The intended or unintended consequences of including race in clinical algorithms and how we can use AI to improve, not harm, health for people from all racial and ethnic backgrounds

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Disclaimer

Any opinions, findings, conclusions or recommendations presented in these materials are only my own and do not necessarily reflect the views of the National Science Foundation, North Carolina State University or any other affiliation.

Research Findings


WE GOT DATA!!!
LET'S USE IT!!
memegenerator.n


U GET DATA, YOU GET
DATA FOR EVERYON
memeg

Health Care Manag Sci
DOI 10.1007/s10729-017-9408-4

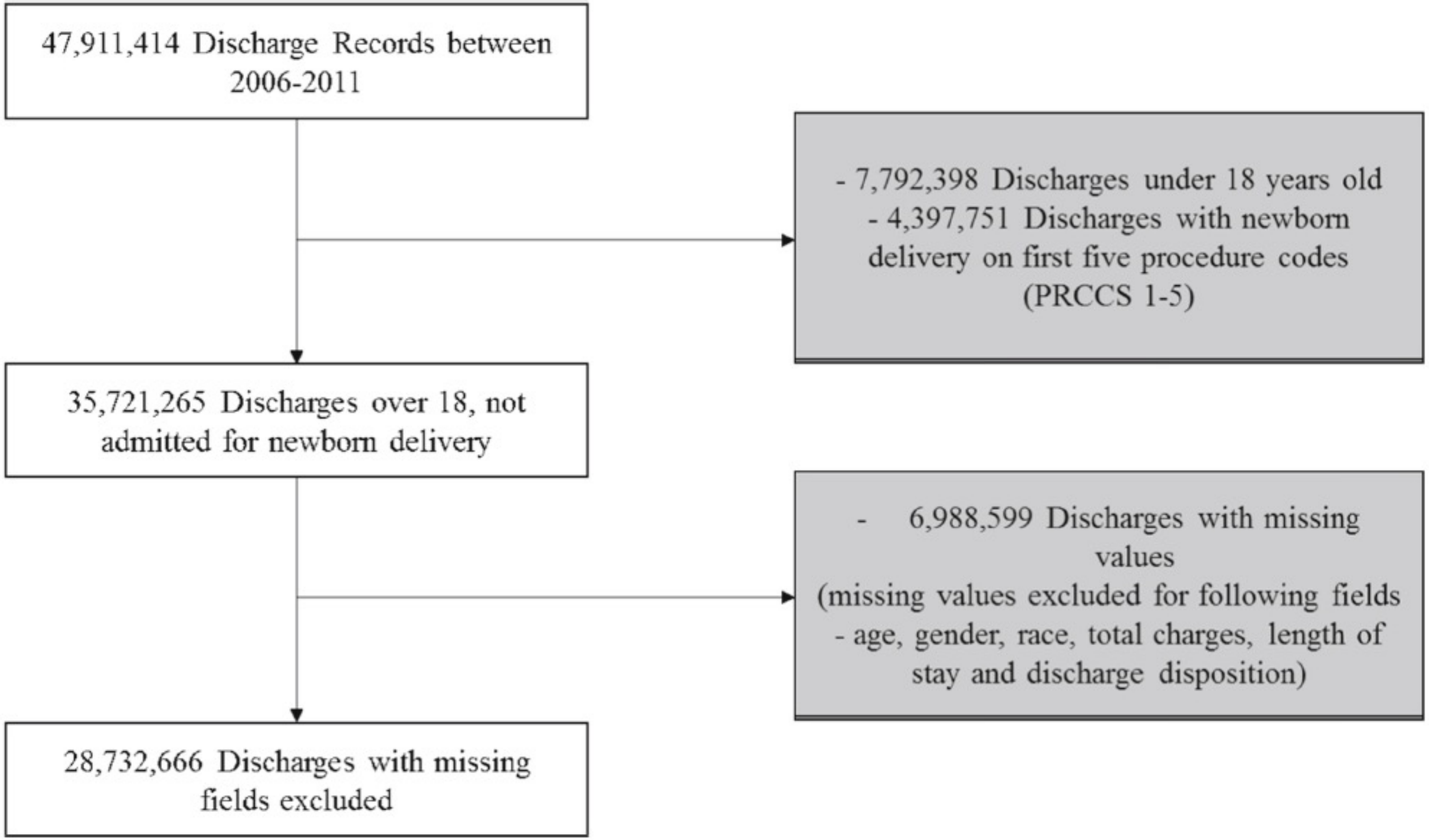
CrossMark

Diabetes and the hospitalized patient

A cluster analytic framework for characterizing the role of sex, race and comorbidity from 2006 to 2011

Nisha Nataraj[1] · Julie Simmons Ivy[1] · Fay Cobb Payton[2] · Joseph Norman[3]

Fig. 2 Overview of sample selection process. Records in grey boxes have been removed from the analysis



