AI for Community Design, Data, and Decisions

Health Equity through Artificial Intelligence (AI) and Machine Learning (ML)

March 2024
Outline

• Definitions to set the stage
  – What is AI? What is ML?
  – What is health equity? What is Health Disparity? What are SDOH?
  – AI Bias & AI Fairness

• AI for community and Health Equity
  – AI Bias Healthcare
  – Strategies for health equity
  – Building Bridges: Community Perspectives on AI
  – Building Bridges: AI for community – Challenges
  – Building Bridges: AI for community – Opportunities
**AI, ML, DL, & NLP**

**AI:** broad field that includes anything related to making machines smart.

**NLP:** branch of AI focused on teaching machines to understand, interpret, and generate human language.

**ML:** subset of AI that involves systems that can learn by themselves.

**DL:** subset of ML that uses models built on deep neural networks to detect patterns with minimal human involvement.

[https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10517477](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10517477)
What is Health Equity? What is Health Disparity?

➢ Health Equity
• everyone has a fair and just opportunity to be as healthy as possible; remove obstacles to health

➢ Health Disparity
• health difference between groups
• closely linked with economic, social, or other disadvantages
• Disparities in health and its determinants are the *metric for assessing health equity*

https://www.rwjf.org/en/library/research/2017/05/what-is-health-equity-.html
Health Disparities and Health Equity: Their Interrelation https://doi.org/10.2105/AJPH.2010.200958
Equality

Equity

What is AI Bias?

“systematic error in decision-making processes that results in unfair outcomes” in AI

AI Fairness

“the absence of prejudice or preference for an individual or group based on their characteristics” in AI systems and applications
Doubling time of medical knowledge in 1950 was 50 years; in 1980, 7 years; and in 2010, 3.5 years. In 2020 it is projected to be 0.2 years—just 73 days. [https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3116346/]
AI MEETS HEALTHCARE

- Predictive Analytics
- Personalized Treatment Plans
- Telemedicine & Remote Monitoring
- Radiology
- Drug Discovery and Development
- Health Chatbots and Virtual Assistants
- AI Enhanced EHR
- Robotics in Surgery
- Mental Health Support
- AI Ethics & Regulations

AI Bias

The challenge of managing AI bias

“bias in AI is complex and multi-faceted. While there are many approaches for mitigating this challenge there is no quick fix.”

Human factors
• participatory design techniques
• multi-stakeholder approaches
• human-in-the-loop important for mitigating risks related to AI bias.

https://tsapps.nist.gov/publication/get_pdf.cfm?pub_id=934464
AI Bias - Healthcare

African-American patients being denied access to healthcare or receiving subpar treatment. Obermeyer et al. 2020

Racial bias found in widely used health care algorithm

An estimated 200 million people are affected each year by similar tools that are used in hospital networks

The Geographic Bias in Medical AI Tools

Patient data from just three states trains most AI diagnostic tools.

Gender bias revealed in AI tools screening for liver disease


Racial Bias in Pulse Oximetry Measurement

Michael W Sjoding, Robert P Dickson, Theodore J Iwashyna, Steven E Gay, Thomas S Valley
Racial Bias in Health Care Algorithms

Algorithms and artificial intelligence are used as analytic tools to assess risk and guide care for patients. The tools can display racial bias in the following ways:

- The explicit use of race to predict outcomes and assess risk. Physicians have recently begun to move away from this more obvious form of bias.

- The use of data that inadvertently captures systemic racism. This form of bias, while unintentional, can result in additional inequities.
AI Bias - Hallucination

Journal of the American Medical Informatics Association, 30(7), 2023, 1237–1245
https://doi.org/10.1093/jamia/ocad072
Advance Access Publication Date: 22 April 2023
Research and Applications

Research and Applications

Using AI-generated suggestions from ChatGPT to optimize clinical decision support

Siri Liu¹, Aileen P. Wright¹,², Barron L. Patterson³, Jonathan P. Wanderer¹,⁴, Robert W. Turer⁵,⁶, Scott D. Nelson ⁷, Allison B. McCoy ⁷, Dean F. Sittig ⁷, and Adam Wright ¹

A Call to Address AI “Hallucinations” and How Healthcare Professionals Can Mitigate Their Risks

Cureus  September 5, 2023
AI BIAS – Sources of Bias

Medical Imaging: Main potential sources of bias in AI

Strategies: Artificial Intelligence and Health Equity

almost two-thirds of all issue-strategy pairs are related to data.

