Culture Inclusion & Equity and Digital Health Action Collaboratives Joint Webinar

Channeling the Potential of AI to Advance Health Equity

August 18, 2021 | 12:00 PM – 4:00 PM EST

Share your thoughts!

@theNAMedicine
Welcome & Introduction

Michael McGinnis
Leonard D. Schaeffer Executive Officer
Stakeholder leaders in private, public, and independent organizations from key health sectors, collaborating under the auspices of the National Academy of Medicine for action on their common interests in advancing effectiveness, efficiency, equity, and continuous learning in health, medical care, and biomedical science.
Advancing the Learning Health System

A learning health system is one in which science, informatics, incentives, and culture are aligned for continuous improvement, innovation, and equity—with best practices and discovery seamlessly embedded in the delivery process, individuals and families active participants in all elements, and new knowledge generated as an integral by-product of the delivery experience.

Leadership Consortium Charter 2006
focus:

COLLABORATION FOR ACTION
COLLABORATIVE ACTION

SCIENCE: Evidence Mobilization Action Collaborative
   FOCUS: continuous learning through real-world evidence

INFORMATICS: Digital Health Action Collaborative
   FOCUS: digital infrastructure & data as a core utility

INCENTIVES: Value Incentives & Systems Action Collaborative
   FOCUS: payment based on health outcomes for people and populations

CULTURE: Culture, Inclusion & Equity Action Collaborative
   FOCUS: full and equitable health engagement for people and communities
CORE ELEMENTS FOR EACH COLLABORATIVE

ORGANIZATIONAL NETWORKS

ANCHOR PRINCIPLES

KEY PROGRESS INDICATORS

COLLABORATIVE PROJECTS
Related NAM LC Initiatives related to Digital Health & Equity

Artificial Intelligence in Health Care: The Hope, the Hype, the Promise, the Peril

Government Accountability Office (GAO) AI Tech Assessments
Related NAM LC Initiatives related to Digital Health & Equity

- Digital Innovation: The Path to a Healthier Future
- Technologies to Enhance Patient, Family and Community Engagement
- Assessing Meaningful Measures of Community Engagement
Emerging Stronger After COVID-19: Priorities for Health System Transformation - National Academy of Medicine (nam.edu)
Culture Inclusion & Equity Action Collaborative Chairs

Mary Naylor
University of Pennsylvania
School of Nursing

Bill Novelli
Georgetown University
Coalition to Transform Advanced Care

Sandra Hernández
California Health Care Foundation
Digital Health Action Collaborative Chairs

Reed Tuckson
Tuckson Health Connections

Jonathan Perlin
HCA Healthcare
<table>
<thead>
<tr>
<th>Time</th>
<th>Session</th>
<th>Speakers/Leaders</th>
</tr>
</thead>
</table>
| 12:00 – 12:20 PM | Welcome                        | Michael McGinnis, National Academy of Medicine  
Sandra Hernández, California Health Care Foundation  
Reed Tuckson, Tuckson Health Connections LLC |
| 12:20 – 1:00 PM | Overview and Strategic Framing | Facilitator: Jonathan Perlin, HCA Healthcare  
Speaker: Marzyeh Ghassemi, Massachusetts Institute of Technology (MIT) |
| 1:00 – 1:50 PM | Ensuring Equity in AI          | Facilitators: Bill Novelli, Georgetown University, & Reed Tuckson, Tuckson Health Connections LLC  
Speakers: Emily Bembeneck, University of Chicago  
Varoon Mathur, New York University  
Irene Dankwa-Mullan, IBM Watson Health  
Reactors: Sonoo Thadaney-Israni, Stanford University  
Nondas Sourlas, CVS Health |
Agenda Continued

Real-World Applications of AI to Support Health Equity 1:50 – 2:45 PM

Facilitator: Jonathan Perlin, HCA Healthcare
Speakers: John Halamka, Mayo Clinic
  Suzanne Tamang, Veterans Health Administration
  Matt Might, University of Alabama at Birmingham
Reactors: Amy Salerno, University of Virginia
  Ngozi Moses, Brooklyn Perinatal Network
  Lebone Moses, Chisara Ventures
  Amy Vreeland, Pathways Community HUB Institute

Discussion and Audience Q & A 2:45 – 3:30 PM

Facilitator: Mary Naylor, University of Pennsylvania School of Nursing
Reactors: Lanay Mudd, National Institutes of Health (NIH)
  Sara Gerke, Pennsylvania State University

Adjourn 3:30 – 4:00 PM

Collaborative Co-Chairs
Michael McGinnis, National Academy of Medicine
Zoom Instructions

Panelists

• Always keep your line muted unless you are called on to speak
• If possible, turn on video while speaking to the group. To enable video click the ‘start video’ option at the bottom left of your screen
• If you would like to say something, use Zoom’s “Raise Hand” feature by clicking the “Participants” button and then pressing “Raise Hand” at the bottom of the participants tab

Attendees - Q & A

• Please type in questions into the Q&A located at the bottom of the screen on your zoom interface
• Question format:
  • Your name and organization
  • To whom
  • Question
Overview and Strategic Framing
Marzyeh Ghassemi,
Massachusetts Institute of Technology (MIT)
The F-ai-rest of them all.

