

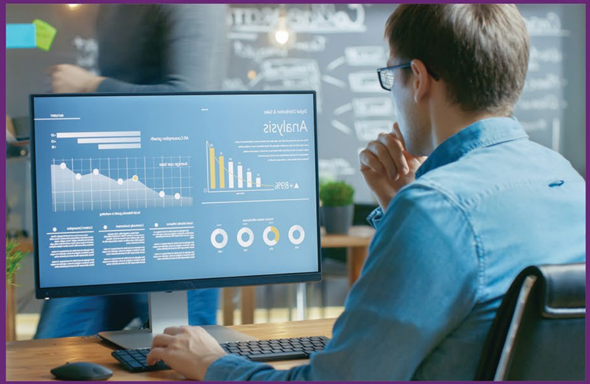
AGENCY FOR HEALTHCARE RESEARCH AND QUALITY

AHRQ

Impact of Healthcare Algorithms on Racial and Ethnic Disparities in Health and Healthcare

March 2, 2023
10:30 a.m.- 3:40 p.m. ET

NIH National Institute on Minority Health and Health Disparities



AGENCY FOR HEALTHCARE RESEARCH AND QUALITY

AHRQ

Welcome

Prashila Dullabh, MD
NORC

Racial Bias and Healthcare Algorithms
March 2, 2023
10:30–10:35 a.m. ET

NIH National Institute on Minority Health and Health Disparities

Zoom Housekeeping

Please use the Q&A feature to send comments or questions to the panelists.

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National Institute on Minority Health and Health Disparities

Disclaimer

- Presentations do not necessarily represent the views of AHRQ or the U.S. Department of Health and Human Services (DHHS); therefore, please do not interpret any statement in this presentation as an official position of AHRQ or of DHHS.

- Additionally, presentations and presenters were selected to include diverse perspectives and do not necessarily represent the views of the consensus panel.



AGENCY FOR HEALTHCARE RESEARCH AND QUALITY

AHRQ

Welcome

Craig Umscheid, MD
AHRQ

Racial Bias and Healthcare Algorithms
March 2, 2023
10:30–10:35 a.m. ET

NIH National Institute on Minority Health and Health Disparities

Welcome Remarks

Dr. Robert Otto Valdez, PhD, MHSA was appointed Director of AHRQ in February 2022. He was previously the Robert Wood Johnson Foundation (RWJF) Professor Emeritus of Family & Community Medicine and Economics at the University of New Mexico (UNM).

Dr. Eliseo Perez-Stable, MD is Director of the National Institute on Minority Health and Health Disparities (NIMHD) at the National Institutes of Health (NIH). He oversees NIMHD's annual budget to advance the science of minority health and health disparities research.

Dr. RDML Felicia Collins, MD, MPH, FAAP is the Deputy Assistant Secretary for Minority Health. As the Director of the Office of Minority Health (OMH), she leads the office in its mission to improve the health of racial and ethnic minority populations through the development of health policies and programs that help eliminate health disparities.

NIH National Institute on Minority Health and Health Disparities



AGENCY FOR HEALTHCARE RESEARCH AND QUALITY

AHRQ Remarks

Robert Otto Valdez, PhD, MHSA
Director, Agency for Healthcare Research and Quality

Racial Bias and Healthcare Algorithms
March 2, 2023
10:35–10:40 a.m. ET

National Institute
on Minority Health
and Health Disparities

AGENCY FOR HEALTHCARE RESEARCH AND QUALITY

NIMHD and ScHARe

Eliseo J. Pérez-Stable, M.D.

Director, National Institute on Minority Health and Health Disparities

eliseo.perez-stable@nih.gov

Racial Bias and Healthcare Algorithms
March 2, 2023
10:40 – 10:45 A.M. ET

National Institute
on Minority Health
and Health Disparities

Populations with Health Disparities

- Racial and ethnic minority populations in census
- Less privileged socio-economic status
- Underserved rural residents
- Sexual and gender minorities
- Social disadvantage that results in part from being subject to discrimination or racism, and being underserved in health care
- A health outcome that is worse in these populations *compared to a reference population group* defines a health disparity

National Institute on Minority Health and Health Disparities

NIMHD Research Framework

National Institute on Minority Health and Health Disparities Research Framework

Domains of Influence (Over the Lifecourse)	Levels of Influence*			
	Individual	**Interpersonal**	**Community**	**Societal**
Biological	Biological Vulnerability and Mechanisms	Caregiver–Child Interaction Family Microbiome	Community Illness Exposure Herd Immunity	Sanitation Immunization Pathogen Exposure
Behavioral	Health Behaviors Coping Strategies	Family Functioning School/Work Functioning	Community Functioning	Policies and Laws
Physical/Built Environment	Personal Environment	Household Environment School/Work Environment	Community Environment Community Resources	Societal Structure
Sociocultural Environment	Sociodemographics Limited English Cultural Identity Response to Discrimination	Social Networks Family/Peer Norms Interpersonal Discrimination	Community Norms Local Structural Discrimination	Social Norms Societal Structural Discrimination
Health Care System	Insurance Coverage Health Literacy Treatment Preferences	Patient–Clinician Relationship Medical Decision-Making	Availability of Services Safety Net Services	Quality of Care Health Care Policies
Health Outcomes	Individual Health	Family/ Organizational Health	Community Health	Population Health

National Institute on Minority Health and Health Disparities, 2018
*Health Disparity Populations: Race/Ethnicity, Low SES, Rural, Sexual/Gender Minority
Other Fundamental Characteristics: Sex/Gender, Disability, Geographic Region

National Institute on Minority Health and Health Disparities

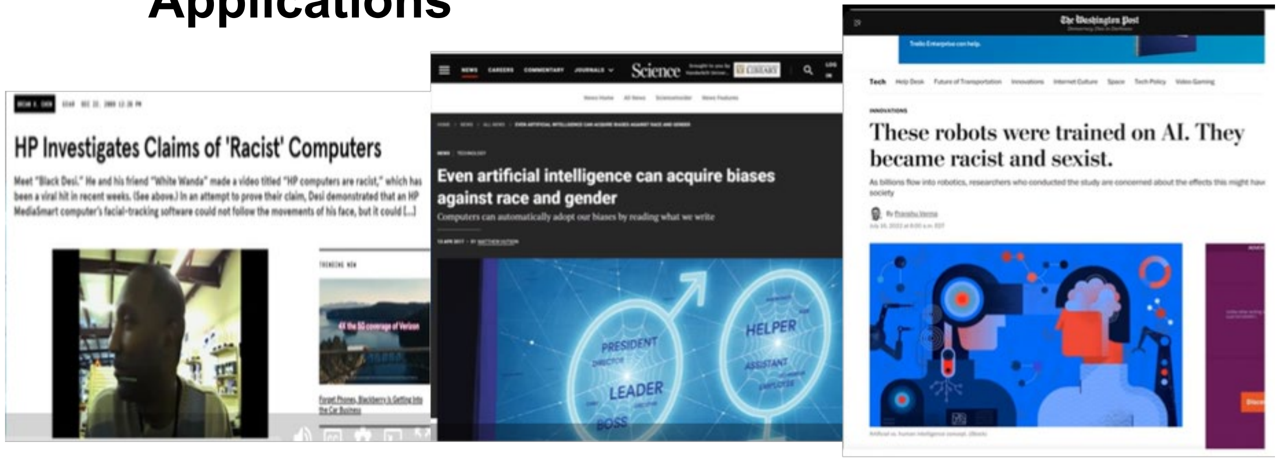
AI/Algorithm Applications

*"For the first time in history, we have technology (AI) that is Opening our eyes to **who we are**, is changing us as we speak, and could allow us to play a conscious role in who we want to become."*

Jennifer Aue

IBM Director for AI Transformation
AI professor at the University of Texas

Who We Are: Human Biases exist in AI/Algorithm Applications



2009 2017 2022

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Agency for Healthcare Research and Quality

Ethical AI/Algorithms

*"For the first time in history, we have technology (AI) that is Opening our eyes to who we are, is changing us as we speak, and could allow us to play a conscious role in **who we want to become**."*

Jennifer Aue

IBM Director for AI Transformation

AI professor at the University of Texas

Who We Want to Become: Ethical AI/Algorithms

Use Models in Context


STAT+ https://www.statnews.com/2022/10/24/epic-overhaul-of-a-flawed-algorithm/

Epic's overhaul of a flawed algorithm shows why AI oversight is a life-or-death issue

- https://jamanetwork.com/journals/jamainternalmedicine/article-abstract/2781313
- The Problem
  - An Epic EHR system developer trained a machine learning model to predict sepsis using a certain population's data
  - When the model was reused with a new population, the performance was substantially worse than the original results suggested

Models in Context – Know Populations

Ensure R's in AI/Algorithms

- **R**epeatability – same result with same data
- **R**eplicability – someone else achieves same result with same data
- **R**eproducibility – same result with different data (generalizable)

Develop AI/Algorithms with Health Equity to Prevent Health Disparities

National Institute on Minority Health and Health Disparities

NIMHD Goals in Data Science and Cloud Computing

- Increase **workforce of underrepresented women and populations with health disparities** in data science and cloud computing
- Utilize social determinants of health and population science **big data** in research to understand and improve health outcomes and reduce disparities
- Develop **ethical AI** utilizing bias mitigation strategies across the continuum of design, data selection, algorithm development and training, and implementation to ensure health equity

ScHARe

Cloud-based **social determinants of health and population science data** platform designed to accelerate research in health disparities and health outcomes, and to develop AI bias mitigation strategies

Register for ScHAe: https://www.nimhd.nih.gov/resources/schare/

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Social Determinants of Health Measures

- PhenX Toolkit on SDOH measures: https://www.phenxtoolkit.org/collections/view/6
- Demographics including family background
- Urban or rural residence or geographic region
- Cultural identity, religiosity, spirituality
- Language proficiency, Literacy, numeracy
- Structural determinants: housing, green space, broadband, economic opportunity, transportation, schools, healthy food access, public safety, political

National Institute on Minority Health and Health Disparities

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https://public.govdelivery.com/accounts/US-NIHNIMHD/subscriber/new

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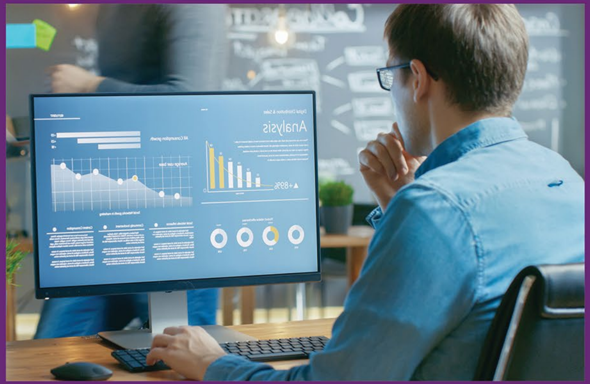


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HHS-OMH Remarks

RDML Felicia Collins, MD, MPH, FAAP

Deputy Assistant Secretary for Minority Health

Director, Office of Minority Health

U.S. Department of Health and Human Services

Racial Bias and Healthcare Algorithms

March 2, 2023

10:45–10:50 a.m. ET

NIH National Institute on Minority Health and Health Disparities



AGENCY FOR HEALTHCARE RESEARCH AND QUALITY

Introduction and Purpose of the Meeting

Anjali Jain, MD
AHRQ

Racial Bias and Healthcare Algorithms
March 2, 2023
10:50 a.m.- 11:10 a.m. ET

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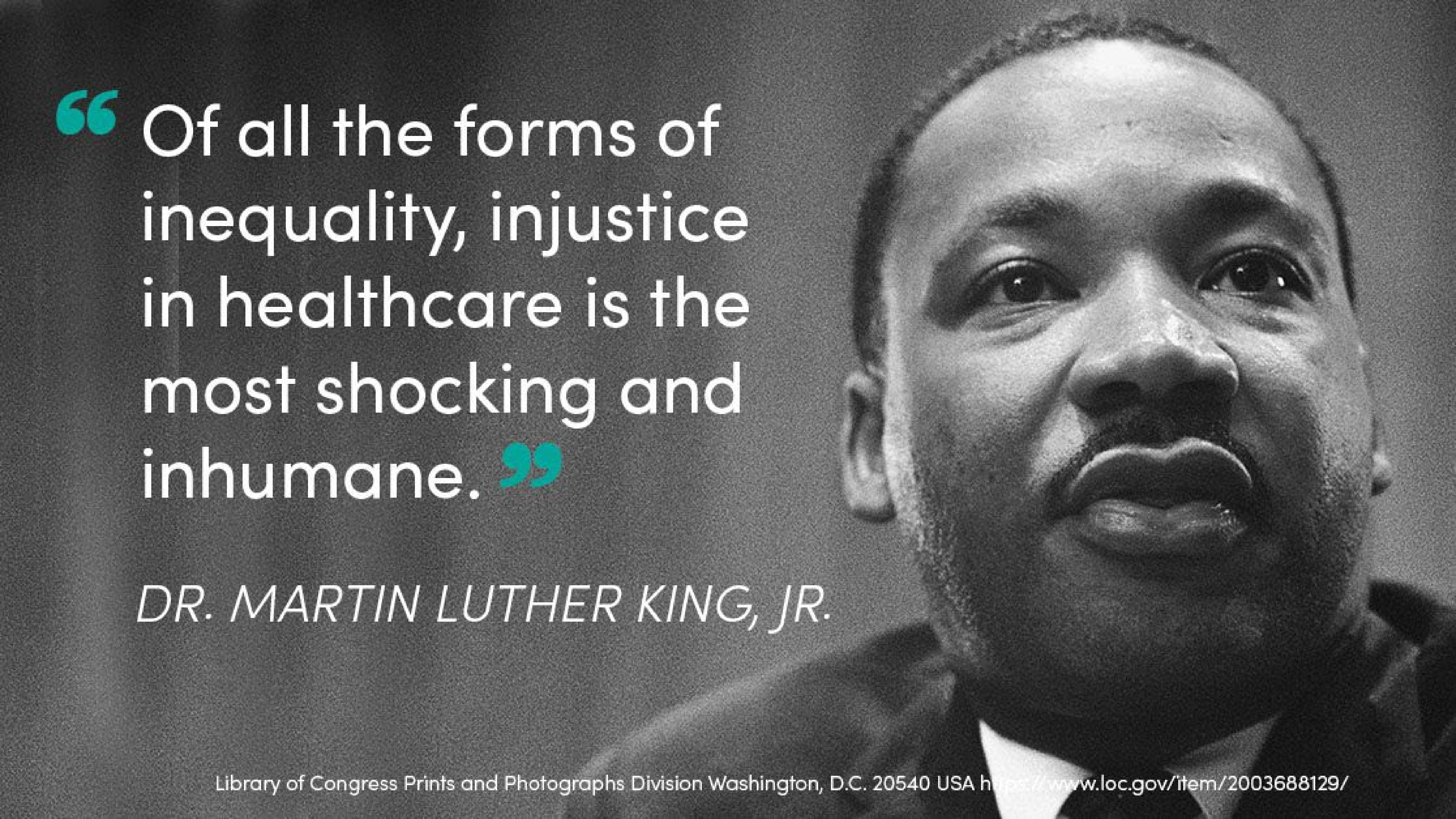
"Of all the forms of inequality, injustice in healthcare is the most shocking and inhumane."
DR. MARTIN LUTHER KING, JR.
Library of Congress Prints and Photographs Division Washington, D.C. 20540 USA https://www.loc.gov/item/2003688129/