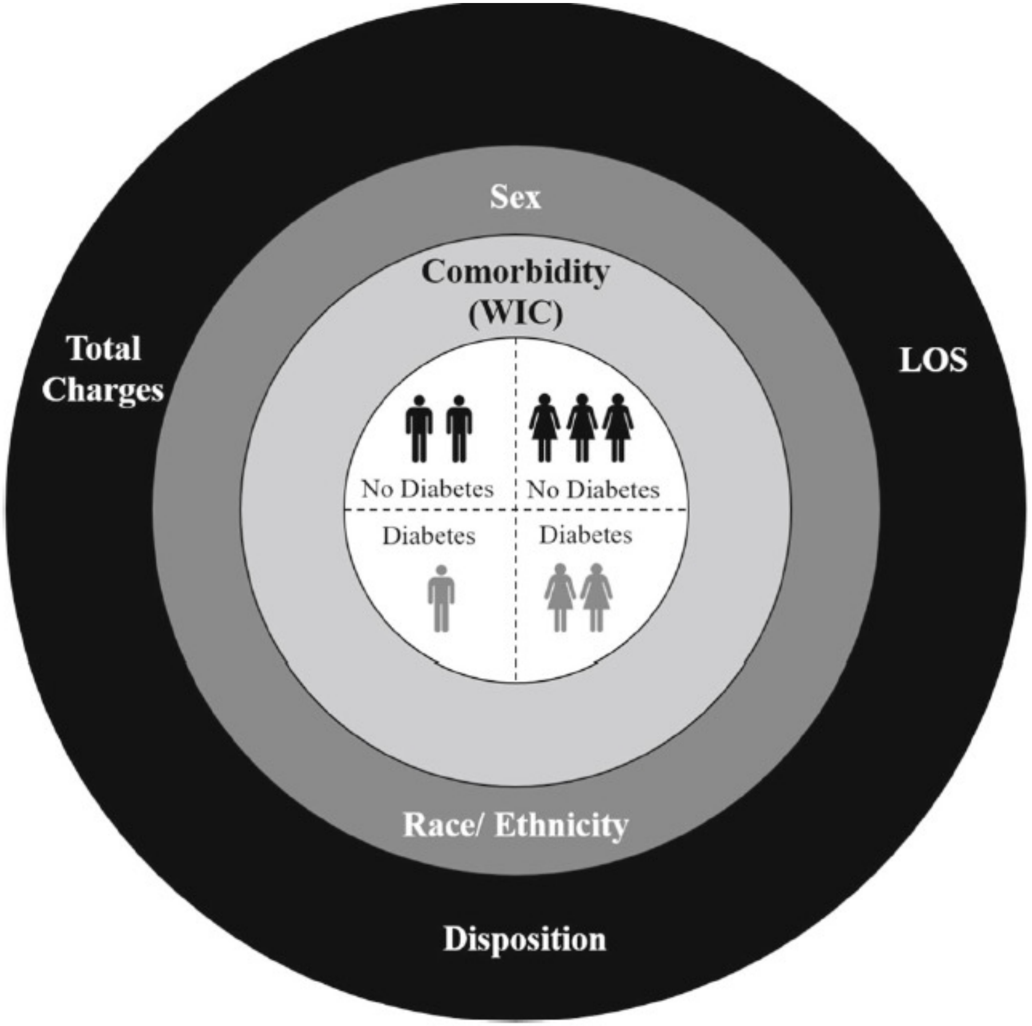


Fig. 1 Schematic representation of relationship between variables and outcomes of interest. The population of interest separated by sex and diabetes prevalence is represented in the inner-most circle. The primary variable of interest, comorbidity, is represented in the *light gray* section. Variables in the following *dark gray* section represent demographic variables while those in the *black* section represent primary outcomes of interest

- Principal reason for the hospitalization: the disparities in outcomes for women and ethnic groups are persistent
- Ethnic groups have poorer outcomes and are less likely to have routine discharges.
- These disparities have persisted over time suggesting that without conscious effort to personalize care for women and diverse groups with diabetes, their outcomes are unlikely to improve.
- Differential impact of diabetes on physiology and treatment in women versus men.
- Homogeneity in patients and comorbidities is rare given the variability in demographic characteristics

IIE Transactions on Healthcare Systems Engineering (2013) 3, 139–146

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Characterizing the impact of mental disorders on HIV patient length of stay and total charges

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er analysis

-9	1 − R^2 Ratio	ICD-9 Codes Description
5	0	**Nondependent abuse of drugs**
3	0.9998	Disturbance of emotions specific to childhood and adoles
5	1.0004	Specific delays in development
5	1.0015	Psychic factors associated with diseases classified elsewher
3	1	Other specified mental retardation
)	1.0012	Unspecified mental retardation
2	0.9635	Drug-induced mental disorders
3	1.0034	Transient mental disorders due to conditions classified els
4	0.0006	**Drug dependence**
1	0	**Depressive disorder not elsewhere classified**
