GRAND ROUNDS

Artificial Intelligence at the Frontlines of Global Health

Presented by:

Neal Lesh, PhD
Chief Strategy Officer
Dimagi, USA

Tuesday, 23rd April 2019 at 9:00 a.m.

Empowering Health for 15 years

ICAP
Columbia University
Mailman School of Public Health

Outline

1. Background
    a. My background
    b. Digital solutions in global health
    c. CommCare /mobile apps for global health
2. Artificial Intelligence
    a. What is AI? What is Machine Learning?
    b. Uses of AI for global health
    c. An example from Mozambique

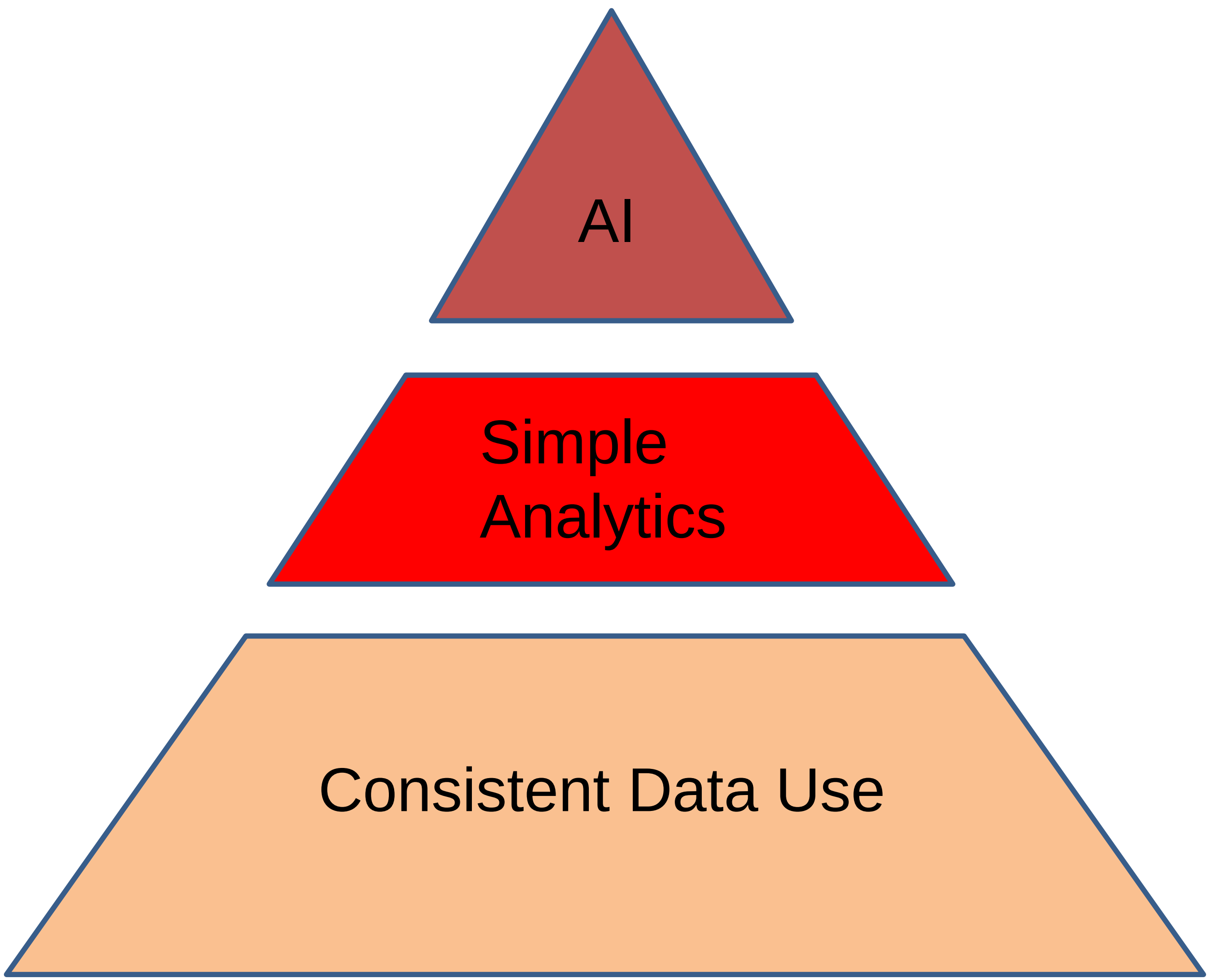
Main message: Digital has huge potential, but is not a magic bullet. Need to have the right expectations. Same for AI.

Quick Orientation

- **Digital Health**: use of digital technology to improve global health efforts, e.g., electronic medical record systems, supply chain systems, mobile apps, messaging. *Note: some divide digital health into 'eHealth' and 'mHealth'*
- **FLW Digital Platforms**: a subset of digital health that focuses on equipping Frontline Workers (FLWs) with apps.
- **Artificial Intelligence in Global H**ealth: the use of a certain, increasingly popular algorithms (AI) as an add-on to existing digital health interventions. Often require data as input.

Crawl, Walk, Run

(with your data)



My background

1991-1997	Got PhD in Artificial Intelligence
1997-2004	Published many papers in AI and Human-Computer Interaction
2004-2005	Left research world, got an MPH
2005-2009	Lived in East Africa, worked on many data systems
2011-2012	Co-founded community-driven org, Spark Microgrants
2008-now	Helped scale CommCare

Unsuccessful report (2005)

date	weeks on arv	ARV	WT	HT	HGB	ALT	cd4	cd4%	vl	WHO	sep-trin	TB	acute problem
23DEC04	.		27.2	132.0	.	.	133	.		3	no	no	none
19JAN05	.		.	.	10.8	32	.	.		3	.	.	
02FEB05	.	NOT b/c: cxr shows tb adenitis	27.4	132.0	.	.	.	.		3	yes	no	BOILS ON THE FA
03MAR05	.	NOT b/c: has tb adenitis	27.3	132.0	.	.	.	.		3	yes	no	ABSCESS ON THE
25MAY05	0	AZT243/ 3TC108/ NVP121 OD	27.0	137.0	.	.	.	.		3	yes	yes	SKIN INFECTION
09JUN05	2	AZT243/ 3TC108/ NVP203 BD	27.0	137.0	9.9	.	.	.		.	yes	no	none
23JUN05	4	AZT200/ 3TC110/ NVP204 BD	27.5	137.5	9.8	.	.	.		.	yes	yes	COUGH
24JUN05	4		.	.	.	55	.	.		.	.	.	
22JUL05	8	d4T200/ 3TC104/ NVP200 BD	26.0	137.1	10.1	.	.	.		.	no	no	none
23JUL05	8		.	.	.	51	.	.		.	.	.	