Background

- AHRQ received a **request from Congress** to review the evidence on the potential of algorithms to contribute to disparities in health care for racial and ethnic minorities

- In response, AHRQ:
    - issued a request for information (RFI) in the federal register
    - commissioned an evidence review with the aim of informing guidance to mitigate bias in healthcare algorithms

AHRQ Request for Information (RFI) on Algorithms with Potential to Introduce Racial/Ethnic Bias

- RFI questions were intended to:
  - Identify algorithms in use with potential for racial/ethnic bias
  - Discover existing approaches to identifying or mitigating bias in algorithms
  - Characterize awareness of algorithms and bias among patients, providers, and others
  - Identify standards for algorithm development, validation, and updating


NATIONAL ARCHIVES

FEDERAL REGISTER

The Daily Journal of the United States Government

Notice

Request for Information on the Use of Clinical Algorithms That Have the Potential To Introduce Racial/Ethnic Bias Into Healthcare Delivery

National Institute on Minority Health and Health Disparities

Responses to the RFI

- **42 respondents**
  - 485 pages of responses
- **Respondents included**
  - 18 clinical and professional associations
  - 9 groups focused on health technology, including algorithm developers
  - 7 universities
  - 4 federal and state agencies (non-AHRQ)
  - 1 payer
  - 4 individuals

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Insights from the RFI

- Responses analyzed using qualitative analysis
- Respondents named 18 algorithms with potential for bias
- Major themes from responses included:
  - Addressing racial bias in healthcare algorithms is urgent and important
  - Algorithms are in widespread use and have a potentially large impact
  - Bias and disparities can result from algorithms whether or not they explicitly include race
  - Great heterogeneity and lack of standardization in how race and social determinants of health data are collected and defined
  - Bias can be introduced at all stages of algorithm development and implementation
  - Organizations making efforts to assess bias related to algorithms and improve inequities
  - Clinicians and patients often unaware of algorithm use and potential for bias
  - Algorithms should be discussed as part of shared decision making between patient and provider

Evidence Review: Impact of Healthcare Algorithms on Racial and Ethnic Disparities in Health and Healthcare

- Evidence review awarded to ECRI/Penn May 2021

- Review conducted since May 2021, includes input from experts and stakeholders as key informants & technical experts

- Draft report posted for public comment, February 9, 2023
    - Comments on the report can be submitted until 11:59 p.m. ET on March 9, 2023 at the link below

  https://effectivehealthcare.ahrq.gov/products/form/racial-disparities-health-healthcare-draft-comments

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Evidence Review: Impact of Healthcare Algorithms on Racial and Ethnic Disparities in Health and Healthcare

- 2 Key questions and 4 contextual questions
  - ***Key Question 1.*** What is the effect of healthcare algorithms on racial and ethnic differences in access to care, quality of care, and health outcomes?
  - ***Key Question 2.*** What is the effect of interventions or approaches to mitigate racial and ethnic bias in the development, validation, dissemination, and implementation of healthcare algorithms?

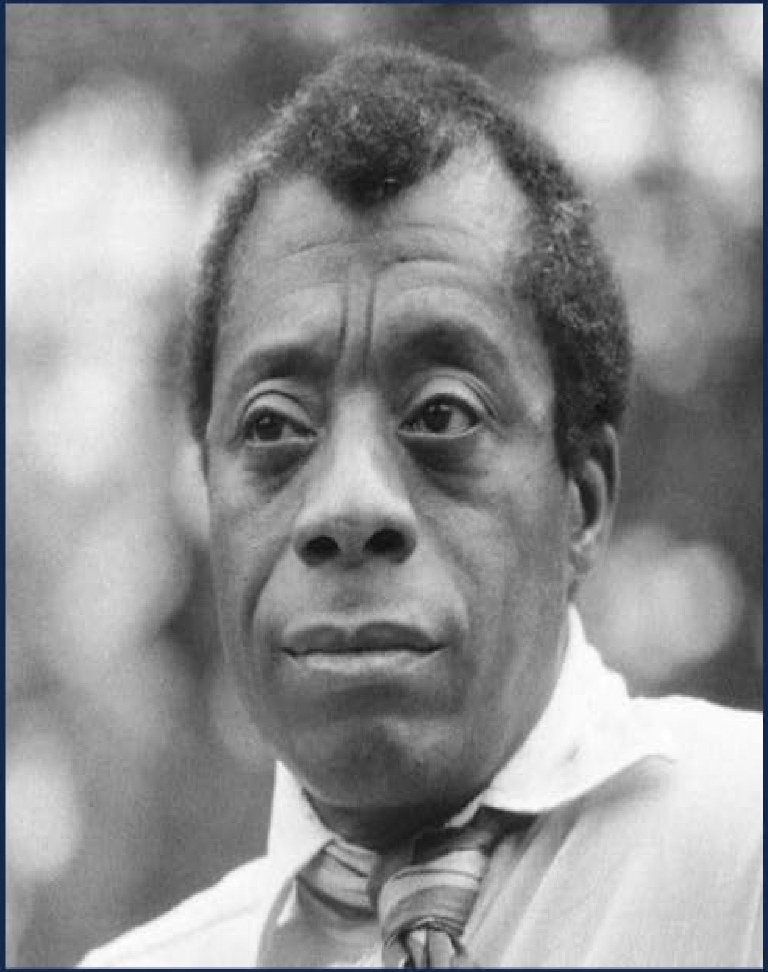
Impact of Healthcare Algorithms on Racial and Ethnic Disparities in Health and Healthcare

- 4 contextual questions to explore practical aspects of algorithmic use and bias, addressed through supplemental literature reviews and conversations with experts and key stakeholders
  - ***CQ 1*** examines the problem's scope within healthcare.
  - ***CQ 2*** describes recently emerging standards and guidance on how racial and ethnic bias can be prevented or mitigated during algorithm development and deployment.
  - ***CQ 3*** explores stakeholder awareness and perspectives about the interaction of algorithms and racial and ethnic disparities in health and healthcare.
  - ***CQ 4*** involved an in-depth analysis of a sample of six algorithms to better understand how their design and implementation might contribute to disparities

"Not everything that is faced can be changed,

but nothing can be changed until it is faced."

~James Baldwin



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Introduction of Keynote Speaker

Arlene Bierman, MD, MS
AHRQ

Racial Bias and Healthcare Algorithms
March 2, 2023
11:10 a.m.- 11:15 a.m. ET

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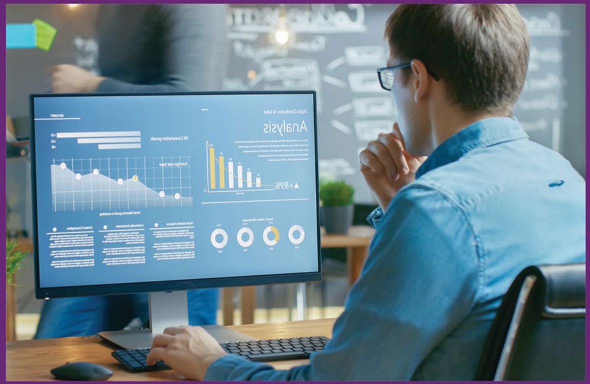


AGENCY FOR HEALTHCARE RESEARCH AND QUALITY

Dissecting Racial Bias

Ziad Obermeyer, MD
UC Berkeley
Blue Cross of California Distinguished Associate Professor of Health Policy and Management

Racial Bias and Healthcare Algorithms
March 2, 2023
11:15 a.m.- 11:45 a.m. ET

National Institute on Minority Health and Health Disparities

Algorithms in health care

- Many great uses of algorithms in health
  - Risk prediction: What will happen
  - Diagnosis: Likelihood that patient has a disease
  - …

- Many worries about disparities in these algorithms

depression, or opioid misuse; and warfarin dosing. We found evidence that algorithms can: a) reduce disparities (i.e., revised Kidney Allocation System, prostate cancer screening tools), b) perpetuate or exacerbate disparities (e.g., estimated glomerular filtration rate [eGFR] for kidney function measurement, cardiovascular disease risk assessments), and/or c) have no effect on racial or ethnic disparities (e.g., HEART Pathway). Further algorithms that perpetuated or

- What makes the difference?

Biased vs. unbiased algorithms

- A common concern: **Race as a predictor**
  - ► a big problem if “hard-coded,” e.g., assumptions about Black lung capacity

- Today: A different concern—and a way to debias algorithms

Figure 2. Conceptual Model for Understanding Racial and Ethnic Biases Introduced During Algorithm/Clinical Decision-Making Tool Development, Translation, Dissemination, and Implementation

(a) Algorithm Development Phase

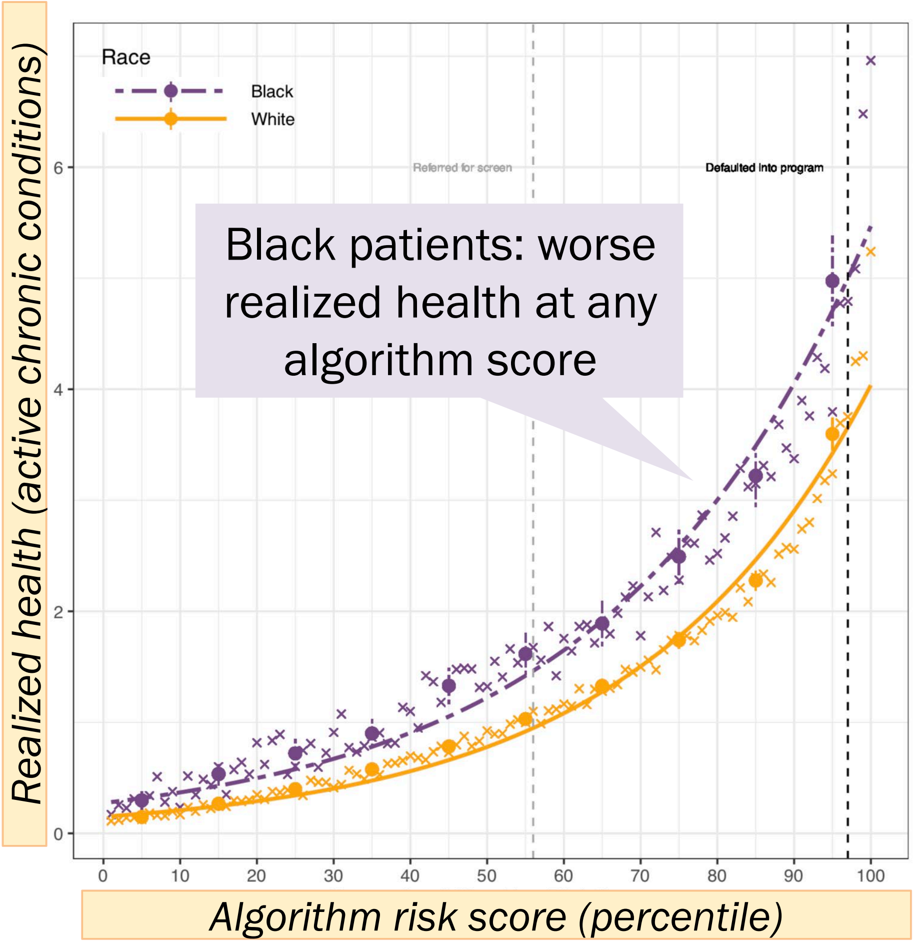
Example 1: Targeting extra help for complex patients

- Complex, chronically ill patients have high costs, poor care
  - Innovation: ‘high-risk care management’
  - But expensive – so targeting critical

- Algorithms are used everywhere for this
  - Specific software we study: 70 million patients/year (US)
  - Market estimates: 150-200 million patients/year (US)

- Common goal: Find patients who are going to get sick
  - As measured by future health care costs
  - So we can target help now

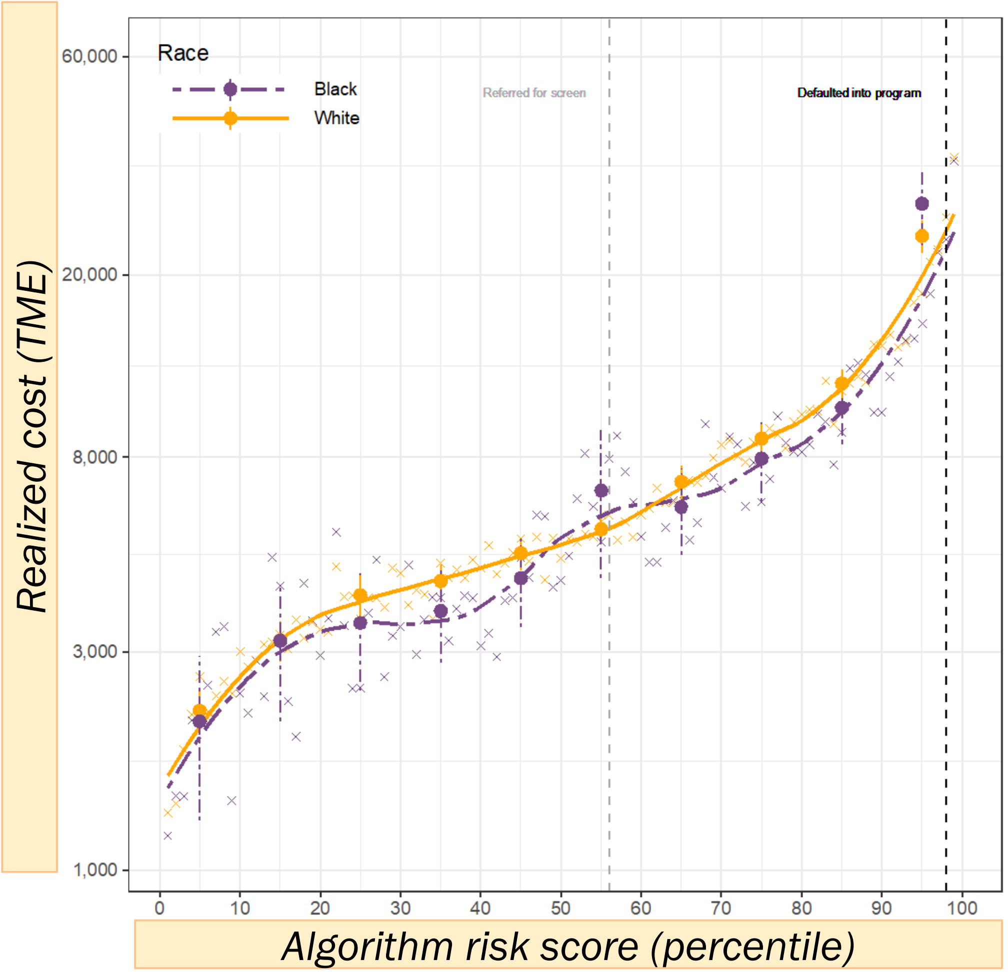
We studied ‘racial bias’



