Digital Phenotyping

mindstrong

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September 15, 2018

The AI Revolution

JAMA | Original Investigation | INNOVATIONS IN HEALTH CARE DELIVERY

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

Varun Gulshan, PhD; Lily Peng, MD, PhD; Marc Coram, PhD; Martin C. Stumpe, PhD; Derek Wu, BS; Arunachalar
Subhashini Venugopalan, MS; Kasumi Widner, MS; Tom Madams, MEng; Jorge Cuadros, OD, PhD; Ramasamy Ki
Rajiv Raman, MS, DNB; Philip C. Nelson, BS; Jessica L. Mega, MD, MPH; Dale R. Webster, PhD

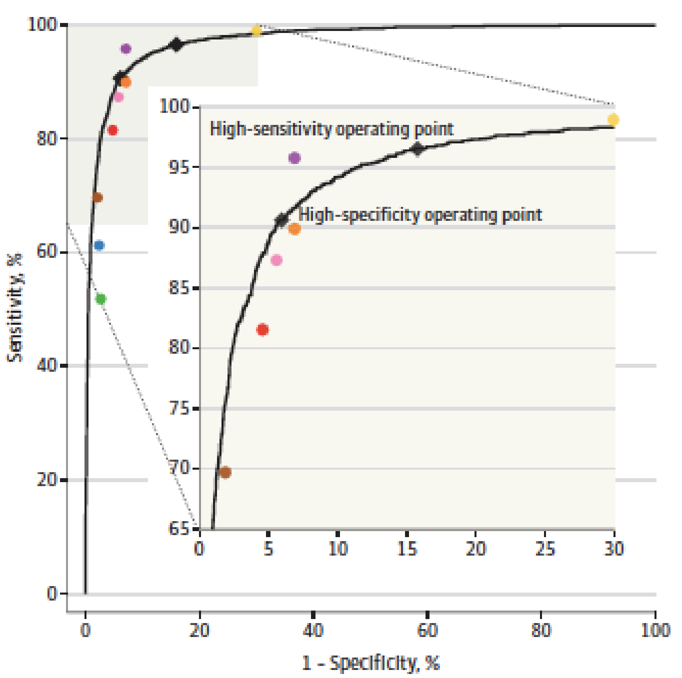
Trained on 1
graded by 5

Validated
9963 images
graded by 8

"Deep convolutional neural net"

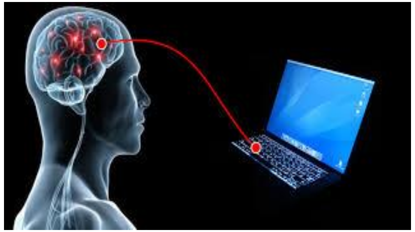
Can a machine learn (program itself) to identify diabetic retinopathy and edema without rules (unsupervised)?

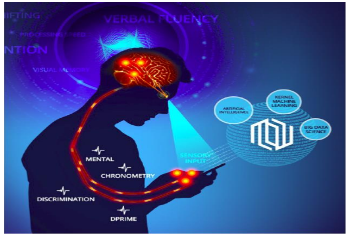
Figure 3. Validation Set Performance for All-Cause Referable Diabetic Retinopathy in the EyePACS-1 Data Set (9946 Images)



Performance of the algorithm (black curve) and ophthalmologists (colored circles) for all-cause referable diabetic retinopathy, defined as moderate or worse diabetic retinopathy, diabetic macular edema, or ungradable image. The black diamonds highlight the performance of the algorithm at the high-sensitivity and high-specificity operating points. For the high-sensitivity operating point, specificity was 84.0% (95% CI, 83.1%-85.0%) and sensitivity was 96.7% (95% CI, 95.7%-97.5%). For the high-specificity operating point, specificity was 93.8% (95% CI, 93.2%-94.4%) and sensitivity was 90.7% (95% CI, 89.2%-92.1%). There were 8 ophthalmologists who graded EyePACS-1. The area under the receiver operating characteristic curve was 97.4% (95% CI, 97.1%-97.8%).

Neurotechnologies in Silicon Valley





- ➢ New tools + Scale = Big Data
- ➢ Big Data + Machine Learning = Solutions
- ➢ Solutions for complex problems = Value