How To Do Healthy Machine Learning in Health.

Dr. Marzyeh Ghassemi
MIT IMES/EECS.CSAIL
CIFAR AI Chair, Azrieli Global Scholar
Machine Learning In The Wild

**DeepMind's new AI predicts kidney injury two days before it happens**

New research from the Google-owned firm hints that AI may be a better way of assessing if someone is at risk of acute kidney injury. But there are still questions about how it handles patient data.

**Automating artificial intelligence for medical decision-making**

Model replaces the laborious process of annotating massive patient datasets by hand.

*Rob Metkeon | MIT News Office*

August 5, 2019

MIT computer scientists are hoping to accelerate the use of artificial intelligence to improve medical decision-making, by automating a key step that’s usually done by hand — and that’s becoming more laborious as certain datasets grow ever-larger.

The field of predictive analytics holds increasing promise for helping clinicians diagnose and treat patients. Machine-learning models can be trained to find patterns in patient data to aid in sepsis care, design safer chemotherapy regimens, and predict a patient’s risk of having breast cancer or dying in the ICU, to name just a few examples.

**Machine Learning Model for Early Sepsis Risk Stratification**

Bradley van Paridon

A new sepsis screening tool developed using machine learning was timelier and more discriminating than several benchmark screening tools, according to data published in the Annals of Emergency Medicine.

**UPMC, Carnegie Mellon to use Amazon’s AI tools in research**

*IMA BANKER*

UPMC and other prominent Pittsburgh research organizations announced Wednesday they plan to leverage an Amazon division’s machine learning capabilities to accelerate breakthroughs in patient care and product commercialization.

Amazon Web Services will share its machine learning—a type of AI—and cloud computing resources with the Pittsburgh Health Data Alliance, a big data consortium formed in 2015 that includes UPMC, the University of Pittsburgh and Carnegie Mellon University.

Source: High-performance medicine: the convergence of human and artificial intelligence
Eric Topol, Nature Medicine Jan 2019
SOTA Methods At/Above Human Performance

Table 3 | Selected reports of machine- and deep-learning algorithms to predict clinical outcomes and related parameters

<table>
<thead>
<tr>
<th>Prediction</th>
<th>n</th>
<th>AUC</th>
<th>Publication (Reference number)</th>
</tr>
</thead>
<tbody>
<tr>
<td>In-hospital mortality, unplanned readmission, prolonged LOS, final discharge diagnosis</td>
<td>216,221</td>
<td>0.93* 0.75 0.85</td>
<td>Rajkomar et al.26</td>
</tr>
<tr>
<td>All-cause 3-12 month mortality</td>
<td>221,284</td>
<td>0.93</td>
<td>Avati et al.26</td>
</tr>
<tr>
<td>Readmission</td>
<td>1,068</td>
<td>0.78</td>
<td>Shameer et al.26</td>
</tr>
<tr>
<td>Sepsis</td>
<td>230,936</td>
<td>0.67</td>
<td>Horng et al.26</td>
</tr>
<tr>
<td>Septic shock</td>
<td>16,234</td>
<td>0.83</td>
<td>Henry et al.26</td>
</tr>
<tr>
<td>Severe sepsis</td>
<td>203,000</td>
<td>0.85*</td>
<td>Culliton et al.26</td>
</tr>
<tr>
<td>Clostridium difficile infection</td>
<td>256,732</td>
<td>0.82**</td>
<td>Oh et al.26</td>
</tr>
<tr>
<td>Developing diseases</td>
<td>704,587</td>
<td>range</td>
<td>Miotto et al.26</td>
</tr>
<tr>
<td>Diagnosis</td>
<td>18,590</td>
<td>0.96</td>
<td>Yang et al.26</td>
</tr>
<tr>
<td>Dementia</td>
<td>76,367</td>
<td>0.91</td>
<td>Cleret de Langavant et al.26</td>
</tr>
<tr>
<td>Alzheimer’s Disease (+ amyloid imaging)</td>
<td>273</td>
<td>0.91</td>
<td>Mathotaarachchi et al.26</td>
</tr>
<tr>
<td>Mortality after cancer chemotherapy</td>
<td>26,946</td>
<td>0.94</td>
<td>Ellefky et al.26</td>
</tr>
<tr>
<td>Disease onset for 133 conditions</td>
<td>298,000</td>
<td>range</td>
<td>Razavian et al.26</td>
</tr>
<tr>
<td>Suicide</td>
<td>5,543</td>
<td>0.84</td>
<td>Walsh et al.26</td>
</tr>
<tr>
<td>Delirium</td>
<td>18,223</td>
<td>0.68</td>
<td>Wong et al.26</td>
</tr>
</tbody>
</table>

LOS, length of stay; n, number of patients (training + validation datasets). For AUC values: *, in-hospital mortality; #, unplanned readmission; @, prolonged LOS; *, all patients; @, structured + unstructured data; +++, for University of Michigan site.


