How can we harness the potential of Big Data & AI in medicine?

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Undergraduate degree in mechanical/mechatronic engineering

Medicine
UNIVERSITY OF TORONTO

UNITY HEALTH
TORONTO
Caring hearts. Leading minds.

Conflicts of Interest

Part-time employee (Provincial Clinical Lead) for Ontario Health

Co-inventor of CHARTwatch, minority shareholder in Signal1

Research funding from various government and non-profit organizations

Learning Objectives

1. Discuss applications of data and analytics for improving healthcare and the vision of a "learning health system".
2. Identify opportunities, progress, and challenges of implementing artificial Intelligence solutions in medicine.
3. Teach learners about artificial intelligence and its implications for clinical practice

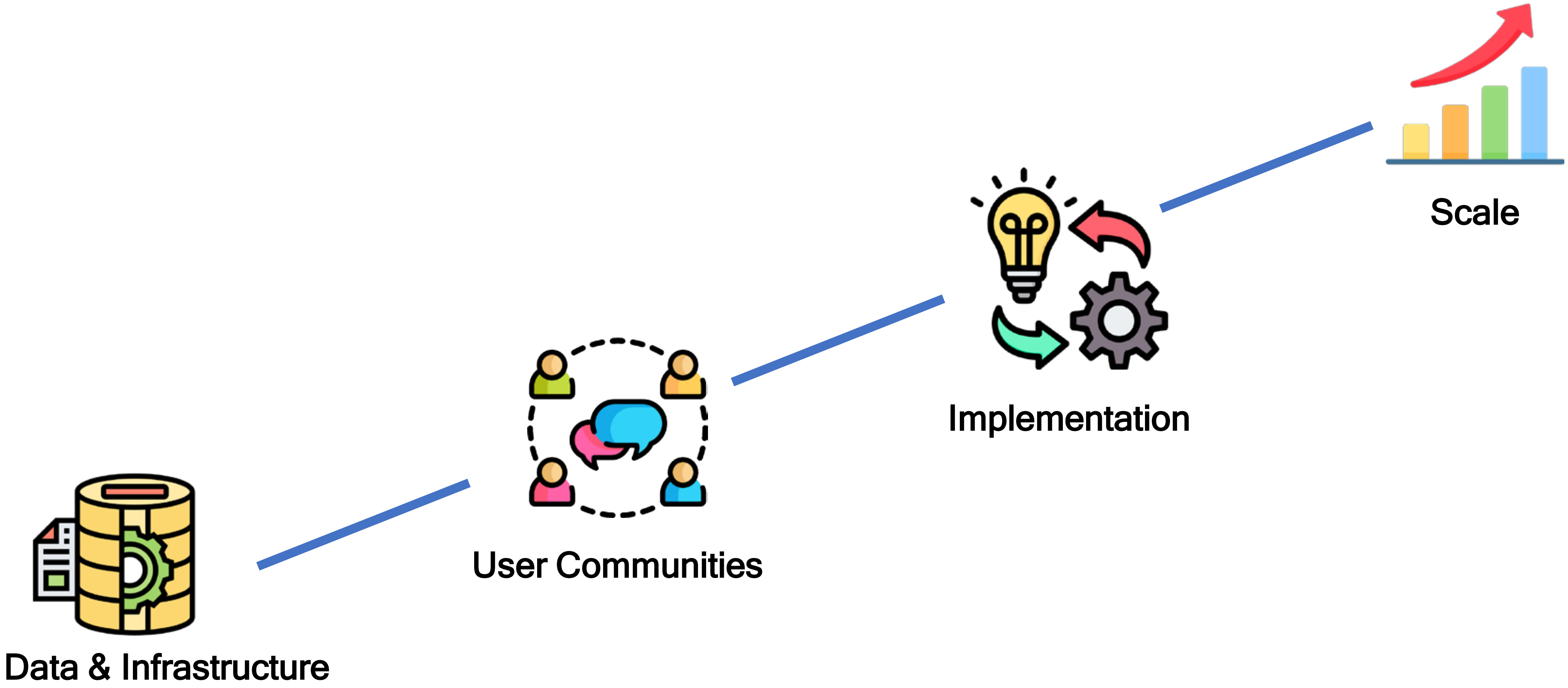
Outline

- Introduction to big data and advanced analytics applications: GEMINI
- Introduction to AI and applications in family medicine
- Using AI to prevent patient deterioration: CHARTwatch
- How should we teach about AI in medicine
- Breakouts and Discussion

Learning Health System

“A health system in which internal data and experience are systematically integrated with external evidence, and that knowledge is put into practice”

- AHRQ


Scale
Implementation
User Communities
Data & Infrastructure

Data & Infrastructure

Data & Infrastructure

- Slow adoption, fragmented systems

2021 Canada Health Infoway National Physician Survey:

Data & Infrastructure

“Canada needs to double its computing resources to reach the average of G7 nations in terms of compute per GDP”

What is the quality of medical care delivered in general medical wards in Toronto hospitals?

“Big data has the potential to transform medical practice by using information generated every day to improve the quality and efficiency of care.”

- Murdoch & Detsky, JAMA 2013

The "General Medicine Inpatient Initiative"

2014-2017

- Electronic data
- 240,000 GIM hospitalizations, 7 hospitals

The GEMINI Data Platform

2022

- 30 hospitals
- ~60% of Ontario’s patients
- >1.6M medical and ICU hospitalizations

GEMINI

The GEMINI Data Platform

2022

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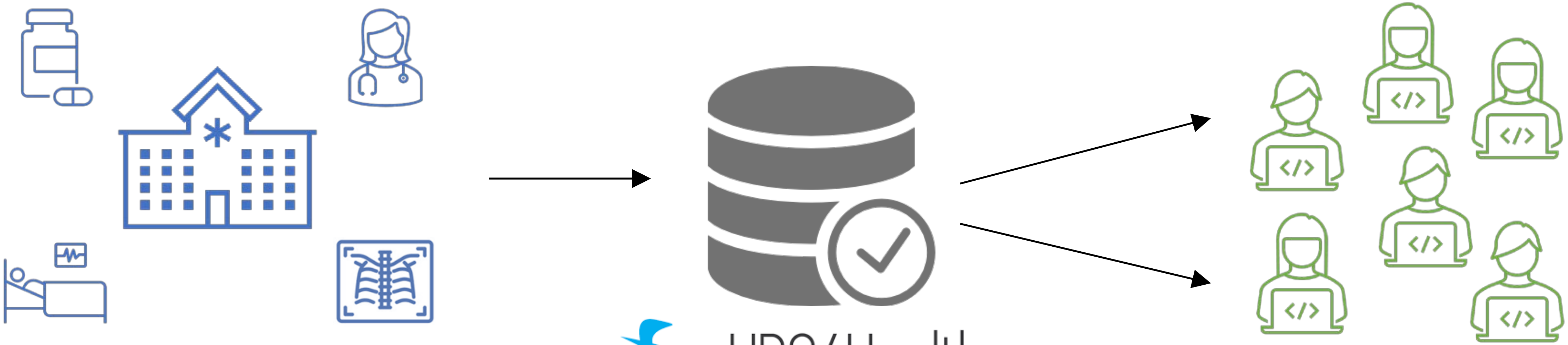
- State-of-the-art computing environment

The GEMINI Data Platform



HPC4Health

2022

- 30 hospitals
- ~60% of Ontario’s patients
- >1.6M medical and ICU hospitalizations

- State-of-the-art computing environment

- >200 scientists & students
- >100 papers & presentations

GEMINI

GEMINI is now among Canada's largest hospital data and analytics networks

GEMINI

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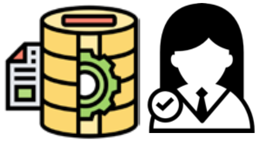
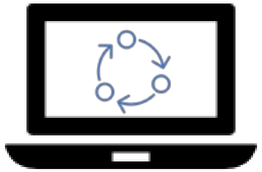
Ensuring High Quality Data



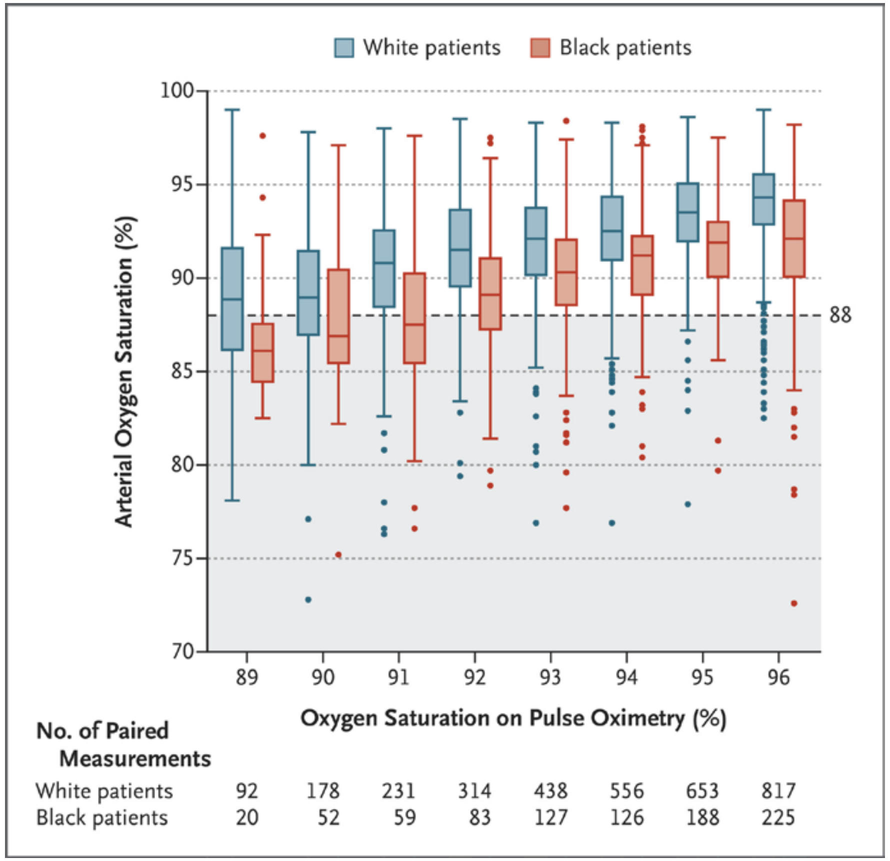
manual validation of 23,400+ data points from 7,400+ admissions

Variable	Laboratory	Radiology	Physicians	Death	ICU Transfer	Transfusion
Data Points Checked	5648	5092	2449	3814	3300	3116
Accuracy	100%	100%	98%	100%	100%	98%



Journal of the American Medical Informatics Association, 2021

Clinical data are only as good as measurement devices



N Engl J Med 2020; 383:2477-2478

Clinical data are only as good as measurement devices

Table 2. Prevalence, Unadjusted Odds, and Adjusted Odds of Fever Using Temporal and Oral Thermometry in Black and White Patients

Temperature cutoff for fever, °C	Black patients (n = 2031)					White patients (n = 2344)				
	Fever, No. (%)		Odds ratio (95% CI)[a]			Fever, No. (%)		Odds ratio (95% CI)[a]		
	Temporal	Oral	Unadjusted	Adjusted	*P* value	Temporal	Oral	Unadjusted	Adjusted	*P* value
37.8	300 (14.8)	344 (16.9)	0.85 (0.72-1.01)	0.85 (0.71-1.00)	.06	333 (14.2)	291 (12.4)	1.17 (0.99-1.38)	1.17 (0.99-1.39)	.07
38.0	206 (10.1)	268 (13.2)	0.74 (0.61-0.90)	0.74 (0.61-0.90)	.002	253 (10.8)	238 (10.2)	1.07 (0.89-1.29)	1.07 (0.89-1.29)	.47
38.3	142 (7)	192 (9.5)	0.72 (0.57-0.90)	0.71 (0.57-0.90)	.004	163 (7)	170 (7.3)	0.96 (0.76-1.19)	0.96 (0.76-1.20)	.69
38.5	108 (5.3)	156 (7.7)	0.68 (0.52-0.87)	0.67 (0.52-0.87)	.002	114 (4.9)	123 (5.2)	0.92 (0.71-1.20)	0.92 (0.71-1.20)	.55

[a] Unadjusted odds ratios were calculated based on the prevalence of fever in temporal vs oral measurements, and adjusted odds ratios were calculated using logistic regression adjusting for age, sex, hospital, and comorbidities (congestive heart failure, chronic obstructive pulmonary disease, diabetes, hypertension, chronic kidney disease, liver disease, and metastatic cancer). An odds ratio crossing 1 represents no significant association between route of measurement (temporal vs oral) in detecting fever. Because oral measurement is the reference standard, an odds ratio above or below 1 represents inaccuracy with temporal measurement. Demographics and comorbidities had no significant interaction with route of measurement.

JAMA. 2022;328(9):885-886. doi:10.1001/jama.2022.12290

Our Core GEMINI Team: ~30 Full Time Staff


Fahad Razak
Co-lead


Amol Verma
Co-lead


Denise Mak
Director, Data Science


Vlad Kushnir
Director, Operations

GEMINI

Integrating clinical care and research:
General Medicine Quality Improvement Network

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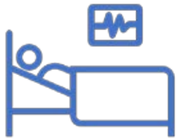
General Medicine Quality Improvement Network

- General Medicine patients are ~40% of emergency admissions to hospital, the single largest group of inpatients.
- Before GeMQIN, there was no systematic approach to measuring and improving the quality of General Medicine care.

Integrating clinical care and research:
General Medicine Quality Improvement Network

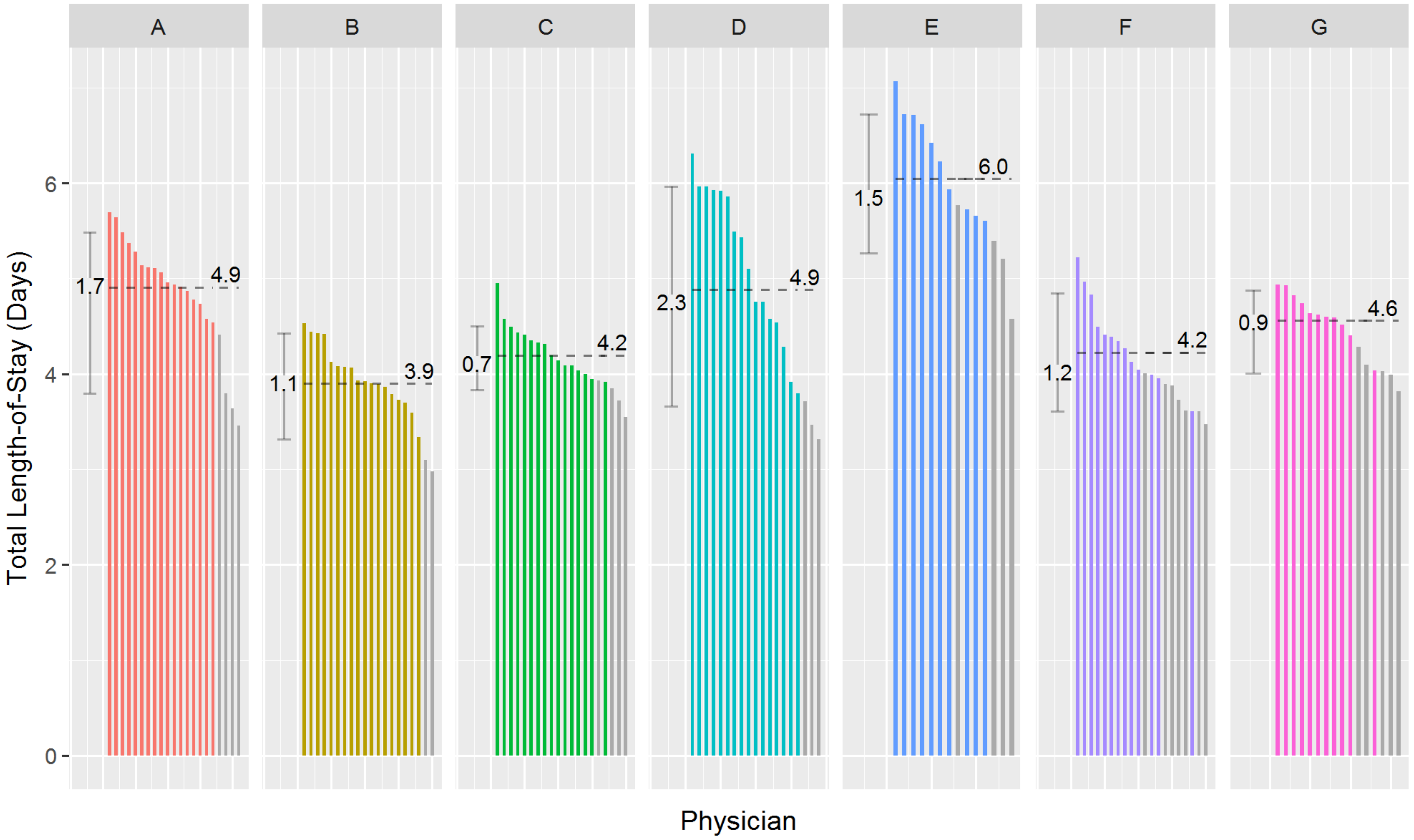
- General Medicine patients are ~40% of emergency admissions to hospital, the single largest group of inpatients.
- Before GeMQIN, there was no systematic approach to measuring and improving the quality of General Medicine care.
- We found large variations in physician practice:



60% longer hospital stay
(3.5 days longer)

78% greater CT or MRI use
(1 extra test)

Length-of-stay



Using Data to Support Quality Improvement

GEMIN produces hospital and physician quality reports for inpatient General Medicine in partnership with Ontario Health

Using Data to Support Quality Improvement

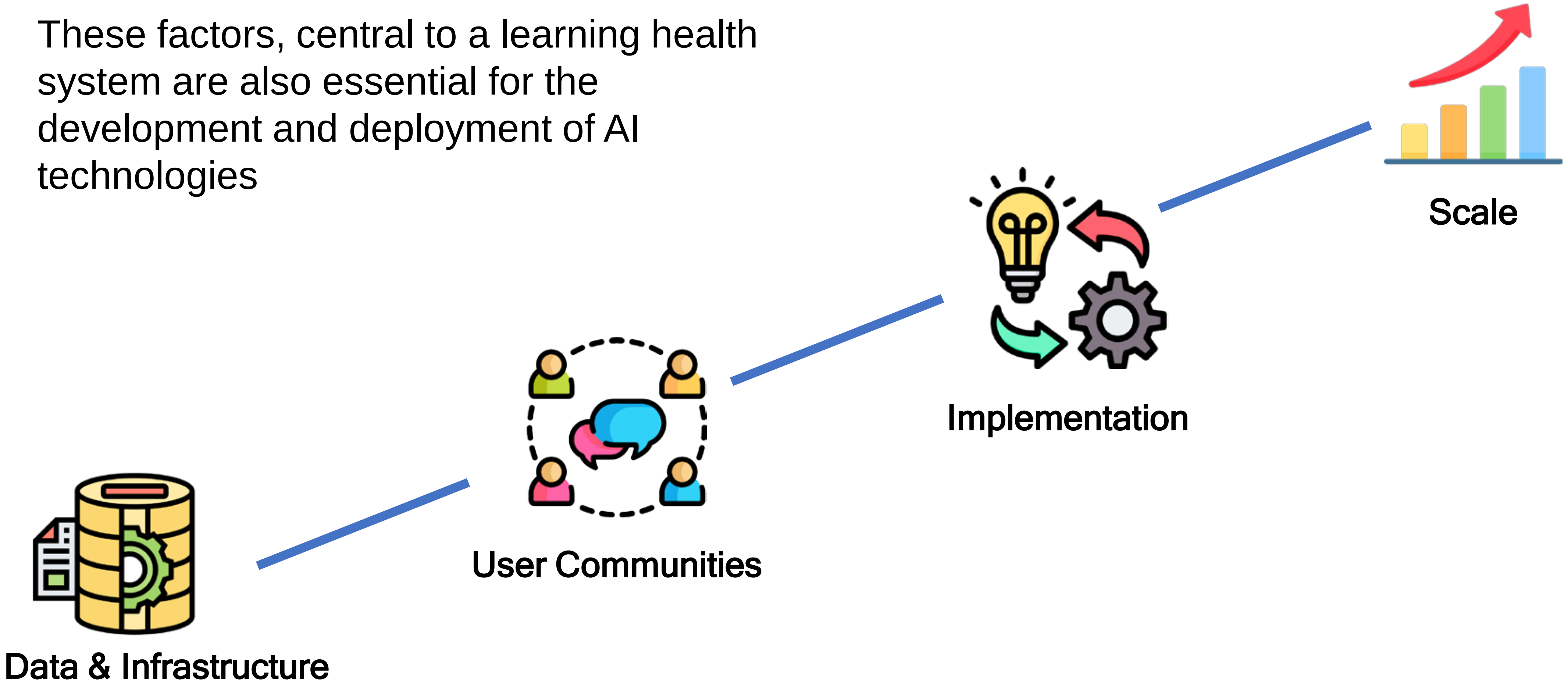
GEMINI/GeMQIN Team at TBRH
Bradley Jacobson
Cindy Fedell
Marcia Gillies
Sonya Lubbers

GEMIN produces hospital and physician quality reports for inpatient General Medicine in partnership with Ontario Health

We are delivering customized quality reports for the first time to ~600 general medicine physicians across Ontario

Ontario Health

These factors, central to a learning health system are also essential for the development and deployment of AI technologies



User Communities

VECTOR INSTITUTE

AMS

Medicine
UNIVERSITY OF TORONTO

Temerty Centre for AI Research and Education in Medicine
UNIVERSITY OF TORONTO

Computer Science
UNIVERSITY OF TORONTO

Dalla Lana
School of Public Health

AI Applications and Methods

- Predicting PPE use in COVID
- Predicting Long COVID
- Predicting COPD deterioration
- NLP to detect VTE
- Comorbidity clusters in pneumonia
- Predicting CV mortality in hospital
- Identifying distribution shifts
- Developing robust predictive models

UNIVERSITY OF TORONTO | Engineering

Schulich School of Business | YORK UNIVERSITÉ UNIVERSITY

UNIVERSITY OF TORONTO | SCHWARTZ REISMAN INSTITUTE FOR TECHNOLOGY AND SOCIETY

UNIVERSITY OF WATERLOO

UPSTREAMLAB

Massachusetts Institute of Technology

55 Active Projects, >100 papers & presentations

AI Applications and Methods

- Predicting PPE use in COVID
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55 Active Projects, >100 papers & presentations

Health Equity
- Disabilities and COVID-19
- Sociodemographics and mortality
- Equity indicators in measuring quality of care
- Outcomes of medically uninsured
- Language proficiency and delirium

AI Applications and Methods
- Predicting PPE use in COVID
- Predicting Long COVID
- Predicting COPD deterioration
- NLP to detect VTE
- Comorbidity clusters in pneumonia
- Predicting CV mortality in hospital
- Identifying distribution shifts
- Developing robust predictive models

Cancer Care
- Cancer care on GIM vs Oncology wards
- Validate cancer-specific data in EMRs
- Characterize inpatient oncology care
- Predict outcomes and cost of inpatient care

GIM Care & Quality
- Physician variations
- Interfacility transfers and capacity
- Palliative care needs in heart failure
- Access to ERCP in cholangitis
- Readmissions for falls
- Morning discharges
- Bedspacing

Disease-Specific Research
- Diabetes
- Liver Disease
- Pneumonia
- Stroke
- COPD

COVID-19
- Characterize hospitalization for COVID-19 vs flu
- Shortage of tocilizumab
- Disability and COVID-19
- COVID-19 and endoscopy for GI bleeding
- Predicting PPE
- Interfacility transfers
- LTC Plus

Delirium
- Identification tool
- Prediction tool
- Language proficiency and care
- Quality of discharge summaries
- Validating ICD-10 codes
- Physician experience co-design in ML
- SES amd model bias

Antimicrobial Use
- Antibiotics in COPD
- Antibiotics in GIM
- Cefriaxone dosing
- IV vs Oral Antibiotics
- SEPSIS Score
- Delays in tailoring

Delirium is common, costly, and severe

- Delirium is an acute confusional state that affects 20-30% of hospitalized patients
- When patients develop delirium they have worse outcomes and use substantially more health system resources

8 days
Longer average hospital stay

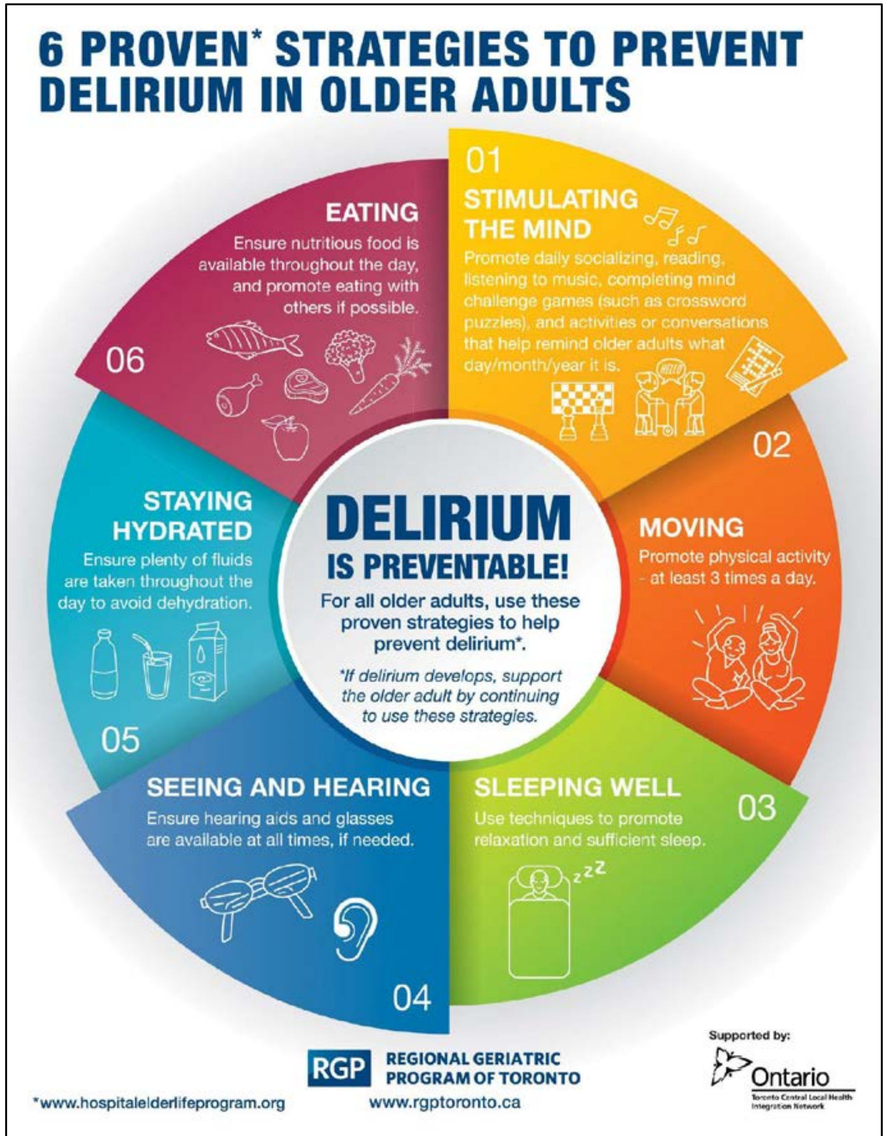
2.0X
Increased mortality

2.4X
Increased placement in nursing home

$10,899
Increased average cost per hospitalization

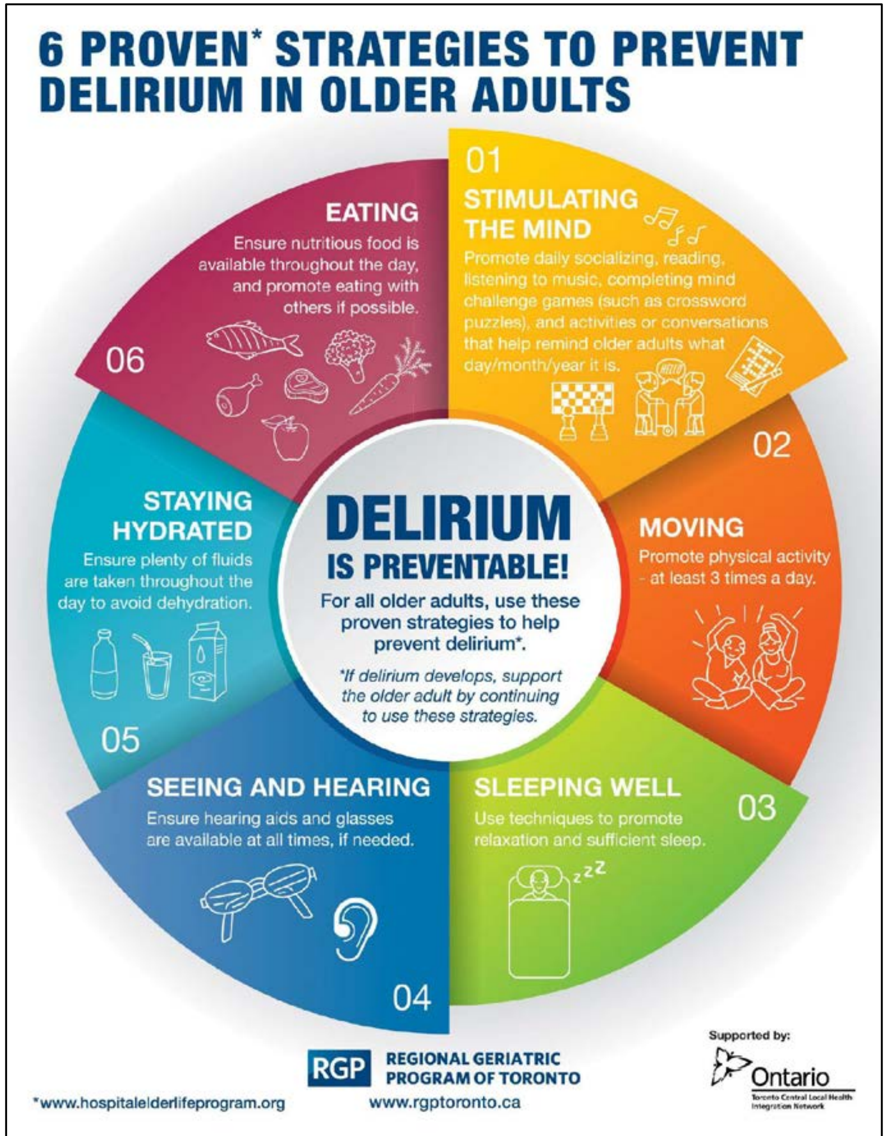
Delirium prevention is not implemented well

- Delirium can be prevented



Delirium prevention is not implemented well

- Delirium can be prevented
- Routinely collected hospital data captures only 25% of delirium cases.
- **This hinders hospitals from making delirium a priority.**



There is currently no sustainable method to reliably measure delirium rates in hospital.