7 Products Used by > 1 Billion People

TECHNOLOGY

The New York Times

How Big Tech Is Going After Your Health Care

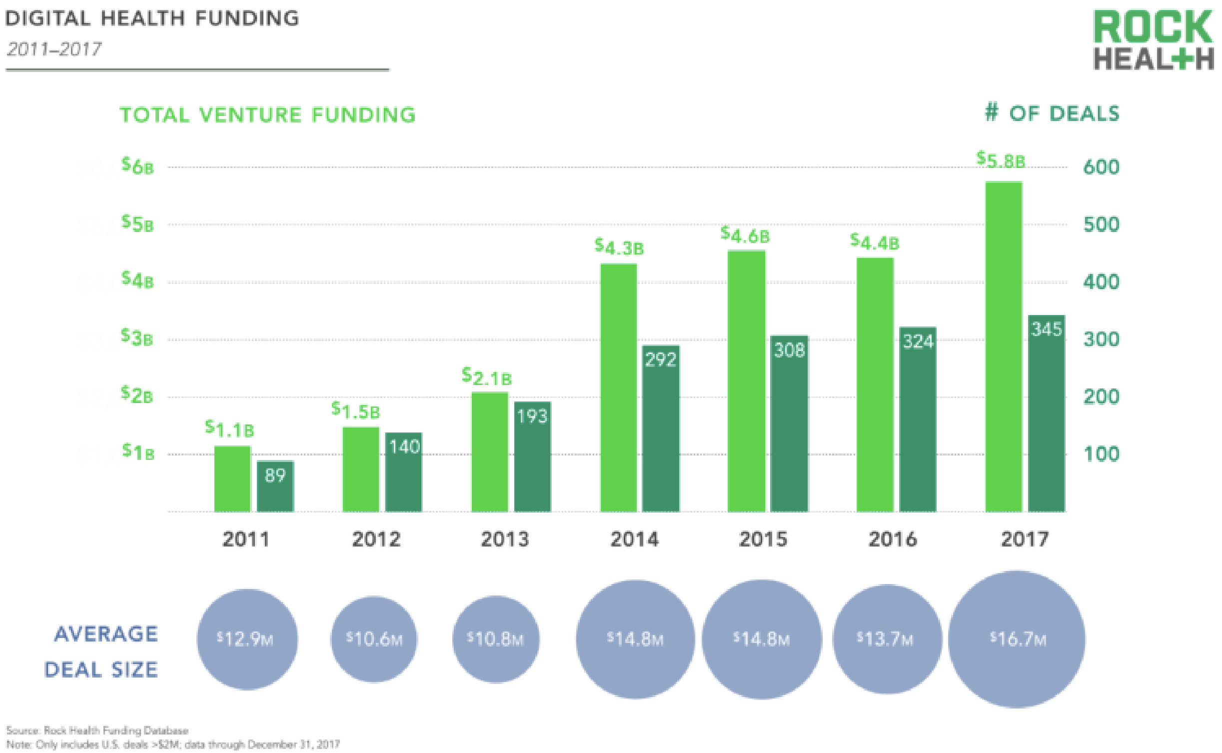
By NATASHA SINGER DEC. 26, 2017

TECHNOLOGY

Amazon, Berkshire Hathaway and JPMorgan Team Up to Try to Disrupt Health Care

By NICK WINGFIELD, KATIE THOMAS and REED ABELSON JAN. 30, 2018

The Changing Ecosystem of Health Research

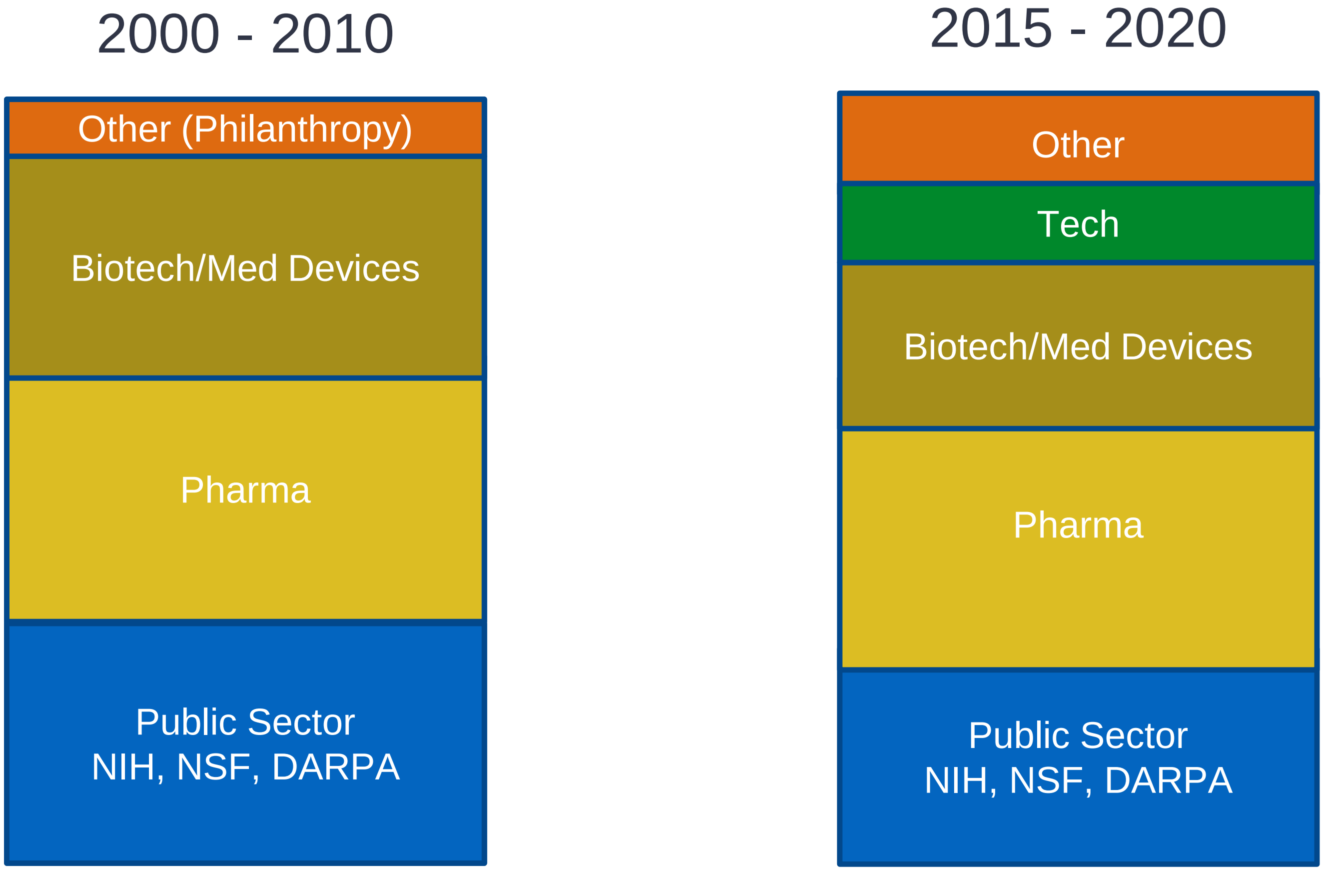


Tech Giants with health/biomedical initiatives:
Alibaba, Alphabet, Amazon, Apple, Facebook, Fitbit, GE, IBM, Intel, Microsoft

Start-ups:
$22B invested in Health Tech since 2011
> 1,000 new companies
(Rock Health, 2018)