Figure: Debbie Maizels / Springer Nature
What’s In Those Boxes?

Forbes
The Chronicles of AI Ethics: The Man, The Machine, And The Black Box
Today, machine learning and artificial intelligence systems, trained by data, have ... Ultimately, the problem of the black box is growing as AI/ML ...  

Tech Xplre
Artificial intelligence and algorithmic irresponsibility: The devil in the machine?
AI tempts people to abandon judgment and moral responsibility in just ... (See "Anormative black boxes: artificial intelligence and health policy," ...  

Council of Europe
Online event “Unpacking the black box – What AI means for ...”
Online event “Unpacking the black box – What AI means for human rights and how we are tackling this”. Strasbourg 12/03/2021. Diminuer la taille du texte ...  

ETCIO.com
AI Blackbox: What's under the hood?
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TechHQ
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This is a complex issue earning the label ‘black box AI’ — and it is becoming a greater problem as artificial intelligence (AI) and machine ... Dec. 1, 2020  

VB VentureBeat
Getting to trustworthy AI
Artificial intelligence will be key to helping humanity travel to new ... they need to create investigative tools to see inside black box algorithms. 1 week ago
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1 week ago
Healthy Machine Learning in Health

Creating actionable insights in human health.
Healthy Machine Learning in Health

Creating actionable insights in human health.
Privacy in Clinical Prediction Models

- Anonymization is not robust to linkage.

MAN, 60, THROWN FROM MOTORCYCLE
A 60-year-old Soap Lake man was hospitalized Saturday afternoon after he was thrown from his motorcycle. Ronald Jameson was riding his 2003 Harley-Davidson north on Highway 25, when he failed to negotiate a curve to the left. His motorcycle became airborne before landing in a wooded area. Jameson was thrown from the bike; he was wearing a helmet during the 12:24 p.m. incident. He was taken to Sacred Heart Hospital. The police cited speed as the cause of the crash. [News Review 10/18/2011]
Why Differential Privacy?

- In healthcare settings, it is crucial that we provide the same level of privacy protection for all individuals.

Sumana is in dataset A: gender, race, age, and zip code.

These properties alone make her identifiable to an adversary who can access the data, or the outputs of a model trained on the data.

Differential privacy protects those with combination of attributes that are uniquely identifiable.
Differential Privacy in Yearly Mortality Prediction

- Evaluate year-to-year performance with privacy guarantee

\[ e = \frac{\sqrt{2\log(1/\delta)}}{\sigma^2 C^2} \]

\[ \Pr[\mathcal{M}(x) \in S] \leq \exp(e) \Pr[\mathcal{M}(y) \in S] + \delta, \]

\[ \mathcal{L}(\theta(x), y) \]

<table>
<thead>
<tr>
<th>Task</th>
<th>Prediction</th>
<th>True Label</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mortality</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

\[ g = \nabla_{\theta} \mathcal{L}(\theta(x), y) \]

\[ \begin{pmatrix}
0.06 & -1.13 \\
1.10 & -0.56
\end{pmatrix} + \mathcal{N}(0, \sigma^2 \cdot C^2) \]

\[ \max \left(1, \frac{||\nabla_{\theta} g||}{C}\right) \]

Differential Privacy vs. Utility Trade-off

- What price are we willing to pay for differential privacy?

![Graph showing AUROC vs. Time, By Model & Privacy Level](image)

Large loss of performance for high privacy models in mortality. Less severe drops in tasks with lower initial performance.

ML is Built on **Finding and Enforcing** Similarity

- Training “data” loses predictive influence on test with more privacy.

- Some patients lose more influence than others.

![Graph showing influence bounds for patient data](image)

<table>
<thead>
<tr>
<th>Privacy Level</th>
<th>Average White Influence</th>
<th>Average Black Influence</th>
<th>Most Helpful Ethnicity</th>
<th>Most Harmful Ethnicity</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>0.48 ± 1.39</td>
<td>0.44 ± 2.19</td>
<td>Black</td>
<td>White</td>
</tr>
<tr>
<td>Low</td>
<td>−0.23 ± 0.75</td>
<td>−0.03 ± 0.18</td>
<td>White</td>
<td>White</td>
</tr>
<tr>
<td>High</td>
<td>−0.40 ± 4.10</td>
<td>0.12 ± 1.45</td>
<td>White</td>
<td>White</td>
</tr>
</tbody>
</table>

Adding privacy changes the most helpful group training data from Black patients to White patients for **Black test patients**.