Engage the broader community

Berdahl CT, Baker L, Mann S, Osoba O, Girosi F
Strategies to Improve the Impact of Artificial Intelligence on Health Equity: Scoping Review
JMIR AI 2023;2:e42936 doi: 10.2196/42936
Emerging AI Community
engagement/participation/empowerment

Communities: Individuals, organizations, and groups affected by or concerned with AI technologies and their impact on society.

• Examples: Academics, ethicists, civil rights organizations, marginalized communities, policymakers, industry experts, and advocacy groups

Artificial Intelligence/Machine Learning Consortium to Advance Health Equity and Researcher Diversity

Artificial Intelligence Community of Practice (AI CoP) – Gov’t

Designing AI Tools for Underserved Populations from the Ground Up – Purposeful AI for the minority

Empowering local communities using artificial intelligence

A Call for Universities to Develop Requirements for Community Engagement in AI Research

https://www.aim-ahead.net/
https://casmi.northwestern.edu/news/articles/2023/designing-ai-tools-for-underserved-populations-from-the-ground-up.html
https://coe.gsa.gov/communities/ai.html
Building Bridges: Community Perspectives on AI and Health Equity

**Community:** Individuals, organizations, and groups interested in or affected by or concerned with AI technologies and their impact on society.

- **Examples:** Academics, ethicists, physicians, payers, civil rights organizations, marginalized communities, policymakers, industry experts, and advocacy groups

Think global, act local

Diversity, Diversity, Diversity

AI/ML becomes a household term

Barriers exist, but can be overcome

Open science platform for health equity

Paving pathways to success


Building Bridges: AI for Community Challenges

**Digital Divide:** Lack of access to technology and the internet can exclude vulnerable communities from participating in AI development and deployment in healthcare.

**Data Bias:** Algorithms trained on biased data can perpetuate health disparities.

**Limited Trust:** Communities with historical mistreatment by healthcare systems may be hesitant to engage with AI in healthcare.

**Lack of Transparency:** Difficulties understanding how AI works and how data is used can create suspicion and hinder community involvement.

**Unequal Benefits:** Concerns exist that AI in healthcare may exacerbate existing inequities, with wealthier communities benefiting more from new technologies.
Building Bridges: AI for Community
Comprehensive Approach

Socio-technical approach
• Collaborative and Participatory Approach from designing to implementing and sustaining
• DEI (multi- and diverse stakeholders)
• Education
• Keeping communities (humans) in the loop
• Interpretation of model output

Explanation in artificial intelligence: Insights from the social sciences:
https://pdf.sciencedirectassets.com/271585/1-s2.0-S0004370218X00125/1-s2.0-S0004370218305988/main.pdf?
Building Bridges: AI Participatory Approach

Multi-stakeholder engagement
- Variety of stakeholders
- Diverse stakeholder along social lines where bias is a concern (racial diversity, gender diversity, age diversity, geographical diversity)

Building Bridges: AI Participatory Approach

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<thead>
<tr>
<th>Participation Goal</th>
<th>Why is participation needed?</th>
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<tbody>
<tr>
<td></td>
<td>To improve the user experience</td>
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<td></td>
<td>To better align AI with stakeholders’ preferences and values</td>
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<tr>
<td></td>
<td>To deliberate about system features</td>
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<tr>
<td></td>
<td>To shape the system’s scope and purpose</td>
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<tr>
<th>Participation Scope</th>
<th>What is on the table?</th>
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<tr>
<td></td>
<td>User interface of the system</td>
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<td>Underlying datasets (e.g., identification, curation, annotation)</td>
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<td></td>
<td>Overall design of system (e.g., task specification, model features)</td>
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<td></td>
<td>Whether and why the system should be built</td>
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<th>Who is involved?</th>
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<tr>
<td>Stakeholders recruited by the project team for discrete feedback</td>
<td>75/80</td>
</tr>
<tr>
<td>Stakeholders recruited by the project team for domain expertise</td>
<td>47/80</td>
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<tr>
<td>Stakeholders designated by the community collaborate in design</td>
<td>6/80</td>
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<tr>
<td>Stakeholders designated by community play central role across project lifecycle</td>
<td>3/80</td>
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<tr>
<th>Form of Participation</th>
<th>What form does stakeholder participation take?</th>
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<td></td>
<td>Giving input on design ideas via questionnaires and interviews</td>
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<td>Group discussions with project team</td>
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<td>Ongoing collaborative prototyping and decision-making</td>
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<td>Reflexively deciding on the participatory approach</td>
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Community Stakeholders may not be familiar with ML, data science, computer science, or other fields traditionally associated with AI

