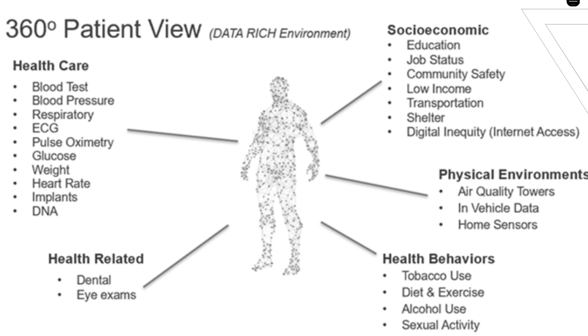
https://eig.org/dci

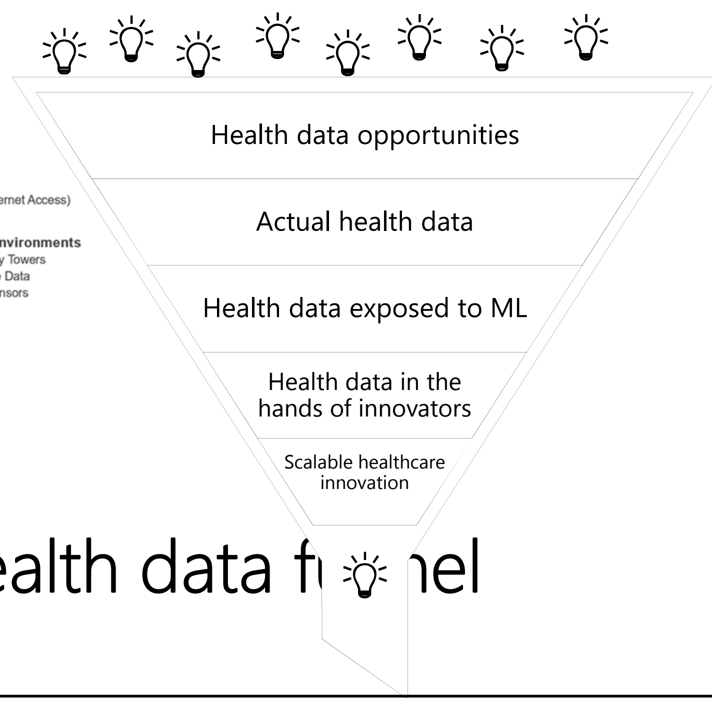


Connected Health Ecosystem

Holistic Healthcare is constrained by silos – *Quadruple Aim*







The health data f nel

npj | Digital Medicine

www.nature.com/npjdigitalmed

ARTICLE OPEN

Scalable and accurate deep learning with electronic health 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[3], 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

Uri Shalit @ShalitUri · Jun 20, 2018
Replying to @ShalitUri
Note the overlap of the confidence intervals for the AUCs of the baseline model & DL model. My takeaway is that *one should use logistic regression over DL* on such tasks. The vastly greater simplicity and interpretability of LR far outweigh the tiny (if at all) gain in accuracy.
3 26 140

Uri Shalit @ShalitUri · Jun 20, 2018
Another possible take: we haven't yet found the right deep learning architectures that will give us the kind of performance boosts we've seen in image, text, and sound modeling

@david_sontag @zacharylipton @DrLukeOR
11 15 88

Pitched as a revolutionary approach to predicting adverse outcomes in health care

Discussion: Importance of Data Ethics

RESEARCH ARTICLE

Dissecting racial bias in an algorithm used to manage the health of populations

Ziad Obermeyer[1,2,*], Brian Powers[3], Christine Vogeli[4], Sendhil Mullainathan[5,*,†]
+ See all authors and affiliations

Science 25 Oct 2019:
Vol. 366, Issue 6464, pp. 447-453
DOI: 10.1126/science.aax2342

"Overall, only 18% of the patients identified by the algorithm as needing more care were black, compared to about 82% of white patients. If the algorithm were to reflect the true proportion of the sickest black and white patients, those figures should have been about 46% and 53%, respectively."

DHH @dhh

Apple and Goldman Sachs have both accepted that they have no control over the product they sell. THE ALGORITHM is in charge now! All humans can do is apologize on its behalf, and pray that it has mercy on the next potential victims. twitter.com/CayucosCat/sta…

Cathrin Eckle @CayucosCat
Replying to @dhh
I had the same experience! Better credit score than my husband, at first they denied credit!! After a day on the phone, an email to Tim Cook I was asked to reapply, got a lower credit limit than my husband, told by an arrogant GS rep "we have an algorithm and have no control!

1,752 11:53 PM - Nov 9, 2019

572 people are talking about this

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There have been extraordinary gains from machine learning in pattern recognition for CT scans, X-Rays but clear in Rajkomar et al.–

It is not clear that predicting in hospital mortality via EHR is the best way to improve health care.

Different question might be which set of measures would be most useful to know in order to leverage an improvement in outcomes?

- identifying patients in the community who are at greatest risk of hospitalization, falls, or ER visits, thus upstream is likely better.