Healthy Machine Learning in Health

Creating actionable insights in human health.
Bias Is Part of the Clinical Landscape

- How does/should ML interact with fairness/health\(^1,2,3,4,5\)?

1. Continuous State-Space Models for Optimal Sepsis Treatment - Deep Reinforcement Learning ... (MLHC/JMLR 2017);
2. Modeling Mistrust in End-of-Life Care (MLHC 2018/FATML 2018 Workshop);
3. The Disparate Impacts of Medical and Mental Health with AI. (AMA Journal of Ethics 2019);
4. ClinicalVis Project with Google Brain. (*In submission);
Model-based Chest X-Ray Diagnosis

A) Overall Population

- Take 3 large chest x-ray datasets (707,626 images).

Model-based Chest X-Ray Diagnosis

A) Overall Population

B) Model Training

- Take 3 large **chest x-ray** datasets (707,626 images).
- Train a DenseNet to predict a **“No Finding”** label, e.g., model says patient is healthy.

Take 3 large chest x-ray datasets (707,626 images).
Train a DenseNet to predict a “No Finding” label, e.g., model says patient is healthy.
Compare false positive rate (FPR) in different subpopulations to examine model underdiagnosis rates.

Model-based Chest X-Ray Diagnosis

Higher model underdiagnosis rates on one subpopulation, such as female patients, would lead to a higher rate of no treatment for those patients if the model were deployed.

Automating CheXclusion With EHR + ML

- Largest underdiagnosis rates in Female

Automating CheXclusion With EHR + ML

- Largest underdiagnosis rates in Female, 0-20

Automating CheXclusion With EHR + ML

- Largest underdiagnosis rates in Female, 0-20, Black

• Largest underdiagnosis rates in Female, 0-20, Black, and Medicaid insurance patients.

• **Intersectional** identities are often underdiagnosed even more heavily than the aggregate group, e.g., Black or Hispanic female patients are **underdiagnosed more** than White female patients.

Auditing Fairness In Predictive Models

- Significant differences in model accuracy for race, sex, and insurance type in ICU notes and insurance type in psychiatric notes.

Hurtful Words: Quantifying Biases in Clinical Contextual Word Embeddings

Prompt: [**RACE**] pt became belligerent and violent. sent to [**TOKEN**] [**TOKEN**]

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SciBERT: caucasian pt became belligerent and violent. sent to hospital.
white pt became belligerent and violent. sent to hospital.

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Prompt: [**RACE**] pt became belligerent and violent. sent to [**TOKEN**] [**TOKEN**]

SciBERT: caucasian pt became belligerent and violent. sent to hospital.
white pt became belligerent and violent. sent to hospital.
african pt became belligerent and violent. sent to prison.
african american pt became belligerent and violent. sent to prison.
black pt became belligerent and violent. sent to prison.

Complex Health Generates Complex Data

- Mobile data
- Social Network
- Medical Records
- Genomic Data
- Internet Usage
- Environmental Data

MEDICAL DATA
How Much Bias Could There Be?

• eBay auction study looked at iPods where researchers randomly varied the skin color on the hand holding the iPod.

• A white hand holding the iPod received 21 percent more offers than a black hand.

Diagnostic X-Ray Advice In Expert/Non-Experts

• What is clinical interaction with “AI” vs. “human” advice?

Evaluate expert (radiologists) vs. non-expert (internal/emergency medicine) clinicians.

Expertise and Algorithmic Aversion

- Task-expert radiologists rate “AI” advice lower than “human” advice.
- Physicians across expertise levels failed to dismiss incorrect advice.

Expertise and **Susceptibility**

- Experts generally have better **diagnostic accuracy** on tasks.

Expertise and Susceptibility

- Experts generally have better diagnostic accuracy on tasks.
- Some doctors are more susceptible to incorrect advice than others.

Healthy Machine Learning in Health

Creating actionable insights in human health.
No Simple Fixes for Ethical ML in Health

- This is an **on-going** process that requires improvement.
- Requires engagement on many levels by diverse teams.

No Simple Fixes for Ethical ML in Health

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- Requires engagement on many levels by diverse teams.

Open Issues for Community Discussion

Heterogeneous Data Losses

- **Data loss** is specific to the **data type**, e.g., randomized controlled trials (RCTs), electronic health records (EHRs), administrative health data, and social media data.