Insel, Nature, 2017

The Changing Ecosystem of Health Research



Moses et al, JAMA 2015

The Changing Ecosystem of Biomedical Research

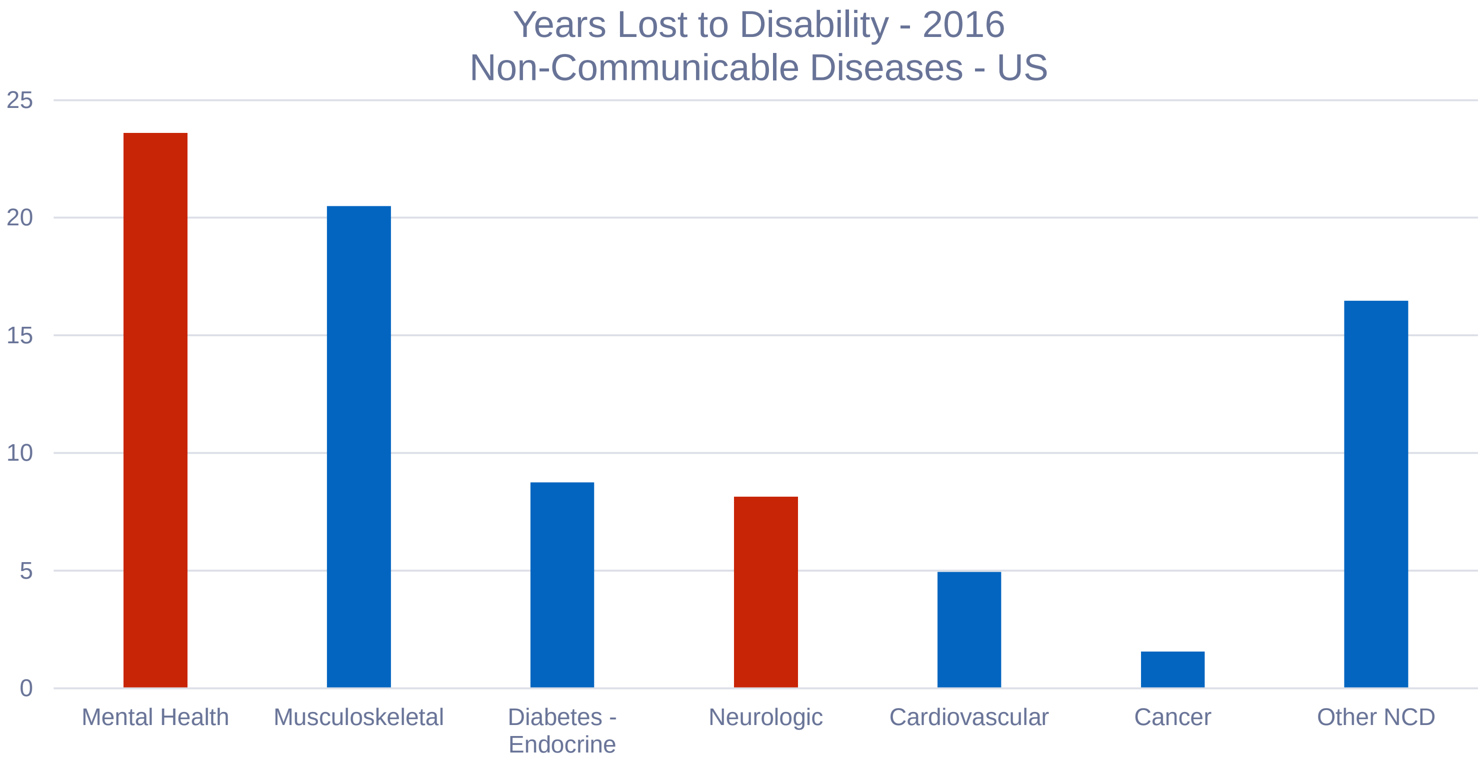
	Public	Private
	Academics	Pharma/Biotech
	Patient Advocates	Tech
Output	Papers/Policies	Products/Profits
Culture	Individual/Tenure	Team/Churn
Science	Basic/Narrow	Translational/Scale
DNA	Educational	Transactional
Resources	Constrained by dollars	Constrained by time
Public Trust	High	Low

Insel, Nature, 2017

The Brain Disorder Problem

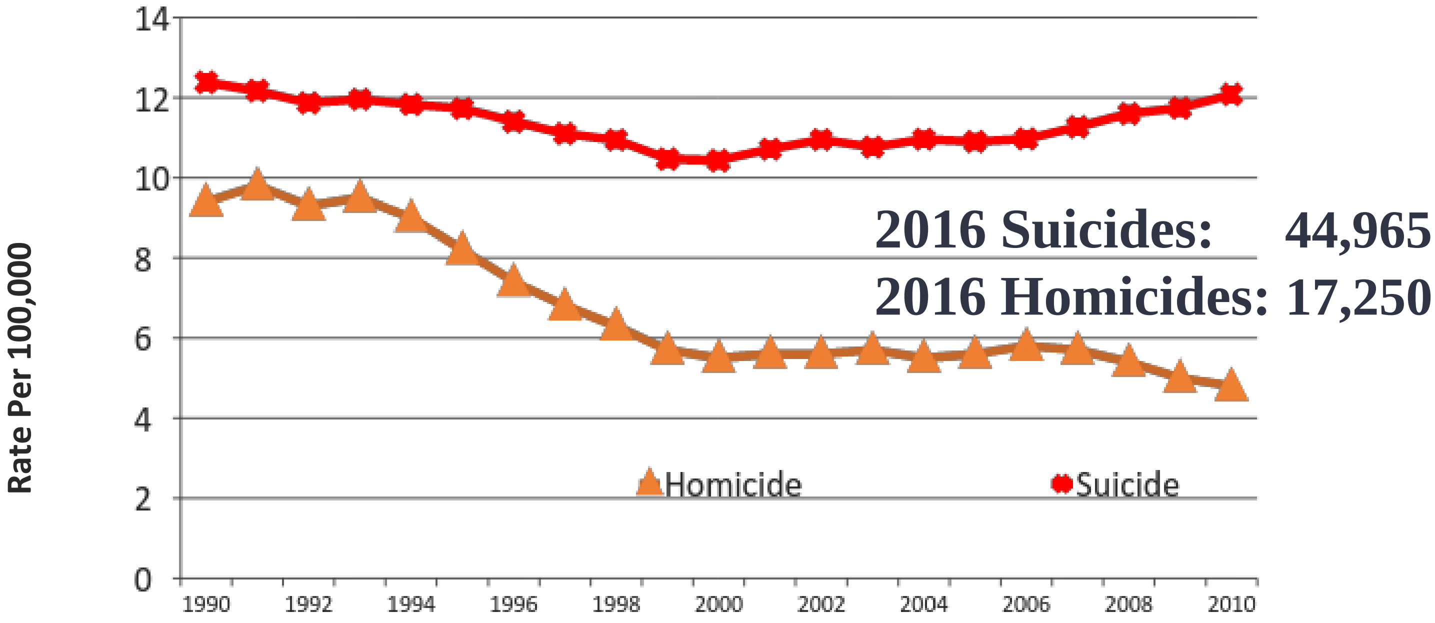
- High morbidity and mortality
- No evidence of improvement

Brain Disorders Have the Highest Disability



Data from (http://ghdx.healthdata.org)