Successful report (2006)

Consultation, 04 Nov 2006

User ID	Name	Age	Attend?	Weight	New weight	Food support today?	Alerts	CD4	TB (current regimen, TB start date)	arv (current regimen,initiation, last change)	accompangateur
.	. .	37	Y N	54 kgs@19Janv06 64 kgs@12Juil06 66 kgs@9Aug06	.	Y N	.	151 @23Janv06 344 @11Aug06	. .	Triomune-40 (1 Co, 2/j) 20Janv06 2Mai06	MBUZUKONGIR A Thadee
.	. .	31	Y N	61 kgs@16Fevr06 65 kgs@22Aug06 69 kgs@18Sep06	.	Y N	late CD4	237 @27Fevr06	RHEZ (4 Co, 4/j) 2006-06-16	3TC 150 mg (1 Co, 2/j); D4T 40 mg (1 Co, 2/j); EFV 200 mg (1 Co, 1/j); EFV 600 mg (1 Co, 1/j) 3Mars06 16Juin06	MUPENZI Faustin
.	. .	36	Y N	55 kgs@19Janv06 63 kgs@12Juil06 65 kgs@9Aug06	.	Y N	.	99 @23Janv06 183 @21Juil06	. .	Triomune-40 (1 Co, 2/j) 19Janv06 21Avril06	UWINGABIRE Pacifique
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.	. .	46	Y N	48 kgs@19Janv06 49 kgs@12Juil06 51 kgs@9Aug06	.	Y N	.	196 @23Janv06 660 @11Aug06	. .	Triomune-30 (1 Co, 2/j) 20Janv06	NIYONSABA Jeannette
.	. .	43	Y N	61 kgs@19Janv06 60 kgs@12Juil06 61 kgs@9Aug06	.	Y N	.	381 @5Janv06 708 @27Juil06	. .	Triomune-40 (1 Co, 2/j) 20Janv06	MPINGANZIMA Marie
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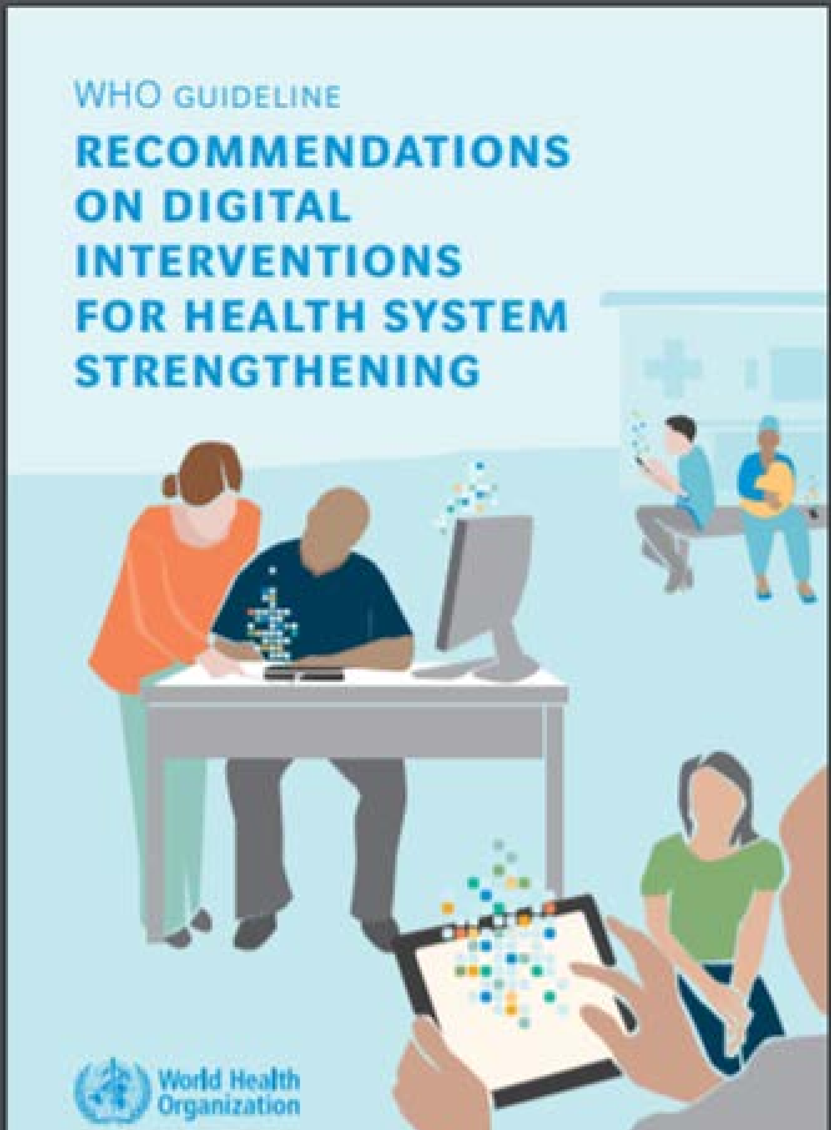
Digital in Global Health



April 17, 2019

WHO releases recommendations on 10 ways that countries can use digital health technology.

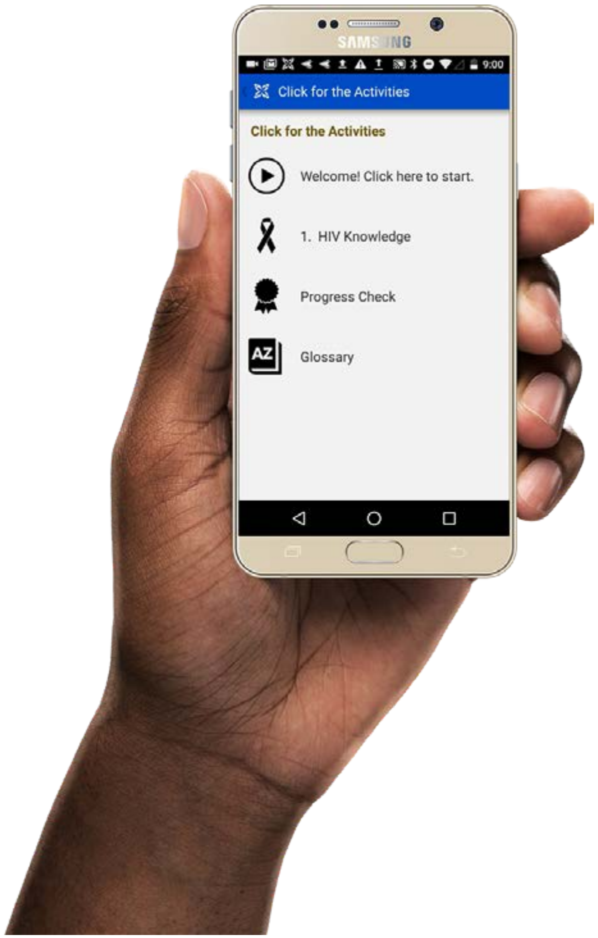
"Harnessing the power of digital technologies is essential for achieving universal health coverage," says WHO Director-General Dr Tedros Adhanom Ghebreyesus.