- This loss **impacts populations** in different ways, e.g., in the US, **uninsured Black and Hispanic** patients are less likely to have primary care providers with EHR systems, as compared to white patients with private insurance.

Open Issues for Community Discussion

Population-Specific Data Losses

- Historically underserved groups are often underrepresented or entirely missing from health data, e.g., autism diagnoses for Hispanic children in California fell following aggressive federal anti-immigrant policies.

- When present, disadvantaged communities are less likely to be accurately captured in data. e.g., documented sex is often discordant with gender identity for transgender and gender-nonconforming individuals.

Open Issues for Community Discussion

Widening Data Ecosystem or Data Gap?

- Target understudied areas like women’s health* via ambulatory health-tracking mobile apps. e.g., crowd-sourcing efforts could accelerate research by collecting data from cohorts that are orders of magnitude larger than those used in previous studies.

- Even small choices constitute strong distinctions that may create problematic data gaps, which leak into human and model learning.
  
e.g., data from online app platforms consist of only individuals with internet access, or limiting samples to desktop versus mobile platforms constitute strong distinctions in non-North American contexts.

* Until 2019 the NIH did not have an R01 grant relating to the influence of sex and gender on health and disease.

Availability of Embodied Data

- All data is valuable; embodied health data particularly so.
- Robust, private, fair, high-quality algorithms require large-scale diverse datasets for research use.
Health Lags Other ML Subfields in Reproducibility

- ML in Health lags in reproducibility metrics:
  - Releasing code (A1)
  - Releasing data (A2)
  - Leveraging multiple data-sets (C1)

Synthetic Data Is Not a Robust Solution

- Biased datasets can have **disparate impacts** on minority downstream classification influence
  - Even when the **real dataset** is not directly used
  - Even when the **synthetic dataset** used for the training is balanced
- Supplementing or replacing datasets with synthetic data does not mitigate the fairness concerns caused by the existing biases in imbalanced datasets.

Neither Is Post-Hoc Balancing

- Bias in data causes **asymmetric** upstream embeddings.

- Biased embeddings **impact** downstream tasks, even with **rebalancing**!

The Tip of The AI-ceberg

- Some issues lie very far under the waterline, and require introspection.

Understand the Data, Models and Process

- Tools like Datasheets\(^1\) for datasets and Modelcards\(^2\) for model reporting.

- “Big Picture” tools to understand potential biases.

- Working towards data, model and process reproducibility and transparency.

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3 https://research.google.com/bigpicture/attacking-discrimination-in-ml/
Dr. Marzyeh Ghassemi

Healthy ML @ MIT IMES EECS.CSAIL

Students

Natalie Dullerud Vinith Suriyakumar Haoran Zhang Aparna Balagopalan Kimia Hamideh Sindhu Gowda Minfan Zhang Taylor Killian Nathan Ng Bret Nestor

Collaborators (Technical and Clinical)

Anna Goldenburg Mehdi Fatemi Shalmali Joshi Amol Verma Fahad Razak Muhammad Mamdani Leo Celi

Funding Sources

- CIFAR AI Chair & CIFAR Azrieli Global Scholar
- Microsoft Research
- Helmsley Trust
- Wellcome Trust
- Quanta Computing
Healthy Machine Learning in Health

What models are healthy?

What healthcare is healthy?

What behaviors are healthy?

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  • To whom
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[Image of Zoom interface with Q&A button highlighted]
Ensuring Equity in AI
Emily Bembeneck  
University of Chicago

Varoon Mathur  
New York University

Irene Dankwa-Mullan  
IBM Watson Health
Emily Bembeneck,
University of Chicago
Algorithmic Bias Initiative

Center for Applied AI at Chicago Booth
Sendhil’s current research uses machine learning to understand complex problems in human behavior, social policy, and especially medicine, where computational techniques have the potential to uncover biomedical insights from large-scale health data.

In past work he has combined insights from economics and behavioral science with causal inference tools—lab, field, and natural experiments—to study social problems such as discrimination and poverty.

Mullainathan is a recipient of the MacArthur “Genius Grant,” has been designated a “Young Global Leader” by the World Economic Forum, was labeled a “Top 100 Thinker” by Foreign Policy Magazine, and was named to the “Smart List: 50 people who will change the world” by Wired Magazine (UK).
Algorithmic Bias Initiative Summary

Our work has shown how algorithms that are carefully developed and deployed can significantly reduce racial disparity in healthcare.

Using our applied framework, we complement the work of providers, payers, vendors, and regulators with the aim of accelerating the application of research insights to make a more equitable healthcare system.
Our research

The algorithm we studied was used to determine which patients should be referred to a high-risk care management program. One may assume that those patients who are most sick would benefit most, but the algorithm chose those patients who would generate the most healthcare costs.
Label Choice Bias Diagram

*Who needs care the most?*

The problem the algorithm is trying to solve. This is the “ideal target.”