5	0.0001	**Episodic mood disorders**
1	0.9968	Personality disorders
3	1.0001	Acute reaction to stress
)	0.9986	Adjustment reaction
)	1	Specific nonpsychotic mental disorders due to brain dama
4	0.998	Hyperkinetic syndrome of childhood
7	0.9993	Mild mental retardation
)	0.9998	Dementias
4	0	**Persistent mental disorders due to conditions classified elsev**
7	0.9999	Special symptoms or syndromes not elsewhere classified
7	0.9997	Delusional disorders
)	0.9998	Pervasive developmental disorders
)	0	**Anxiety, dissociative and somatoform disorders**
2	0.9982	Sexual and gender identity disorders
5	0.9983	Physiological malfunction arising from mental factors
2	1	Disturbance of conduct not elsewhere classified
1	0.8952	Alcohol-induced mental disorders
3	0.0034	**Alcohol dependence syndrome**
5	0.0002	**Schizophrenic disorders**
3	1.0016	Other nonorganic psychoses

es in each cluster are highlighted in bold.

. Results for principal component analysis

Description of Condition
Nondependent abuse of drugs
Drug dependence
Depressive disorder not elsewhere classified
Episodic mood disorders
Anxiety, dissociative and somatoform disorders
Persistent mental disorders due to conditions classified elsewhere
Alcohol dependence syndrome
Schizophrenic disorders
Drug-induced mental disorders
Other nonorganic psychoses

- Longer stay lengths, comorbid conditions affected HIV
- patient outcomes.

- Mental disorders generally results in a decrease in both LOS and total charges.

- Patients with mental illness are more likely to be transferred to other facilities so that their true LOS will not be observed.

- The most important conditions were drug related
- mental disorders (304, 305), mood disorders (296),
- depression (311) and anxiety (300).

- Health services delivery approach to adherence and treatment to better address chronic diseases and their severity with comorbidity.