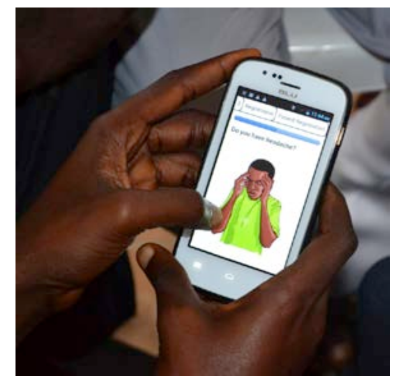
Recommendations #6-8

Contribution to universal health coverage (UHC)	Digital health intervention	Recommendation
Contact coverage **Continuous coverage**	**Recommendation 6** Targeted client communication via mobile devices	WHO recommends targeted client communication via mobile devices for health issues regarding sexual, reproductive, maternal, newborn, and child health under the condition that potential concerns about sensitive content and data privacy can be addressed *(Recommended only in specific contexts or conditions)*
Effective coverage	**Recommendation 7** Health worker decision support via mobile devices	WHO recommends the use of decision support via mobile devices for community and facility-based health workers in the context of tasks that are already defined within the scope of practice for the health worker. *(Recommended only in specific contexts or conditions)*
Effective coverage **Accountability coverage**	**Recommendation 8** Digital tracking of clients' health status and services (digital tracking) combined with decision support	WHO recommends digital tracking of clients' health status and services, combined with decision support under these conditions: • in settings where the health system can support the implementation of these intervention components in an integrated manner; and • for tasks that are already defined as within the scope of practice for the health worker. *(Recommended only in specific contexts or conditions)*

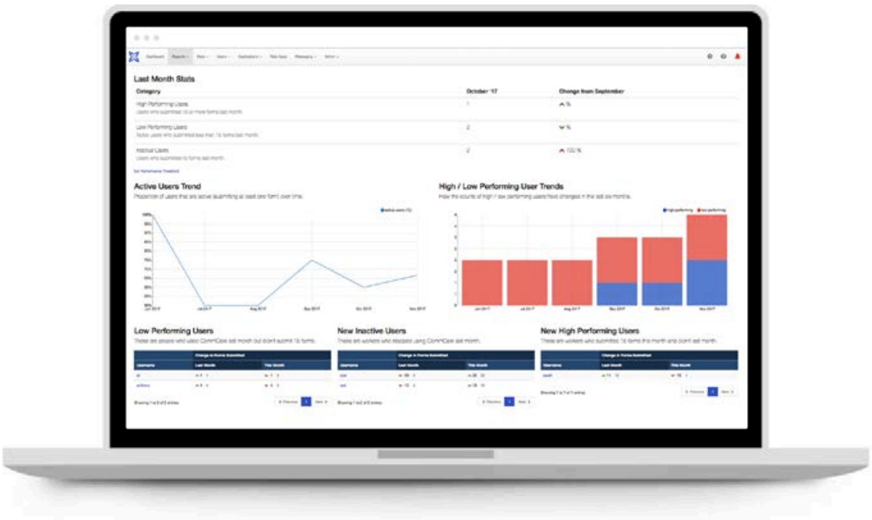
CommCare

CommCare


Click for the Activities
Click for the Activities
Welcome! Click here to start.
1. HIV Knowledge
Progress Check
Glossary

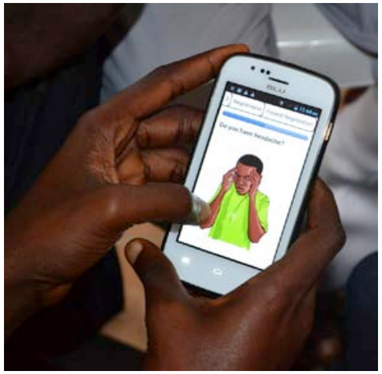


CommCare

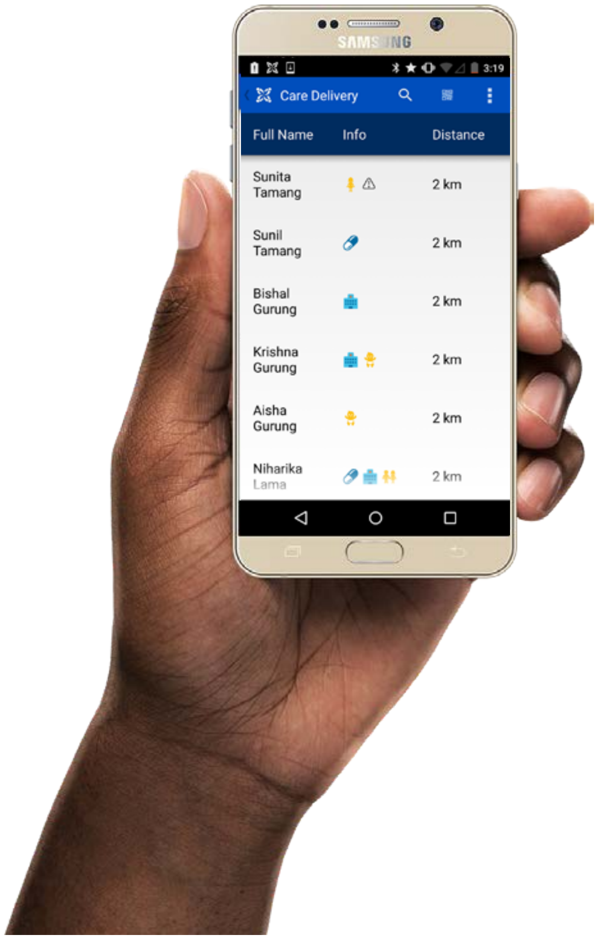

Last Month Stats
Active Users Trend
High / Low Performing User Trends
Low Performing Users
New Inactive Users
New High Performing Users