*Who costs the most?*

The problem the algorithm is actually solving. This is the “actual target.”

Label Choice Bias

The discrepancy between the ideal target and the actual target leads to a gap where bias can arise. In our study, this bias manifested as Black patients needing to be more sick than White patients to receive the same care.
Label choice bias

For two patients at a similar health level, the White patient was far more likely to be referred than the Black patient due to label choice bias.
The solution to label choice bias is to choose an actual target that is closer to the ideal target.

**Ideal target:** need

The decision:
Which patients will benefit most from the high-risk care management program?

The algorithm:
Which patients have the highest number of comorbidities?

Doing so led to nearly twice as many Black patients being referred to the program.

**Actual target:** health
Additional research

The Algorithmic Bias Playbook is a guide to assessing and mitigating bias in your organization. It provides a step-by-step approach to applying our research insights to your context. With case studies and references, your team will be well-equipped to create an inventory of algorithms in your organization, assess them for bias, and apply mitigation strategies to ensure equitable outcomes that result in higher-quality healthcare decisions.
The Playbook Framework

The Playbook’s four steps provide a blueprint for how organizations can begin to address the landscape of potential algorithmic bias within their systems.

01 INVENTORY
- Make a list of all algorithms in your organization.
- Designate a “steward” to maintain the inventory.

02 SCREEN
- Articulate the ideal target for each algorithm, the actual target, and any discrepancies.
- Analyze performance for populations of interest against ideal target.

03 RETRAIN
- Analyze feasibility of fixes, or suspend use of biased algorithms

04 PREVENT
- Establish structures for preventing bias in both existing and future algorithms.
Join Our Community

The Center is planning ongoing thought leadership and events dedicated to catalyzing the development of solutions to algorithmic bias.

Visit our website to sign up and to download the *Algorithmic Bias Playbook* in full.

https://www.chicagobooth.edu/research/center-for-applied-artificial-intelligence
Get in touch with us

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Irene Dankwa-Mullan,
IBM Watson Health
Culture, Inclusion and Equity and Digital Health Collaboratives

Channeling Potential of AI-ML to Advance Health Equity

Irene Dankwa-Mullan MD MPH
Chief Health Equity Officer
Deputy Chief Health Officer, IBM Watson Health
Key Point #1
The AI/ML research and development process for health equity should be considered as a TRANSLATIONAL SCIENCE continuum...

To Ensure Equity, opportunities to address BIAS into AI-enabled tools needs to occur along the entire science translational and technical development steps.
Opportunities to address BIAS needs to occur along the entire science translational and technical development steps.

We need to develop better strategies and standards around how our science is conducted, reviewed, published and disseminated – for incorporation into AI-ML enabled decision tools.
Determinants of health, and causes of disease are complex, and dependent on multiple - biological, environmental and social and economic factors.

Our efforts at bringing technology, advanced analytics and AI to the forefront of health interventions should be able to sufficiently address this complexity.
Leverage potential of AI-ML to Address Disparities

AI/ML research and development should seek to integrate the complete etiological “context” of a patient’s health.

And provides informed interventions focused on evidence in similar patient or population groups, in similar settings and one that considers:

- Patient needs and values
- Life course experience
- Determinants of their health

.....Anything short of that promotes bias
Key Point #3
Incorporate Health equity and racial justice principles with Ethical AI into the Data Generation and AI/ML research and development lifecycle.

Key Point #3
Incorporate Health equity and racial justice principles with Ethical AI into the Data Generation and AI/ML research and development lifecycle.

### Summary: Address Bias in Translational Research, Data Science and AI-ML Algorithms

<table>
<thead>
<tr>
<th>Type of Bias</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Translational Research Bias</td>
<td>Failure to establish equitable standards around how our science is conducted, reviewed, published and disseminated – for incorporation into AI-ML enabled decision tools</td>
</tr>
<tr>
<td><strong>Explicit</strong></td>
<td></td>
</tr>
</tbody>
</table>
| Human Bias                | Building and analyzing the datasets without a health equity lens  
                             Misuse of health data that disproportionately impacts marginalized communities  |
| Embedded Data Bias        | Bias in health data, e.g., missing data or incomplete data in EHR’s  
                             Favoring those groups who have robust health data profiles  |
| Dataset Bias              | Labeling, handling, sample selection, modeling structure  |
| Algorithmic Bias          | Lack of cohort diversity  
                             Training data is not representative  |
| **Implicit**             |                                                                                                                                         |
| Data Invisibility         | Lack of data on certain important factors that can trigger discriminatory outcomes  |
| Data Empathy              | Lack of knowledge and experience about the people, places, factors that make up the data – unable to recognize the bias and optimize analysis due to lack of knowledge of data source and real-world evidence or implications |
Considerations

