Emancipatory Data Science

A Liberatory Framework for Mitigating Data Harms and Fostering Social Transformation

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ABSTRACT

The cross-cutting and interdisciplinary nature of data work has created an opportunity to engage more students from diverse backgrounds in data science and has expanded pathways for entry for future data professionals. However, without greater representation of Black, Indigenous, and other marginalized people of color in data science, we risk reinforcing existing systems of differentiated power that oppress as opposed to empower these groups. In this paper, the term *emancipatory data science* is coined to highlight the unique contributions of individuals who use their expertise to mitigate data harms for minoritized, and marginalized populations and to suggest a way forward for the data science workforce and research community given our increasingly algorithmic society.

CCS CONCEPTS

Social and professional topics~Professional topics~Computing and business~Socio-technical systems • Social and professional topics~User characteristics~Race and ethnicity • Social and professional topics~User characteristics~Gender~Women

KEYWORDS

Emancipation; Liberation; Data harms; Data science; Data justice; Critical race theory; Critical quantitative theory

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1 Introduction

Data science today is mostly male,[1] and mostly White.[2] Scholars have called attention to this problem finding that just 15% of data scientists (i.e., individuals who code, collaborate, and communicate by transforming data into insights using techniques in statistics, analytics, and machine learning)[3] identify as female,[2] 8% as Latinx and 4% as Black,[4] despite representing 51%, 18.5% and 13% of the population respectively.[5] These disparities matter, as research shows that for members of marginalized, minoritized and vulnerable communities (i.e., Black, Indigenous among others) *who* provides the service (e.g., medicine [6], education[7], finance[8]) affects service quality. The resulting impact is that having same race doctors and teachers lead to greater standards of care and improved educational outcomes for members of these groups. Data science (defined as the ecosystem dedicated to the systematic collection, management, analysis, visualization, explanation and preservation of structured and unstructured data) [9], is also an applied social science, and therefore faces a similar problem as its members have often neglected their own conditions, problems and behaviors[10] in favor of examining others' data. The result has been the homogenization of the field (i.e., dominated by white males), resulting in failures to allay data harms that negatively affect the public, and marginalized, minoritized and vulnerable populations in particular.

According to the U.S. Department of Labor, data science occupations are expected to rise +Δ 25.9% and outpace projections of every other computer occupation (+Δ 12.7%)[11] However, despite the growth in data analytics talent, the supply of data workers is not expected to keep up with growing industry demand. [12,13]. Building workforce capacity will require enhanced training in data visualization, data engineering, machine learning and artificial intelligence, all of which are key to addressing the high demand for workers with data-related skills including Black, Indigenous and other marginalized people of color.[14]

Data science however is also distinct from its disciplinary predecessors (i.e., computer science, information systems (IS), statistics) [15] as status quo data science models are frequently trained on datasets that reflect broader structural inequalities thereby reinforcing or exacerbating data harms which negatively impact all members of society. This problem necessitates having more data scientists with diverse lived experiences to identify and combat biases pre-deployment.[16]

The sections that follow begin with an overview of the relevant literature on data harms, emancipation and critical quantitative research. Then, the counter storytelling methodology is introduced, and exemplary cases of emancipatory data science (and data scientists) are presented and discussed. Lastly, the

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emancipatory data science framework is discussed with recommendations to advance emancipatory data science research from a workforce development and research perspective.

2 Background and Context

2.1 Data Harms

All data are people [17], and data science leverages statistical and machine learning approaches to create generalizable knowledge from data [18]. Ultimately then, data scientists collect and utilize data *from*, *by*, *about* and *affecting* people and society. As a consequence, biases in data work are not unexpected. However, the breadth and depth of data harms (preliminarily defined as the adverse effects caused by uses of data that may impair, injure, or set back a person, entity or society's interests)[19] caused by status-quo, majoritarian data science and logics illustrate the unevenness of this bias towards minoritized people of color. The examples that follow begin to paint this picture:

2.1.1 Facial recognition. Buolamwini and Gebru [20] exposed data harms caused by facial recognition software that disproportionately misclassified darker skinned female compared to lighter skinned males. The impact of these systems are wide reaching, especially when used in concert with massive law-enforcement databases with images of over 117 million U.S. adults (>50% of the U.S. population) for police and government surveillance, that in turn lead to the false identification of innocent suspects. [21]