Empower end-users


Track data over time



CommCare



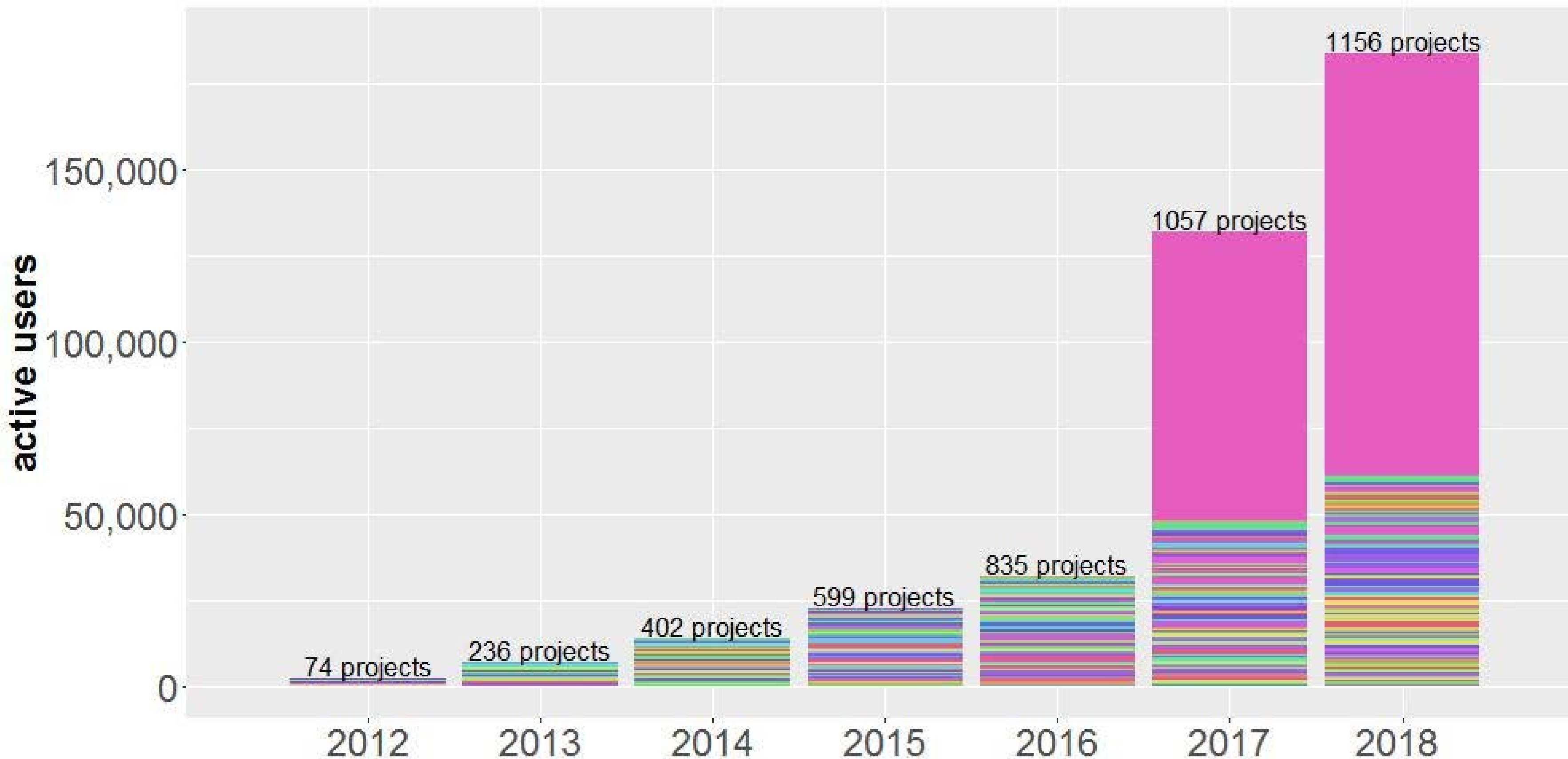
Empower end-users

Track data over time

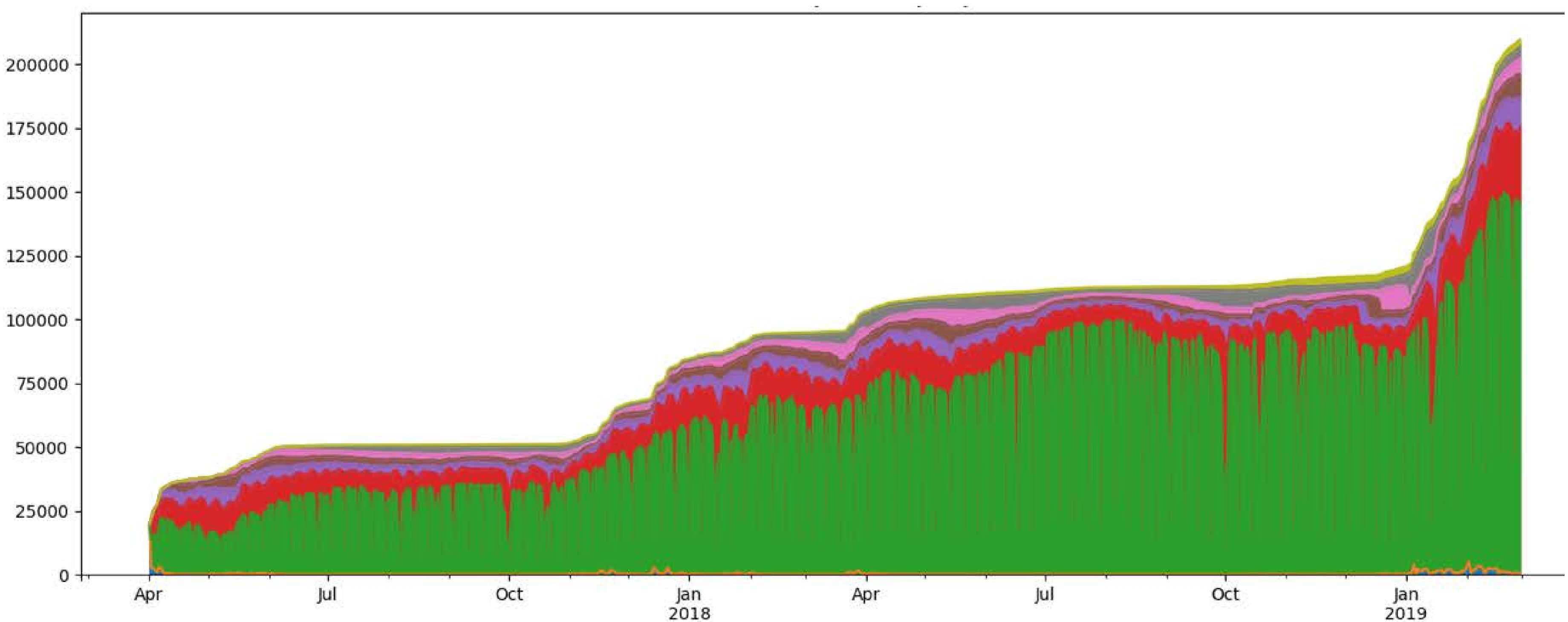
Work offline

Start small or scale

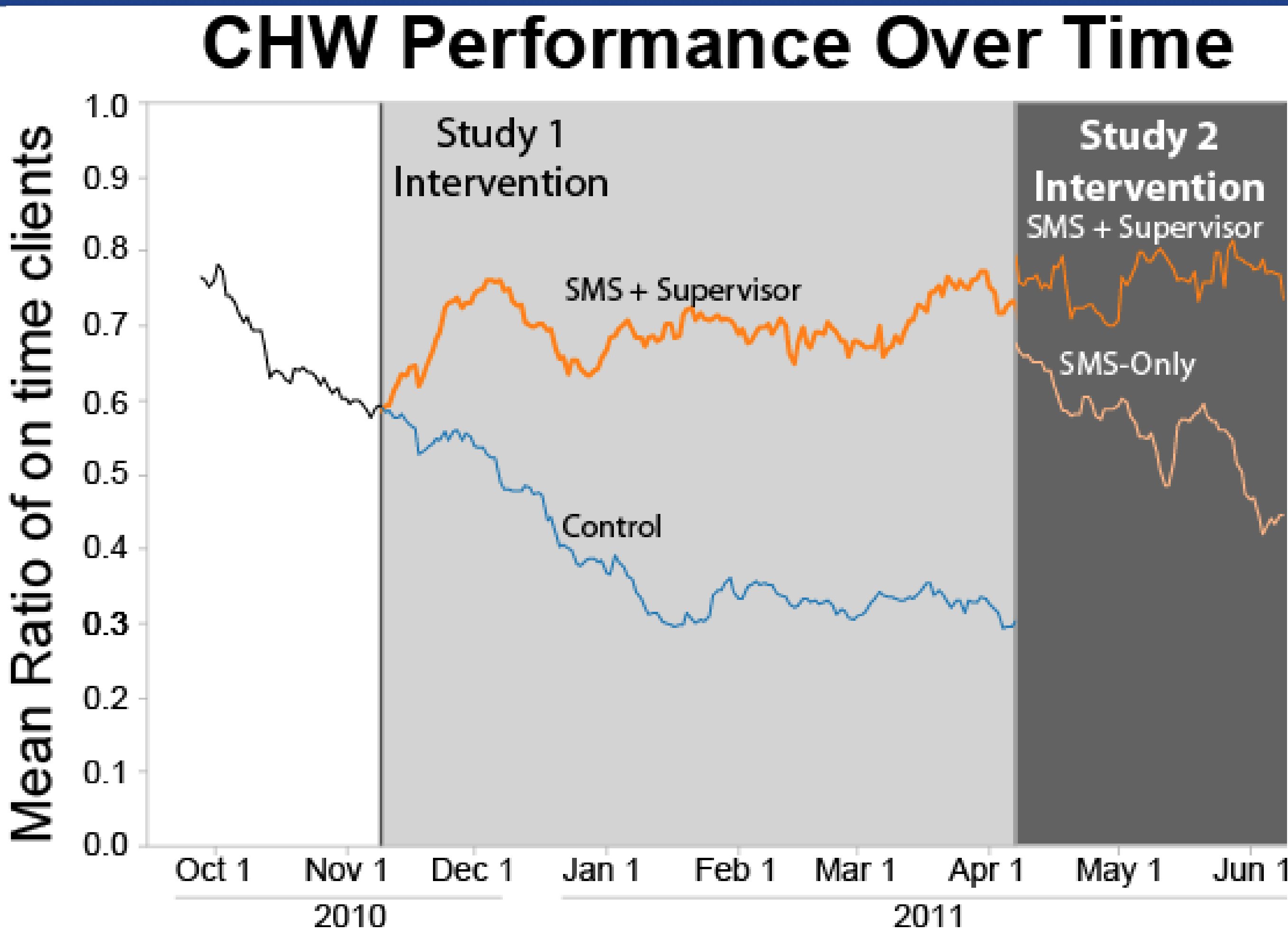
Growth of CommCare



Large Scale in India



Another Cautionary Tale



B. DeRenzi, L. Findlater, G. Borriello, J. Jackson, J. Payne, B. Birnbaum, T. Parikh, N. Lesh, "Improving Community Health Worker Performance Through Automated SMS", ICTD 2011, to appear

Definition of Artificial Intelligence

"the use of computers for automated decision-making to perform tasks that normally require human intelligence."

From a recent report entitled "Artificial Intelligence in Global Health Defining a Collective Path Forward", by the Rockefeller Foundation, USAID, Center for Innovation and Impact, and Bill and Melinda Gates Foundation.

Uses of AI

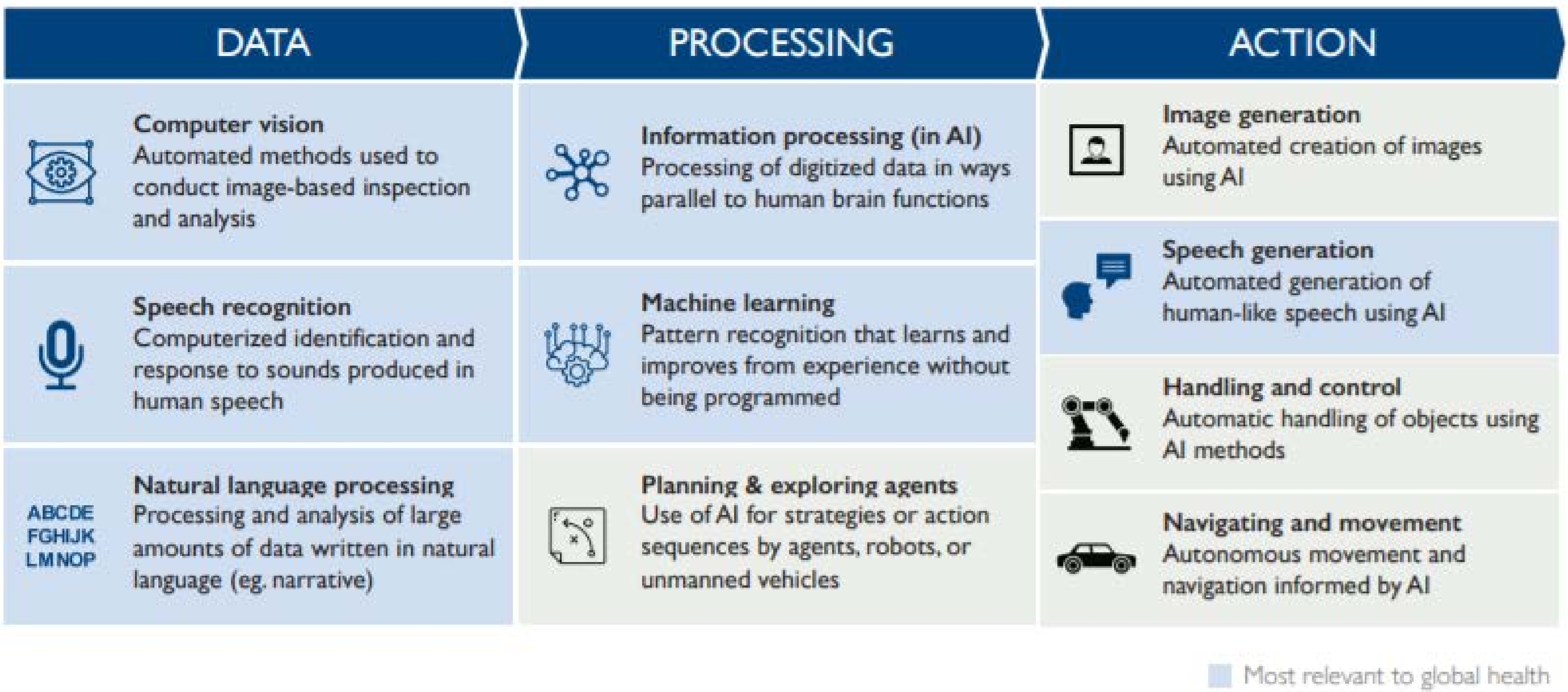
General

- Detect fraud
- Predict customer behavior
- Optimize operational processes
- Segment consumers and tailor marketing

FLQ Digital Platforms

- Identify FLWs who submit suspicious data
- Identify high risk clients
- Reduce stock outs
- Segment clients to tailor behavior change communication

Building Blocks of AI



Artificial Intelligence in Global Health Defining a Collective Path Forward", by the Rockefeller Foundation, USAID, Center for Innovation and Impact, and Bill and Melinda Gates Foundation.

Dimagi AI Priorities

DATA

Computer vision
Automated methods used to conduct image-based inspection and analysis

Speech recognition
Computerized identification and response to sounds produced in human speech

Natural language processing
Processing and analysis of large amounts of data written in natural language (eg. narrative)

PROCESSING

Information processing (in AI)