Work with **communities** to inform a framework for ethical and equitable AI-ML technologies

- Respect the dignity of individuals
- Connect with each other sincerely, openly, and inclusively
- Protect the priorities of social values, justice, and public interest
- Promote *racial equity and social justice* as a moral and ethical imperative
Thank you!
Zoom Instructions

Panelists

• Always keep your line muted unless you are called on to speak
• If possible, turn on video while speaking to the group. To enable video click the ‘start video’ option at the bottom left of your screen

Attendees - Q & A

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  • Your name and organization
  • To whom
  • Question
Real-World Applications of AI to Support Health Equity
John Halamka,
Mayo Clinic
Real World Applications of AI to Support Health Equity

John Halamka, M.D.
President
Mayo Clinic Platform
MAYO CLINIC PLATFORM

Gather
Collect, harmonize, curate, and store

Validate
Validation of algorithms

Deliver
Delivery of insights and content into workflow

Discover
Develop algorithms and insights

MAYO CLINIC CLOUD

Clinical Record
(Inpatient, Outpatient, Consumer) Telemetry, Imaging, Labs

Medical Devices

Bias Detection
Fit for Purpose

Data Quality

Model Training

Data Exploration

Analytics Tools

Clinical Applications

Devices

Patient Applications

Telemetry, Imaging, Labs

Clinical Record

Medical Devices

Bias Detection

Fit for Purpose

Data Quality

Model Training

Data Exploration

Analytics Tools

Clinical Applications

Devices

Patient Applications
CASE STUDIES

- Cardiology – Anumana, Lucem
- Radiology – Body composition
- Radiation therapy – Autocontouring
- Oncology – Breast cancer
- CHANGE Healthcare analysis
- HOUSES index
### RadAbd

#### Summary

Machine learning-based decision support software to augment medical imaging-related diagnosis of abdominal CT scans

#### Type of algorithm employed

Convolutional neural network

#### Population composition

<table>
<thead>
<tr>
<th>Ethnic composition</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-Hispanic White</td>
<td>60%</td>
</tr>
<tr>
<td>Hispanic and Latino</td>
<td>18%</td>
</tr>
<tr>
<td>Black/African American</td>
<td>13%</td>
</tr>
<tr>
<td>Asian</td>
<td>6%</td>
</tr>
<tr>
<td>Other</td>
<td>3%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Gender balance</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Male/Female</td>
<td>55/45%</td>
</tr>
</tbody>
</table>
Matt Might,
University of Alabama at Birmingham
AI in precision medicine
What's *not* in this talk
What is precision medicine?
Non-AI approaches to it
AI except for drug repurposing
A role for AI in repurposing
Examples of AI in repurposing
Achieving equity with AI?
Hint: Human intelligence!
An AI to find treatments?
An AI to find treatments?
mediKanren

Will Byrd, Ph.D.  Michael Patton

Phase I and II funded by NIH NCATS Translator Program
Translator Community

Biomedical Data Translator

The Translator program is funded through the Cures Acceleration Network (CAN). CAN is designed to advance the development of high-need cures and reduce significant barriers between research discovery and clinical trials. Learn more about the Biomedical Data Translator program.

Deconstructing the Translational Tower of Babel

Find out how NCATS’ Biomedical Data Translator program aims to help bridge informatics gaps in an editorial by NCATS leadership in Clinical and Translational Science.

100s of data sets
So, what is mediKanren?
old school logic
high-speed automated reasoning
(super-)human-like deduction
...with clinical insight
What inhibits $X$?
What may treat X?
Overactive bladder: 145 Rx
How did we do this?
We read 30 million abstracts.
+ Translator data sets
gene, drug, etc. relates to gene, drug, etc.
prevacid inhibits ENGase
increases
Example: ADNP-driven autism
mediKanren => Clinical trial
Two years ago

Sandra Sermone, ADNP Foundation
Q: What upregulates ADNP?
mediKanren: low dose ketamine
Will upregulate ADNP
February 2020
Additional Information:

Ketamine as treatment for ADNP Syndrome was researched over the course of a year and presented to Mount Sinai as a viable treatment by Matt Davis, father to Benjamin and Sandra Sermone, mother to Tony, both are parents of children with ADNP Syndrome.

A very special Thank You goes to Dr. Joseph Buxbaum who was open enough to collaborate with two parents trying desperately to help their children; to Dr. Alex Kolevzon who has gone beyond the call of duty to accelerate the study; and to Dr. Matt Might for his suggestion of putting ketamine on our radar.
Huge breaking news!!! ADNP clinical drug trial is underway - first child in today for the first ever low dose infusion 😘

Awesome news, God bless this little one 🧡

Awesome news - so exciting and hoping for positive outcome.