Using AI to measure delirium

- We used a gold-standard chart review method to identify delirium in 5,500 hospital admissions in GEMINI
- We used ML to identify the occurrence of delirium using routinely-available data: demographics, lab, radiology, and pharmacy

An AI model reliably detects delirium

3-fold better case detection than ICD-10 codes alone

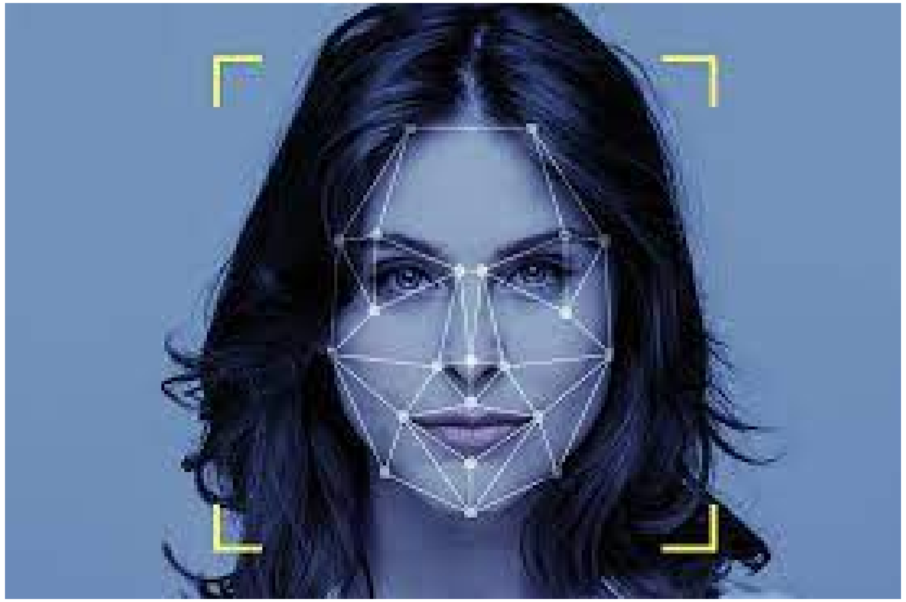
Accuracy	Sensitivity	PPV	Positive Likelihood Ratio	Negative Likelihood Ratio	AUROC	F1-Score
0.89	0.81	0.74	12.2	0.27	0.84	0.78

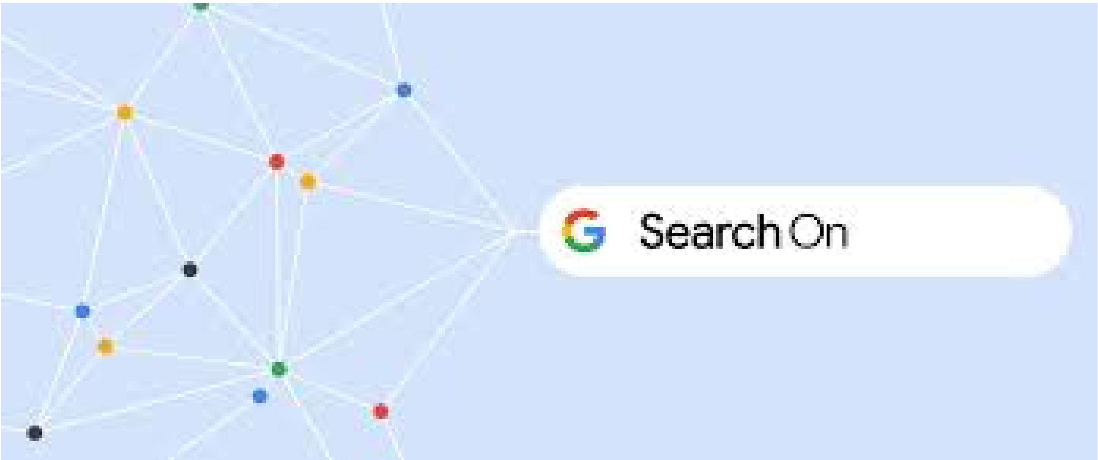
GEMINI Delirium Identification Tool

Implementation

TAHSN QI/PS Community of Practice will implement the GEMINI-Delirium identification tool to target prevention efforts

TAHSN




Search On

Computer Vision

Apps and Wearables

Robotic Surgery

Predictive Analytics

Automation

Dall-E: “northern ontario doctor in the style of group of seven”

Dall-E:"northern ontario doctor in the style of group of seven"

Artificial Intelligence and Family Medicine

Trevor Bruen, MD, PhD
PGY 2
NOSM University

Conflicts

I have no conflicts to declare

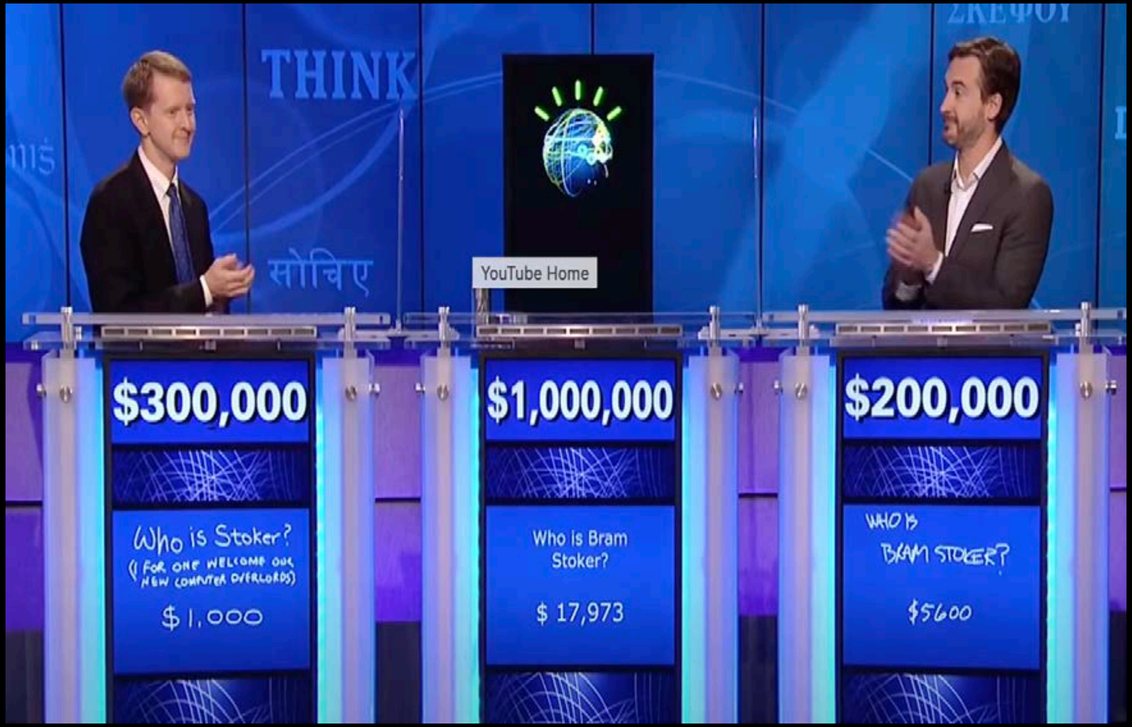
Structure

I. Artificial Intelligence (AI) Overview

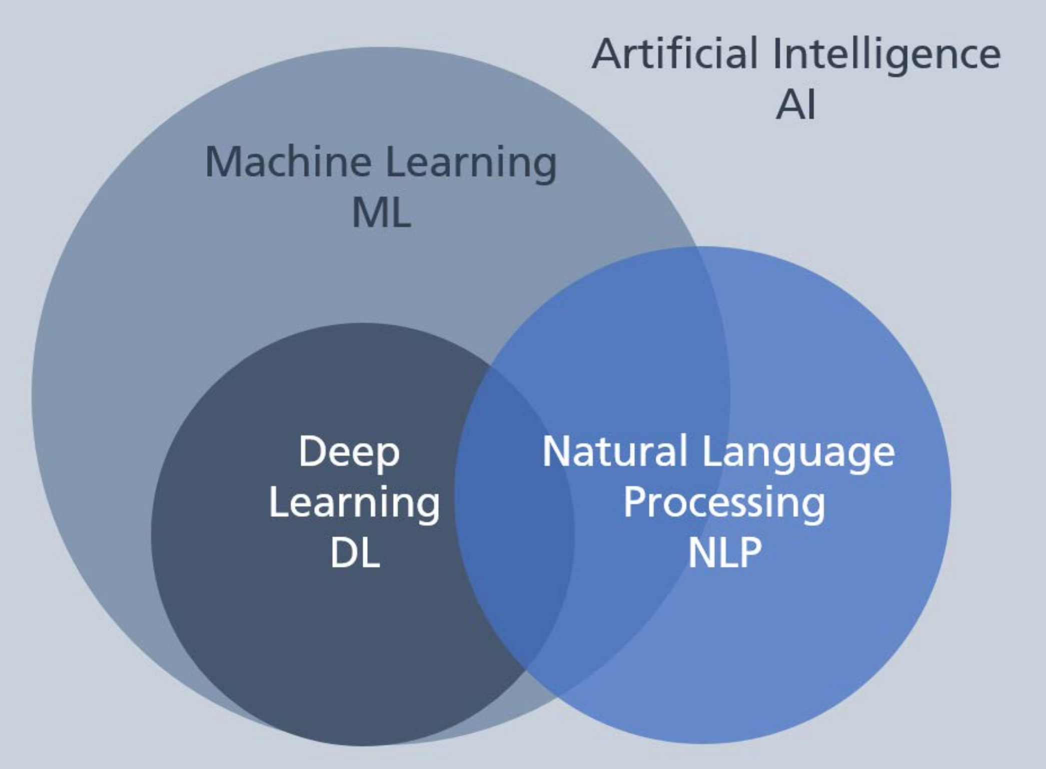
II. Family Medicine and AI

AI Overview

- Loosely defined as machines displaying “human” like cognitive skills
- Weak vs Strong AI
  - Weak: capable of specific tasks only (today’s AI)



AI Methods



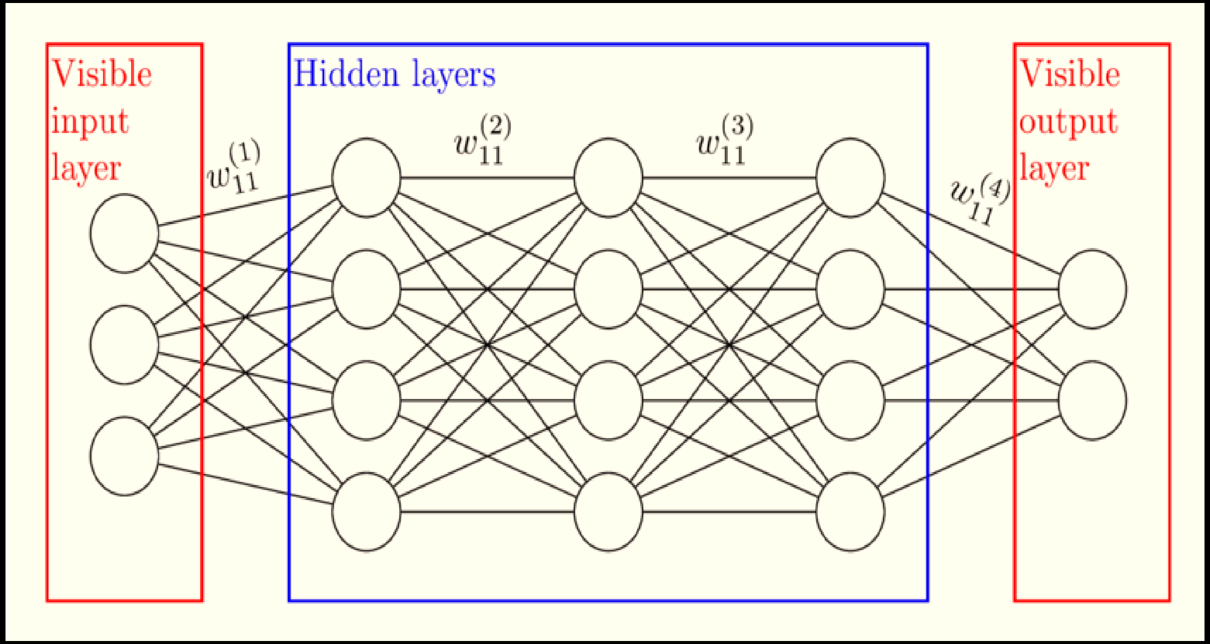
Rule-based → Data - based **Machine Learning**

Transparency → Accuracy **Black Box**

Siri

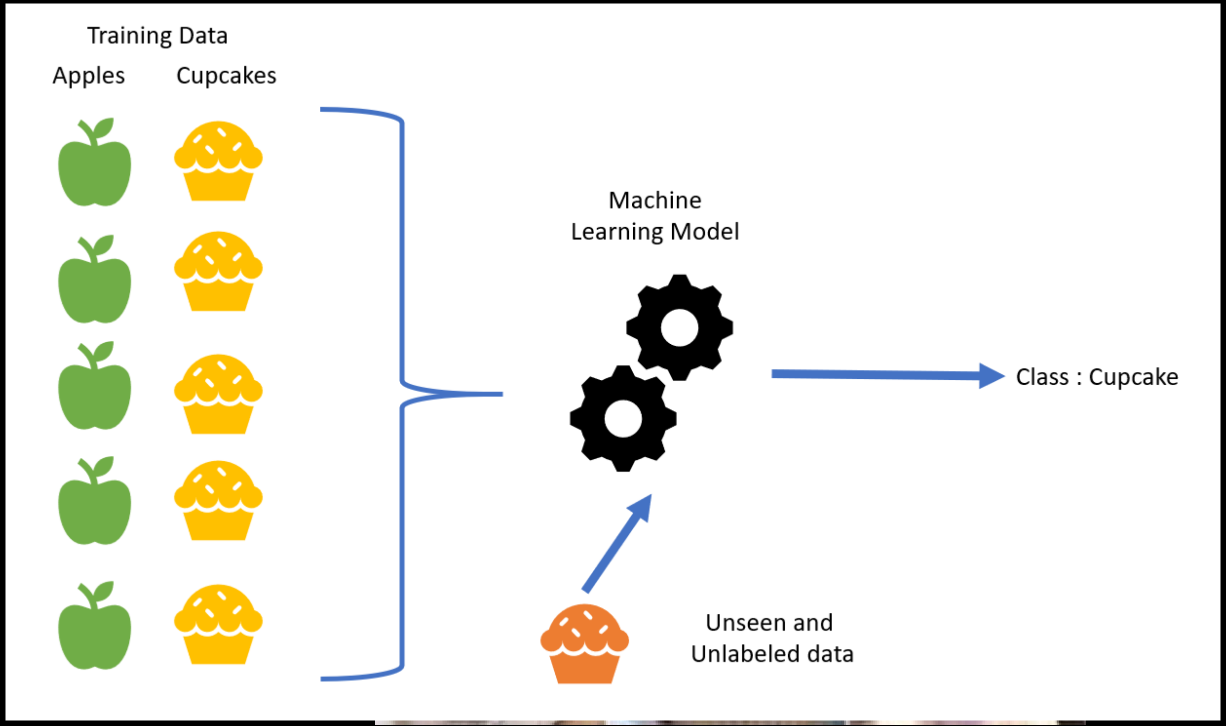
Deep Learning

- Neural Networks
  - Inspired by biology
  - Closely related to statistical inference (logistic regression)
- **Deep** learning is a NN with more than 1 "hidden" layer
  - Usually relies on supervised learning with training data



Deep Learning Example

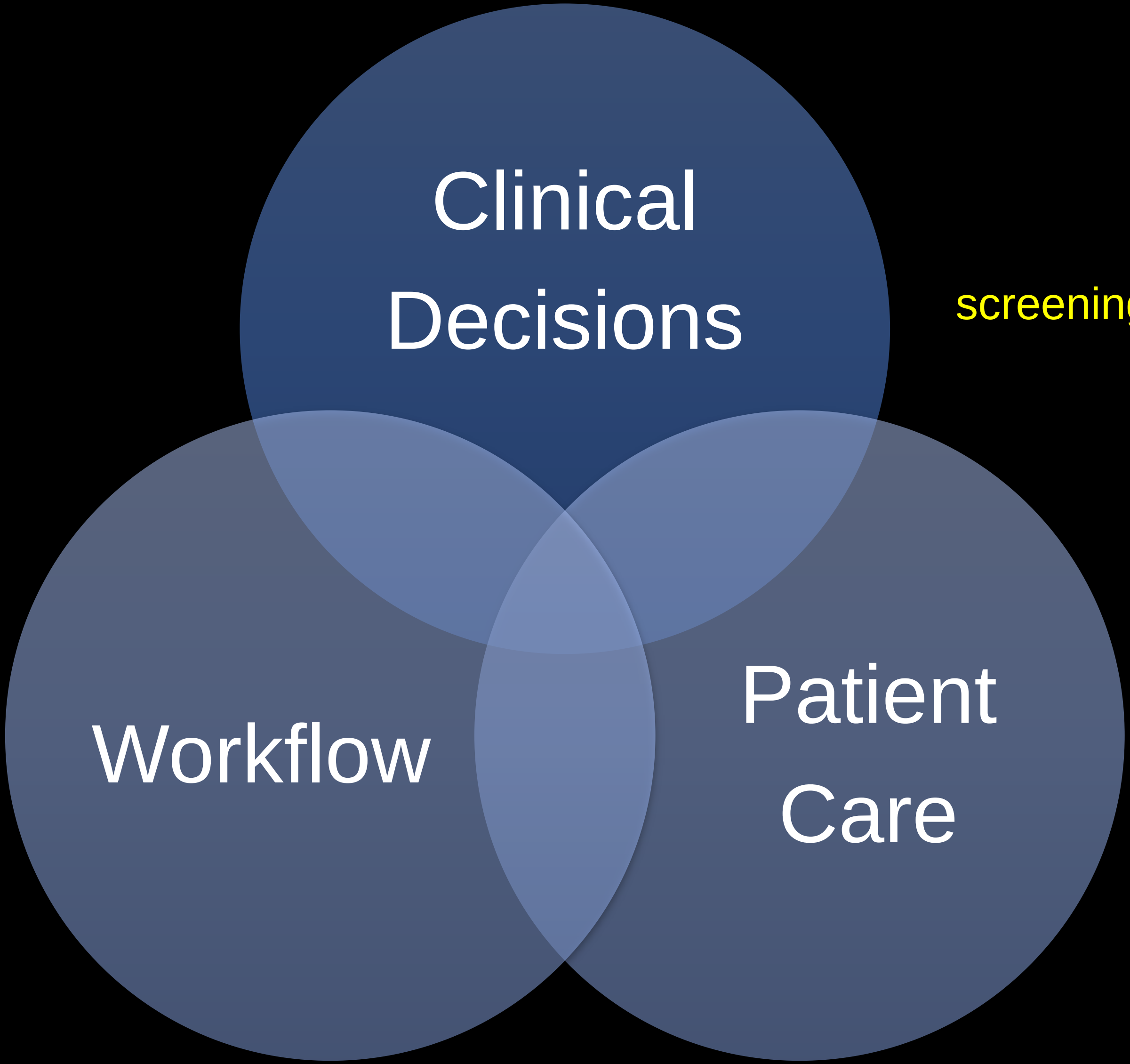
- Supervised
  - Label data set (e.g. dog vs muffin)
- Training
  - Use many (possibly millions) of examples



AI & Family Medicine

OTHER
Systems/Public Health
Ethics & Medico-Legal
Quality Improvement
Research…

screening



digital assistant

Wearables & monitoring

AI – Clinical Decisions

- Screening - e.g. diabetic retinopathy
  - patient adherence or remote regions
  - Limited in terms of diagnosable conditions/confounders
  - 87% summed sensitivity/90% specificity meta-analysis
  - 49% PPV and 98% NPV in primary care setting

[1]Wewetzer L et al., PLoS One. 2021

AI – Patient Care

- Extending patient care
  - E.g. digital coaches
  - Wearables and closer monitoring
- Physician/patient relationship
  - Beyond technical knowledge – e.g. social, emotio caring..
  - Relationship itself is therapeutic
  - Limited trustworthiness of AI systems

AI - Workflow

- EHR has led to increased admin time
  - AI reclaim patient relationship?
- E.g. digital assistant
  - concern re medico-legal context
  - technically more challenging vs literal speech to text
  - Active area of research e.g. AAFP

AI & FM – Looking ahead

- Emerging technology
- Ethics
- Bias and equity
- Competing interests
- Regulation

Implementation

Harnessing AI to improve hospital care

73 year-old retired banker, cholangitis

Had advanced GI procedure, plan for discharge home next day

MD called at 18:30: shortness of breath, ordered CXR and labs

Vital signs checked twice overnight (Midnight and 06:00)

MD called at 08:30, decreased blood pressure, distress, ICU team called

Patient did not want ICU and died that day

Family distraught. “We would never have left his bedside.”