U.S. Suicide Rate Trending Up

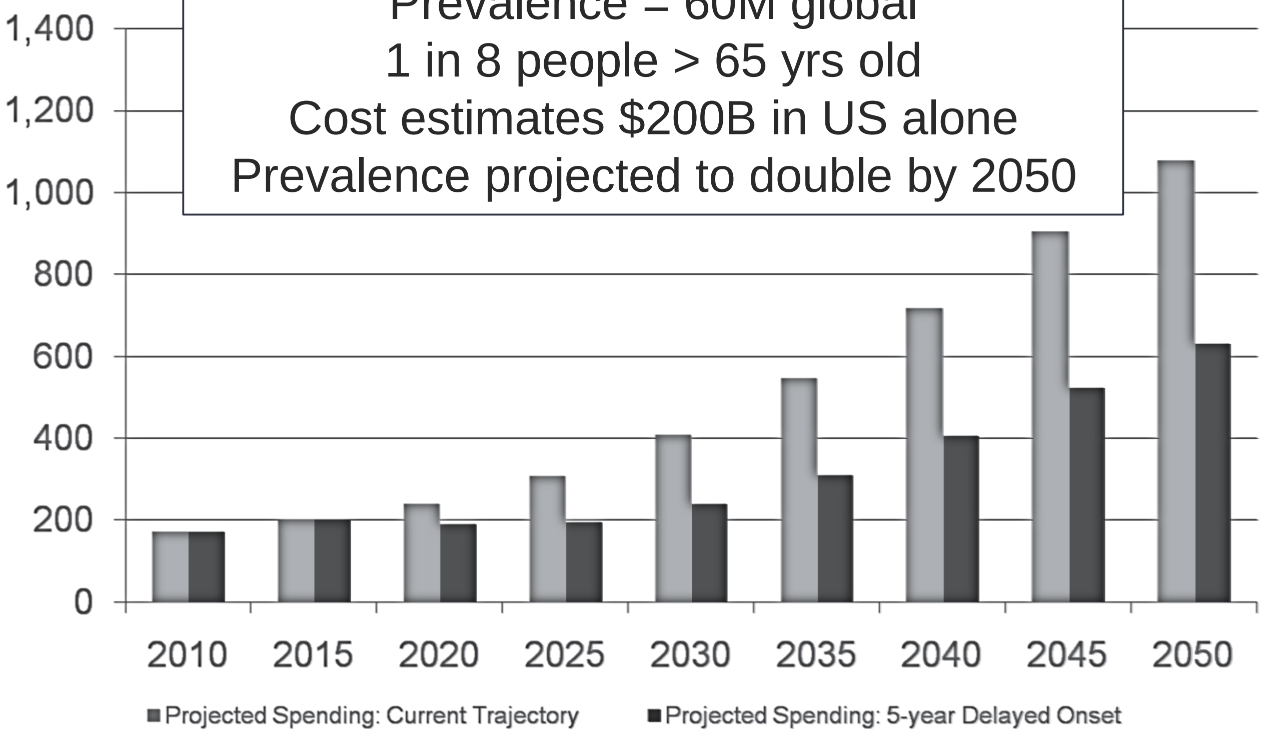


Homicides dropped from 9.8/100,000 in 1992 to 4.8/100,000 in 2010 (15,000/yr)

SOURCES: Bureau of Justice Statistics (homicide); Centers for Disease Control (suicide)

Burden of Alzheimer's Disease Over Time: *Projected Spending*

Prevalence = 60M global
1 in 8 people > 65 yrs old
Cost estimates $200B in US alone
Prevalence projected to double by 2050



Source: Alzheimer's Association, *Changing the Trajectory of Alzheimer's Disease: A National Imperative* (2010).

Why have we failed to bend the curve?

Imprecise Dx	*Lack of biological validity*
Lack of Engagement	*60% not receiving care*
Quality	*Fragmented, episodic, reactive*
Lack of Measurement	*We don’t manage what we don’t measure*

The Technology Revolution

	2006	2018
Smartphones	64M	3B
Facebook users	12M	2B
YouTube hrs/day	65K	1.0B
Google searches	250M/day	> 3.5B/day
Apps in App Store	<15K	2M
Analytics	Parametric	Machine Learning

Smartphones

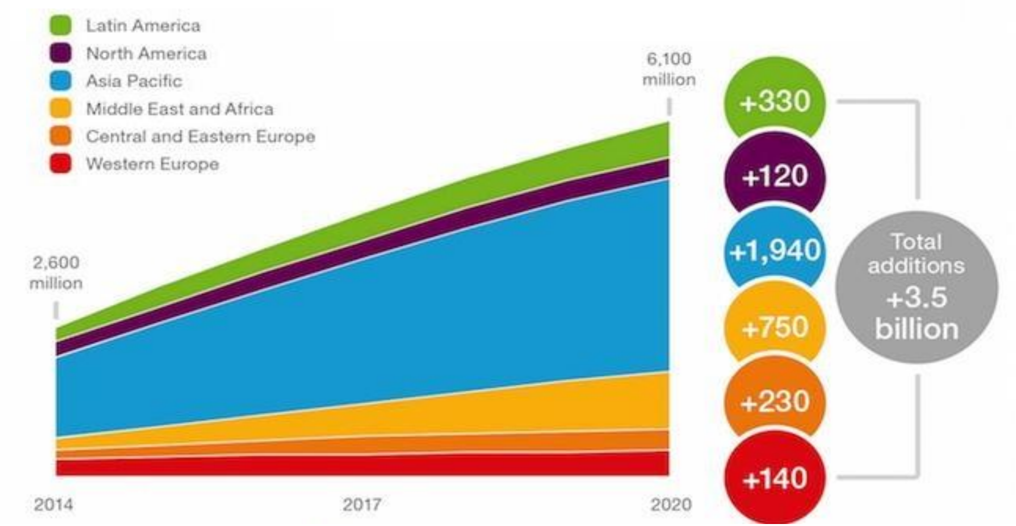
A supercomputer in every pocket

	Cray-2 Supercomputer	iPhone
GFLOPS	1.9	300-400
CPU Speed	244MHz	1.85GHz
Memory	?MB	128GB
Weight	2500KG	0.135KG
Cost (2010$s)	$32M	$999

Smartphones

A medical tool for global health – improving diagnosis and connecting care

Smartphone subscriptions per region 2014-2020



Over 3 billion globally and 6 billion by 2020

Over 70 daily checks

Over 2600 daily "touches"