Processing of digitized data in ways parallel to human brain functions

Machine learning
Pattern recognition that learns and improves from experience without being programmed

Planning & exploring agents
Use of AI for strategies or action sequences by agents, robots or unmanned vehicles

ACTION

Image generation
Automated creation of images using AI

Speech generation
Automated generation of human-like speech using AI

Handling and control
Automatic handling of objects using AI methods

Navigating and movement
Autonomous movement and navigation informed by AI

Most relevant to global health

Adding Chatbot to FLW apps

Predictive Analytics with Machine Learning

FLW Use Case #1: Chatbots

Idea: Extend a FLW app with a direct-to-client (d2c) experience that engages clients after FLW encounter, using a persona and natural language processing (NLP).

Poshan Didi Chatbot

Examples:

- Adherence Bot for HIV/TB care
- Follow up after IMCI session
- Nutrition counseling to augment Growth Monitoring

FLW Use Case #1: Chatbots

Idea: Extend a FLW app with a direct-to-client (d2c) experience that engages clients after FLW encounter, using a persona and natural language processing (NLP).

Poshan Didi Chatbot

Opportunities:

- Deliver existing content in a way that will be more engaging for many clients
- Strengthen health system while making care more consumer centered
- Extend range of services, e.g., possibly mental health counseling

FLW Use Case #1: Chatbots

Idea: Extend a FLW app with a direct-to-client (d2c) experience that engages clients after FLW encounter, using a persona and natural language processing (NLP).

Challenges:

- Literacy / speech recognition in local languages
- Phone availability / Smartphone penetration
- NLP for local languages

Poshan Didi Chatbot

What is Machine Learning?