The #1 root cause of unplanned transfer to ICU is clinicians *failing to rescue* patients because they didn’t recognize clinical deterioration soon enough.

We asked: Can an artificial-intelligence based tool *help clinicians intervene earlier* by providing an early warning signal before patients become seriously ill?

CHARTwatch is an artificial intelligence-based tool that uses data from the electronic health record to predict unplanned ICU transfers and death in hospital

Our goals were:

- reduce mortality in GIM by 10% in 1 year
- improve communication with patients and families
- improve coordination between physicians
- improve end-of-life care

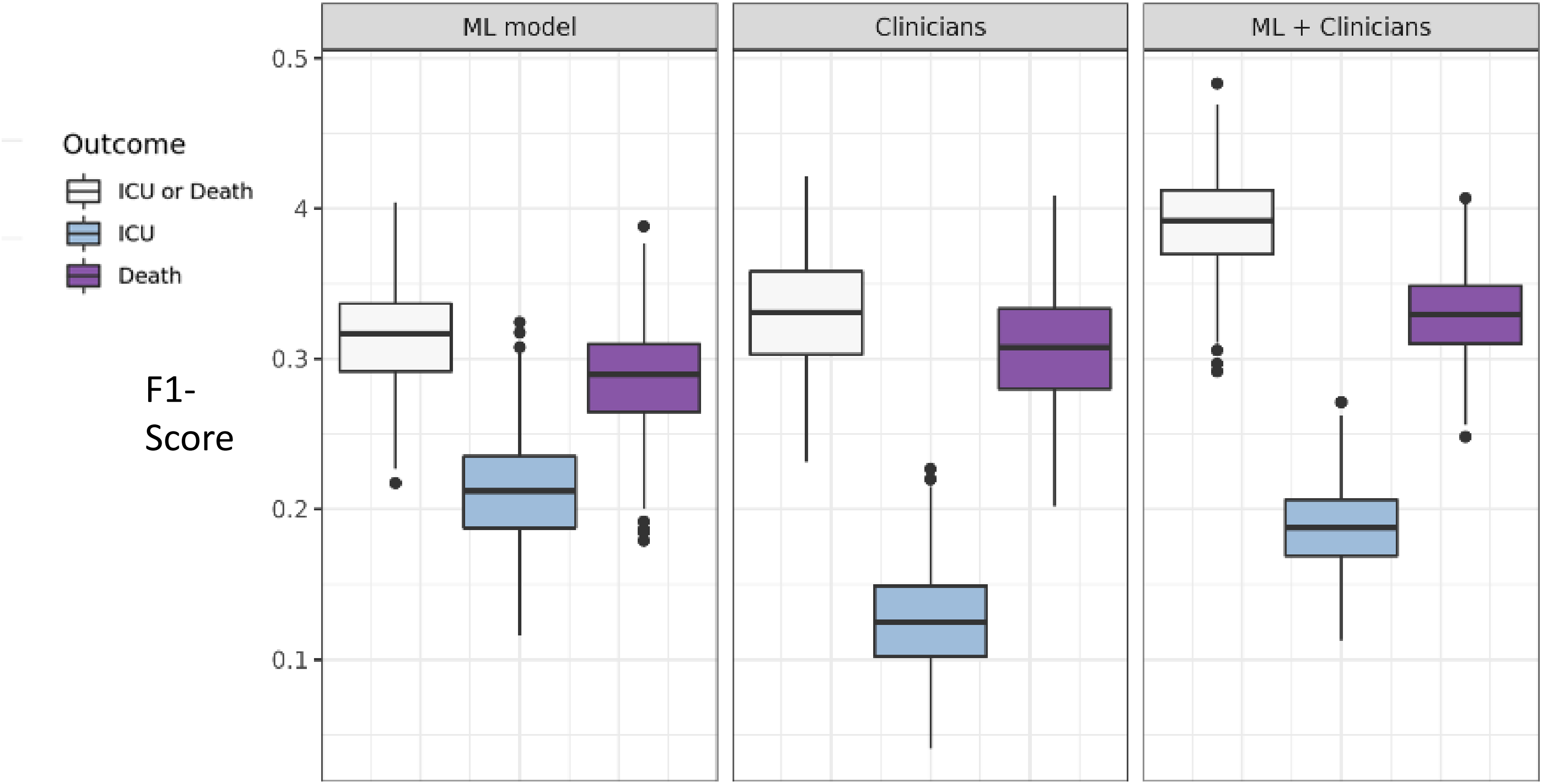
Since 2017, we:

- Consulted with patients and families
- Engaged physicians, nurses, administrators
- Learned from leading organizations (Kaiser, Duke, NYU)
- Developed an AI-based model, that uses >100 data elements collected in real-time from the electronic medical record
- Designed a clinical care pathway
- Implemented the solution in September 2020

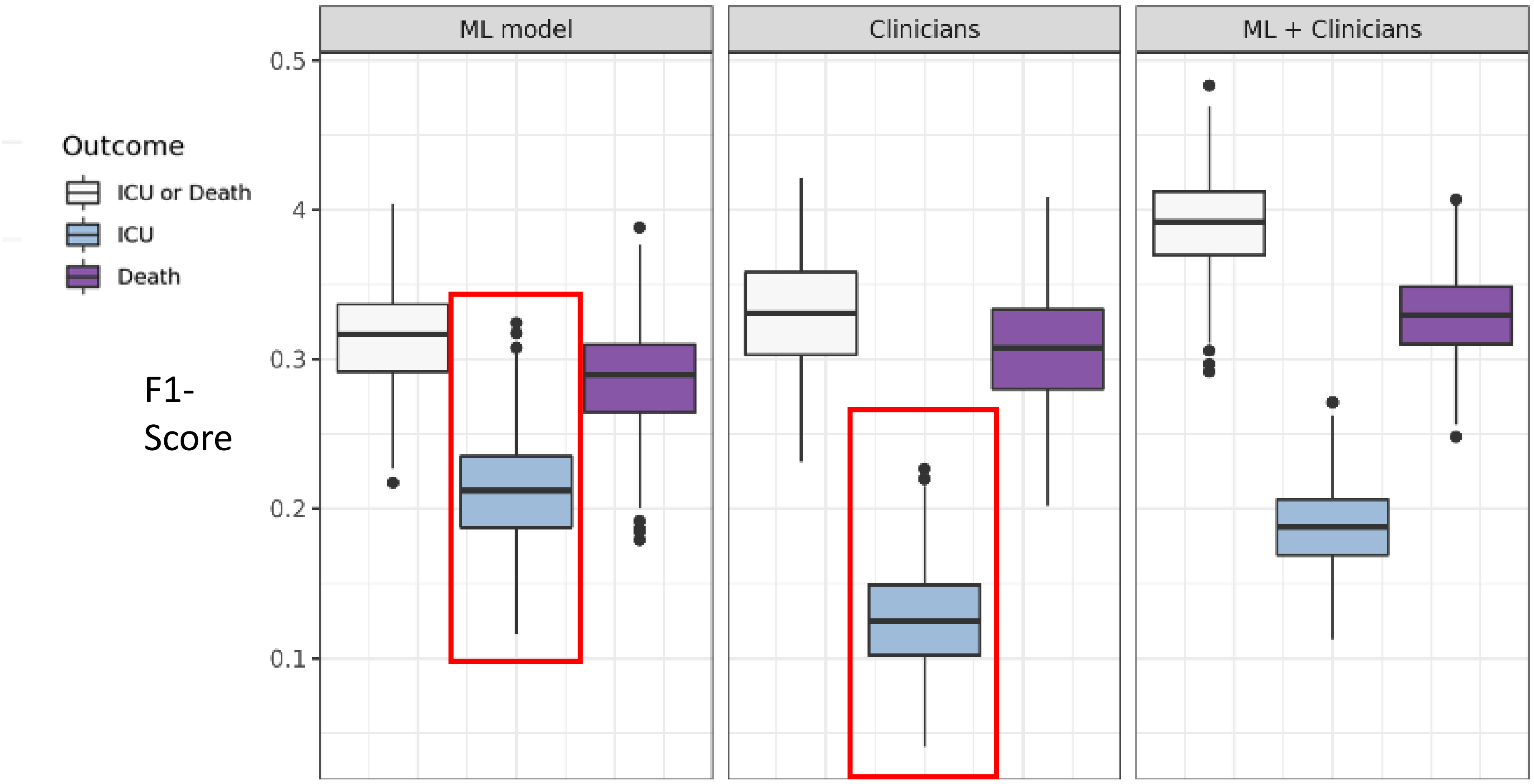
Human-Computer Collaboration

- Trained the CHARTwatch model on 20,000 patient visits from 2011-2019
- Compared CHARTwatch predictions to >3,000 clinical predictions (2,000 MD and 1,000 RN) over 4 months
- “Which patients will die or need ICU in hospital?”