Original Paper

Manifesting Its Ugly Roots: Text Mining Mental Health Reports for Issues Impacting Today's College Students

Fay Cobb Payton[1*], PhD; Lynette Kvasny Yarger[2*], PhD; Anthony Thomas Pinter[3*], MS

Cluster	Name	Description	Document Frequency	Percentage of Sample
1	Age	Age factors in mental health experiences	7	4%
2	Race	Racial factors in mental health experiences	30	18%
3	Crime	Factors related to crime that lead to mental health experiences	3	2%
4	Servic es	What institutions are doing to assist with mental health experiences	113	68%
5	After math	What happens after a mental health experience	4	2%
6	Victim	Factors related to victimization that lead to mental health experiences	8	5%

When Race (Inclusion) is Excluded

- Race-blinded algorithms may be well-intended
- Race-blinded ----→ heighten disparate conditions/experiences/health outcomes
- Race-blinded ----→heighten **structural** inequities
- Race-blinded---→ health costs as a **proxy** for health needs
  - Fewer resources spent on Black patients who have the same level of need
  - Algorithm falsely concludes that Black patients are healthier than equally sick White patients (Obermeyer, et al 2019 in ***Science***)

So, What Was/Is Missing?

The Healthy People 2020 Social Determinants of Health topic area is organized into 5 place-based domains:

1. Economic Stability
2. Education
3. Health and Health Care
4. Neighborhood and Built Environment
5. Social and Community Context

Discrimination is a key issue in the Social and Community Context domain.

Washington Post

‘Big data’ was supposed to fix education. It didn’t. It’s time for ‘small data.’ - The Washington Post

Here Comes the #Engagement: A serious health initiative made trendy

Creating a user experience to communicate the seriousness of HIV prevention and awareness can be both educational while entertaining. This combination along with a sense of cultural influence helps to both attract and engage millennials.

By Fay Cobb Payton and KaMar Galloway

DOI: 10.1145/2691362

#Activist UX
MyHealthImpactNetwork

Historical Context

- Think about the time period of the story and things like technology, events, or issues related to this particular time frame.
- How could the author be using the historical context to impact the plot?
- How is he using characters, events to make a point to the reader?

Parting Thoughts on It’s Not Just A Data Issue

Algorithmic Equity in the Hiring of Underrepresented IT Job Candidates

Authors
Lynette Yarger, Penn State
Fay Cobb Payton, NC State
Bikalpa Neupane, Penn State

- Dataset bias: data used to train machine learning models does not represent the diversity of the customer base (e.g., Voice recognition technologies that only work well for male users because the initial training data excluded women.)

- Association bias: data used to train a model reinforces and multiplies a cultural bias (e.g., Language translation tools that make gender assumptions.)

- Automation bias: automated decisions override social and cultural considerations (e.g., Beautification photo filters reinforcing a European notion of beauty on facial images.)

- Interaction bias: humans interact with AI and create biased results (e.g., Humans deliberately input sexist language into a chatbot to train it to say offensive things.)