- **Algorithmic Literacy:**
  - Awareness that algorithms are not neutral; Difference by SES
- **AI training series.**
  - Fundamental
  - Advanced
  - Targeted Training
- **Equip with Tools**
  - Responsible AI
  - Effective AI implementation

- Installation of hardware, software, and mobile applications, visualizations
The Gender Shades project piloted an intersectional approach to inclusive product testing for AI. Gender Shades was active from January 2017 to August 2020. 

http://gendershades.org/overview.html

Citizen Science Framework: RISE, the first large-scale video dataset for Recognizing Industrial Smoke Emissions

Figure 1: Dataset samples and the deployed camera system.
While statistical methods are indeed necessary, they are not sufficient for addressing the AI bias challenges associated with datasets.

Keeping humans at the center of AI design
Human-centered design (HCD) is an approach to the design and development of a system or technology that aims to improve the ability of users to effectively and efficiently use a product.
Focus groups were conducted among 31 women, during which participants selected the campaign’s logo and chatbot name and created the tagline.

Participants reviewed chatbot responses and designed Layla’s appearance and features, and Black/Hispanic women are featured in website and promotional photos.

A community campaign manager pairs digital strategies with grassroots partnerships among a diverse group of stakeholders, including social media influencers, hair salons and health clinics.
**Interpretability**: refers to the ability to understand the decision-making process of an AI model

- **Builds Trust**: When we understand how AI models arrive at decisions, we can trust their outcomes more readily.

- **Identifies Bias**: Interpretability helps us detect and mitigate bias within the data or model's algorithms.

- **Improves performance**: Understanding the model's inner workings allows for easier identification and correction of errors.

- **Enhances Transparency**: Interpretability fosters clear communication about AI decision-making processes

**Feature Importance**: Identifies the most influential features used by the model to make predictions.

**Partial Dependence Plots**: Show the average effect of a single feature on the model's output.
Example: Global Interpretation - Predictive Analytics – Low Value Care & Costs

Iloabuchi C, Dwibedi N, LeMasters T, Shen C, Sambamoorthi U. Low-Value Care and Excess Out-Of-Pocket Expenditure Among Older Adults with Incident Cancer: A Machine learning approach. Journal of Cancer Policy, October 2021,

N = 27,067
Example: Interpretable Predictive Analytics – Treatment

Original Research

**Prescription Non-Steroidal Anti-Inflammatory Drugs (NSAIDs) and Incidence of Depression Among Older Cancer Survivors With Osteoarthritis: A Machine Learning Analysis**

N = 14,992

Nazneen Fatima Shaikh¹, Chan Shen²,³, Traci LeMasters¹, Nilanjana Dwibedi⁴, Amit Ladani⁵, and Usha Sambamoorthi⁶
Example: Local Interpretable Predictions

Tools: Evaluation of AI output

- Ensure scientific validity, clarity of presented results, reproducibility, and adherence to ethical standards
  - CLAIM (Checklist for Artificial Intelligence in Medical Imaging)
  - STARD-AI
  - TRIPOD-AI
  - PROBAST-AI
  - SPIRIT-AI
  - CONSORT-AI
  - FUTURE-AI
  - MI-CLAIM (Minimum Information about Clinical Artificial Intelligence Modelling)
  - MINIMAR (MINimum Information for Medical AI Reporting)
  - Radiomics Quality Score (RQS)

Guidelines for Reporting AI Research by Michail Klontzas, MD, PhD, https://pubs.rsna.org/page/ai/blog/2022/09/ryai_editorsblog0928
AI For community – Have Participation, Monitoring and Controls at Every stage

Design

Data

Algorithm training /testing

Implementation/Deployment

Continuous updates of the design, data, and algorithm

Responsible AI takes the ethically created AI applications to individuals at the implementation level – Explaining and making sure there is no Bias or inequity when an individual receives the benefits of AI.
Thank You!!!!
All my collaborators

All credit goes to You!!!
Questions?

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