Human-Computer Collaboration



Human-Computer Collaboration



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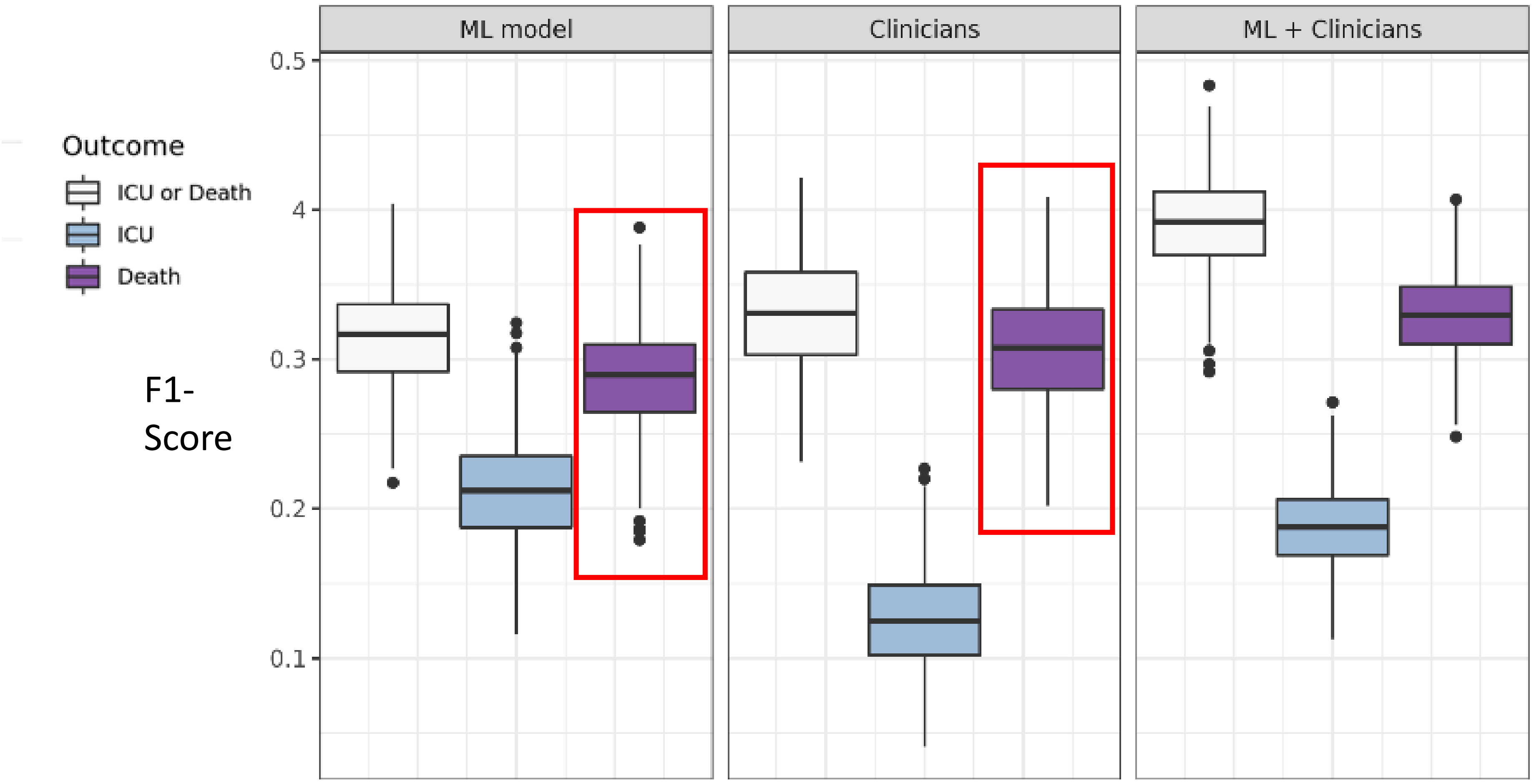
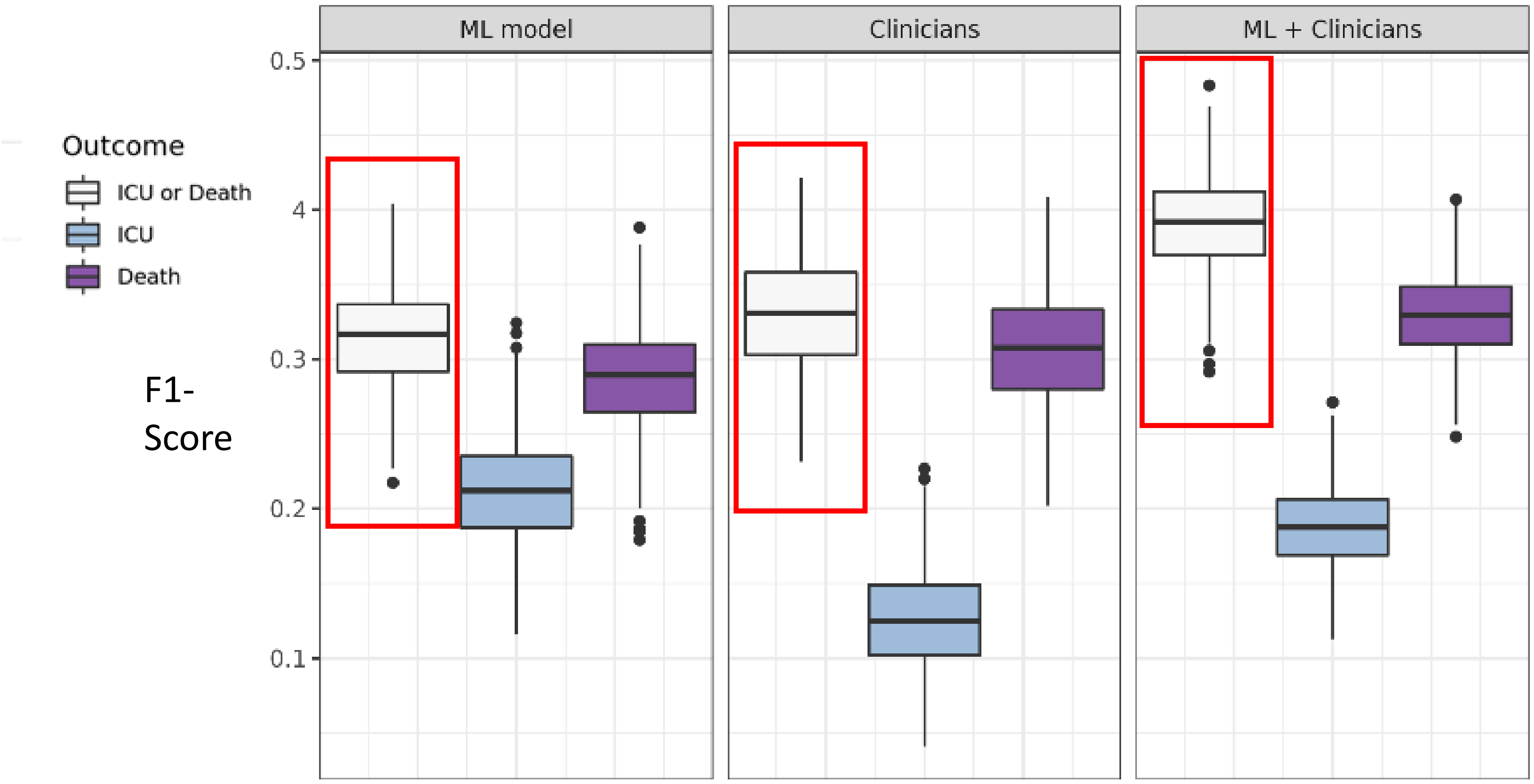
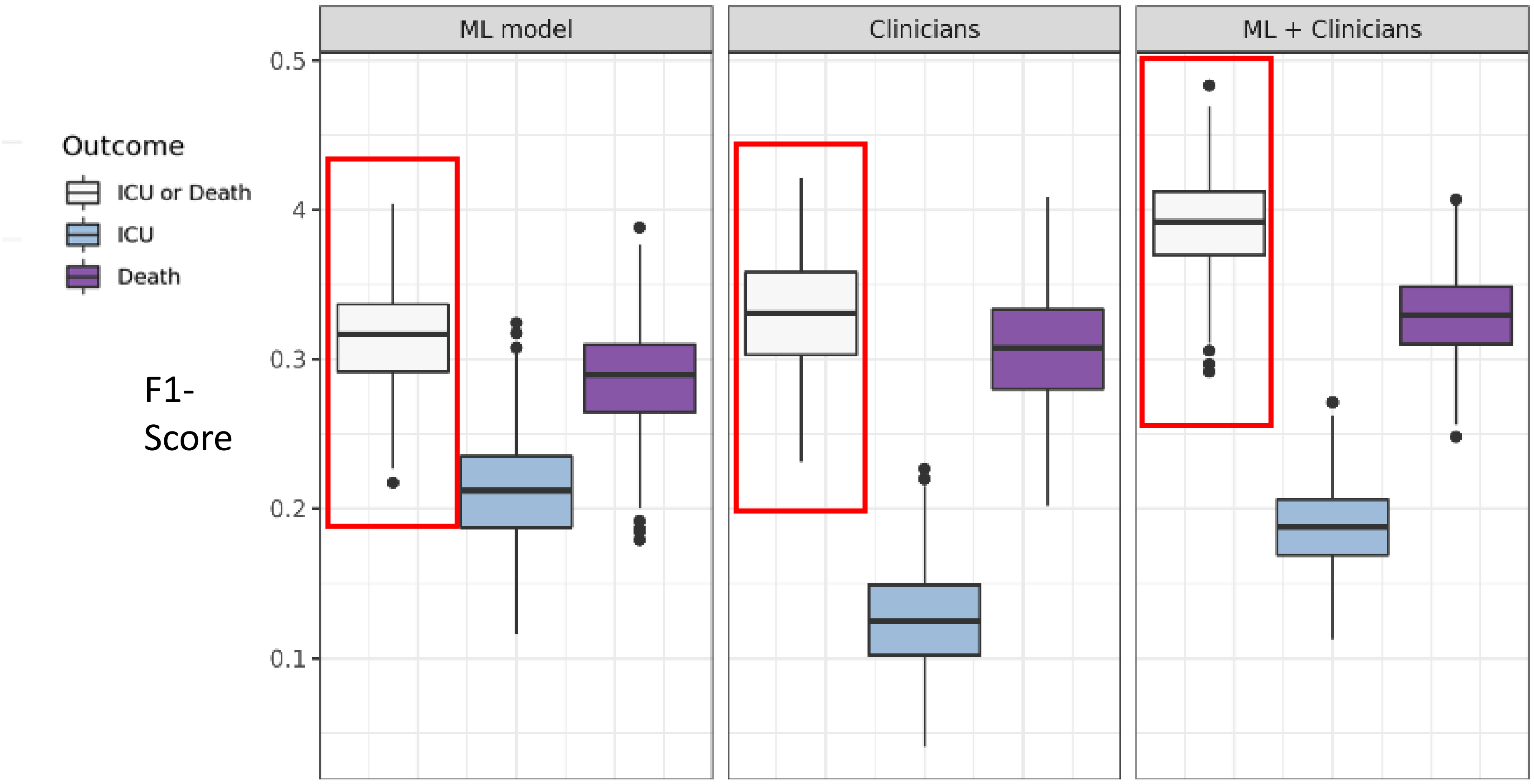


Human-Computer Collaboration

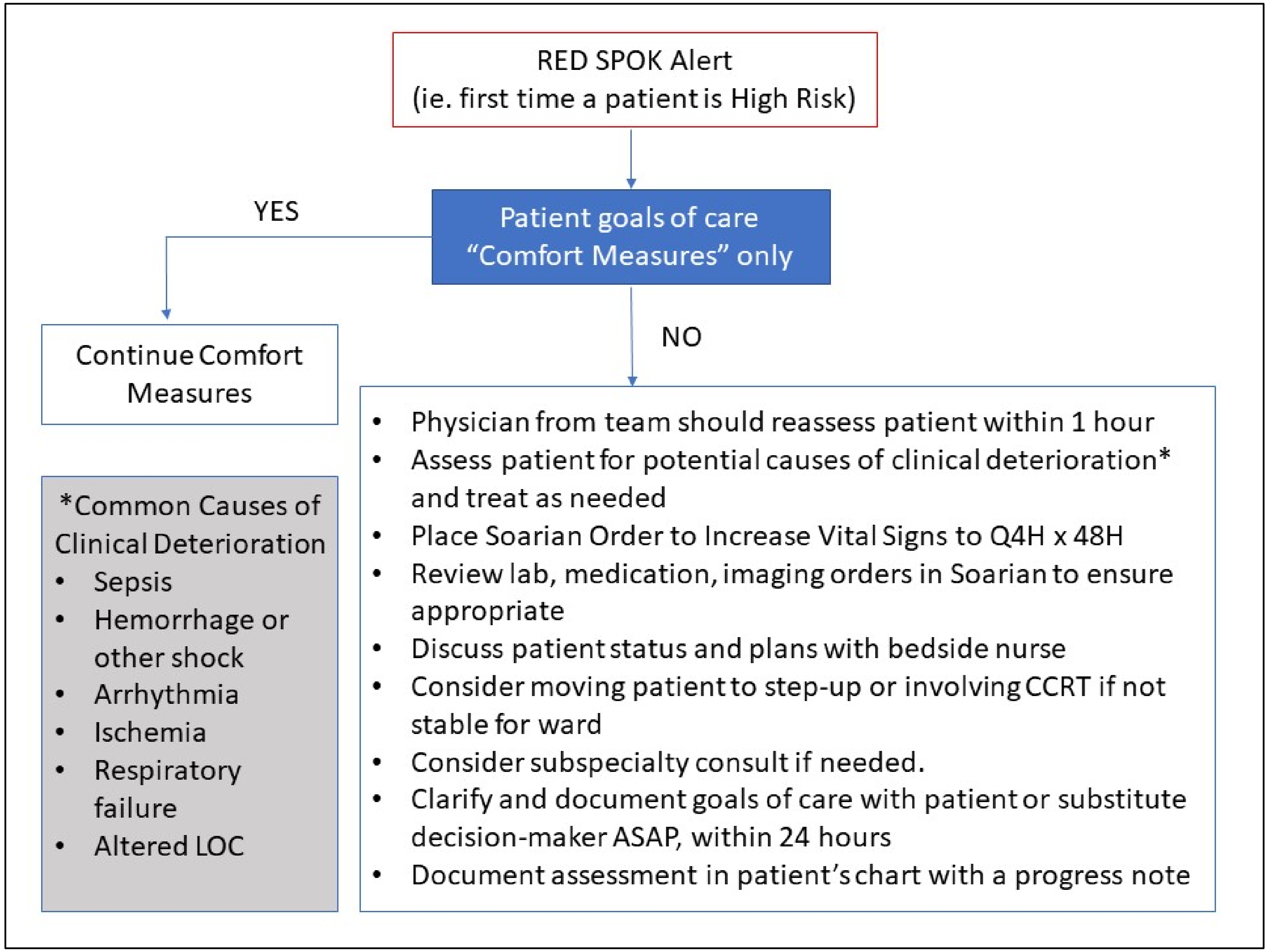


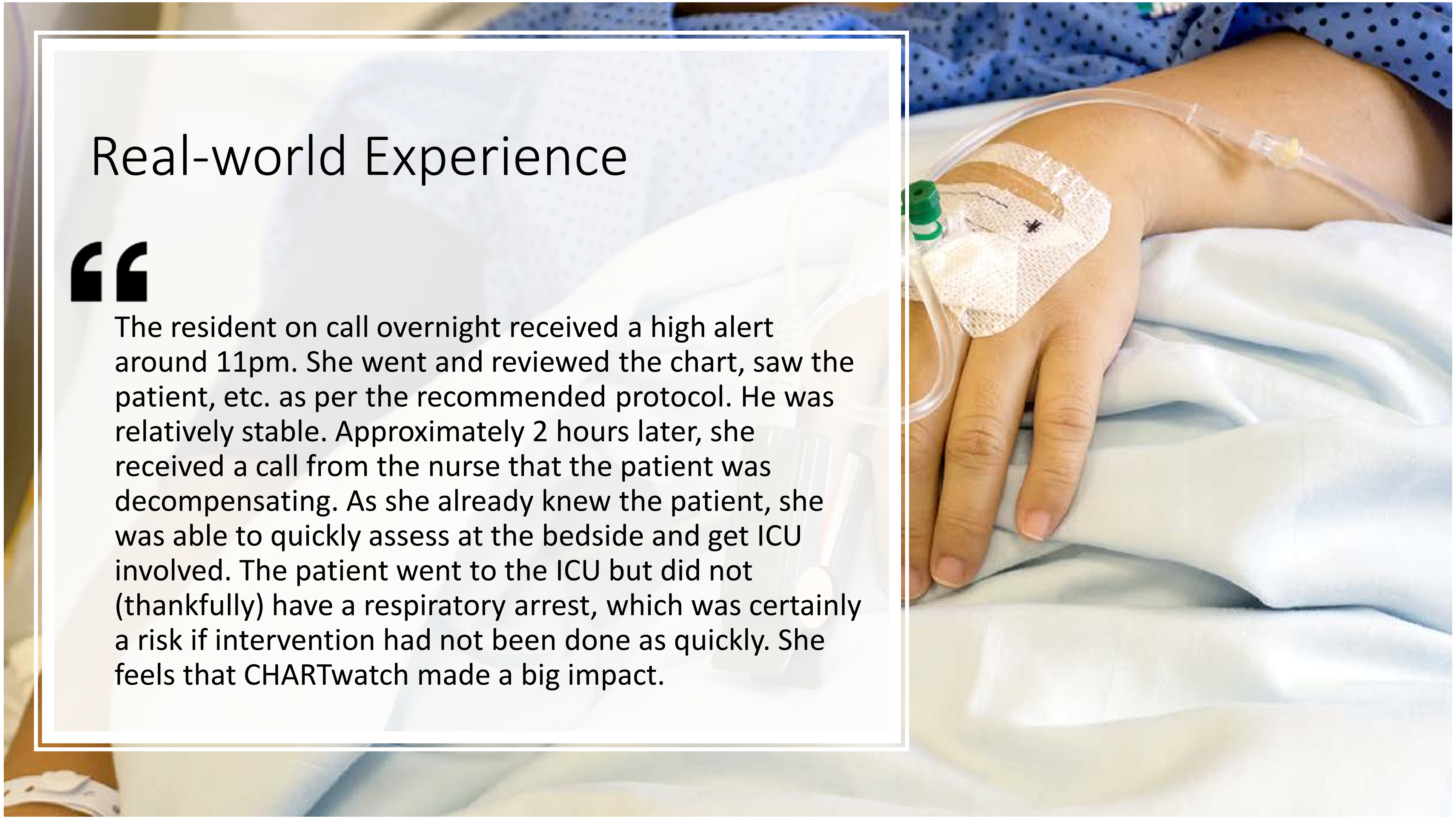
Human-Computer Collaboration



Combining human and model predictions improved detection of outcomes by 16% compared to clinicians alone and 24% compared to the model alone

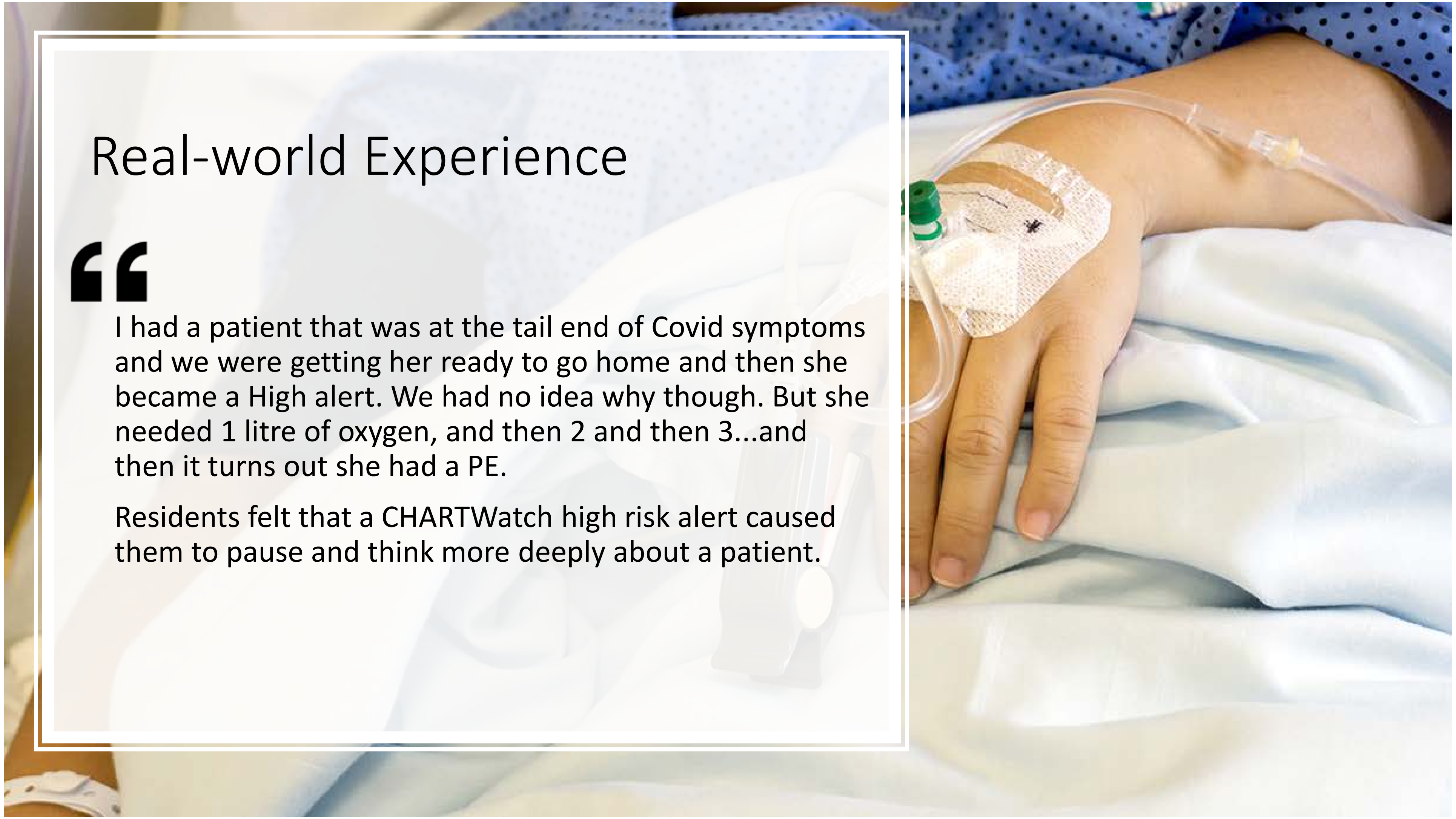
CHARTwatch is more than just an alert, it's a care pathway





Real-world Experience

> "The resident on call overnight received a high alert around 11pm. She went and reviewed the chart, saw the patient, etc. as per the recommended protocol. He was relatively stable. Approximately 2 hours later, she received a call from the nurse that the patient was decompensating. As she already knew the patient, she was able to quickly assess at the bedside and get ICU involved. The patient went to the ICU but did not (thankfully) have a respiratory arrest, which was certainly a risk if intervention had not been done as quickly. She feels that CHARTwatch made a big impact.