2.1.2 Search engine algorithms. Bias in search engine traffic has long been recognized as a concern.[22] However, Noble further discovered that this bias extended to terms like "Black girls" and "Black women" yielding pornographic and profane first page search results in Google search. [23]

2.1.3 Recidivism risk models. ProPublica investigative journalists found that Black defendants when subjected to the COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) tool were twice as likely to be misclassified as higher risk when compared to white defendants. Thereby creating a pernicious feedback loop that directly targets and helps to ensure the continued marginalization and oppression of Black people in the U.S. [24;;;27]

In order to combat data harms like, the field of data science needs a theoretical framing to help mitigate data harms pre-deployment. To this end, this paper utilizes the theory of emancipatory social science, critical quantitative theory and the logic of counter-storytelling to advance data science and AI ethics research with the dual goal of 1) advocating for more inclusive data science by explicitly articulating the need for more data scientists from minoritized groups to enter the field and 2) outlining key elements needed to make data science work better for more people.

2.2 Emancipation Theory in IS

The term emancipation has roots in the abolitionist movement and was used to refer to the freedom of enslaved Africans from physical and psychological bondage in the U.S. and is frequently used interchangeably with the term liberation. Wright later used the term "emancipatory social science" to refer to the generation of "scientific knowledge relevant to the collective project of challenging various forms of human oppression.[28, p. 10]"

The concept of emancipation is also not new to IS. In their meta-analysis of IS emancipation research, Young, Zhu and Venkatesh (2021) find that emancipation research consists of four primary components: agency (i.e., systems subverting human users, computer-mediated control of workers, behavioral control, punishment from surveillance); dialogue (i.e., democratization of discourse, truth exposure, ideal speech, creative expression, voice-giving); inclusion (i.e., inclusion of marginalized groups, economic inclusion, political inclusion, ICT4D, digital divide) and rationality (i.e., constrained rationality, ideological control, distorted frames of meaning, manipulation, bias).[29]

This manuscript extends the inclusion component of emancipation research in IS [30, 31, 32, 33] to the field of data science coining the term "*emancipatory data science*," to outline the explicit ways in which the fields most responsible for producing the future data science workforce (IS, computer science, statistics) can knowingly address systemic biases in data models, measures and analytical practices by prioritizing the inclusion of marginalized and minoritized groups in the field.

2.3 Critical Race Theory and Critical Quantitative Theory

Emancipatory data science is defined as data work that frees members of marginalized communities from being the 'object' to the 'subject' of data science framings and where decisions regarding *why, how, what, when*, and *where* data are collected, managed, analyzed, interpreted and communicated are maintained by and for members of minoritized, marginalized and vulnerable communities. In addition to falling under the broad umbrella of IS inclusion research, this conceptualization is also fundamentally related to the concepts of *critical race theory* and *critical quantitative studies*. Critical race theory (CRT) emerged from the legal scholarship on disputes regarding the meaning and significance of race.[34,35,36] However, until recently, most critical race scholars applied qualitative methodologies to address longstanding inequities in social, political, and economic spaces.[37,38] This is not surprising as scholar hesitancy to employ statistical approaches to CRT studies is grounded in the recognition that statistics as a discipline has eugenicist and therefore racist and white supremacist origins. In fact, the "founding fathers" of statistics were respected leaders and champions of the eugenics movement in the 19th and 20th centuries as evidenced by the following quotes [39, 40, 41]:

….There is nothing either in history of domestic animals or in that of evolution to make us doubt that a race of sane men may be formed, who shall be as much superior mentally and morally to the modern European, as the modern European is to the lowest of the Negro races. - Galton 1892

….Superior and inferior races cannot coexist; if the former are to make effective use of global resources; the latter must be extirpated. - Pearson 1901

….The socially lower classes have a birth-rate, or, to speak more exactly, a survival rate, greatly in excess of those who are, on the whole, distinctly their eugenic superiors. It is to investigate the cause and cure of this phenomenon that the eugenic society should devote its best efforts. - Fisher 1914