- Principle: Same score
  → Treated the same
  - ► Should have same needs
- Color of their skin should not matter
- But it does
  - ► Black patients have worse realized health
  - ► At every algorithm score

Obermeyer, Powers, Vogeli, Mullainathan, *Science* 2019

Dissecting the bias



- We'd like to understand where the algorithm is going wrong
- One clue: where it is going right
- Algorithm predicts total health costs well for Black and White patients

Obermeyer, Powers, Vogeli, Mullainathan, *Science* 2019

Biased for health, unbiased for cost

- Algorithm is accurately predicting cost
- Black patients have lower costs at the same health status
  1. White patients have better access to health care
  2. The health system treats Black patients differently
- Result: biased health prediction
  - With or without race adjustment
  - In this case: No race adjustment

Finding better targets for prediction

- Insight: We have other proxy variables besides cost
  - ► Total cost vs. avoidable cost vs. health outcomes

- We worked with developer to re-train algorithm on health
  - ► Huge benefits for equity: 84% less bias
  - ► Better fit with business purpose

- Suggests finding better proxies is a high-value activity
  - ► Practical: Same dataset, same pipeline, different label

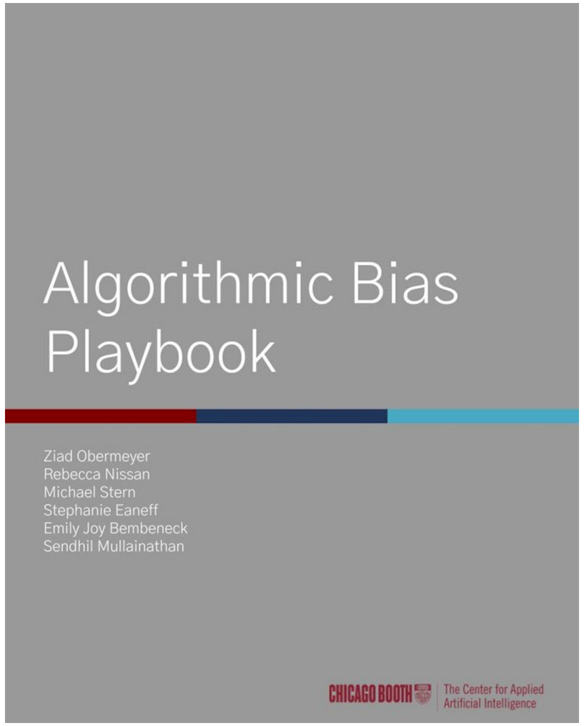
Obermeyer, Powers, Vogeli, Mullainathan, *Science* 2019

Our ‘playbook’—inspired by work over past 2 years

- Bad news: We found bias almost everywhere we looked
  - ► Population health resource allocation
  - ► Clinical disease prediction
  - ► Operational decisions

- Good news: Almost all fixable
  - ► By retraining on less biased label

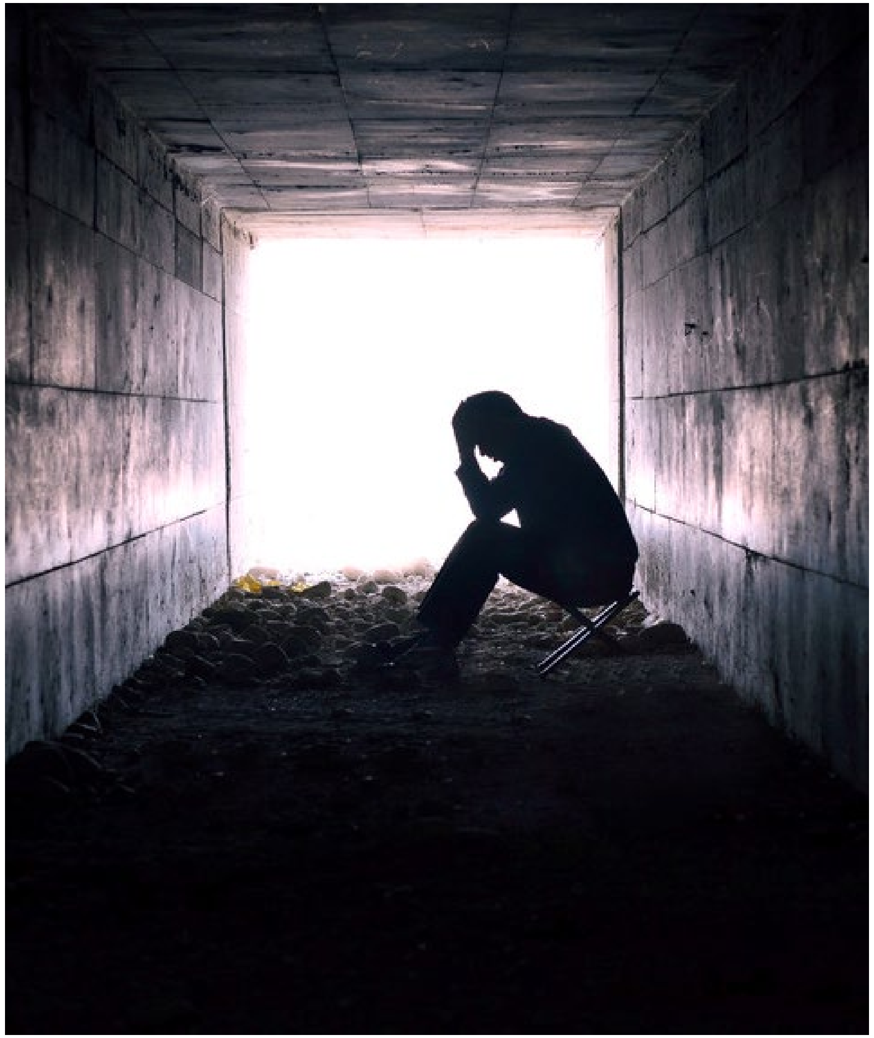
DOWNLOAD THE PLAYBOOK



Example 2: Pain is concentrated in most disadvantaged

- But story isn't as simple as it looks
- Typical exercise in literature, e.g., for knee osteoarthritis:
  - Two patients, similar x-rays
  - Compare pain scores
- Black, lower-income, lower-education: still have more pain
  - At every level of x-ray graded disease severity

Some explanations from the literature



- If it's not in their knees…
- Maybe it's in their heads?
  - Stress makes similar stimuli more painful
  - Psychosomatic factors
  - Coping skills
- Or in the medical system
  - Access to therapies

Concrete clinical scenario

Pain

X-ray

Looks normal

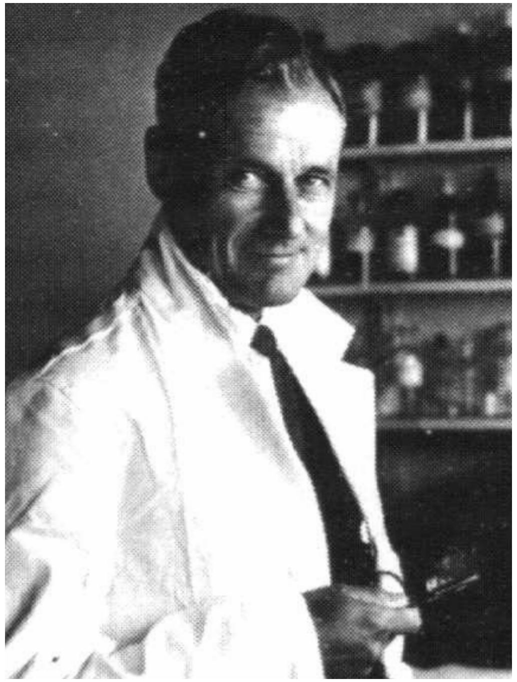
'Not in the knee'

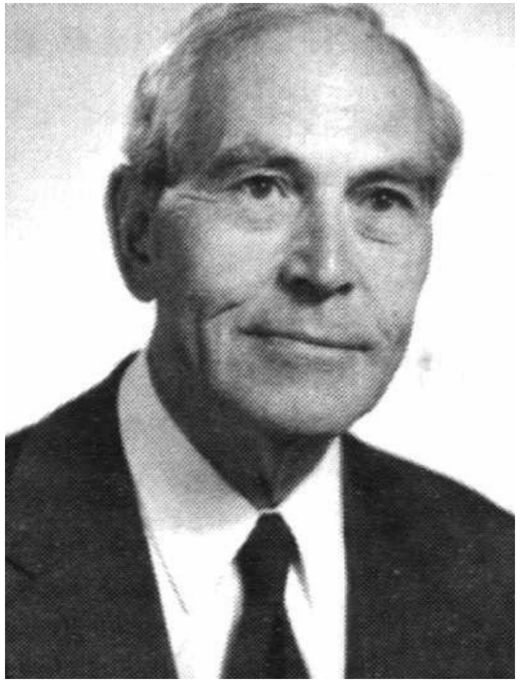
- Implication of literature
  - Black patients' pain not reflected in disease severity
- Leads to allocation of non knee-based treatments
- But what do we mean by 'disease severity'?
  - How do we measure it?

Current SOTA

Measuring osteoarthritis severity

- Objective grading scales, based on x-ray appearance
- Most common: Kellgren-Lawrence, 1957 (KLG)





- Original studies on coal miners in Lancashire, England
  - No mention of subjects' race, sex

A good job for an algorithm?


PLOS | ONE

RESEARCH ARTICLE

A preliminary examination of the diagnostic value of deep learning in hip osteoarthritis

Yanping Xue[1], Rongguo Zhang[2], Yufeng Deng[2]*, Kuan Chen[2], Tao Jiang[1]*

1 Department of Radiology, Beijing Chaoyang Hospital Affiliated to Capital Medical University, Beijing, China,
2 Infervision, Beijing, China


www.nature.com/scientificreports

SCIENTIFIC REPORTS

OPEN

Automatic Knee Osteoarthritis Diagnosis from Plain Radiographs: A Deep Learning-Based Approach

Aleksei Tiulpin[1], Jérôme Thevenot[1], Esa Rahtu[3], Petri Lehenkari[2] & Simo Saarakkala[1,4]

Received: 21 July 2017

natureresearch

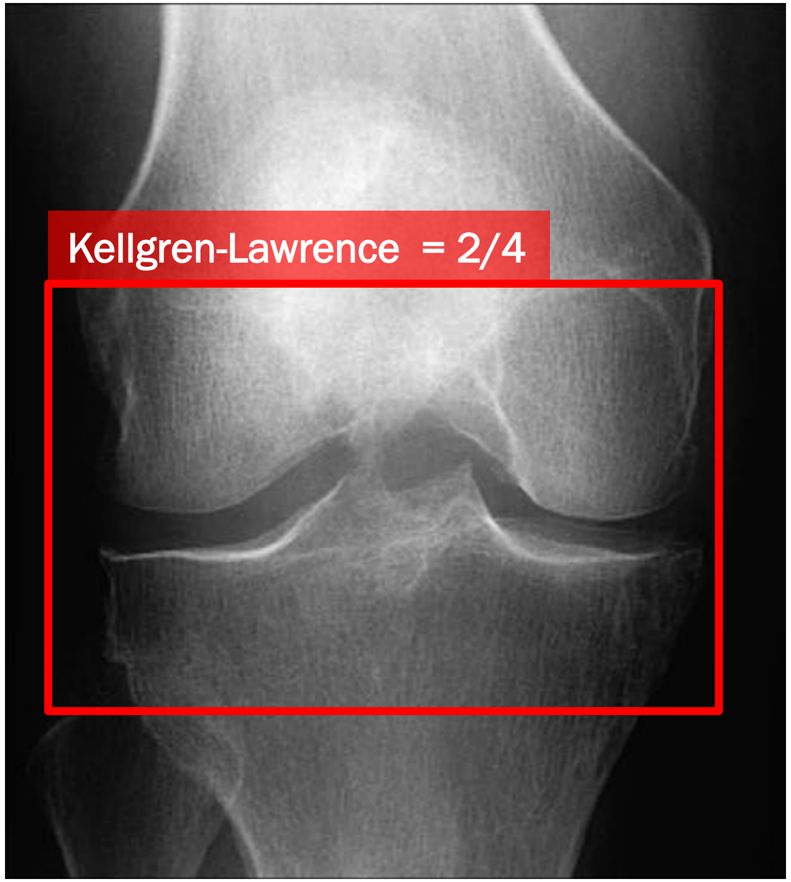

Deep Learning Predicts Total Knee Replacement from Magnetic Resonance Images

Aniket A. Tolpadi[1,2], Jinhee J. Lee[2], Valentina Pedoia[2] & Sharmila Majumdar[2]*

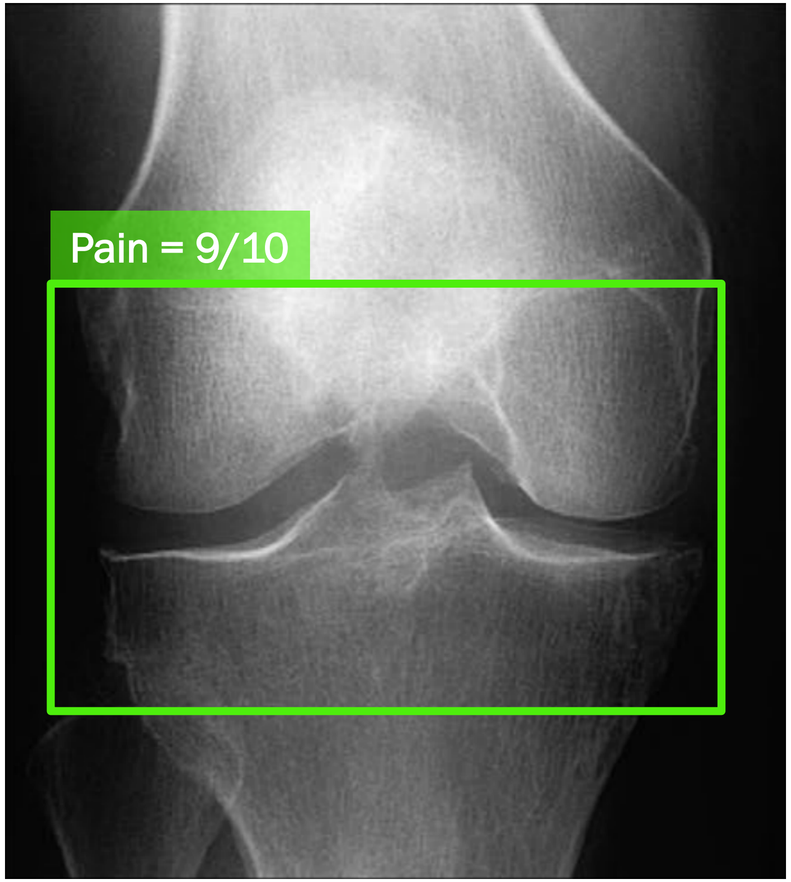
- Human radiologists may overlook causes of pain in disadvantaged groups
- We'd like an algorithm to help—but…
  - Typical approach: train to match human performance
- Exactly what we don't want to do!