More ubiquitous than clean water, indoor plumbing, and stable electricity

MEASURING MOOD, COGNITION, AND BEHAVIOR

WHAT WE DO TODAY

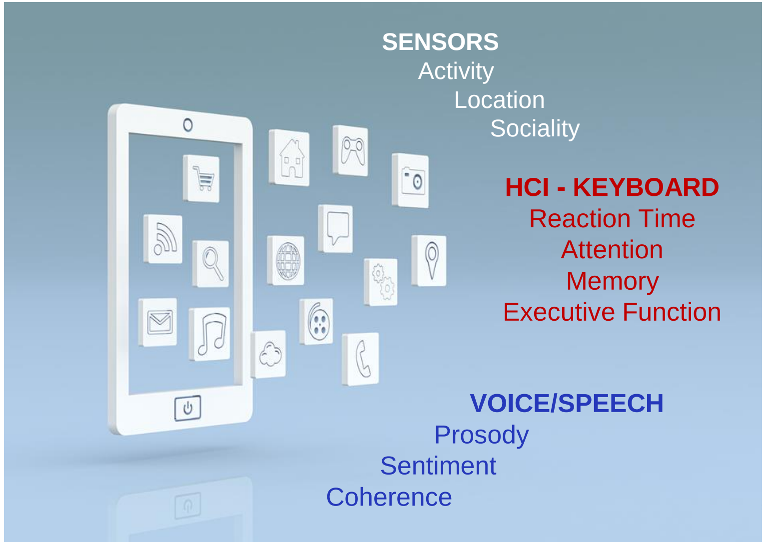
- Subjective
- Episodic
- Clinic-based
- High burden

WHAT WE NEED

- Objective
- Continuous
- Ecological
- Passive

DIGITAL PHENOTYPING

A New Kind of Biomarker

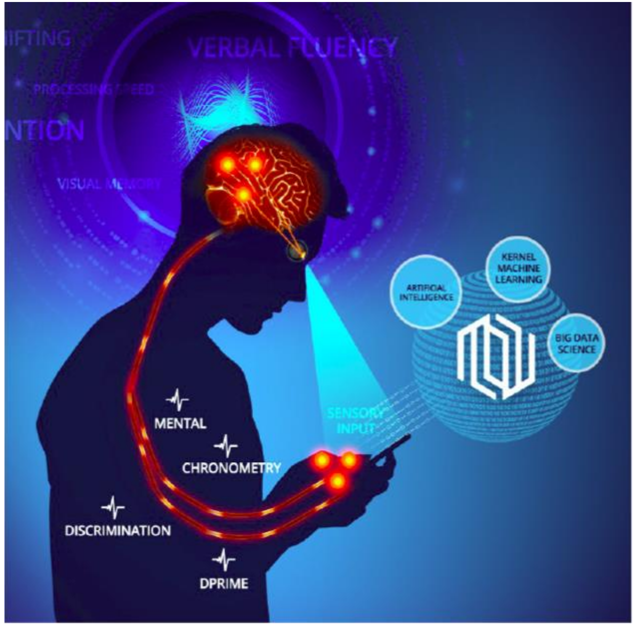


MACHINE LEARNING
Pattern Identification
Feature Extraction

Raw Features → **Digital Biomarkers** → **Digital Phenotype**

N.B. digital phenotype can also include "digital exhaust" (social media posts, search terms, AI personal assistants etc.)