Subsequently, reconciling quantitative approaches with critical race scholarship required re-imagining and ultimately defining a commonplace that allowed CRT to engage with the statistics discipline. The field of education provides a compelling case for this need. According to Ladson-Billings and Tate,[42] persistent inequalities in the schooling experiences of white and Black children in the U.S. are "a logical and predictable result of a racialized society in which discussions of race and racism continue to be muted and marginalized (p. 11)." Critical quantitative studies emerged to articulate a way for CRT scholars to advance investigations of disparities in teacher and student performance by race and ethnicity while applying increasingly sophisticated statistical analyses to these phenomena.[43 , 44] These scholars explicitly resisted the normative white supremacist philosophical worldviews within educational research discipline that disproportionally and intentionally harmed minoritized students.[45,46]

Given the profound impact of statistics on education policies which have for generations harmed marginalized students in the United States, it is not unreasonable to extend this concern to the realm of data science. As a sub-field of statistics, data science is subject to the same cautions as its disciplinary predecessors. Ultimately, the question of how to use data responsibly requires rejecting what Zuberi and Bonilla-Silva term the *logic* of white supremacy.[47] That is, the context in which the illusion of white supremacy has defined the techniques and processes employed to analyze data as well as the reasoning used by researchers to understand society. In the world of data science this requires a critical reassessment of the logic behind and implications of data science products and processes.

3 Methods and Evidence

Counter-archival analysis or counter archiving has been referenced a "method of dissent"[48] a form of epistemic resistance[49] and a critical intervention that challenges established forms of representing and responding to violence.[50] This methodological approach is an extension of the counter-stories or counter-narratives method of telling the stories of those at the margins of society. It empirically evaluates marginalized people's lived experiences to build community, challenge the presumed wisdom of the majoritarian society, expand possibilities for those at the margins, and instruct others of the value of pluralistic vantage-points to enrich the story being told.[51,52] In this paper, I employ what Stoler refers to as a *counter-racial* archival approach,[53] in an effort to "thicken the present with alternatives" that empower as opposed to dismiss the victims of racialized data crimes. Specifically, I use one historical example, and return to two contemporary examples introduced above in order to demonstrate that emancipatory data science, does not predate its use in practice. By describing the accomplishments and struggles of these *emancipatory data scientists* I hope to "strengthen traditions of social, political, and cultural survival and resistance[49]" in the field.

3.1.1 Ida B. Wells.

Figure 2. Ida B. Wells, head-and-shoulders portrait, facing slightly right. , 1891. [Published] [Photograph] Retrieved from the Library of Congress, https://www.loc.gov/item/93505758/.

One of the earliest examples emancipatory data science comes from Ida B. Wells' text: The Red Record: Tabulated Statistics and Alleged Causes of Lynching in the United States, 1892-1893-1894: Respectfully submitted to the nineteenth century civilization in the 'land of the free and the home of the brave.'[54] Born into chattel slavery, Wells emerged a self-made sociologist, critical race activist and data journalist capable and willing to deconstruct the white supremacist rhetoric employed by Southern white property owners over the illegal lynching of Black men and women. In her data-driven and justice seeking work, she challenged the rationalization for these acts of terror which included: 1) fear of "insurrection" or "race riots," 2) fear of "Negro domination" and 3) fear of Negro men "raping white women." Wells challenged this reasoning by leveraging data published in the Chicago Tribune (the leading journalistic outlet at that time). She pioneered by debunking each of these myths finding that those murdered were often 1) never accused of a crime, 2) were killed for misdemeanors or minor transgressions or for 3) "demanding basic human rights and fair treatment."[55,56] By critically examining the logic of the narrators Wells' leveraged publicly available data (which included the lynching victim's name, race and gender, geographic location and purported justification) to defy white supremacist normative rhetoric [54] and sensitize those who would listen to these mostly (albeit not entirely) Southern horrors.[57] This early example illustrates how data has been used to provide power and voice to efforts aimed at ensuring the safety and welfare of Black people. Wells' personal identity as a Black woman, and heroism are what helped to distinguish her work as emancipatory as opposed to 'fair' or 'kind.' Her willingness to "struggle for radical social change"[28] with data as her weapon epitomizes the liberatory nature of emancipatory data science and data scientists [58].