Finding a better target for prediction

Learn from the radiologist



Listen to the patient

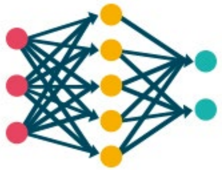


Finding the data: Not straightforward

- Easy to find: x-rays + radiologist interpretation
  - ► Sitting on every hospital's PACS system

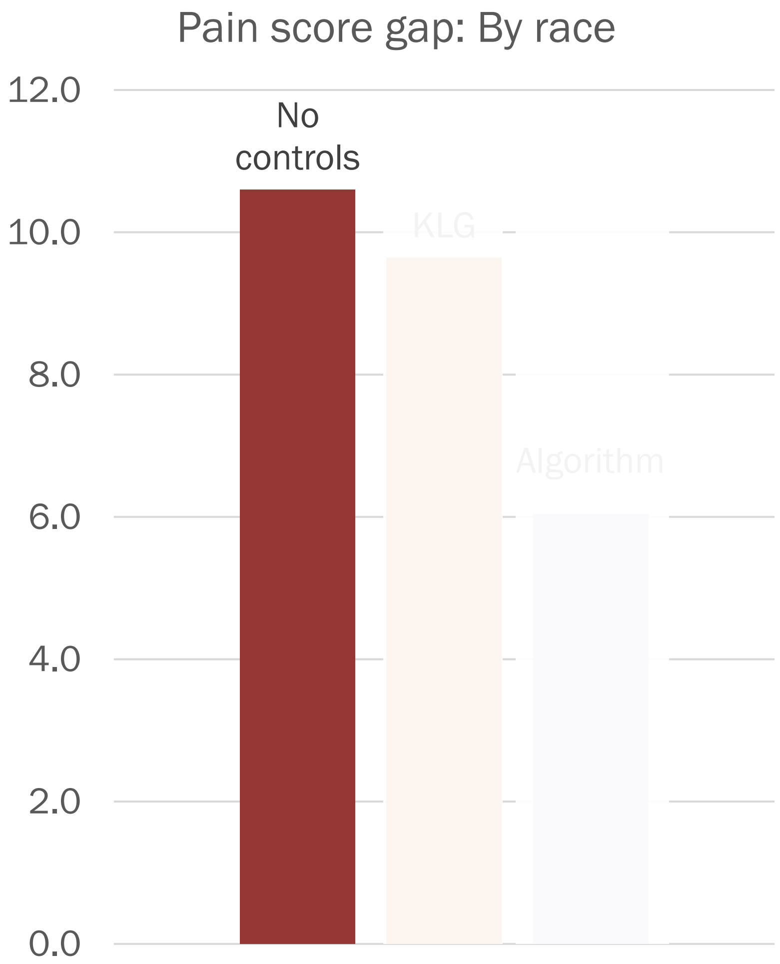
- Much harder to find: x-rays + patient pain experience

- But once we have data: a very straightforward ML problem



  - ► If pain is predictable from knee image
    - – …Pain is in the knee (not in the head, coping, …)

Algorithm closes nearly half the pain gap



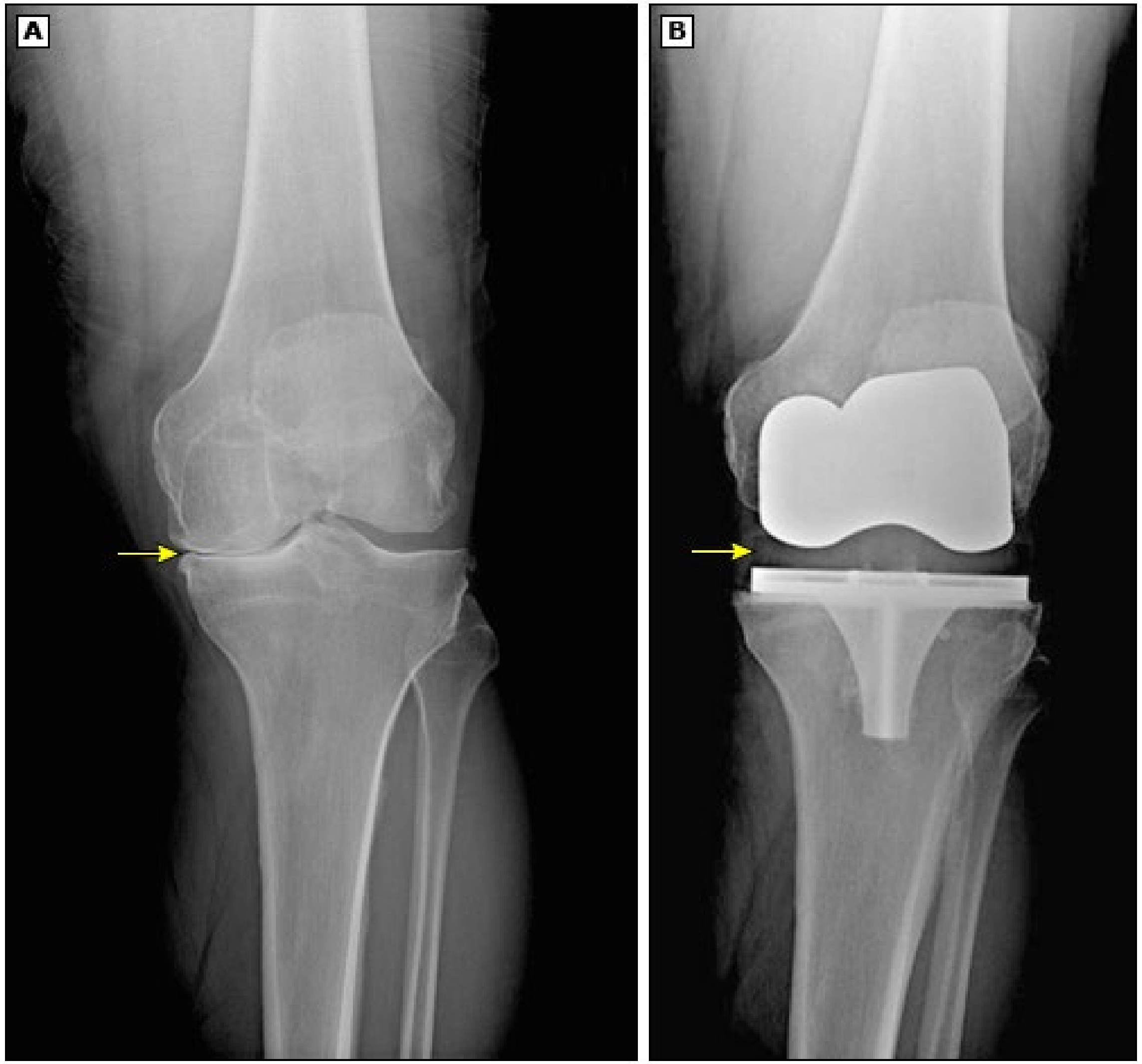
- Adjusting for standard severity measure: –9%
- Adjusting for algorithmic severity measure: –43%
  - 4.7x more than standard measure
    - 95% CI: 3.2-11.8
- Similar results for
  - Income: 2.0x
  - Education: 3.6x

Koos score: Max 100, severe ≤86

Pierson, Cutler, Leskovec, Mullainathan, Obermeyer, *Nature Medicine* 2019

The stakes are high

- Take patients with severe pain
- Simulate swapping in algorithm severity, not radiologist
- Double fraction of Black knees eligible for surgery



Summary

- Algorithmic bias is often decided early
  - How we ask the question for algorithms to answer
  - Not how the algorithm answers the question
- Suggests problem formulation is a critical area
  - This is understudied
  - Because it's difficult: What are we trying to do?

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Consensus Panel Co-Chair Comments

Marshall Chin, MD, MPH
University of Chicago

Racial Bias and Healthcare Algorithms
March 2, 2023
11:45 a.m.- 11:50 a.m. ET

NIH National Institute on Minority Health and Health Disparities

Consensus Panel for Racial Bias and Healthcare Algorithms

- Consensus Panel Composition:
  - 2 co-chairs
  - 7 panelists
  - Diverse perspectives represented
- Consensus Panel Role: Identify and formulate:
  - Guiding principles for racial/ethnic bias prevention, identification, and mitigation
  - Potential solutions, approaches and resources to address such bias
  - Actionable next steps for stakeholders
- Panel will present findings at a virtual public meeting on May 15, 2023

Impact of Healthcare Algorithms on Racial and Ethnic Disparities in Health and Healthcare

Break

March 2, 2023

11:50 a.m.– 12:00 p.m. ET

Please take ten minutes for a break

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AGENCY FOR HEALTHCARE RESEARCH AND QUALITY

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Evidence Review

Methods, Key Question 1, and Contextual Question 1

Kelley Tipton, MPH

ECRI

Shazia M. Siddique, MD, MSHP

University of Pennsylvania School of Medicine

Racial Bias and Healthcare Algorithms

March 2, 2023

12:00-12:20 p.m. ET

NIH National Institute on Minority Health and Health Disparities

Use of Race and Ethnicity in Healthcare Algorithms

Agency for Healthcare Research and Quality

The NEW ENGLAND JOURNAL of MEDICINE

MEDICINE AND SOCIETY

Debra Malina, Ph.D., *Editor*

Hidden in Plain Sight — Reconsidering the Use of Race Correction in Clinical Algorithms

Darshali A. Vyas, M.D., Leo G. Eisenstein, M.D., and David S. Jones, M.D., Ph.D.

Table 1. Examples of Race Correction in Clinical Medicine.*

Tool and Clinical Utility	Input Variables	Use of Race	Equity Concern
Cardiology			
The American Heart Association's Get with the Guidelines–Heart Failure[8] (https://www.mdcalc.com/gwtg-heart-failure-risk-score) *Predicts in-hospital mortality in patients with acute heart failure. Clinicians are advised to use this risk stratification to guide decisions regarding initiating medical therapy.*	Systolic blood pressure Blood urea nitrogen Sodium Age Heart rate History of COPD Race: black or nonblack	Adds 3 points to the risk score if the patient is identified as nonblack. This addition increases the estimated probability of death (higher scores predict higher mortality).	The original study envisioned using this score to "increase the use of recommended medical therapy in high-risk patients and reduce resource utilization in those at low risk."[9] The race correction regards black patients as lower risk and may raise the threshold for using clinical resources for black patients.
Cardiac surgery			
The Society of Thoracic Surgeons Short Term Risk Calculator[10] (http://riskcalc.sts.org/stswebriskcalc/calculate) *Calculates a patient's risks of complications and death with the most common cardiac surgeries. Considers >60 variables, some of which are listed here.*	Operation type Age and sex Race: black/African American, Asian, American Indian/Alaskan Native, Native Hawaiian/Pacific Islander, or "Hispanic, Latino or Spanish ethnicity"; white race is the default setting. BMI	The risk score for operative mortality and major complications increases (in some cases, by 20%) if a patient is identified as black. Identification as another nonwhite race or ethnicity does not increase the risk score for death, but it does change the risk score for major complications such as renal failure, stroke, and prolonged ventilation.	When used preoperatively to assess a patient's risk, these calculations could steer minority patients, deemed higher risk, away from these procedures.
Nephrology			
Estimated glomerular filtration rate (eGFR) MDRD and CKD-EPI equations[11] (https://ukidney.com/nephrology-resources/egfr-calculator) *Estimates glomerular filtration rate on the basis of a measurement of serum creatinine.*	Serum creatinine Age and sex Race: black vs. white or other	The MDRD equation reports a higher eGFR (by a factor of 1.210) if the patient is identified as black. This adjustment is similar in magnitude to the correction for sex (0.742 if female). The CKD-EPI equation (which included a larger number of black patients in the study population), proposes a more modest race correction (by a factor of 1.159) if the patient is identified as black. This correction is larger than the correction for sex (1.018 if female).	Both equations report higher eGFR values (given the same creatinine measurement) for patients identified as black, suggesting better kidney function. These higher eGFR values may delay referral to specialist care or listing for kidney transplantation.
Organ Procurement and Transplantation Network: Kidney Donor Risk Index (KDRI)[12] (https://optn.transplant.hrsa.gov/resources/allocation-calculators/kdpi-calculator/) *Estimates predicted risk of donor kidney graft failure, which is used to predict viability of potential kidney donor.†*	Age Hypertension, diabetes Serum creatinine level Cause of death (e.g., cerebrovascular accident) Donation after cardiac death Hepatitis C Height and weight HLA matching Cold ischemia En bloc transplantation Double kidney transplantation Race: African American	Increases the predicted risk of kidney graft failure if the potential donor is identified as African American (coefficient, 0.179), a risk adjustment intermediate between those for hypertension (0.126) and diabetes (0.130) and that for elevated creatinine (0.209–0.220).	Use of this tool may reduce the pool of African-American kidney donors in the United States. Since African-American patients are more likely to receive kidneys from African-American donors, by reducing the pool of available kidneys, the KDRI could exacerbate this racial inequity in access to kidneys for transplantation.
Obstetrics			
Vaginal Birth after Cesarean (VBAC) Risk Calculator[13,14] (https://mfmunetwork.bsc.gwu.edu/PublicBSC/MFMU/VGBirthCalc/vagbirth.html) *Estimates the probability of successful vaginal birth after prior cesarean section. Clinicians can use this estimate to counsel people who have to decide whether to attempt a trial of labor rather than undergo a repeat cesarean section.*	Age BMI Prior vaginal delivery Prior VBAC Recurring indication for cesarean section African-American race Hispanic ethnicity	The African-American and Hispanic correction factors subtract from the estimated success rate for any person identified as black or Hispanic. The decrement for black (0.671) or Hispanic (0.680) is almost as large as the benefit from prior vaginal delivery (0.888) or prior VBAC (1.003).	The VBAC score predicts a lower chance of success if the person is identified as black or Hispanic. These lower estimates may dissuade clinicians from offering trials of labor to people of color.
Urology			
STONE Score[15,16] *Predicts the risk of a ureteral stone in patients who present with flank pain*	Sex Acute onset of pain Race: black or nonblack Nausea or vomiting Hematuria	Produces a score on a 13-point scale, with a higher score indicating a higher risk of a ureteral stone; 3 points are added for nonblack race. This adjustment is the same magnitude as for hematuria.	By systematically reporting lower risk for black patients than for all nonblack patients, this calculator may steer clinicians away from aggressive evaluations of black patients.
Urinary tract infection (UTI) calculator[17] (https://uticalc.pitt.edu/) *Estimates the risk of UTI in children 2–23 mo of age to guide decisions about when to pursue urine testing for definitive diagnosis*	Age <12 months Maximum temperature >39°C Race: Describes self as black (fully or partially) Female or uncircumcised male Other fever source	Assigns a lower likelihood of UTI if the child is black (i.e., reports a roughly 2.5-times increased risk in patients who do not describe themselves as black).	By systematically reporting lower risk for black children than for all nonblack children, this calculator may deter clinicians from pursuing definitive diagnostic testing for black children presenting with symptoms of UTI.
Oncology			
Rectal Cancer Survival Calculator[18] (http://www3.mdanderson.org/app/medcalc/index.cfm?pagename=rectumcancer) *Estimates conditional survival 1–5 yr after diagnosis with rectal cancer*	Age and sex Race: white, black, other Grade Stage Surgical history	White patients are assigned a regression coefficient of 1, with higher coefficients (depending on stage) assigned to black patients (1.18–1.72).	The calculator predicts that black patients will have shorter cancer-specific survival from rectal cancer than white patients. Clinicians might be more or less likely to offer interventions to patients with lower predicted survival rates.
National Cancer Institute Breast Cancer Risk Assessment Tool (https://bcrisktool.cancer.gov/calculator.html) *Estimates 5-yr and lifetime risk of developing breast cancer, for women without prior history of breast cancer, DCIS, or LCIS.*	Current age, age at menarche, and age at first live birth First-degree relatives with breast cancer Prior benign biopsies, atypical biopsies Race/ethnicity: white, African American, Hispanic/Latina, Asian American, American Indian/Alaska Native, unknown	The calculator returns lower risk estimates for women who are African American, Hispanic/Latina, or Asian American (e.g., Chinese).	Though the model is intended to help conceptualize risk and guide screening decisions, it may inappropriately discourage more aggressive screening among some groups of nonwhite women.
Breast Cancer Surveillance Consortium Risk Calculator[19] (https://tools.bcsc-scc.org/BC5yearRisk/calculator.htm) *Estimates 5- and 10-yr risk of developing breast cancer in women with no previous diagnosis of breast cancer, DCIS, prior breast augmentation, or prior mastectomy*	Age Race/ethnicity: white, black, Asian, Native American, other/multiple races, unknown BIRADS breast density score First-degree relative with breast cancer Pathology results from prior biopsies	The coefficients rank the race/ethnicity categories in the following descending order of risk: white, American Indian, black, Hispanic, Asian.	Returns lower risk estimates for all nonwhite race/ethnicity categories, potentially reducing the likelihood of close surveillance in these patients.
Endocrinology			
Osteoporosis Risk SCORE (Simple Calculated Osteoporosis Risk Estimation)[20] (https://www.mdapp.co/osteoporosis-risk-score-calculator-316/) *Determines whether a woman is at low, moderate, or high risk for low bone density in order to guide decisions about screening with DXA scan*	Rheumatoid arthritis History of fracture Age Estrogen use Weight Race: black or not black	Assigns 5 additional points (maximum score of 50, indicating highest risk) if the patient is identified as nonblack	By systematically lowering the estimated risk of osteoporosis in black patients, SCORE may discourage clinicians from pursuing further evaluation (e.g., DXA scan) in black patients, potentially delaying diagnosis and intervention.
Fracture Risk Assessment Tool (FRAX)[21] (https://www.sheffield.ac.uk/FRAX/tool.aspx) *Estimates 10-yr risk of a hip fracture or other major osteoporotic fracture on the basis of patient demographics and risk-factor profile. Calculators are country-specific.‡*	Age and sex Weight and height Previous fracture Parent who had a hip fracture Current smoking Glucocorticoid use Rheumatoid arthritis Secondary osteoporosis Alcohol use, ≥3 drinks per day Femoral neck bone mineral density	The U.S. calculator returns a lower fracture risk if a female patient is identified as black (by a factor of 0.43), Asian (0.50), or Hispanic (0.53). Estimates are not provided for Native American patients or for multiracial patients.	The calculator reports 10-yr risk of major osteoporotic fracture for black women as less than half that for white women with identical risk factors. For Asian and Hispanic women, risk is estimated at about half that for white women. This lower risk reported for nonwhite women may delay intervention with osteoporosis therapy.
Pulmonology			
Pulmonary-function tests[22] *Uses spirometry to measure lung volume and the rate of flow through airways in order to diagnose and monitor pulmonary disease*	Age and sex Height Race/ethnicity	In the U.S., spirometers use correction factors for persons labeled as black (10–15%) or Asian (4–6%).	Inaccurate estimates of lung function may result in the misclassification of disease severity and impairment for racial/ethnic minorities (e.g., in asthma and COPD).[23]