Real-world Experience

> I had a patient that was at the tail end of Covid symptoms and we were getting her ready to go home and then she became a High alert. We had no idea why though. But she needed 1 litre of oxygen, and then 2 and then 3...and then it turns out she had a PE.

Residents felt that a CHARTWatch high risk alert caused them to pause and think more deeply about a patient.

Real-world Experience

"54 year-old man from a shelter with a history of schizophrenia and recurrent aspiration pneumonia with background bronchiectasis. Multiple previous admissions resulting in ICU admission. Palliative care was activated as part of CHARTwatch alert and had not been involved on prior hospitalizations. Patient received medical care but deteriorated and was transferred to palliative care unit to receive comfort-based care with significant improvement in symptoms. He passed away peacefully on the unit.

Real-world Experience

"I went to speak to a patient after a CHARTwatch alert, and I asked the patient whether they would be interested in receiving palliative care. This made the patient angry, and they did not want to be cared for by me again. This made me hesitant to tell patients about CHARTwatch, even though I find it useful because it helps me reassess patients. I find it frustrating not knowing why predictions are being made.

Educating Learners About AI - How Should We Teach Medical Students About AI?

LEG Meeting 2022

Presented by: Daniel Lamoureux

November 4, 2022

Disclosure

I have no conflicts of interest to disclose.

Table of contents

01

Teaching AI in Medicine

NPJ Digit Med. 2020; 3: 86.
PMCID: PMC7305136
Published online 2020 Jun 19. doi: 10.1038/s41746-020-0294-7
PMID: 32577533

What do medical students actually need to know about artificial intelligence?

Liam G. McCoy,[1,2] Sujay Nagaraj,[1,3] Felipe Morgado,[1,4] Vinyas Harish,[1,2] Sunit Das,[1,5] and Leo Anthony Celi[6,7,8]

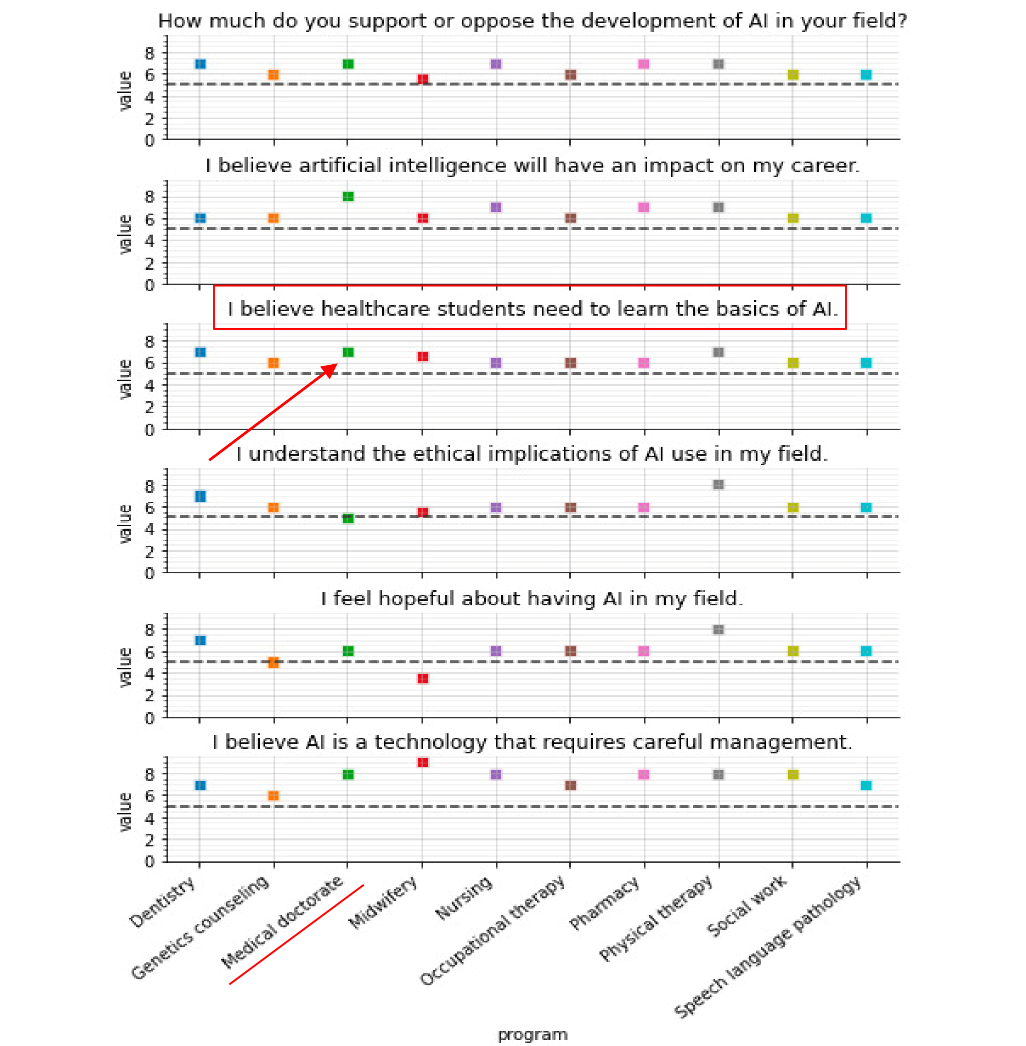
▸ Author information ▸ Article notes ▸ Copyright and License information Disclaimer

“Physicians need to understand AI in the same way that they need to understand any technology impacting clinical decision-making.”

Need to be able to:

- Use the technology
- Interpret the results
- Communicate the results

Does AI need to be integrated in the curriculum?



Teng, M., Singla, R., Yau, O., Lamoureux, D., Gupta, A., Hu, Z., Hu, R., Aissiou, A., Eaton, S., Hamm, C., Hu, S., Kelly, D., MacMillan, K. M., Malik, S., Mazzoli, V., Teng, Y. W., Laricheva, M., Jarus, T., & Field, T. S. (2022). Health Care Students' Perspectives on Artificial Intelligence: Countrywide Survey in Canada. *JMIR medical education*, *8*(1), e33390. https://doi.org/10.2196/33390

Does AI need to be integrated in the curriculum?

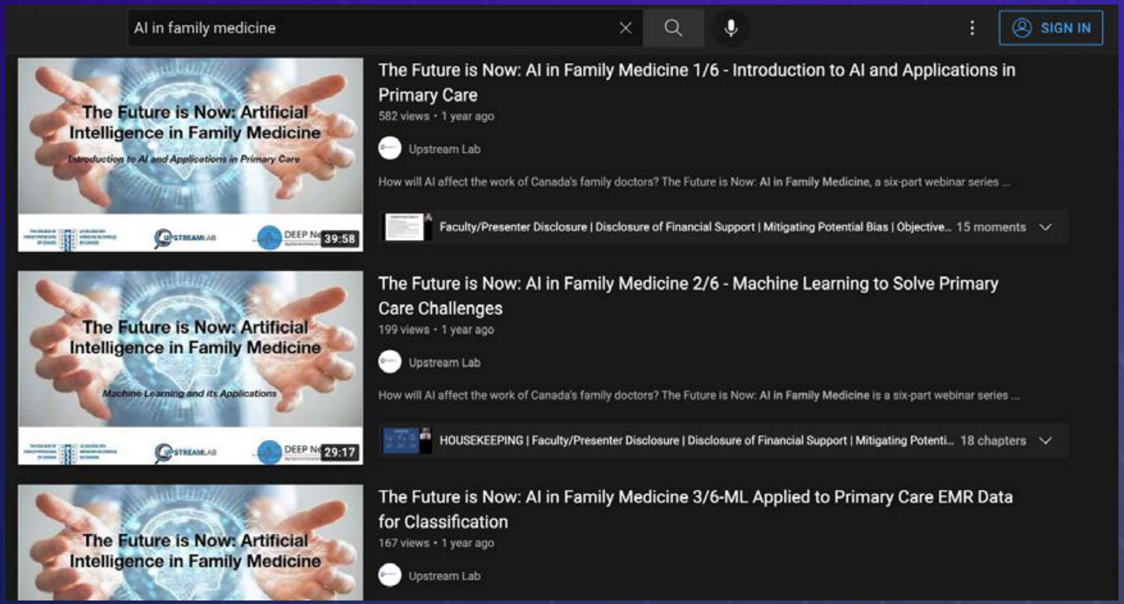
- Basics of AI
- Ethical considerations in AI
- Opportunities for those that are keen
- Benefit of including multiple populations

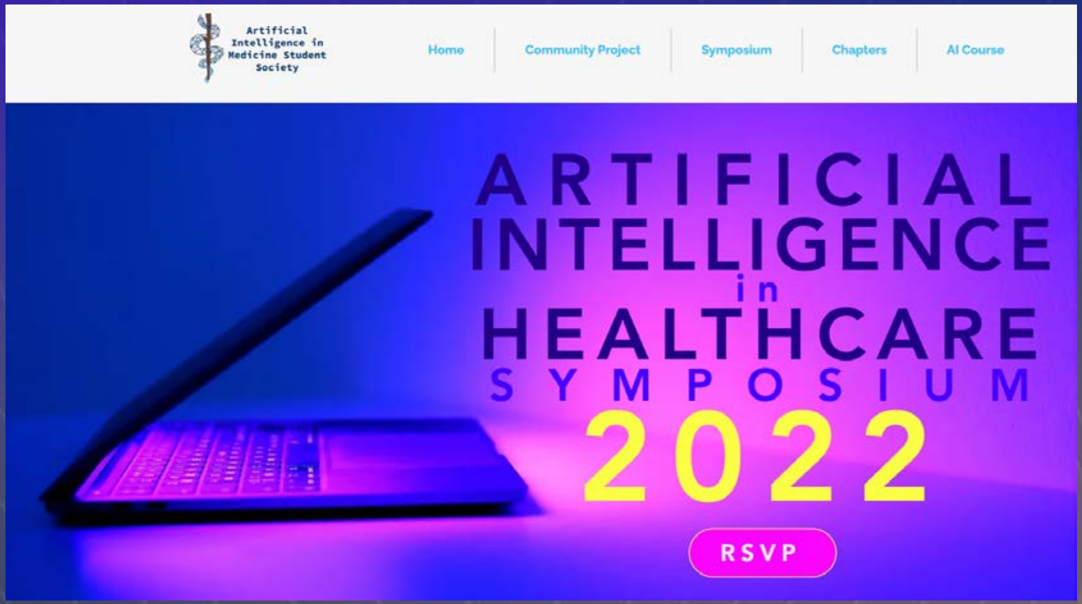
Content Type	Title
Certificate Course	Computing for Medicine
Curricular Lecture	Intro to Machine Learning in Healthcare
Curricular Lecture	AI, Medicine, and the Future of Doctoring
Student-Organized Workshop	Design Thinking
Student-Organized Lecture	AI + Medicine — Mythology, Hype, and Reality
Student-Organized Lecture	Explainable AI in Healthcare: Interpretability, Humans-in- the-Loop, and policies and politics
Student-Organized Lecture	Doing No Harm: Ensuring AI Embodies Medical Ethics
Student-Organized Lecture	AI and the Future of Medicine
Student-Organized Lecture	Using Big Data to Measure and Improve Health Care
Student-Organized Lecture	Optimizing Cancer Care Using Artificial Intelligence (Cancelled due to COVID-19)
Student-Organized Lecture	Natural Language Processing in Clinical Systems
Student-Organized Lecture	UHN’s Tech Stack 2.0
Student-Organized Lecture	Will Machine Learning and Big Data Solve Neuroscience’s Problems?
Student-Organized Lecture	AI in Medicine: What Is and What Is To Come
Student-Organized Lecture	Machine Learning in Medicine and What Does it Mean for the Future?

McCoy, L. G., Nagaraj, S., Morgado, F., Harish, V., Das, S., & Celi, L. A. (2020). What do medical students actually need to know about artificial intelligence?. NPJ digital medicine, 3, 86. https://doi.org/10.1038/s41746-020-0294-7