Human-Computer Interaction (HCI): Measuring Brain Function Passively

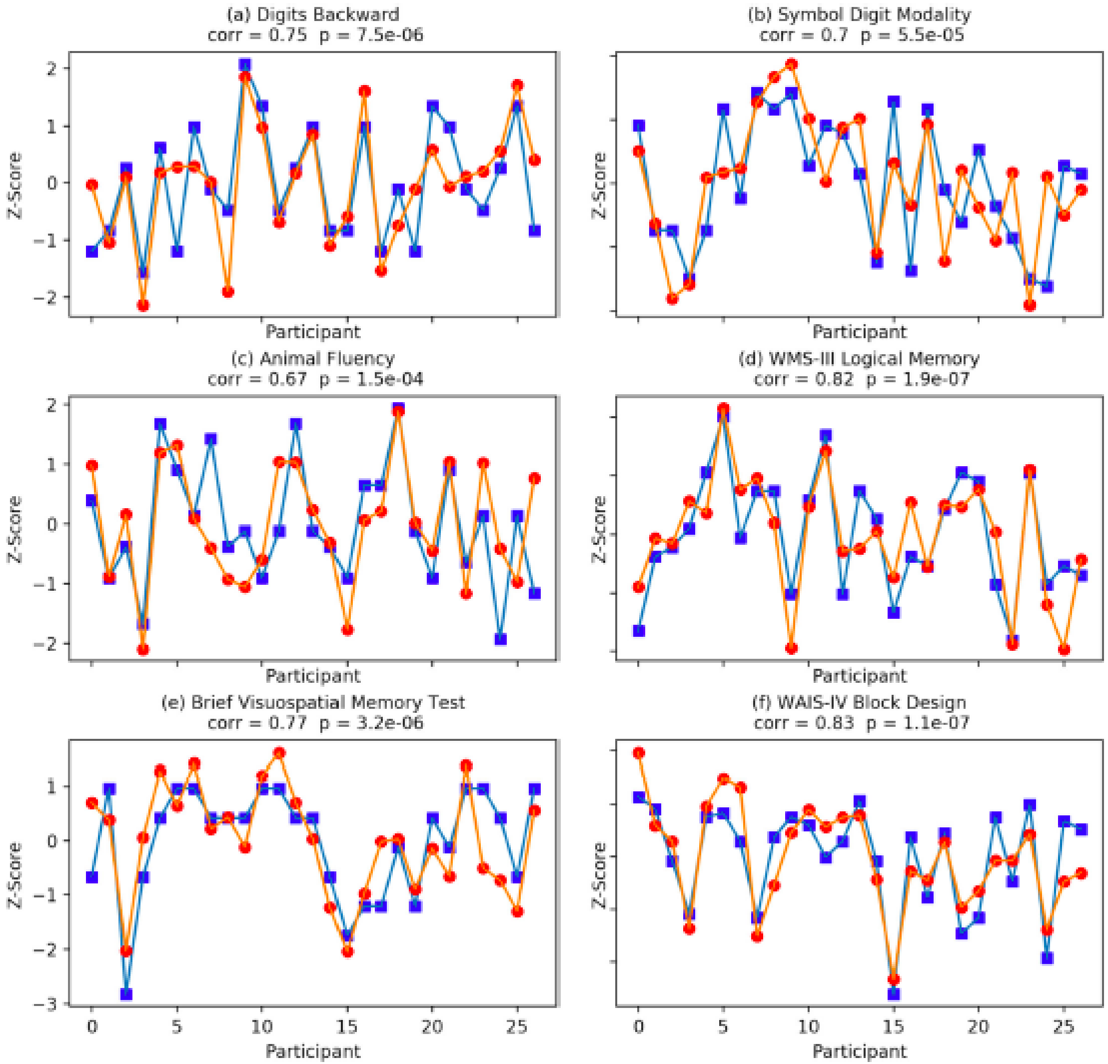


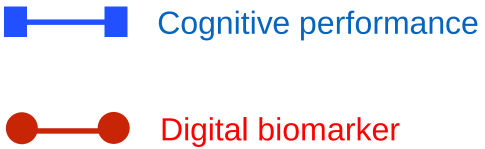
- 45 keyboard and scroll patterns (e.g., latency between space and character, scrolling patterns)
- Time-series of performance measures from each of the 45 patterns
- Apply 23 signal processing transforms to each time-series to derive 1,035 potential digital biomarkers
- Test highest performing biomarkers with 2-fold cross validation and with replication studies to avoid overfitting errors

Validate in clinical trials along three dimensions:

(1) psychometric properties; (2) clinical constructs; (3) neural correlates

Digital Biomarkers and Cognitive Traits





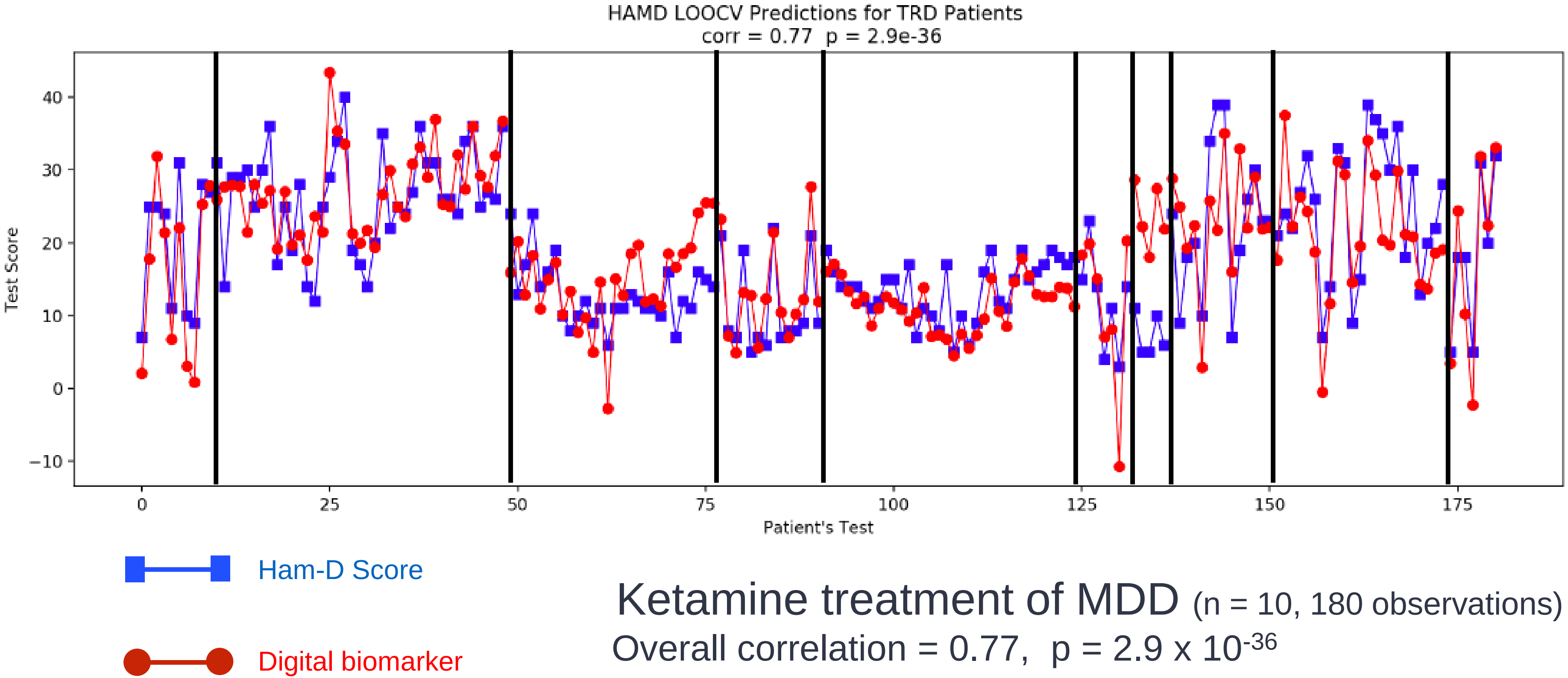
Volunteers (n = 27) compared on neurocognitive tests and digital biomarkers.

Correlations across multiple cognitive trait measures = .7 - .8 (roughly test–retest variance)

Dagum, Digital Medicine, 2018

Digital Biomarkers and Affective States – Tracking Depression

Source: Unpublished data Mindstrong and Kadima Clinic



Ketamine treatment of MDD (n = 10, 180 observations)