Vyas DA, Eisenstein LG, Jones DS. Hidden in plain sight - reconsidering the use of race correction in clinical algorithms. N Engl J Med. 2020 Aug;383(9):874-82.

Key Questions (KQs)

- KQ 1: What is the effect of healthcare algorithms on racial and ethnic differences in access to care, quality of care, and health outcomes?
- KQ 2: What is the effect of interventions, models of interventions, or other approaches to mitigate racial and ethnic bias in the development, validation, dissemination, and implementation of healthcare algorithms?

Contextual Questions (CQs)

- CQ 1: How widespread is the inclusion of input variables based on race and ethnicity in healthcare algorithms?
- CQ 2: What are existing and emerging national or international standards or guidance for how algorithms should be developed, validated, implemented, and updated to avoid introducing bias that could lead to health and healthcare disparities?
- CQ 3: To what extent are patients, providers (e.g., clinicians, hospitals, health systems), payers (e.g., insurers, employers), and policymakers (e.g., healthcare and insurance regulators, state Medicaid directors) aware of the inclusion of input variables based on race and ethnicity in healthcare algorithms?
- CQ 4: Select a sample of approximately 5-10 healthcare algorithms that have the potential to impact racial and ethnic disparities in access to care, quality of care, or health outcomes and are not included in KQs 1 or 2. For each algorithm, describe the type of algorithm, its purpose (e.g., screening, risk prediction, diagnosis, etc.), its developer and intended end-users, affected patient population, clinical condition or process of care, healthcare setting, and information on outcomes, if available.

Conceptual Model for Understanding Racial and Ethnic Biases Introduced During Algorithm/Clinical Decision-Making Tool Development, Translation, Dissemination, and Implementation

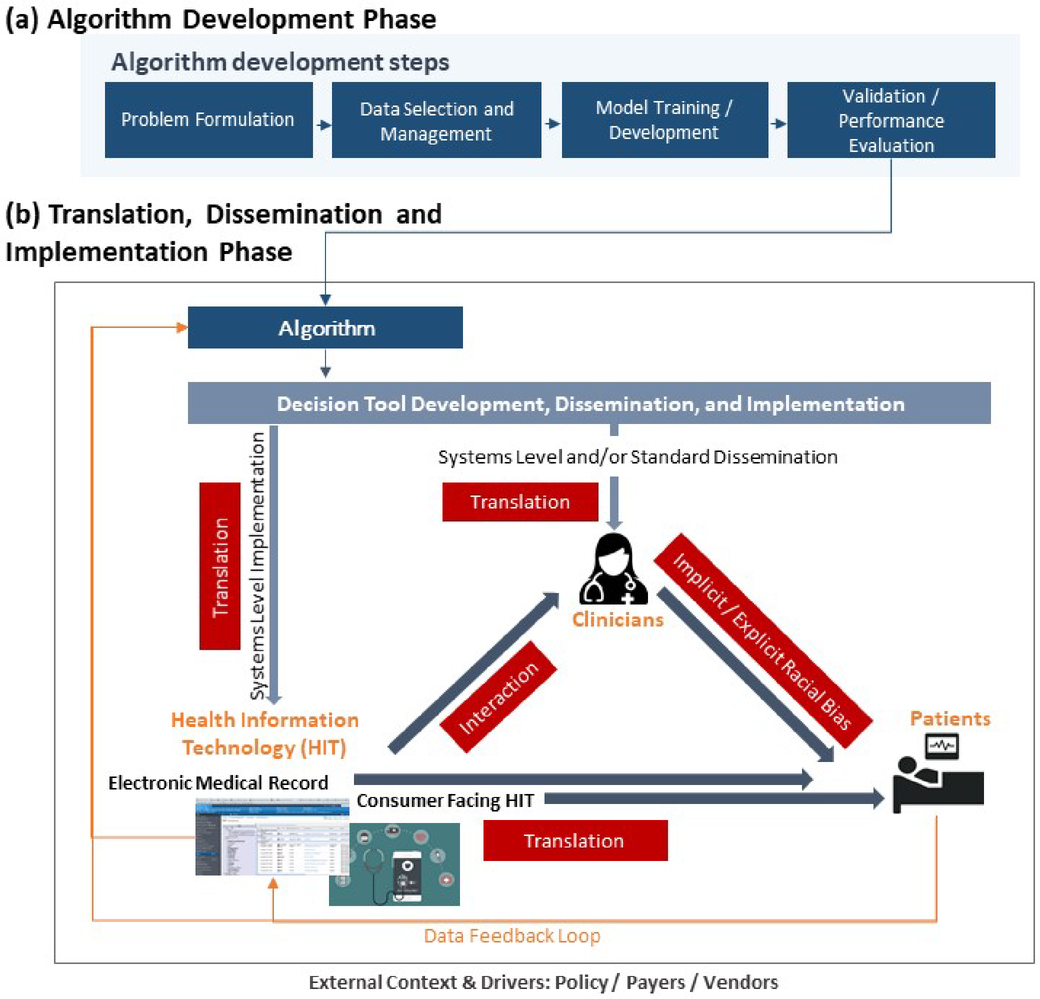

Figure informed by Sittig DF, Singh H. A new socio-technical model for studying health information technology in complex adaptive healthcare systems. In: Patel V, Kannampallil T, Kaufman D, eds. Cognitive Informatics for Biomedicine Health Informatics. Springer International Publishing; 2015:59-80; **and** Rajkomar A, Hardt M, Howell MD, et al. Ensuring fairness in machine learning to advance health equity. Ann Intern Med. 2018 Dec;169(12):866-72.

Definitions of Key Terms

Term	Definition
Algorithm	A mathematical formula or model that combines different input variables or factors to inform a calculation or an estimate, such as an estimate of disease or risk of a particular health outcome.
Algorithmic bias	Differential performance of an algorithm in different groups (such as racial or ethnic groups) due to intrinsic attributes of the algorithm.
Risk of bias (ROB)	The likelihood that a study’s reported results are misleading due to methodologic issues in study design.

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Analytic Framework/PICOTS for KQs

Population

Patients whose healthcare could be affected by algorithms

Intervention and Comparators

KQ 1

Intervention:

- Algorithms that have been, or are currently being, used for screening, risk prediction, diagnosis, prognosis, treatment, or resource allocation

Comparators:

- No algorithm
- Same algorithm with or without race or ethnicity
- Same algorithm with or without other input variables that may contribute to bias
- Different algorithm designed for the same purpose
- No comparator

KQ 2

Intervention:

- Interventions, models of interventions, or approaches to mitigate bias associated with use of algorithms

Comparators:

- Original algorithm, dataset, or approach
- Alternative mitigation strategies

Outcomes

Access to Care

- Patient use of or eligibility for healthcare services
- Patient use of population health services
- Direct costs to patients

Quality of Care

- Appropriateness of diagnosis, treatment, and/or monitoring (e.g., diagnostic/prognostic accuracy)
- Timeliness of care
- Patient experience/satisfaction
- Hospital readmission
- Hospital length of stay

Health Outcomes

- Mortality/survival
- Morbidity
- Quality of life
- Functional status

Settings

Hospital: Inpatient, emergency department, observation unit
Ambulatory: Post-acute care, primary, specialty, rehabilitation care sites, long-term care
Non-clinical site: Home care (telemedicine, self-care)

Overview of Project Methods

- Systematic literature search of Embase, MEDLINE, PubMed, Cochrane Library, and grey literature (1/1/2011 to 1/12/2022)
  - Updated search performed through 2/7/2023
- Used predefined criteria and dual review to screen all records for KQ 1 and KQ 2; selected eligible full-length research studies published in English for one or both KQs
- Assessed studies' methodologic ROB using ROBINS-I and piloted an appraisal supplement to assess racial and ethnic equity-related ROB
- Completed a narrative synthesis, catalogued study characteristics and outcome data
- CQs addressed through supplemental searches, review of RFI responses, and discussions with SMEs, TEP, and KIs
- External peer review completed; report posted for public comment on 2/9/2023

Study Flow Diagram

Articles identified through database literature searches (n=8,500)

→ Articles excluded at title level (n=4,038)

Abstracts screened (n=4,462)

→ Articles excluded at abstract level (n=4,202)

Full-text articles assessed (n=260)

→ Articles excluded at full-text level (n=218)

Key Question 1 (n=218):
- Does not examine a clinical algorithm or algorithm-based tool (n=90)
- Does not examine the effect of a clinical algorithm or algorithm-based tool on racial or ethnic differences (n=37)
- Does not report an outcome of interest (n=34)
- Does not report outcomes by race or ethnicity (n=4)
- Derivation study with only internal validation (n=6)
- Non-US population (n=26)
- Not a full-length primary study (n=21)

Key Question 2 (n=218):
- Does not examine the effect of an intervention to mitigate bias of a clinical algorithm or algorithm-based tool (n=171)
- Does not report an outcome of interest (n=21)
- Does not report outcomes by race or ethnicity (n=5)
- Not a full-length primary study (n=21)

42 studies included*

12 for Key Question 1
33 for Key Question 2
*3 studies were included for both

Classification of Studies by Key Question

- KQ 1: included studies evaluated an algorithm’s effect on health or healthcare outcomes stratified by racial and ethnic groups
- KQ 2: included studies intended to develop an intervention or strategy to mitigate
  - racial and ethnic algorithmic bias **OR**
  - a known racial and ethnic disparity associated with an algorithm
- Studies included in **both KQ 1 and 2** described
  - a racial and ethnic disparity associated with an algorithm, **AND**
  - an intervention on the algorithm to mitigate the disparity

KQ 1 Results: Overview

- 12 included studies
  - ► Algorithms reduce disparities (n=4 studies)
  - ► Algorithm with no effect on disparities (n=1 study)
  - ► Algorithms that perpetuate or exacerbate disparities (n=7 studies)
- KQ 2 with further evidence of algorithms that perpetuate or exacerbate disparities, thereby warranting mitigation strategies
- Studies were appraised at moderate-to-high risk of bias

KQ 1: Algorithms Shown to Reduce Disparities

Clinical Assessment	Number of Studies	Algorithm(s)	Comparator	Includes race or ethnicity? (Y/N)	Primary outcome
Kidney Transplant Suitability	1 [Zhang 2018]	Kidney Allocation System (KAS)	Pre-implementation of KAS	Y	Waitlisting rate
Lung Transplant Suitability	1 [Wille 2013]	Lung Allocation Score (LAS)	Pre-implementation of LAS	N	Death while on waitlist or ineligibility due to morbidity while on waitlist
Prostate Cancer Risk	2 [Presti 2021] [Carbanaru 2019]	KPPC RC PCPT	Compared KPPC RC models PBCG	Y	Biopsies avoided and clinically significant prostate cancers missed

KPPC RC=Kaiser Permanente prostate cancer risk calculator; N=no; PCPT=Prostate Cancer Prevention Trial algorithm; PBCG=Prostate Biopsy Collaborative Group algorithm; Y=yes

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Takeaway: Existing disparities were identified prior to algorithm development and implementation. These algorithms were implemented as part of an intentional effort to tackle disparities

KQ 1: Algorithms with No Effect on Disparities

Clinical Assessment	Number of Studies	Algorithm	Comparator	Includes race or ethnicity? (Y/N)	Primary outcome
Emergency Department Triage	1 [Snavely 2021]	HEART Pathway	Pre-implementation of HEART Pathway	N	30-day death or myocardial infarction

Takeaway: The HEART Pathway did not significantly impact death or MI rates for BIPOC individuals. However, non-white patients and women were more likely to be classified as low risk and discharged early. Longer term implications have not been assessed.
Of note, non-adherence to the pathway was higher for women, but non-significant for non-White individuals, providing insight on pragmatic challenges of algorithm implementation.