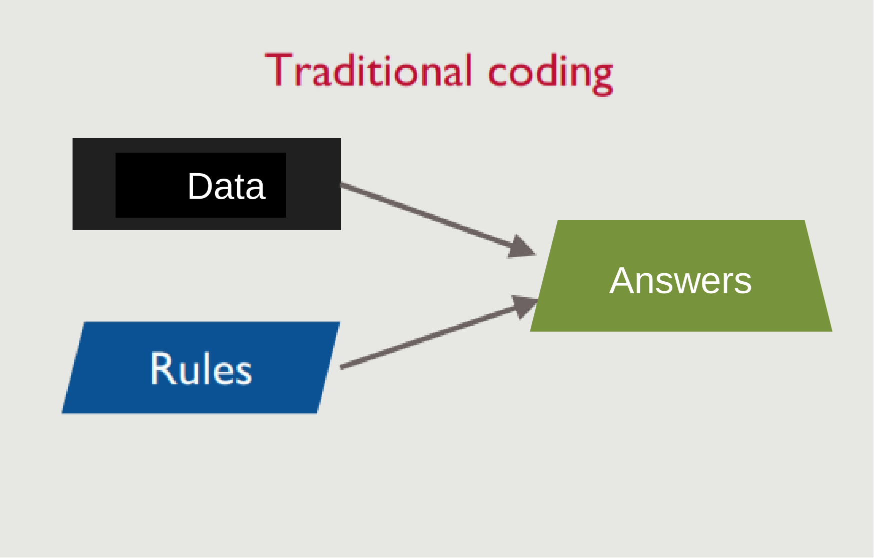
"a subset of AI that uses algorithms that give computers the ability to learn without being explicitly programmed"

Artificial Intelligence in Global Health Defining a Collective Path Forward", by the Rockefeller Foundation, USAID, Center for Innovation and Impact, and Bill and Melinda Gates Foundation.

"Machine learning (ML): A subfield of AI that is specifically concerned with learning. ML uses computers to detect patterns in data and use these patterns to make inferences about unseen data. Most modern AI applications rely on ML."

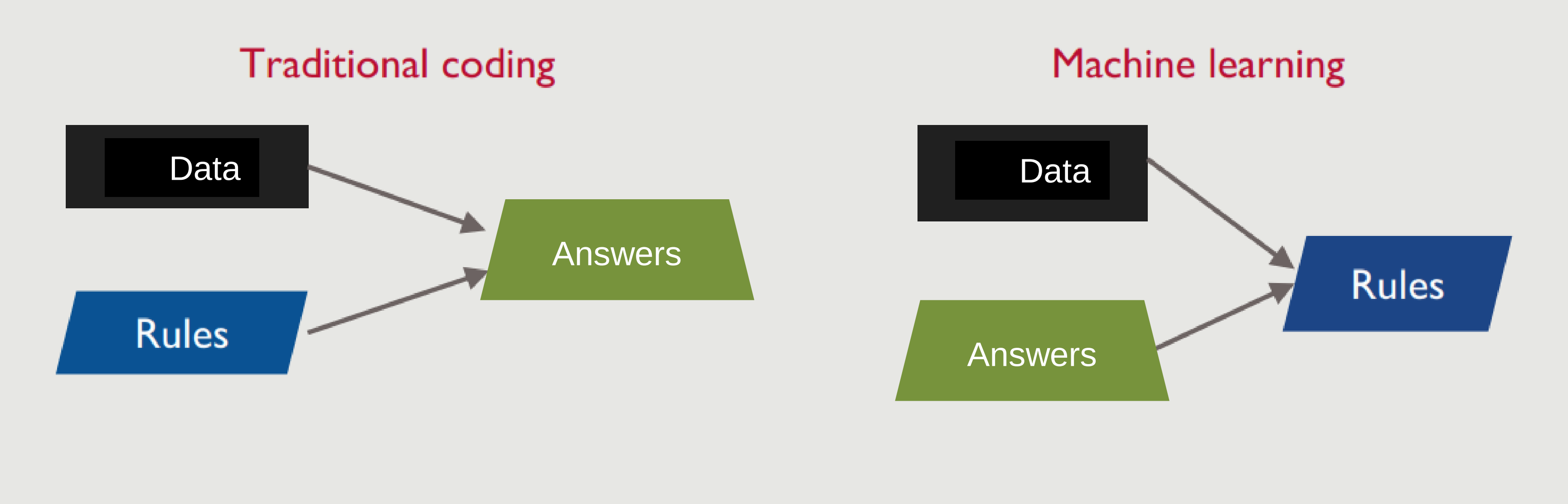
Introduction to AI and AI for Good, Craig Jolley, Ph.D., U.S. Global Development Lab October 2018

Machine Learning



Adapted from, “Introduction to AI and AI for Good”, Craig Jolley, Ph.D., U.S. Global Development Lab, October 2018

Machine Learning



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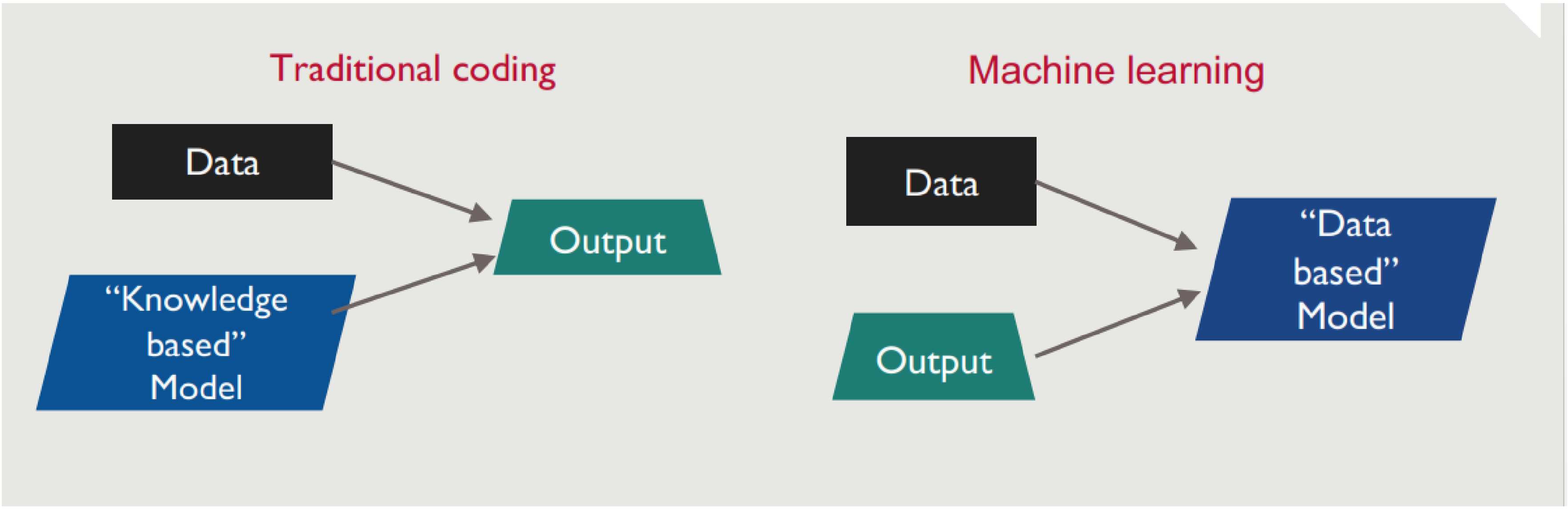
Machine Learning



"Introduction to AI and AI for Good", Craig Jolley, Ph.D., U.S. Global Development Lab October 2018

Use of Machine Learning

- Image classification
  - Infer nutrition status from images or videos
  - Classification of radiologic images

- Predictive Analytics
  - Predict who will give birth at home vs. hospital
  - Predict which patients will default from treatment, or miss their next visit.