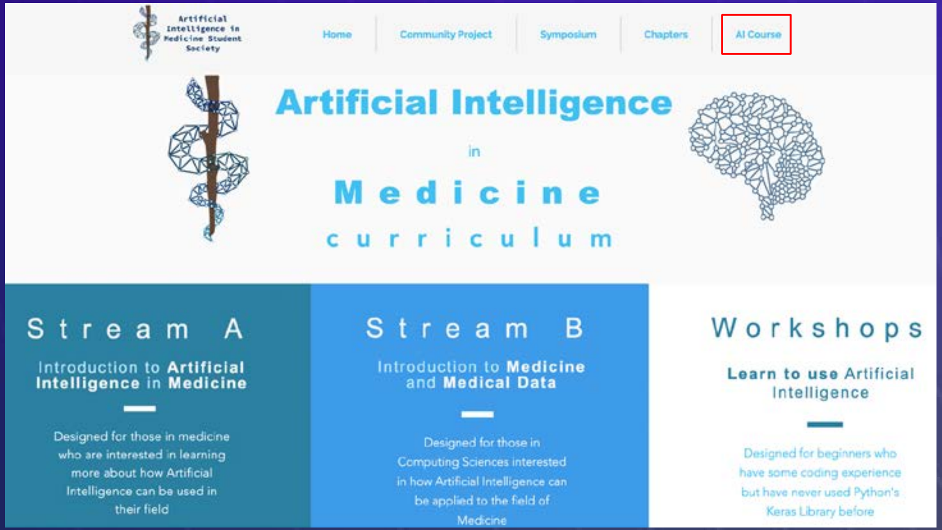
02 Current Opportunities

Exploring AI in the Field of Medicine

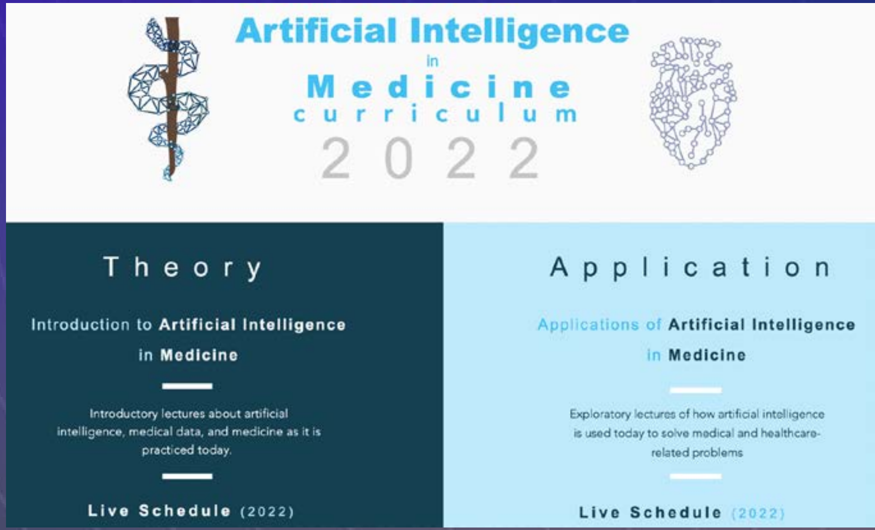




Artificial Intelligence in Medicine Student Society

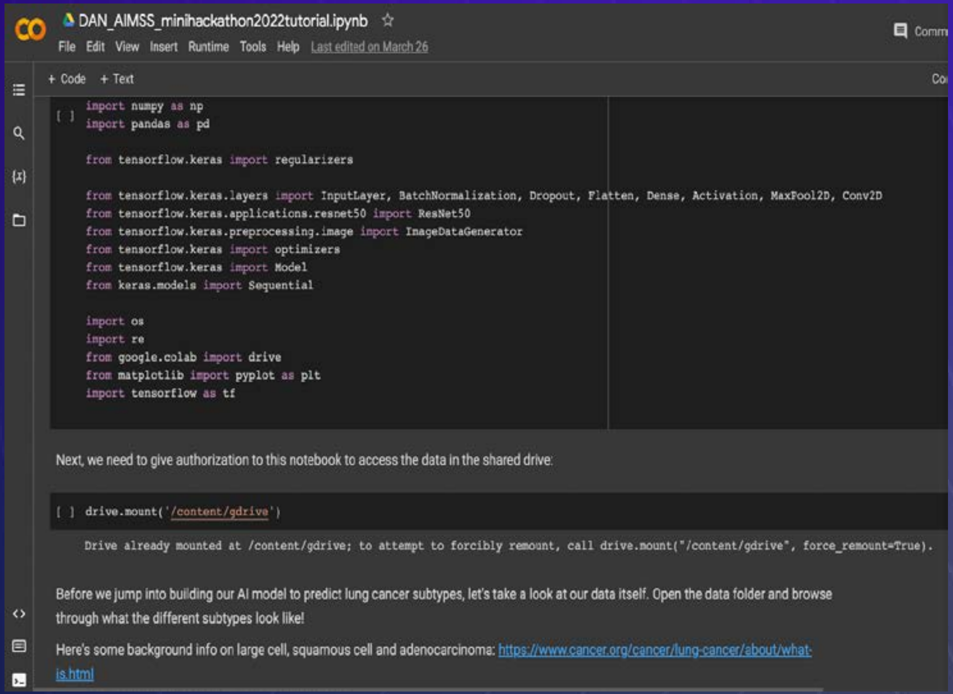


2021

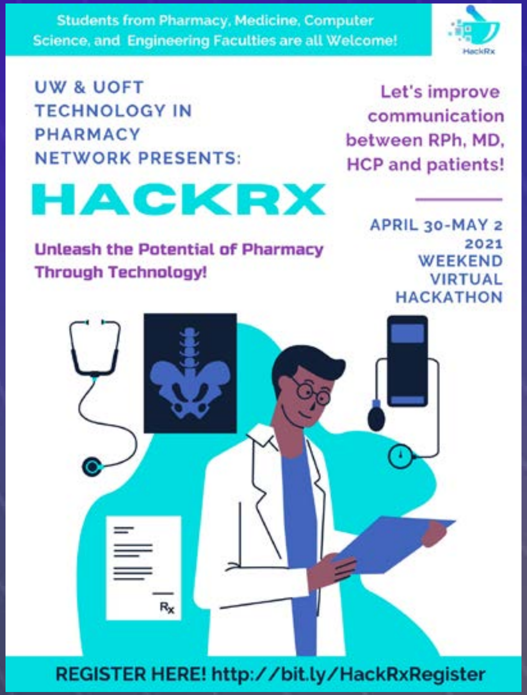


2022

Hackathons



DAN_AIMSS_minihackathon2022tutorial.ipynb
File Edit View Insert Runtime Tools Help Last edited on March 26
+ Code + Text
import numpy as np
import pandas as pd
from tensorflow.keras import regularizers
from tensorflow.keras.layers import InputLayer, BatchNormalization, Dropout, Flatten, Dense, Activation, MaxPool2D, Conv2D
from tensorflow.keras.applications.resnet50 import ResNet50
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras import optimizers
from tensorflow.keras import Model
from keras.models import Sequential
import os
import re
from google.colab import drive
from matplotlib import pyplot as plt
import tensorflow as tf
Next, we need to give authorization to this notebook to access the data in the shared drive:
drive.mount('/content/gdrive')
Drive already mounted at /content/gdrive; to attempt to forcibly remount, call drive.mount("/content/gdrive", force_remount=True).
Before we jump into building our AI model to predict lung cancer subtypes, let's take a look at our data itself. Open the data folder and browse through what the different subtypes look like!
Here's some background info on large cell, squamous cell and adenocarcinoma: https://www.cancer.org/cancer/lung-cancer/about/what-is.html



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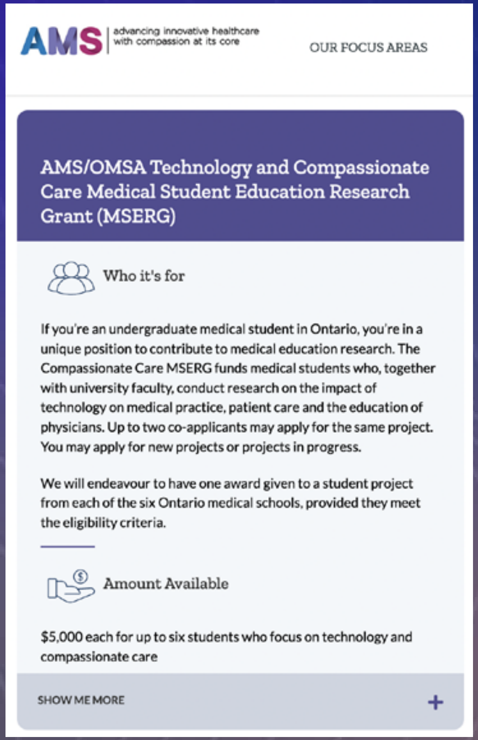
Research Opportunities

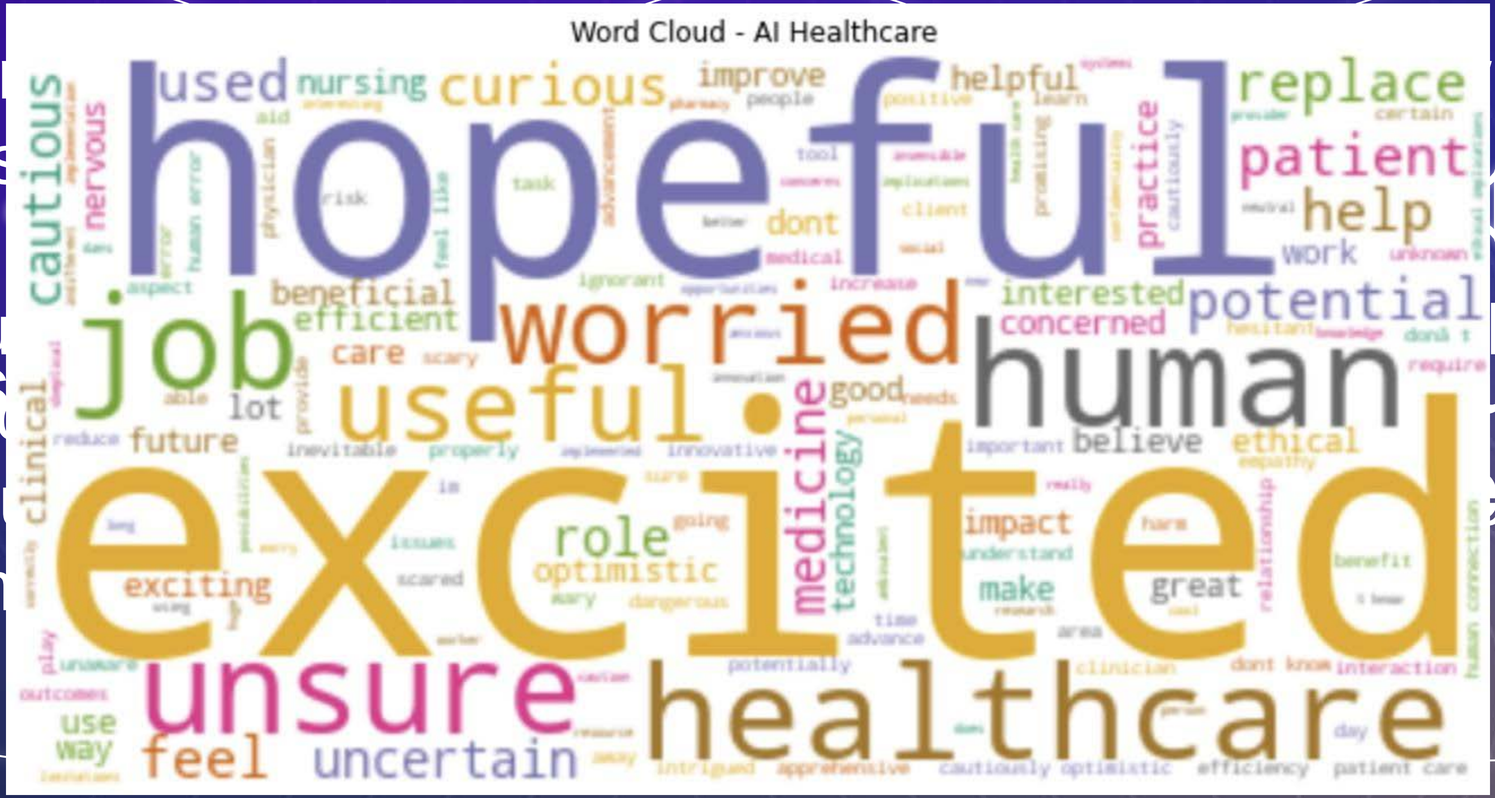


03 Summary and Questions

Summary

- Most r … the
  basics
- It wou … lum

Us … unicate
tech … esults



Thanks!

Do you have any questions?

dlamoureux@nosm.ca
(705) 923-0073

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Resources

McCoy, L. G., Nagaraj, S., Morgado, F., Harish, V., Das, S., & Celi, L. A. (2020). What do medical students actually need to know about artificial intelligence?. NPJ digital medicine, 3, 86. https://doi.org/10.1038/s41746-020-0294-7

Teng, M., Singla, R., Yau, O., Lamoureux, D., Gupta, A., Hu, Z., Hu, R., Aissiou, A., Eaton, S., Hamm, C., Hu, S., Kelly, D., MacMillan, K. M., Malik, S., Mazzoli, V., Teng, Y. W., Laricheva, M., Jarus, T., & Field, T. S. (2022). Health Care Students' Perspectives on Artificial Intelligence: Countrywide Survey in Canada. JMIR medical education, 8(1), e33390. https://doi.org/10.2196/33390

Photos:

- https://4rai.com/blog/why-the-3-tesla-mri-is-the-best-scanner-for-diagnostic-imaging
- https://medium.datadriveninvestor.com/how-artificial-intelligence-can-change-medicine-forever-if-implemented-strategically-a3a5a4ec4246
- https://www.aimss.ca/
- https://tcairem.utoronto.ca/summer-research-studentships
- https://www.ams-inc.on.ca/funding-opportunities/