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KQ 1: Algorithms Shown to Perpetuate Disparities

Clinical Assessment	Number of Studies	Algorithm	Comparator	Includes race or ethnicity? (Y/N)	Primary Outcome
Severity of Illness Scores Applied to Crisis Standards of Care	3 [Ashana 2021] [Sarkar 2021] [Miller 2021]	SOFA and LAPS2 SOFA, OASIS, APACHE IVa SOFA tiering systems	Compared models/tiering systems	N	In-hospital mortality

APACHE IVa=Acute physiology and chronic health evaluation; LAPS2=Laboratory-based Acute Physiology Score version 2; N=no; NR=not reported; OASIS=Oxford Acute Severity of Illness Score; SOFA=Sequential Organ Failure Assessment

Takeaway: Applying severity of illness scores outside of its original intended application (e.g. Crisis Standards of Care for the COVID-19 pandemic) results in less resources for BIPOC (Black and Hispanic) individuals, thereby leading to disparities.

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KQ 1: Algorithms Shown to Perpetuate Disparities

Clinical Assessment	Number of Studies	Algorithm	Comparator	Includes race or ethnicity? (Y/N)	Primary Outcome
Severity of Illness Scores Applied to Crisis Standards of Care	3 [Ashana 2021] [Sarkar 2021] [Miller 2021]	SOFA and LAPS2 SOFA, OASIS, APACHE IVa SOFA tiering systems	Compared models/tiering systems	N	In-hospital mortality
Lung Cancer Risk	**2** **[Pasquenelli 2021]** **[Han 2020]**	**USPSTF-2013**	**PLCOm2012**	**N (Y for comparator)**	**Lung cancer screening eligibility**

<u>Takeaway:</u> Both studies found that USPSTF-2013 resulted in higher proportions of Black patients being ineligible for lung cancer screening.
However, this is not a pre-post study. Downsides of potential over-screening were not assessed.

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KQ 1: Algorithms Shown to Perpetuate Disparities

Clinical Assessment	Number of Studies	Algorithm	Comparator	Includes race or ethnicity? (Y/N)	Primary Outcome
Severity of Illness Scores Applied to Crisis Standards of Care	3 [Ashana 2021] [Sarkar 2021] [Miller 2021]				In-hospital mortality
Lung Cancer Risk	2 [Pasquenelli 202 [Han 2020]			(comparator)	Lung cancer screening eligibility
Opioid Misuse Risk	**1** **[Thompson 2021]**	**Natural language processing classifier**	**None**	**NR**	**Referral for education, treatment options, and care pathways**
High-Risk Care Management	**1** **[Obermeyer 2019]**	**Commercial risk prediction calculator**	**None**	**N**	**Eligibility for a care management program**

Takeaway: Algorithms that do not include race can lead to disparities: Obermeyer studied an algorithm which predicted healthcare costs, as a proxy for healthcare needs. This is flawed because the association between costs and health differs across racial and ethnic groups.

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Further evidence from KQ 2: Algorithms Perpetuate Disparities

Summary Evidence Map

Clinical Category	Algorithm	Key Question	Study	Study Design[a]	Disparities in Health outcome[b]	Disparities in Access[b]	Disparities in Quality[b]
Kidney function measurement	eGFR[c]	KQ 2	*Ahmed 2021*[21]	Modelling[d]	*	↑	*
	eGFR[c]	KQ 2	*Inker 2021*[23]	Modelling[d]	*	*	↑
	eGFR[c]	KQ 2	*Casal 2021*[61]	Modelling[d]	*	↑	↑
	eGFR[c]	KQ 2	*Duggal 2021*[62]	Modelling[d]	↑	*	↑
	eGFR[c]	KQ 2	*Hoenig 2022*[64]	Modelling[d]	*	*	↑
	eGFR[c]	KQ 2	*Inker 2021*[65]	Modelling[d]	*	*	↑
	eGFR[c]	KQ 2	*Mahmud 2022*[67]	Modelling[d]	↑	*	*
	eGFR[c]	KQ 2	*Miller 2021a*[68]	Modelling[d]	*	*	↑
	eGFR[c]	KQ 2	*Panchal 2022*[69]	Modelling[d]	↑	↑	*
	eGFR[c]	KQ 2	*Shi 2021*[71]	Modelling[d]	↑	*	*
	eGFR[c]	KQ 2	*Tsai 2021*[72]	Modelling[d]	↑	*	*
	eGFR[c]	KQ 2	*Yap 2021*[74]	Modelling[d]	*	*	↑
	eGFR[c]	KQ 2	*Zelnick 2021*[75]	Modelling[d]	↑	*	↑
	eGFR[c]	KQ 2	*Coresh 2019*[78]	Modelling[d]	*	*	↑
Kidney transplant allocation	Kidney Donor Index	KQ 2	*Julian 2017*[81]	Modelling[d]	*	*	↑
	Revised KAS[c]	KQ 1	*Zhang 2018*[58]	Pre-post	*	↓	*
Severity of illness scores for Crisis Standards of Care	SOFA	KQ 1	*Miller 2021b*[51]	Modelling[d]	*	↑	*
	SOFA, LAPS2	KQ 1 and 2	*Ashana 2021*[88]	Modelling[d]	↑	↑	*
	APACHE Iva, OASIS, SOFA	KQ 1	*Sarkar 2021*[54]	Modelling[d]	↑	*	*
Prostate Cancer Risk	PCPT[c]	KQ 1	*Carbanaru 2019*[57]	Modelling[d]	*	*	↓
	KPCC RC[c]	KQ 1	*Presti 2021*[53]	Modelling[d]	*	*	↓

Direction of Effect: (arrow direction)

↑ Increase

↓ Decrease

↔ No effect

*Not reported

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Further evidence from KQ 2: Algorithms Perpetuate Disparities

Agency for Healthcare Research and Quality

Evidence Map (Continued)

Clinical Category	Algorithm	Key Question	Study	Study Design[a]	Disparities in Health outcome[b]	Disparities in Access[b]	Disparities in Quality[b]
Liver transplantation	Donor Risk Index	KQ 2	*Shores 2013*[86]	Modelling[d]	*	*	↑
Cardiovascular risk	ASCVD[c]	KQ 2	*Weale 2021*[73]	Modelling[d]	*	*	↑
	Modified ASCVD[c]	KQ 2	*Topel 2018*[79]	Modelling[d]	↑	*	*
	ASCVD[e]	KQ 2	*Fairman 2020*[76]	Modelling[d]	↑	↑	*
	Pooled cohort equations[c]	KQ 2	*Yadlowsky 2018*[80]	Pre-post	*	*	↑
	Framingham risk score[c]	KQ 2	*Fox 2016*[82]	Modelling[d]	*	↑	*
	Framingham risk score[c]	KQ 2	*Drawz 2012*[87]	Modelling[d]	*	*	↑
Lung Cancer Screening	USPSTF-2013	KQ 1	*Pasquinelli 2021*[52]	Modelling[d]	*	↑	*
	USPSTF-2013	KQ 1	*Han 2020*[56]	Modelling[e]	*	*	↑
	USPSTF-2020	KQ 1	*Landy 2021*[66]	Modelling[d]	↑	↑	*
Lung Transplant Allocation	Lung Allocation System	KQ 1	*Wille 2013*[59]	Pre-post	*	↓	*
Lung Function	GLI Spirometry Equation	KQ 2	*Baugh 2022*[60]	Modelling[d]	*	*	↑
	GLI Spirometry Equation	KQ 2	*Elmaleh-Sachs 2021*[63]	Modelling[d]	↑	*	*
Anticoagulation	Warfarin dosing algorithms[c]	KQ 2	*Kimmel 2013*[85]	RCT	↑	*	*
	Warfarin dosing algorithms[c]	KQ 2	*Limdi 2015*[84]	Prospective cohort	↑	*	*
	CHA_2DS_2-VASc	KQ 2	*Kabra 2016*[83]	Modelling[d]	*		↑
Emergency Department Triage	HEART Pathway	KQ 1	*Snavely 2021*[55]	Pre-post	↔	*	↑[f]
Other	Novel algorithm for high-risk care management	KQ 1 and 2	*Obermeyer 2019*[5]	Modelling[d]	*	↑	*
	Natural language processing algorithm	KQ 1 and 2	*Thompson2021*[89]	Modelling[d]	*	*	↑

Direction of Effect: (arrow direction)	↑ Increase
	↓ Decrease
	↔ No effect
	*Not reported

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KQ 1 Summary

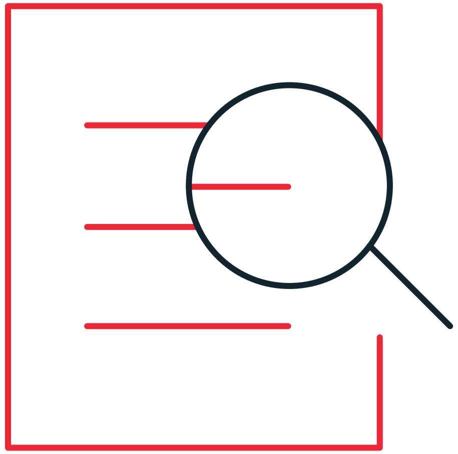
- The effect of algorithms is complex, and some have been shown to perpetuate or exacerbate disparities, some reduce disparities, and others have no effect
- Additionally, an algorithm may exacerbate disparities for one outcome, but reduce disparities for another outcome
- Many algorithms in clinical use perpetuate or exacerbate racial and ethnic disparities (e.g. eGFR, ASCVD)
- Disparities can be reduced, regardless of whether race and ethnicity are utilized in the algorithm, when disparities are outlined and used to inform algorithm development (e.g. KAS, prostate CA screening)
- Most of the evidence focused on non-AI algorithms

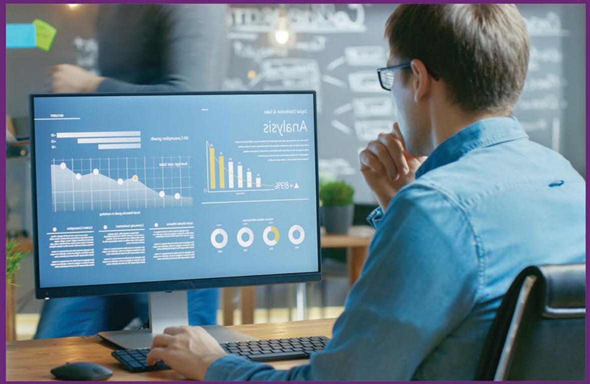
Contextual Question 1: Extent of inclusion of input variables based on race and ethnicity in algorithms?

- We examined 45 algorithms
  - 17 include race and ethnicity
  - 5 include measures that may serve as proxies for race and ethnicity (e.g., SDOH, healthcare costs)
  - Clinical category, setting, and purpose varied
  - Developers included clinical research teams, organizations setting healthcare policy, health plans, EHR vendors
- We examined additional resources (e.g., websites)
  - MDCalc – 14 of 700+ algorithms include race and ethnicity

Contextual Question 1: Extent of inclusion of input variables based on race and ethnicity in algorithms?

- Excluded >800 studies due to study design and outcome reporting
  - Many included similar algorithms included in our review
  - Some conducted in specialties not included in our review
- Algorithms likely affect every medical specialty, healthcare setting, and patient population
- Tip of the iceberg – review was limited in scope and may not fully represent larger environment





AGENCY FOR HEALTHCARE RESEARCH AND QUALITY

AHRQ

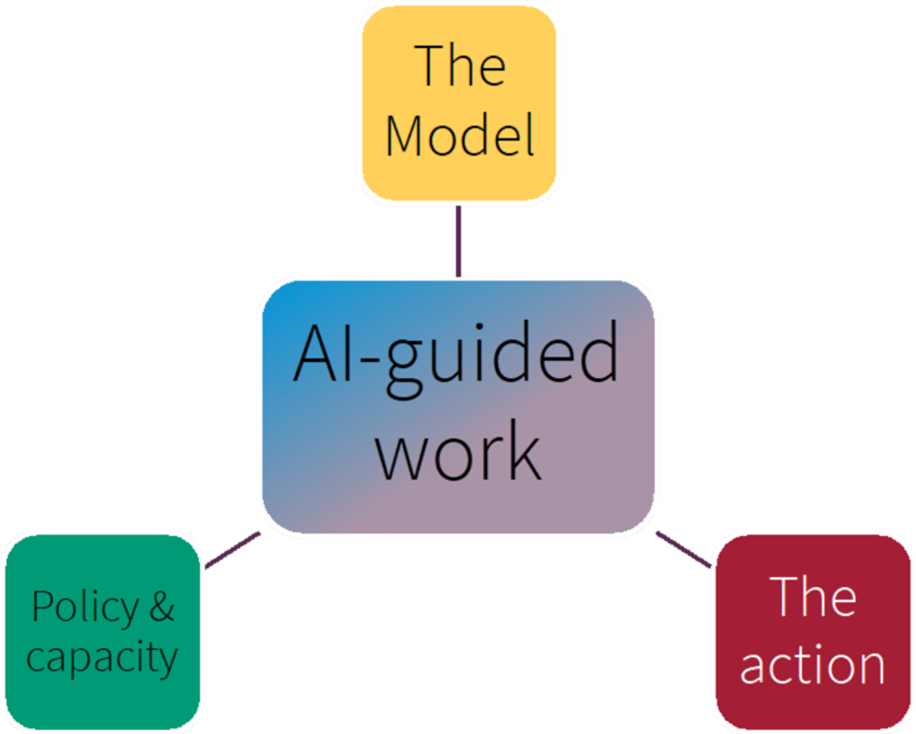
Creating Fair, Reliable and Useful Models

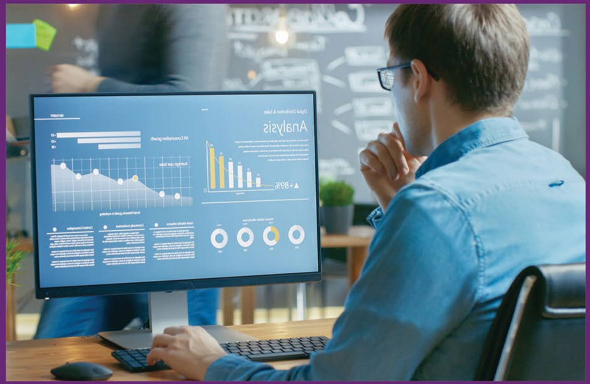
Nigam H. Shah, MBBS, PhD
Professor of Medicine and Biomedical Data Science
Chief Data Scientist, Stanford Healthcare
Associate Dean for Research, Stanford School of Medicine