Case Study: Using ML to Predict Missed Appointments by People on ART in Mozambique

Programmatic Challenge

- Mozambique has made great progress in scaling up HIV diagnosis, prevention and treatment services
- However, missed appointments and suboptimal retention are still important challenges

Digital Platform

- CommCare has been adapted for use in Mozambique's health system, with the support of the Ministry of Health and USAID
- The local version of CommCare is called *Infomovel*

Rational for AI

- What if patients at high risk for default could be identified *before* they miss appointments? This might enable more efficient and effective targeting of interventions
- Dimagi and ICAP proposed using machine learning to develop a way to identify and flag at-risk patients
- HRSA supported a rapid program of development and user feedback, "kick starting" the project via the OpCon funding mechanism
- All work done in collaboration with MOH and CDC

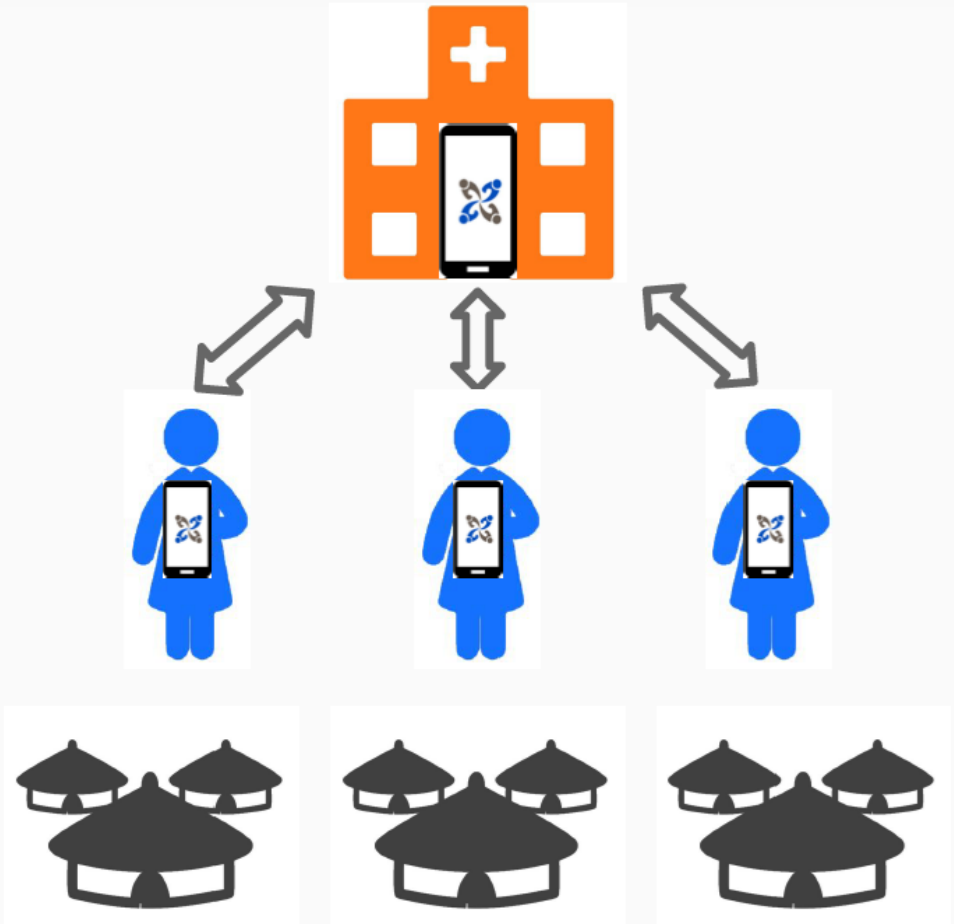
Infomovel

The Infómovel application supports community-based HIV and TB care in Mozambique.

Patients are first enrolled in HIV care at the health facility by the facility focal point.

The facility focal point assigns HIV+ patients to the Community Health Workers (CHWs) to be followed-up with in their homes.

Patients and their household members are visited by the CHW to reinforce adherence if they are a key population in follow-up, or if they have defaulted from their treatment.



Project Objectives

- Using machine learning, develop a framework to assign a defaulter risk score to clients currently in Infómovel
- Use the defined framework to assign a "flag" (*e.g.*, a visual alert) to the 20% of clients predicted to have the highest risk of defaulting
- Assess the risk scores against historical data and data from June – August 2018 from 4 sites in 2 provinces, to determine what percentage of actual defaulters were/would have been flagged
- Obtain user feedback from CHWs and facility level staff in two facilities in Nampula Province

Building a Dataset

Site	Patients	Visits
Akumi	313	910
Muhala	146	487
Namacata	19	88
16 de Junho	13	62
Total	**491**	**1,547**

The team's definition of defaulter was any patient that missed a scheduled visit by 7 days or more. Additional slides will demonstrate results when visits were missed by 7, 10, 14 and 28 days

Machine Learning Results: Summary

Interpretation for cross facility data

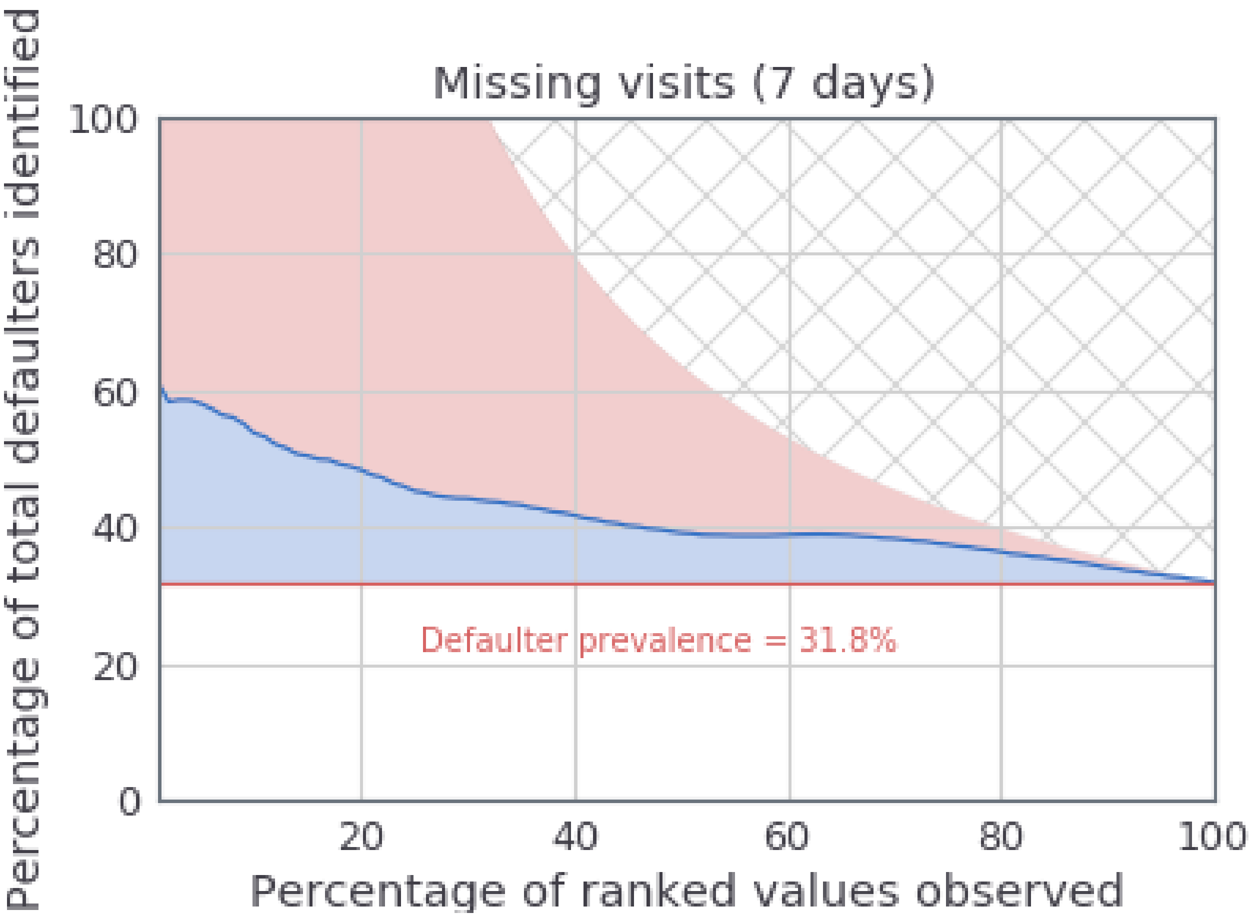
# days a visit was missed by	Prevalence Rate	ML Predictor for top 20% of at-risk
7	31.80%	~50%
10	28.30%	~43%
14	26.20%	~40%
28	19.80%	~ 38%