Innovative partnerships to scale AI solutions in healthcare

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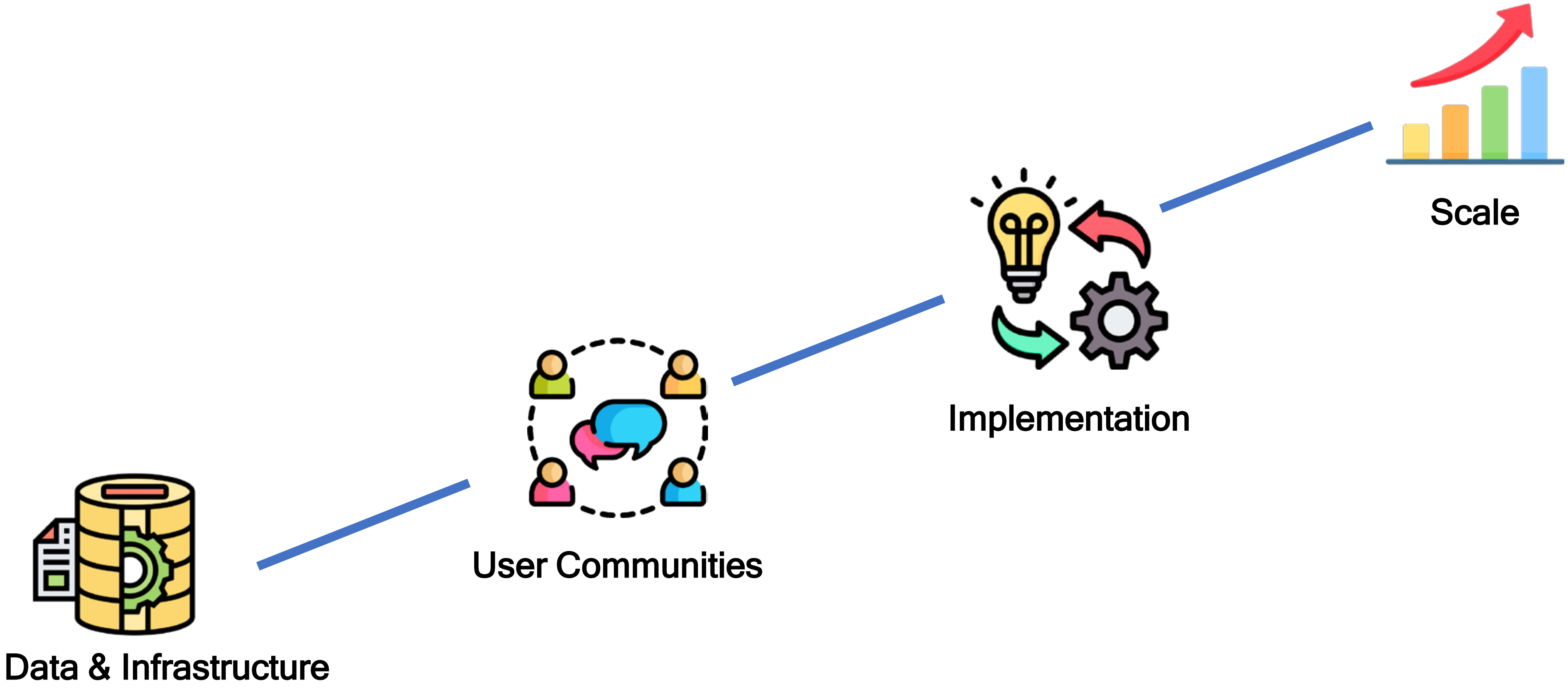
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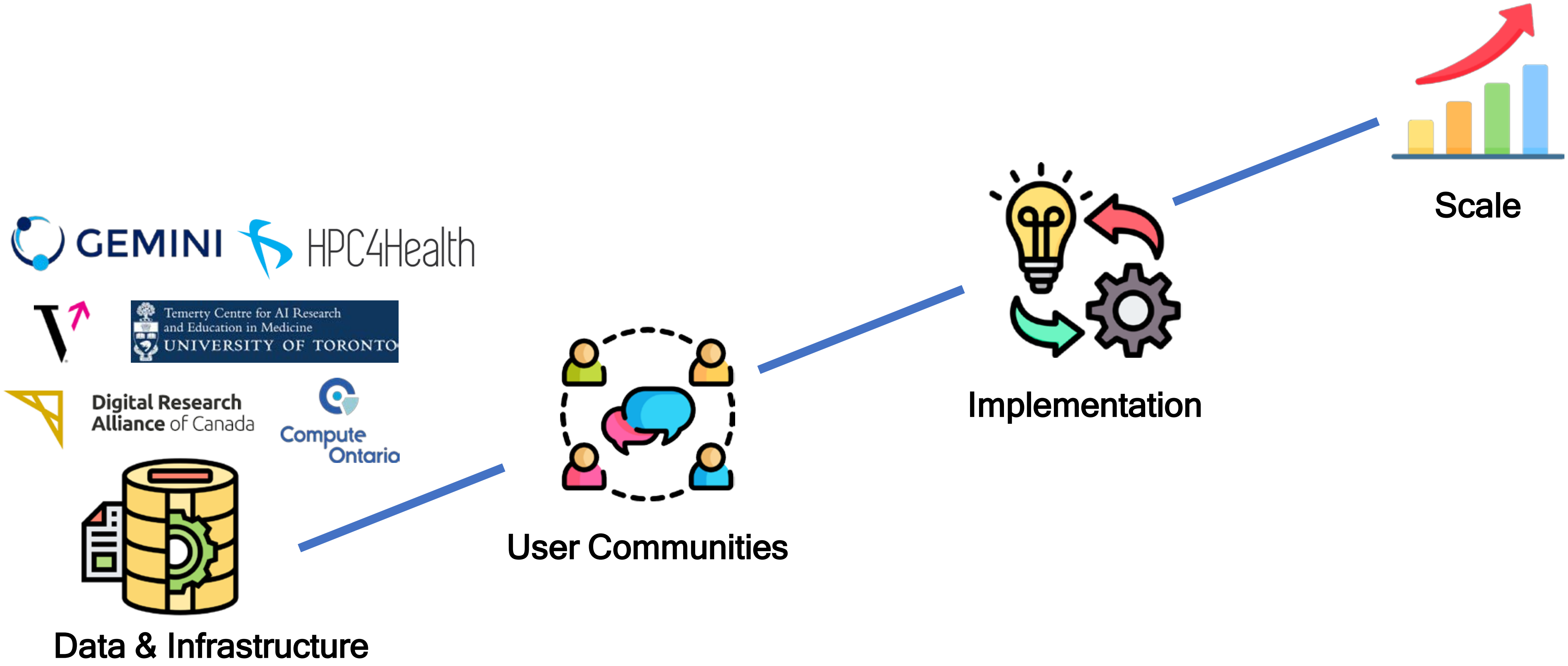
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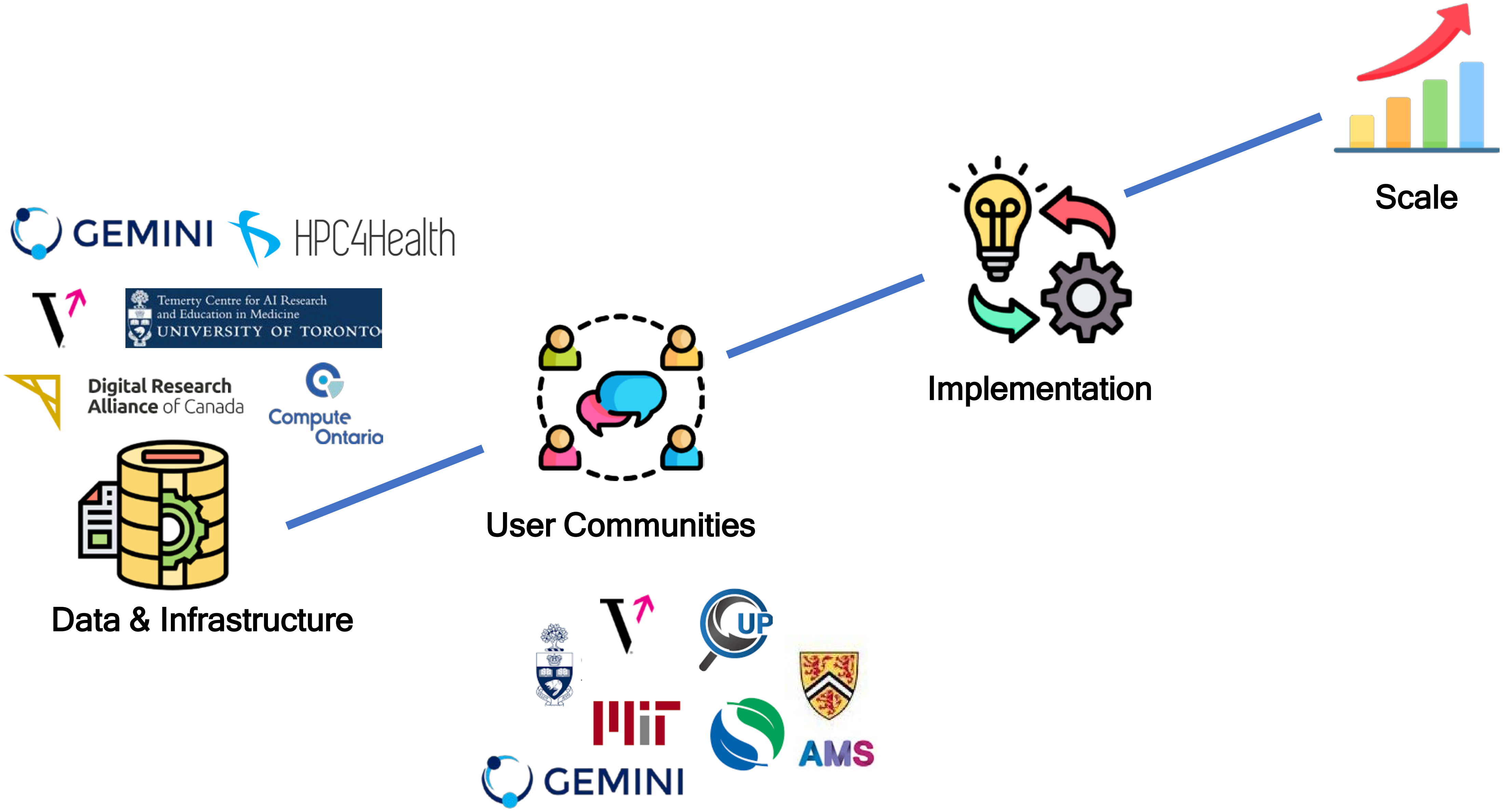
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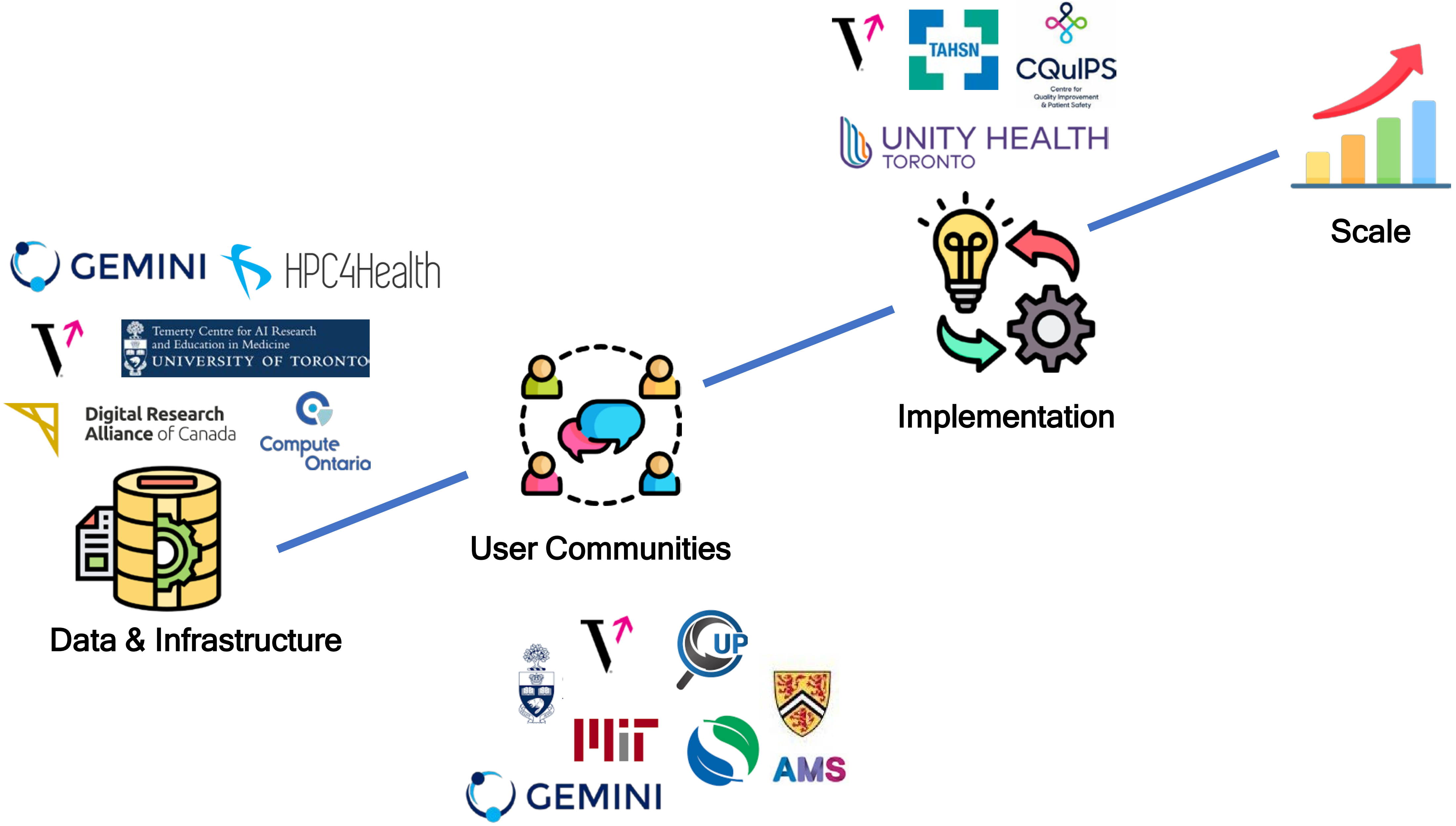

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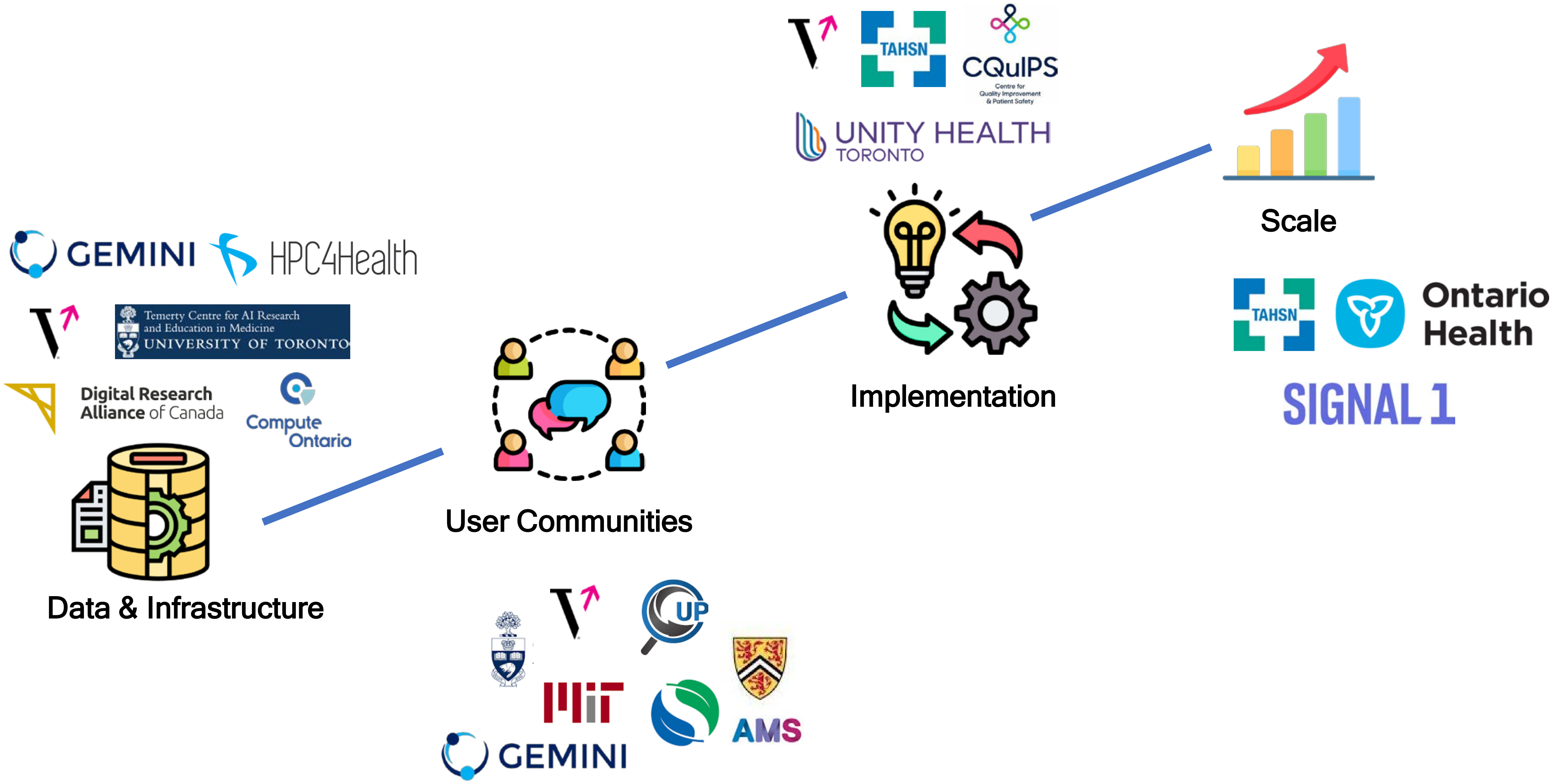

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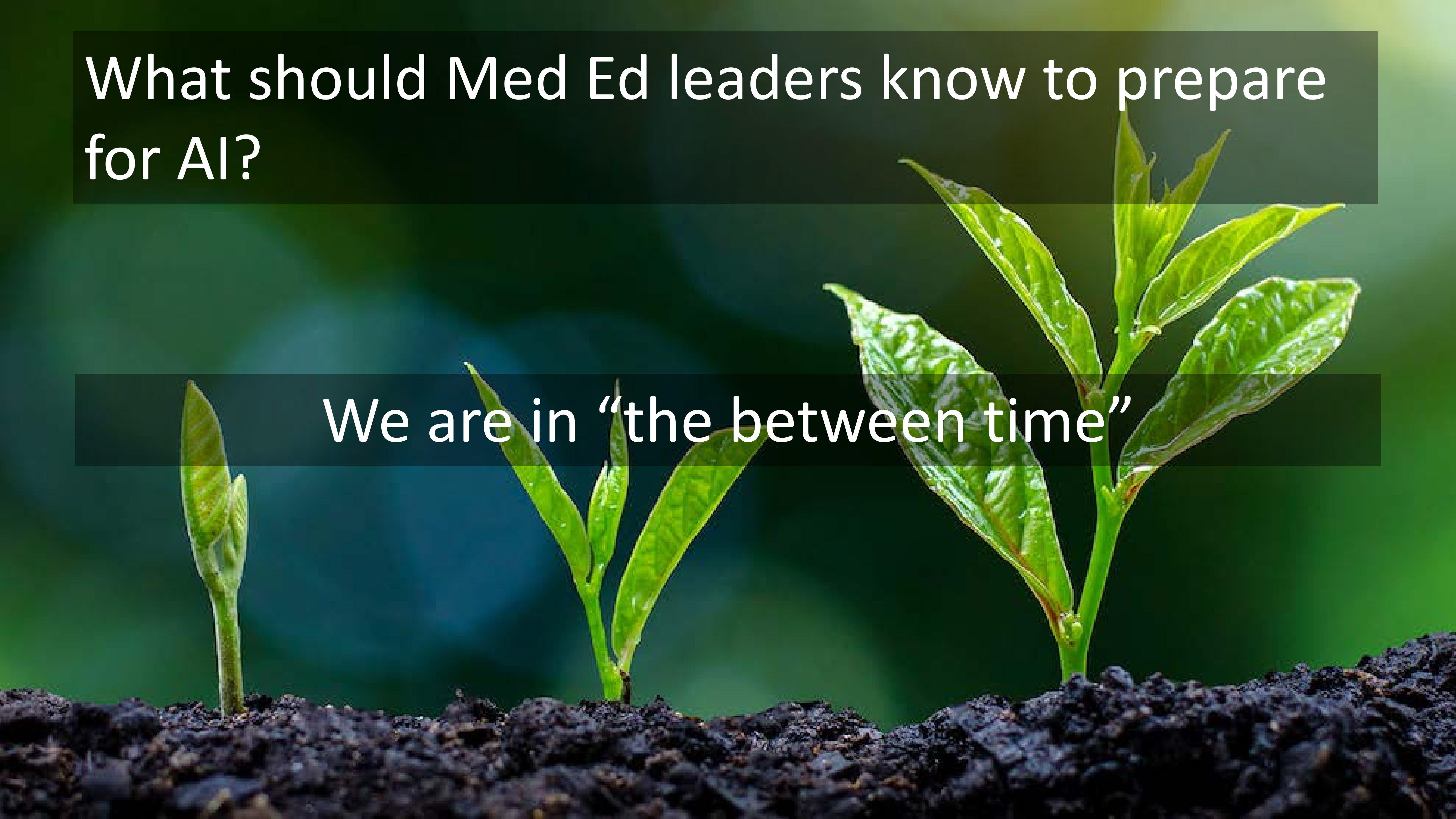
What should Med Ed leaders know to prepare for AI?

We are in “the between time”



What should Med Ed leaders know to prepare for AI?

- Driven by data: governance, quality, representativeness
- Requires diverse communities
- Implementation needs careful attention
- Scaling needs innovative partnerships
- Many possible futures

Breakout Discussion

- How can or should education at NOSM change to include more about data analytics and AI for learners?
- How can healthcare settings in Northern Ontario take advantage of, and contribute to, advances in data and analytics/AI in medicine?
- Did any other aspects of the discussion today strike you as particularly noteworthy or relevant?

Our generation’s challenge is to integrate data, analytics, and advanced computing in medicine to improve quality and humanism

Thank you

amol.verma@mail.utoronto.ca

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