Overall correlation = 0.77, p = 2.9 x 10^{-36}

MEASURING MOOD, COGNITION, AND BEHAVIOUR

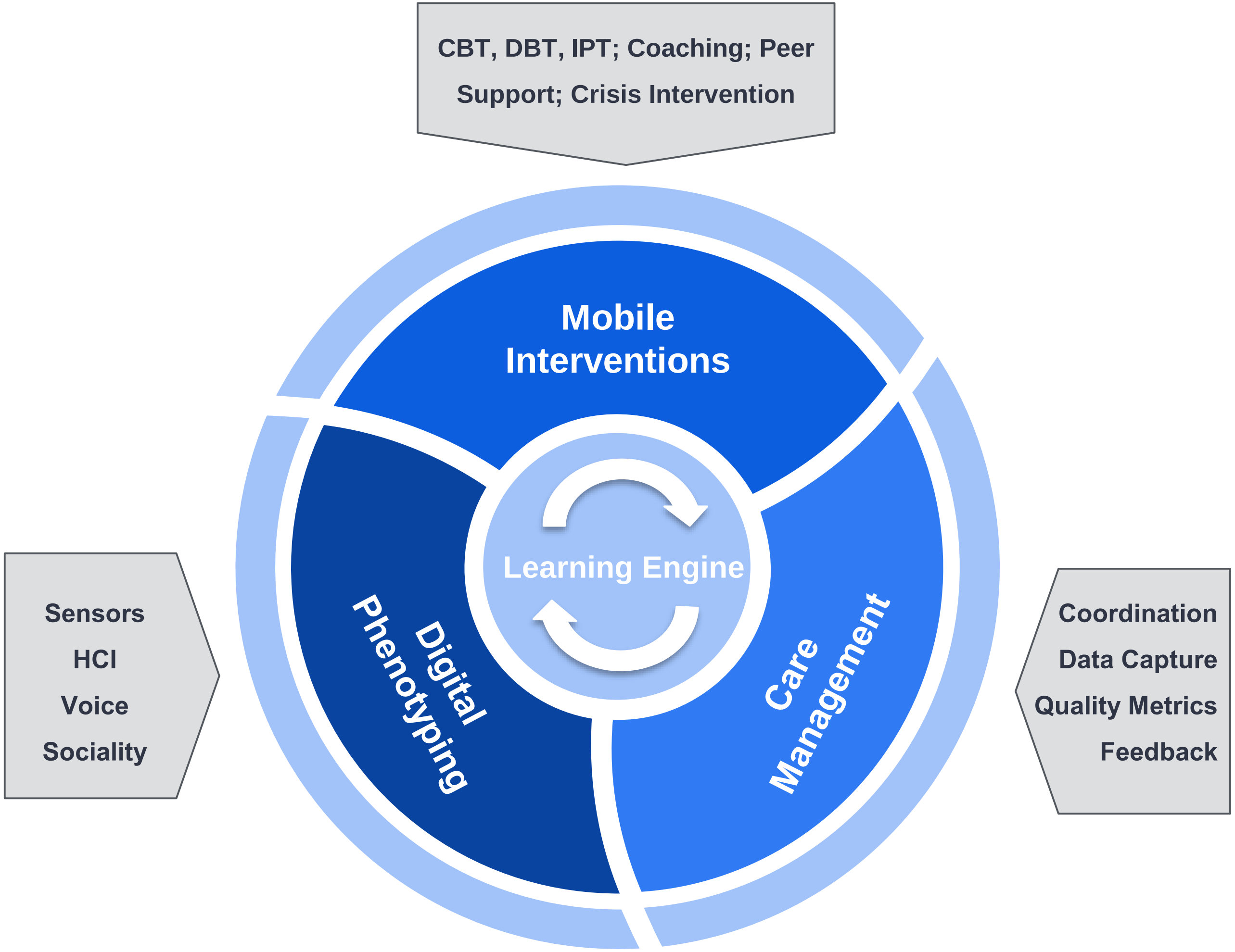
WHAT WE DO TODAY

- Subjective
- Episodic
- Clinic-based
- High Burden

WHAT WE NEED

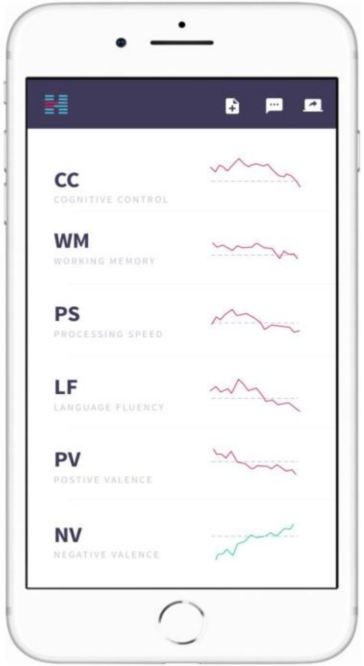
- ✓ Objective
- ✓ Continuous
- ✓ Ecological
- ✓ Passive