Refining the Model: Facility-Specific Focus

Results when we build the model for just one site

Missing days	Prevalence Rate	ML prediction for 20%
7	35.7%	60%
28	23.1%	45%

Machine Learning Prediction: 7 day Missed Visit Results



The horizontal line is the sample defaulter prevalence

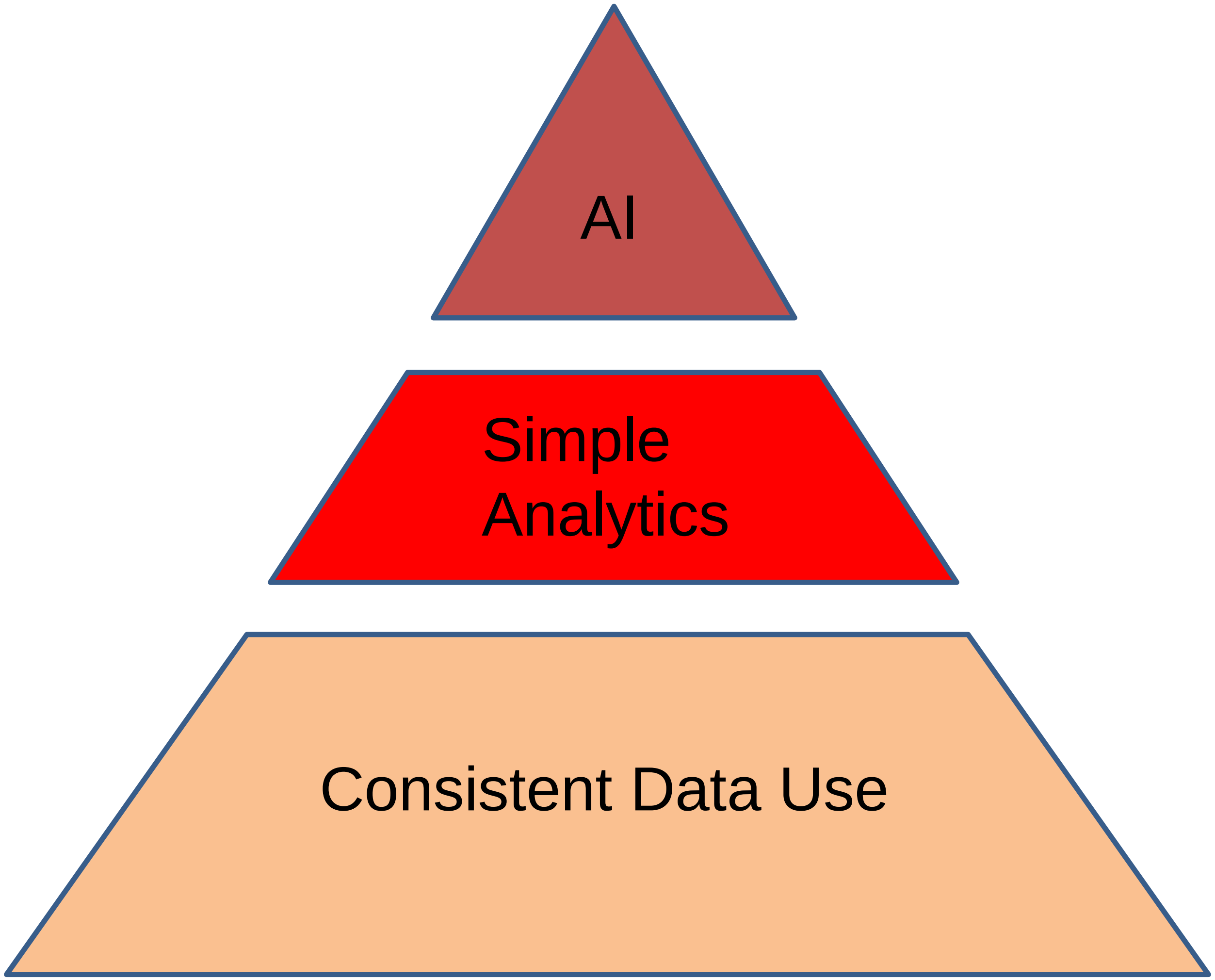
The blue area of the graph shows us how the true defaulters vary over risk rankings

The red area of the graph show us the best possible performance the algorithm could do

Overall Findings

- Machine learning was able to flag the subset of patients at highest risk of defaulting
  - More work needs to be done to refine the model
- Use of the flag was of high interest to CHWs and health facility staff
  - Workflows and Infomovel use will need to be optimized/adapted in order to implement it with maximal effect

Crawl, Walk, Run
(with your data)



Acknowledgements

This project is supported by the U.S. President's Emergency Plan for AIDS Relief, through the Health Resources and Services Administration (HRSA) of the U.S. Department of Health and Human Services (HHS) under grant UJ7HA31180, *Optimizing Momentum toward Sustainable Epidemic Control*. This information or content and conclusions should not be construed as the official position or policy of, nor should any endorsements be inferred by HRSA, HHS or the U.S. Government.

Questions?

Feel free to contact me at nlesh@dimagi.com

Please Join Us:

Tuesday, 21st May 2019 at 9:00am EST

Breaking Down Barriers to Care: Reducing Stigma and Discrimination in Health Facilities

with

Laura Nyblade, PhD & Rebecca Mbuya-Brown

Laura Nyblade, PhD
Fellow, RTI International
Senior Technical Advisor, Stigma & Discrimination
HP+

Rebecca Mbuya-Brown
Fellow, RTI International
Senior Associate, Health
HP+/Palladium

Empowering Health for 15 years

ICAP
Columbia University
Mailman School of Public Health