Racial Bias and Healthcare Algorithms
March 2, 2023
12:20-12:28 p.m. ET

NIH National Institute on Minority Health and Health Disparities

Stanford Medicine Program for AI in Healthcare

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AHRQ

Supporting Algorithmic Equity in a Public Healthcare System: a Case Study in Opioid Safety

Suzanne Tamang, PhD
Veterans Affairs

Racial Bias and Healthcare Algorithms
March 2, 2023
12:36-12:44 p.m. ET

NIH National Institute on Minority Health and Health Disparities

STORM: Family of Decision Support Tools to Support Safe Care of Patients Exposed to Opioids

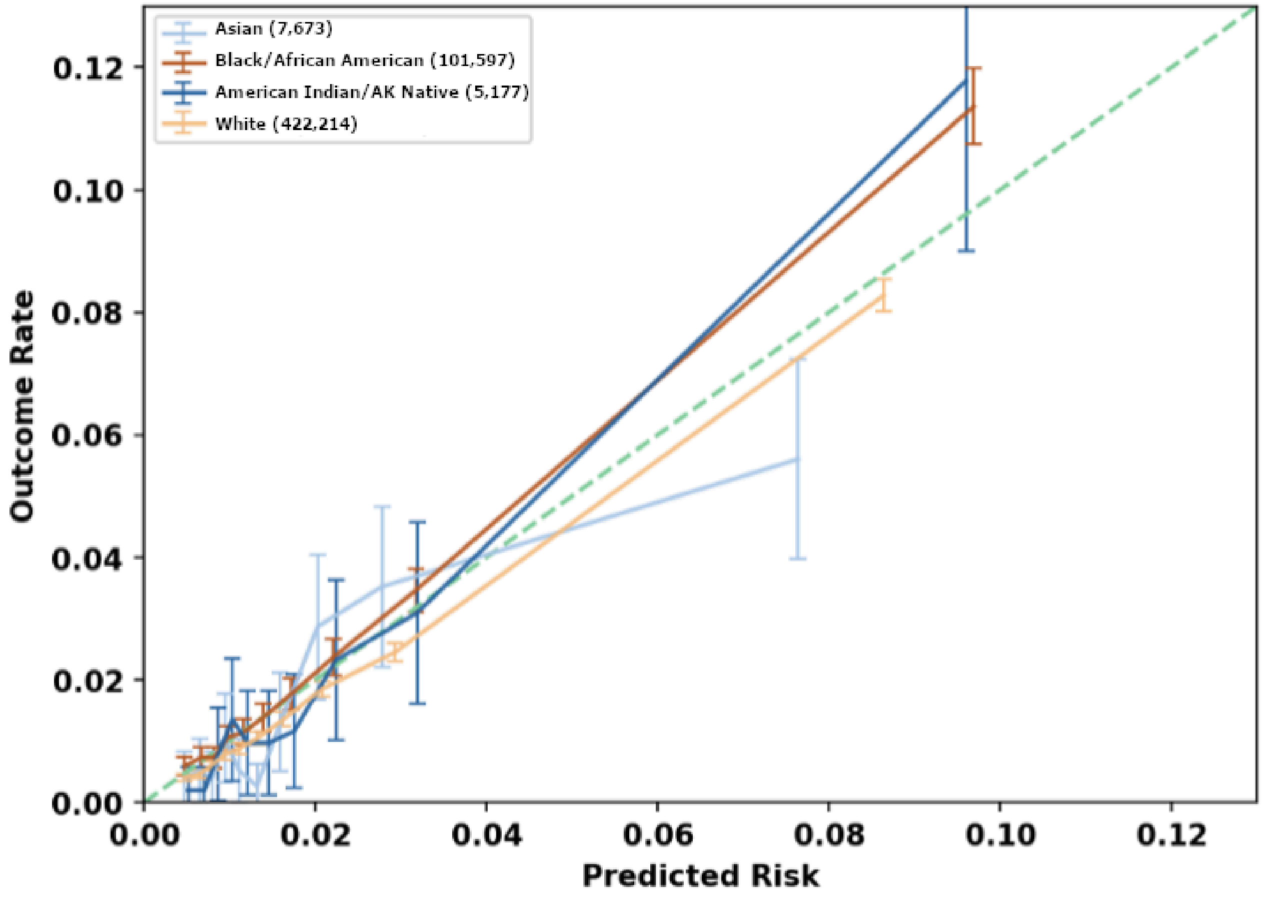
Includes: Predictive analytics for risk stratification, flexible population management, summary information on risk mitigation implementation for targeting QI and education, recommendation and tracking of risk mitigation, and patient level care review.

STORM-DeID (2019)

- In 2019, PERC worked with *Data Science for Social Good* and the *FDA's Office of Minority Health & Health Equity* to develop a performance evaluation framework on de-identified data (2014-15)
- Using a diverse set of stakeholders, and visually driven model "diagnostics", we quantified differences in performance, by gender, age, race/ethnicity
  - AUROC
  - PR Curves
  - Calibration
  - False-negative and false-positive parity rates
- We found evidence of algorithmic bias, but also salient challenges interpreting results of under-represented minority groups (e.g., American Indian/Alaskan Native, Asian) and "interactions" (e.g., female and >65, female and Black or African-American).

Example #1 of Racial & Ethnic Bias: Calibration

- Calibration is defined as the following property:
    - *"If we assign some group a risk of **x**, the actual outcome incidence rate should also be **x**"*
- For example, if we assign a group of people a risk of 40%, the actual overdose/suicide-related incidence rate should also be 40%.



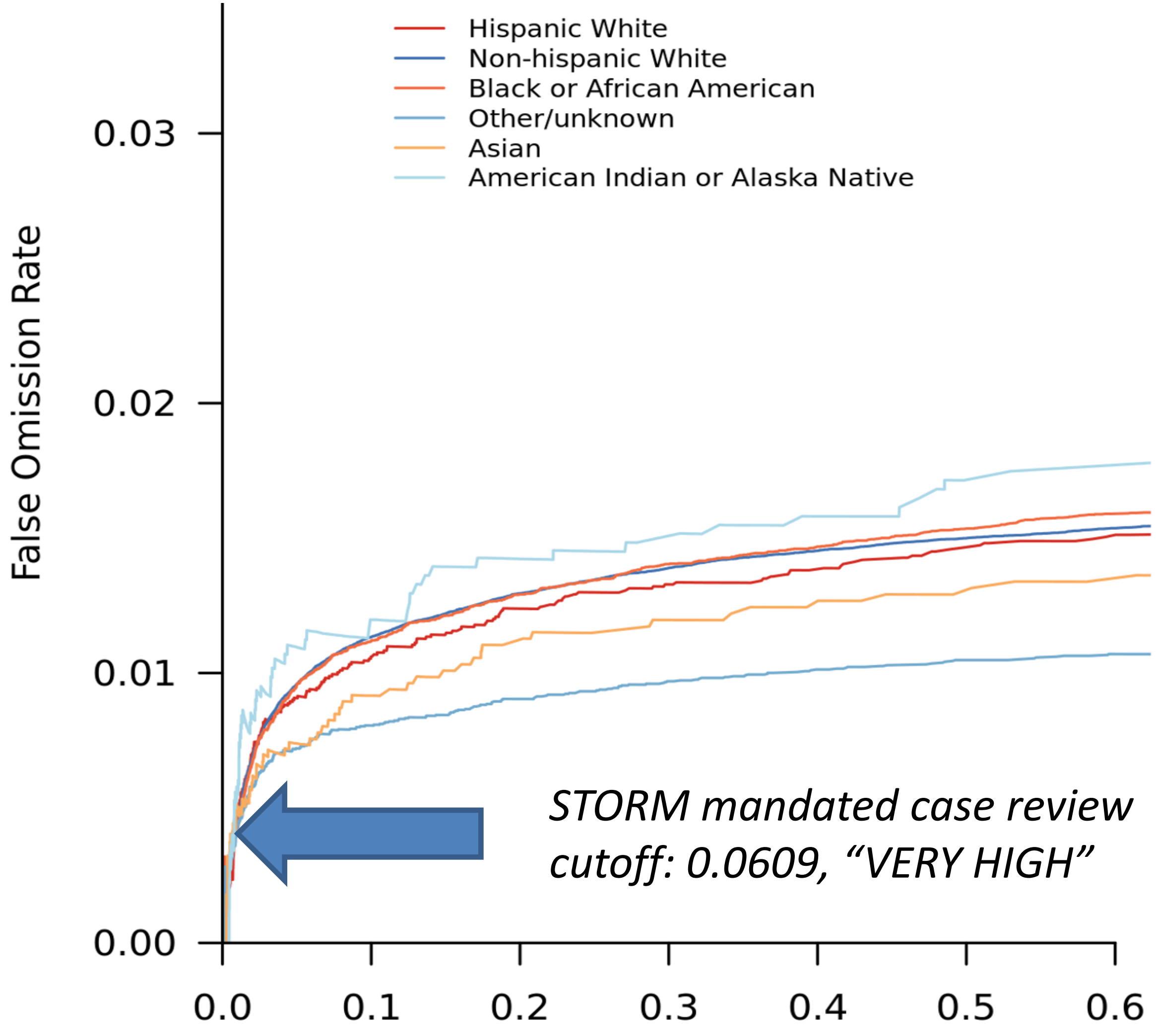
STORM-2 (2021)

- In 2021, PERC applied the framework to STORM-2 (2014-1015)
- STORM-2 is three models:
  - ► No opioids in the observation window
  - ► Discontinued during the observation window
  - ► Actively on opioids on the index date
- Extended PERC framework to include:
  - ► Per true-positive plot: for each true positive, how many false-negatives and false-positives are detected?
  - ► False Omission Rate: Given a ***negative*** prediction, the FOR tells you the probability that the true value is ***positive***.

Example #2 of Racial & Ethnic Bias: FOR

- False Omission Rate for ActiveRx

Esther Meerwijk PhD, Data Scientist, Ci2i, Palo Alto VA



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Where Are We in 2023?

- Fostering and engaging a *VA Community of Practice* for modeling and monitoring
  - STORM, REACH VET, CAN, Rockies NLP
  - NAII Datasheets and Model Cards
- Next steps for suicide and overdose prediction models
  - Apply framework to more recent data (2016-2020) and new subgroups
  - Comparing methods for mitigating bias *(Duncan McElfresh PhD, HSR&D Fellow)*
    - <u>Regression calibration</u> – apply a subgroup specific transformation
    - <u>Subgroup-specific models</u> – fit separate models
    - <u>Subgroup-specific cut points</u> – define different high-risk cutoffs
  - Develop dashboard to monitor performance over time
    - Empirically inform recalibration of model, predictors to include in STORM and alternative prediction algorithms

Acknowledgements

PERC Team

- Esther Meerwijk, PhD
- Duncan McElfresh, PhD
- Jodie Trafton, PhD
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- Amy Robinson, PharmD
- Elizabeth Oliva, PhD

Partners

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- Michael Jonathan Stringer
- Christine Lee PharmD
- John Scott, MD
- Jonathan Nebeker, MD

- OMHSP
- PERC
- PERC Platform Support
- HDAP
- BISL
- OIT

Stanford

Center for Population Health Sciences

Stanford MEDICINE

Impact of Healthcare Algorithms on Racial and Ethnic Disparities in Health and Healthcare

Consensus Panel Discussion/Q & A

March 2, 2023

12:45– 1:30 p.m. ET

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Discussion Questions

- What's missing, in terms of other experience and insights from the audience or related topics that were not covered in this session?

- What guidance is needed to mitigate bias/what are the next steps, for different parts of AI lifecycle, implementation perspective?
  - When/what/where/how to use algorithms?
  - Addressing bias in <u>existing</u> algorithms?

Impact of Healthcare Algorithms on Racial and Ethnic Disparities in Health and Healthcare

Break

March 2, 2023

1:30 – 2:00 p.m. ET

Please take thirty minutes for lunch

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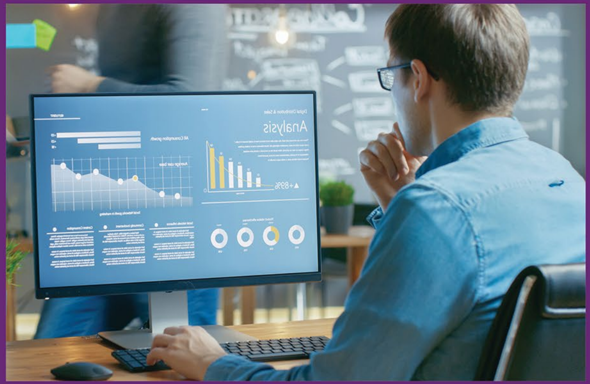


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AHRQ

Evidence Review

Contextual Question 3

Brian Leas, MS, MA

University of Pennsylvania School of Medicine

Racial Bias and Healthcare Algorithms

March 2, 2023

2:00-2:20 p.m. ET

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Contextual Question 3

To what extent are patients, providers (e.g., clinicians, hospitals, health systems), **payers** (e.g., insurers, employers), and **policymakers** (e.g., healthcare and insurance regulators, state Medicaid directors) **aware** of the inclusion of variables based on race and ethnicity in healthcare algorithms?

CQ 3: Methodology

- Primary literature searches
- AHRQ's Request for Information
- Technical Expert Panel and Key Informants
- Feedback from peer reviewers

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CQ 3: Key Informants and Technical Expert Panel

12 Key Informants (KIs)

10-member Technical Expert Panel (TEP)

- Experts in research and practice
  - Healthcare algorithm development, use, and auditing
  - Health and healthcare disparities; health equity; race and ethnicity in healthcare
- Healthcare providers
  - Clinicians, health systems, academic medical centers, public and community health, specialty societies
- Patient advocates
- Payers (commercial and government)
- Vendors of health IT systems and healthcare algorithms
- Federal agencies

CQ 3: Patient Perspectives

Challenges

- Limited awareness and understanding
  - How algorithms are used in healthcare
  - How race and ethnicity interacts with health and healthcare
- Literacy (health, science, tech)
- Views shaped by personal/family experiences

Opportunities

- Patient-centered care and shared decisionmaking
- Personalized medicine and genetics

CQ 3: Provider Perspectives

Individual Clinicians

- Limited understanding
  - Know how and when to use algorithms
  - Don't understand development, implementation, sources of bias
- Deference and trust
  - Regulators, societies, health systems, EHRs

Hospitals and health systems

- Focused on implementation, not potential sources of bias
- Adapt EHR products to patient population, incentives, priorities ("off-label" use)
- Minimal transparency

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CQ 3: What About the Curriculum?

Medical education is an opportunity to address many concerns

- Critical thinking about algorithms
- Use of clinical practice guidelines and EHR tools
- Human genetics
- Race, ethnicity, biology
- Disparities and equity
- Population health

CQ 3: Payers

- Not highly focused on disparities
- Just following the data
- Minimal transparency
- Decentralized operations, disjointed regulations

CQ 3: Policymakers

- All sectors anticipating federal guidance
- Substantial activity in last 3 years

Challenges

- Multiple agencies with overlapping stakes
- Who should guidance/regulation address?
  - EHR vendors, algorithm and AI developers, auditors, payers, providers
- How to address proprietary data and systems?
- Limited evidence!