@mattmight
Phase 1 trial completed!
ADNP expression doubled!
Broad improvement across clinical and parent-reported measures
With a nudge from AI, ketamine emerges as a potential rare disease treatment

By Katie Palmer  Aug. 6, 2021 | Reprints
Example: Intractable cyclic vomiting
19 y/o woman
Multiple episodes per day
78 pounds
Tried all "known" treatments
30 million papers
64,000 on nausea
4,000 on treating nausea
347 distinct treatments
169 papers for zofran
"Unknown known"?
nasally inhaled isopropyl alcohol
8 months later...
125 pounds
Diagnosis in 2.127 seconds: Solving a years-long vomiting mystery using AI, research and brain power

by Bob Shepard
How to scale equitably?
Need a secret ingredient
OUR SECRET INGREDIENT
IS OUR PEOPLE
NOW HIRING
Brilliant students!
Not the first to figure this out
Using nursing trainees as the interface to medical literature for underserved communities in New York City
AI needs human intelligence
Thank you!
Suzanne Tamang,
Veteran’s Health Administration
Channeling the Potential of AI to Advance Health Equity

August 18, 2021 | 12:00 PM – 4:00 PM ET

nam.edu/LeadershipConsortium | #NAMLeadershipConsortium
### Patient Information and Risk of Suicide/Overdose

- **Risk:** Suicide or Overdose (1 yr)
  - Very High - Active Opioid Rx
  - ROSEOD Score: 3 Risk Class: 1
- **Active Stations:** 512 Maryland HCS (Baltimore MD)
- **Chart Review Note:** 

### Contributing Risk Factors

<table>
<thead>
<tr>
<th>Factor</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Substance Use Disorder</td>
<td>Alcohol</td>
</tr>
<tr>
<td>Mental Health</td>
<td>Depression</td>
</tr>
<tr>
<td>Medical</td>
<td>Congestive Heart Failure</td>
</tr>
<tr>
<td>Weight Loss</td>
<td></td>
</tr>
</tbody>
</table>

### Risk Mitigation Management

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>MEDE 40%</td>
<td>12/4/2017</td>
</tr>
<tr>
<td>Ventolin</td>
<td>12/12/2017</td>
</tr>
<tr>
<td>Timely Follow-up</td>
<td></td>
</tr>
<tr>
<td>Timely UDS</td>
<td></td>
</tr>
<tr>
<td>Psychosocial Assessment</td>
<td></td>
</tr>
<tr>
<td>Bowel Regimen</td>
<td></td>
</tr>
<tr>
<td>POMR</td>
<td></td>
</tr>
<tr>
<td>Data-based Opioid Risk Review</td>
<td></td>
</tr>
</tbody>
</table>

### Care team & Follow-up

- **Care Providers:**
  - Primary Care
  - BHP Team
  - MTx Coordinator
  - Other
- **Recent Appts:**
  - 12/6/2017 Primary Care
  - 11/26/2017 Mental Health
  - 12/16/2017 Other
- **Upcoming Appts:**
  - 1/3/2018 Primary Care
  - 1/2/2018 Mental Health
  - 1/6/2018 Mental Health
Calibration: Race

In Sample

Out Sample
SAE Trends X Race during modeling period

Sharp jump in drug poisoning rates between 2015 and 2018

Increase varied by race/ethnicity

Large relative increase in drug poisoning rates in Black population:

<table>
<thead>
<tr>
<th>Year</th>
<th>Black</th>
<th>White</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015</td>
<td>12.2</td>
<td>21.1</td>
</tr>
<tr>
<td>2017</td>
<td>20.6</td>
<td>27.5</td>
</tr>
</tbody>
</table>

Emphasizes the need for on-going calibration of predictive models, particularly when population risk is evolving rapidly.
Thank you!

Email: stamang@stanford.edu
Twitter: @suzanntee
Amy Salerno  
University of Virginia

Ngozi Moses  
Brooklyn Perinatal Network

Lebone Moses  
Chisara Ventures

Amy Vreeland  
Pathways to Community Hubs Institute
Zoom Instructions

Panelists

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  • Question
Discussion and Audience

Q & A
Lanay Mudd
National Institutes of Health (NIH)

Sara Gerke
Pennsylvania State University
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Call to Action
Closing Remarks and Adjourn

Thank you for joining!

For more information about the National Academy of Medicine’s initiatives, please visit us at: nam.edu
Culture Inclusion & Equity and Digital Health Action Collaboratives

For more information about the Culture Inclusion & Equity and Digital Health Collaboratives or to share opportunities to address and advance this work, please contact:

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Elaine Fontaine (EFontaine@nas.edu)
Asia Williams (AsWilliams@nas.edu)