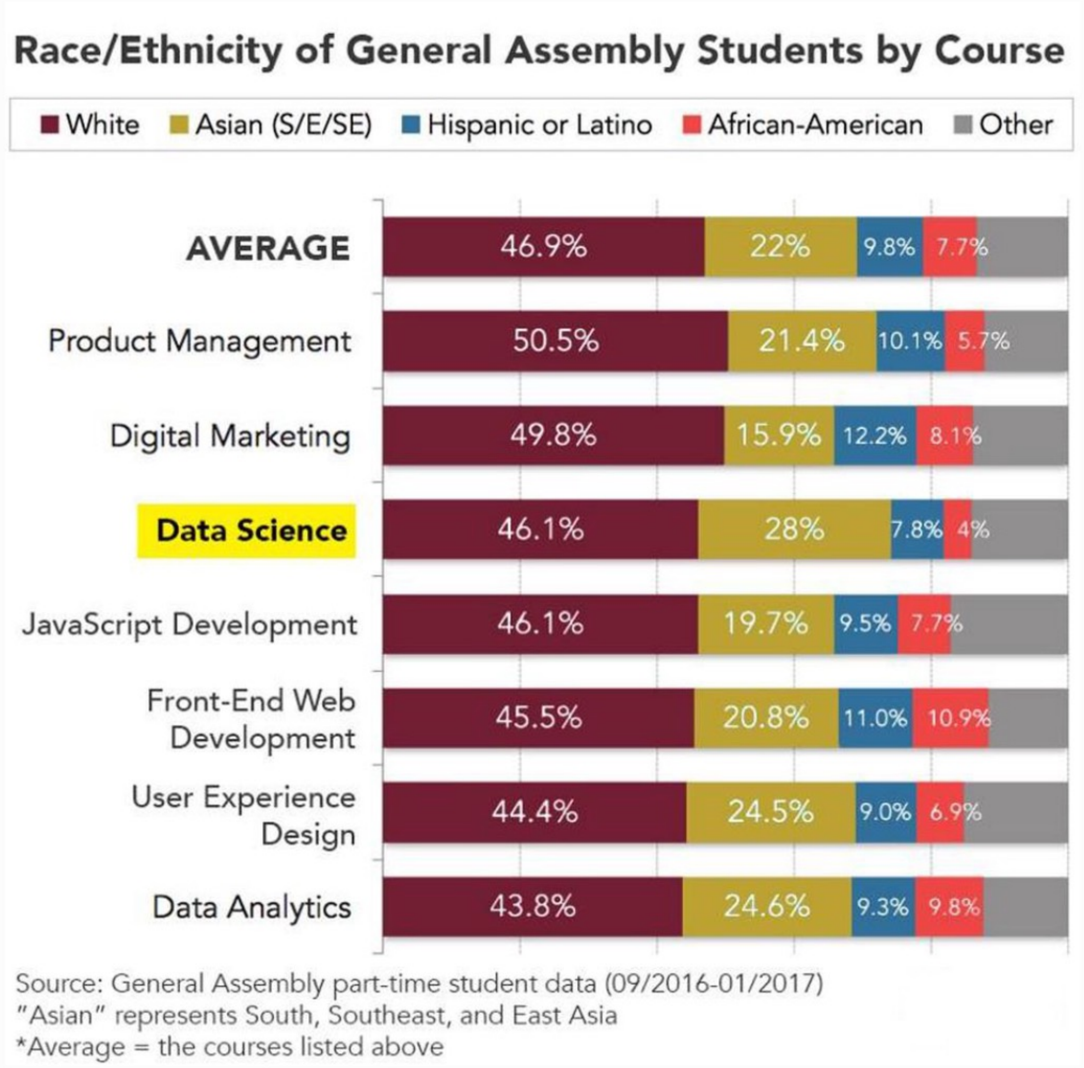
- Confirmation bias: overly simplified personalization makes biased assumptions for a group or an individual (e.g., Job advertisements for executive positions are displayed only to male users.)

A STAT INVESTIGATION

‘Health equity tourists’: How white scholars are colonizing research on health disparities

By Usha Lee McFarling Sept. 23, 2021 | Reprints

A glaring example occurred in August when the Journal of the American Medical Association — a leading medical journal already under fire for how it handles issues of race — published a special themed issue on racial and ethnic health disparities in medicine. Meant to highlight JAMA’s new commitment to health equity, it served up an illustration of the structural racism embedded in academic publishing: Not one of the five research papers published in the issue included a Black lead or corresponding author, and just one lead author was Hispanic.



Course enrollment by demographic. GENERAL ASSEMBLY

Data source: General Assembly

Data Science Inclusion

Health Disparities (De)Colonization

The Lived Experience & Algorithmic Biases - Fairness

Small Data → Social Determinants of Health → Place and Space

Design Justice: Centering Race in Design

Ecosystem Thinking → Data Sanitation → Context Matters

Data Sanitation

Training Data

Validation Data

Test Data

Context Matters

- Augmentation of AI Findings/Results Interpretation

Overfitting vs Underfitting Has Implications.

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