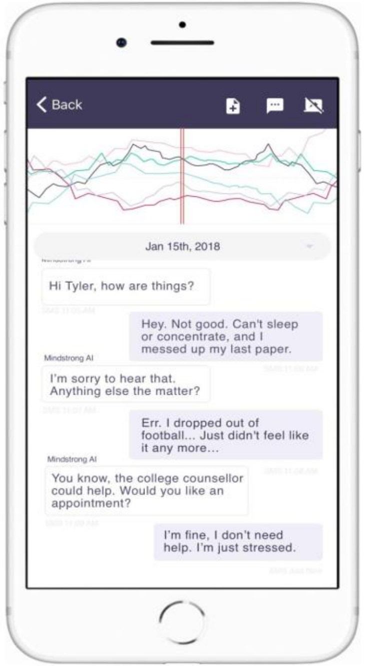
The Digital Health Landscape

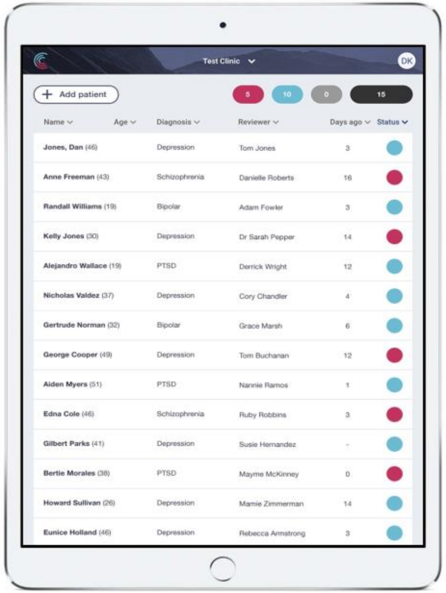


health
mindstrong

care
mindstrong





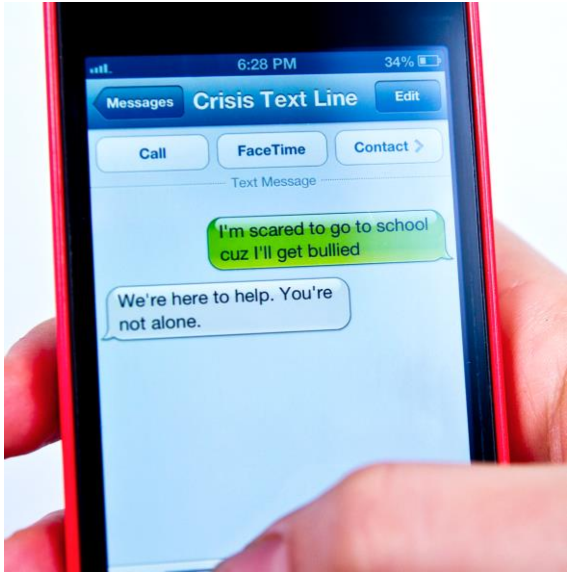


Digital Phenotyping

AI Nurse

Connected Care

Manager Dashboard



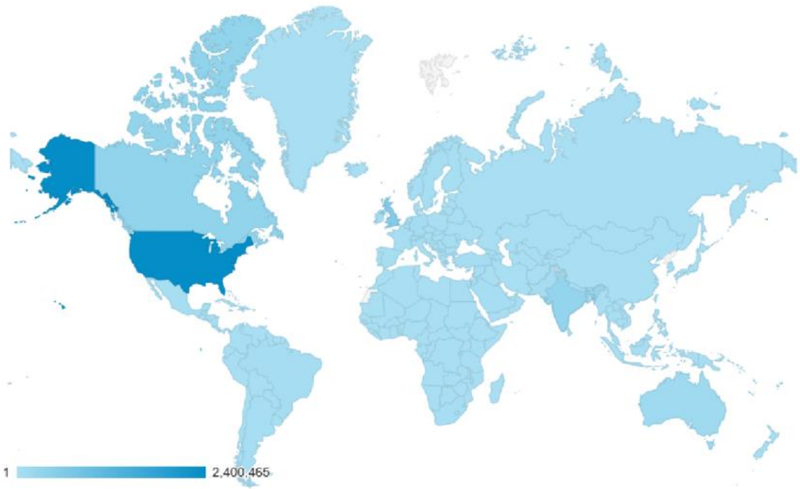
CRISIS TEXT LINE ™

Text 741741
Immediate access
Support for free 24/7

>53M messages since 2013, >2M/month
1/3 of messages — depression and suicide
19% from 10% lowest income zipcodes
9% Native American; 14% Hispanic
> 3K active rescues

7 Cups – an online global peer support system

2M monthly users — 220K listeners
189 countries providing support in 140 languages.



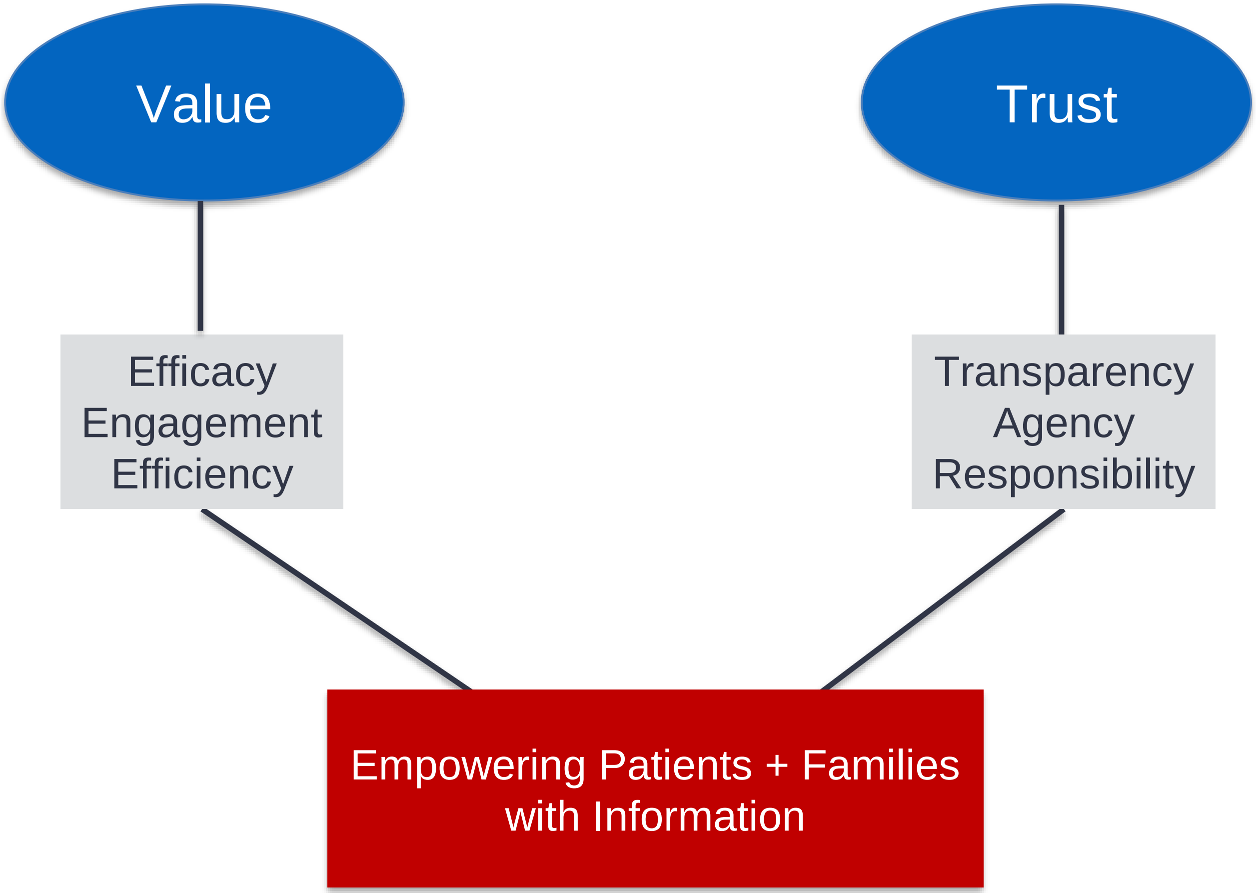
7 Cups approach:

- Anonymous – no stigma
- Community-focused
- On demand 24/7
- Convenience – smartphone/laptop
- Task shifting/stepped care
- Data driven

How Smartphones Will Transform Brain Health

Imprecise Dx	Objective, continuous, ubiquitous measures
Lack of Engagement	Anonymous, person-centered online care
Lack of Quality	Coordinated, connected care with quality metrics
Lack of Measurement	Digital smoke alarms for early detection of recovery and relapse

The Digital Mental Health Challenge



Thank You!

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Transforming Brain Health

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