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AHRQ

Addressing Racial Bias in Healthcare Algorithms: Steps You Can Take Today

Crystal Grant, PhD

Technology Fellow, Speech, Privacy, and Technology Project, American Civil Liberties Union

Racial Bias and Healthcare Algorithms

March 2, 2023

2:20-2:30 p.m. ET

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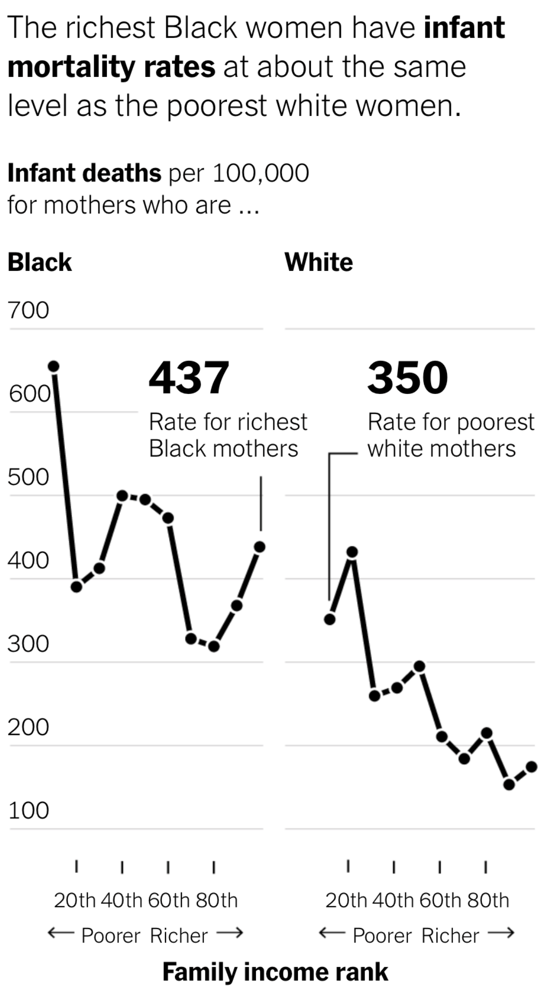
Assume the Healthcare Algorithm is Biased.

- Garbage in, Garbage out. Bias in, bias out.
- The data on which algorithms are trained reflects all sociocultural and environmental realties of racism in America's present and past and its effects on people's biology.
  - ► There is no genetic basis of race. Race is a social construct with real-world effects.
- While techniques exist that attempt to mitigate these biases in the training data, they too present limitations.



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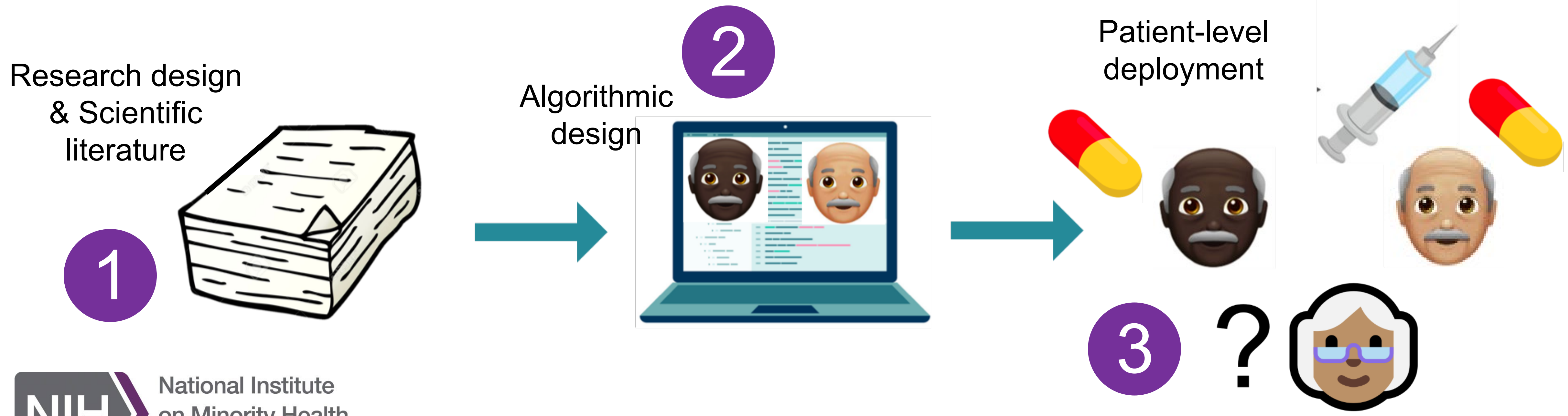
Childbirth Is Deadlier for Black Families Even When They're Rich, Expansive Study Finds

Assume the Algorithm is Incorrect.

- Algorithm developers are not subject matter experts in patient care. Yet, in creating a healthcare tool, they are making what amount to clinical and medical decisions.



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Assume the Algorithm Has not Had Adequate Oversight or Regulation.

- Many healthcare algorithms undergo <u>no</u> oversight and do not require FDA approval.
- Among tools regulated by FDA, in obtaining approval/clearance:
  - Assessments of performance bias across racial or ethnic groups are not required
  - If provided, this data isn't made accessible to the public or researchers
  - Overuse of the 510(k) clearance process claiming substantial similarity may lead to less rigorous testing than is ideal for influential health algorithms
- After approval or clearance, degradation in the performance of an algorithm when deployed in RWD can occur, yet the FDA doesn't penalize those who fail to conduct post-market studies.

Conclusion: Steps You Can Take Today

- If we assume the healthcare algorithm we plan to use is biased, incorrect, and under-regulated:
  - ► Administrators: Demand more transparency from vendors on how a tool was built, results from bias testing, interrogate why certain outputs result given certain inputs. Partner with researchers to conduct ongoing reviews.
  - ► Clinicians: Question an algorithm that uses patients' race to assume biological information about them; stay alert for "anecdotal" bias in tools.
  - ► Researchers: Push federal regulatory bodies to make data from algorithm developers available. Assess whether performance of a tool at approval/clearance holds up in use with RWD, and if any biases emerge.

Email: cgrant@aclu.org, Twitter: @itscrystalgrant

ACLU WHITE PAPER: AI IN HEALTH CARE MAY WORSEN MEDICAL RACISM



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Strategies to Address Algorithmic Bias in Medicine

Helen Burstin, MD, MPH, MACP

CEO, Council of Medical Specialty Societies

Racial Bias and Healthcare Algorithms

March 2, 2023

2:30-2:40 p.m. ET

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CMSS Member Societies

AHRQ Agency for Healthcare Research and Quality

ATS American Thoracic Society
ASCO American Society of Clinical Oncology — Making a World of Difference in Cancer Care
ASCP
shm Society of Hospital Medicine
The Society of Thoracic Surgeons — Established 1964
aga
NASS North American Spine Society
American Society of Plastic Surgeons
ACP American College of Physicians — Leading Internal Medicine, Improving Lives
American Psychiatric Association
American Society of Hematology
aahpm American Academy of Hospice and Palliative Medicine
ACPM American College of Preventive Medicine
ACR American College of Radiology
American Academy of Ophthalmology — Protecting Sight. Empowering Lives.
AES American Epilepsy Society
Society of Interventional Radiology
American College of Rheumatology — Empowering Rheumatology Professionals
ACMG
American College of Cardiology
AMIA — Informatics Professionals. Leading the Way.
asrm American Society for Reproductive Medicine
SGIM Society of General Internal Medicine — Creating Value for Patients
The American Academy of Pediatrics
American Urological Association
IDSA Infectious Diseases Society of America
SGO
American College of Surgeons — Omnibus per Artem Fidemque Prodesse
AACE
ACOG The American College of Obstetricians and Gynecologists
ASCRS American Society of Colon & Rectal Surgeons
SVS Society for Vascular Surgery
ASN American Society of Nephrology
American College of Emergency Physicians — Advancing Emergency Care
SNMMI
CAP
ASTRO Targeting Cancer Care
American Academy of Neurology
ACOEM American College of Occupational and Environmental Medicine — 1916
AAAAI American Academy of Allergy Asthma and Immunology
AAD American Academy of Dermatology Association
AAFP
aapm&r American Academy of Physical Medicine and Rehabilitation
Society of Critical Care Medicine — The Intensive Care Professionals
American Society of Anesthesiologists
AAOS American Academy of Orthopaedic Surgeons
AGS Geriatrics Healthcare Professionals — Leading Change. Improving Care for Older Adults.

Widespread Issue in Clinical Algorithms*

- Cardiology
- Nephrology
- Hematology/Oncology
- Neurology
- Hepatology
- Endocrinology
- Infectious diseases
- Obstetrics
- Pulmonary medicine
- Transplant medicine
- Urology
- Addiction medicine
- Surgery
- Mental health

* Specialties represented in 45 algorithms included in AHRQ report

Draft Recommendations: Specialty Societies

- Promote stakeholder awareness (including patients) of potential algorithmic risk
- Work with policymakers to review clinical algorithms, and address those that result in racial and ethnic inequities
- Ensure that algorithms included in clinical guidelines and recommendations statements are assessed from a health equity lens and that methods are adequately reported
- Invest in further research to assess the effect of algorithms on racial and ethnic disparities before widespread implementation

Nephrology: Comprehensive Approach

Establishing a Task Force to Reassess the Inclusion of Race in Diagnosing Kidney Diseases

A joint statement from the National Kidney Foundation and the American Society of Nephrology

July 2, 2020

- Recognize that any change in eGFR reporting **must consider the multiple social and clinical implications,** be based on rigorous science, and be part of a national conversation about uniform reporting of eGFR across health care systems
- Attempt to incorporating **concerns of patients and the public**, especially in marginalized and disadvantaged communities, while rigorously assessing the underlying scientific and ethical issues embedded in current practice
- Working towards an **unbiased approach to assessment of kidney function** so that laboratories, clinicians, patients, and public health officials can make informed decisions to ensure equity and personalized care for patients with kidney diseases
- Keep laboratories, clinicians, and other kidney **health professionals apprised**
- Identify any potential **long-term implications of removing race** from the eGFR formula

National Kidney Foundation®

ASN

American Society of Nephrology

Pediatrics: Broad Based Approach

PEDIATRICS

OFFICIAL JOURNAL OF THE AMERICAN ACADEMY OF PEDIATRICS

Eliminating Race-Based Medicine

Joseph L. Wright, MD, MPH, FAAP, Wendy S. Davis, MD, FAAP,
Madeline M. Joseph, MD, FAAP, Angela M. Ellison, MD, MSc, FAAP,
Nia J. Heard-Garris, MD, MSc, FAAP, Tiffani L. Johnson, MD, MSc, FAAP,
and the AAP Board Committee on Equity

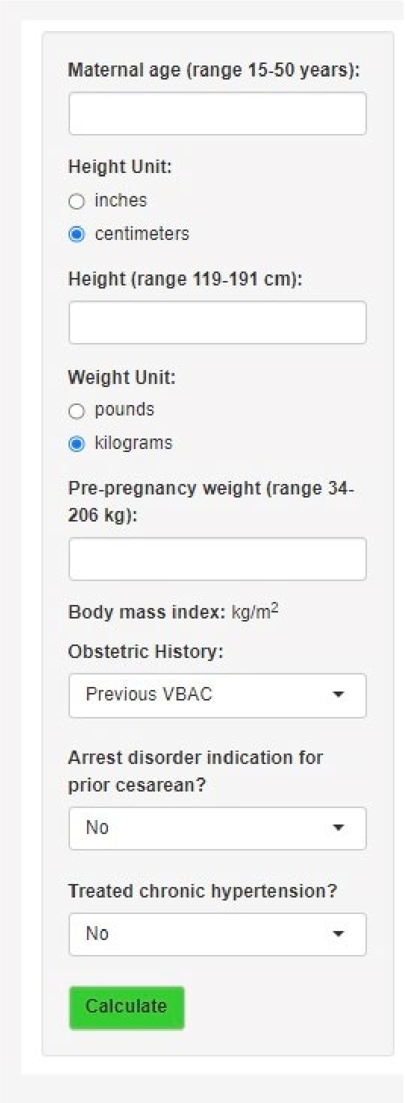
"Race-based medicine has been pervasively interwoven into the fabric of health care delivery in the United States for more than 400 years. **Race is a historically derived social construct that has no place as a biologic proxy.**

In addition to valid measures of social determinants of health, the effects of racism require consideration in clinical decision-making tools in ways that are evidence informed and not inappropriately conflated with the limiting phenotype of race categorization.

This policy statement addresses the elimination of race-based medicine part of a broader commitment to dismantle the structural as and systemic inequities that lead to racial health disparities."

Obstetrics: Implementation Approach

- Vaginal Birth after C-section (VBAC) Calculator
  - ▶ VBAC Calculator revised
    - – MFM Network, May 2021
  - ▶ Analysis with and without race and ethnicity
    - – Am J Ob Gyn, Dec 2021
  - ▶ Updated VBAC online calculator from MFM does not include race/ethnicity; added new variable related to treatment for chronic hypertension
  - ▶ Further clinician and patient education and dissemination



Potential Next Steps (1)

- Develop standards regarding inclusion of race in clinical research that support development of clinical guidelines and algorithms
- Support research that assesses the impact of race in clinical algorithms, recognizing importance of context, intentionality, and outcomes
- Support research that assesses the impact of other drivers, including SDOH and structural racism
- Effectively communicate and educate patients and clinicians on the potential impact of race in clinical algorithms

Potential Next Steps (2)

- Cross-specialty learning to develop best approaches to assess/remove race in clinical algorithms, assess long-term implications, and effective dissemination/implementation strategies
- Cross-disciplinary partnerships to develop AI/ML data sets that could support prospective assessment of race in clinical algorithms
- Broad stakeholder engagement that leads to changes in clinical research standards and clinical practice

Impact of Healthcare Algorithms on Racial and Ethnic Disparities in Health and Healthcare

Consensus Panel Discussion/Q & A

March 2, 2023

2:40– 3:25 p.m. ET

National Institute on Minority Health and Health Disparities

Discussion Questions

- What works, what's missing in terms of related topics, experience, and insights, including trust issues related to algorithmic biases?

- What guidance is needed to mitigate bias/what are the next steps, for different parts of AI lifecycle?
  - Approaches to increasing awareness and building trust among health professionals and communities, especially vulnerable groups and minorities?
  - Approaches to involving patients and clinicians more fully in these efforts?

Impact of Healthcare Algorithms on Racial and Ethnic Disparities in Health and Healthcare

Closing Remarks

Craig Umscheid, MD, MS

Senior Science Advisor and Director, EPC Division, AHRQ

Racial Bias and Healthcare Algorithms

March 2, 2023

3:25-3:40 p.m. ET

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Thank you!

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