3.1.2 Ms. Joy Buolamwini and Dr. Timnit Gebru

Figure 3a. Joy Buolamwini (Left). Retrieved from Twitter. https://twitter.com/jovialjoy. Figure 3b. Timnit Gebru. (Right) Retrieved from Wikipedia. https://en.wikipedia.org/wiki/Timnit_Gebru

Boulamwini and Gebru's [20] research identified unprecedented [59] data harms caused by the rapid deployment of facial recognition software which disproportionately negatively affected people of color. In particular, they found that the misclassification rate for darker-skinned female faces (34.7%) was 43 times higher than lighter-skinned males (0.8%) across three commercially available gender classification systems. Buolamwini later founded the Algorithmic Justice League (https://www.ajl.org/) to garner further attention to data harms embedded in facial recognition software. Gebru founded Black in AI (https://blackinai.github.io/#/) creating a global community for AI researchers of African-descent. The impact of their research extends beyond the reach of a peer reviewed academic publications and is credited with ultimately leading tech giants IBM, Microsoft and Amazon to stop selling their software to law enforcement.[60] However, Gebru, in large part due to her high-profile role as a champion of AI ethics, was later fired for her AI ethics work.[61, 62] What protections are in place to protect critical technologists and data scientists? What systems can we devise to fully embrace critique within data science and the scientific process? This is an emancipatory data issue, requiring new ways of problem framing and new people engaged in solution finding.

3.1.3 Dr. Safiya Umoja Noble

Figure 4. Safiya Umoja Noble. Retrieved from Center for Critical Internet Inquiry. https://www.c2i2.ucla.edu/

Noble [23] published her work on algorithmic bias demonstrating how search engines produced quintessentially racist results from Google's algorithm when keywords for "Black girls," or "Black women" yielded first page search results associated with pornography and profanity. Members of other minoritized racial/ethnic groups were also maligned by Google search results including "Asian girls" "Latina girls" "Hispanic girls" etc.; however, as Noble notes these results were not nearly as offensive as those of Black girls when she began the study. Library discovery systems and commercial search have, to quote Noble, "upheld and perpetuated racist hegemonies… We need to know the violent, racist & sexist power of classification schemes, because most digital technologies & AI are predicated up on these very same logics."[63] For Noble, the next step beyond critically identifying these data harms involves "restoration and reparation." By countering the logic of Silicon Valley's data protagonists, Noble has "improv[ed] the internet for women and people marginalized by tech…"[64]

This sampling of what I term emancipatory data science embodies the acts needed to curb the upward trajectory of data harms. These scholars are more than expert data scientists or AI ethics researchers. They are activists with a vested interest in the liberation and empowerment of marginalized people.

4. An Emancipatory Data Science Framework

Data science is social science [65,66]; therefore the application of social science theories are appropriate, particularly with regard to education and workforce training. The emancipatory social science framework outlined by Wright [28] consists of three progressive stages: 1) diagnosis and critique; 2) envisioning viable alternatives and 3) social transformation. Using counter-stories as exemplars this framing helps situate the experiences and quests of emancipatory data scientists whose aim is to liberate minoritized, marginalized and vulnerable populations from the institutionalized biases that dominate the field [67]. This framework can be used to provide a means of envisioning a data future that reflect the values, protections and empowerment of those at the margins. Next, I discuss each stage of emancipatory data science framework and outline avenues for future research.

4.1 Diagnosis and Critique of Data Harms

Arguably, this is this first task toward any exercise in liberation. Documenting the multiple harms[68] generated by the current system clarifies the condition of those being marginalized or oppressed in the current state (or status-quo) and creates shared ground on which to base any future claims for change. Wright argues that behind every emancipatory theory there is "an implicit theory of justice" suggesting that in the pursuit of justice (social, racial and political) one must be able to articulate what conditions need to be met in order to satisfy the requirements of a just society."[28] An appropriate first step for change agents within the data science community would require a careful cataloguing the data harms generated via the deployment of models with a disproportionate impact on members of marginalized groups [69]and the public writ-large.[70] As described below, there is no shortage of evidence in this respect:

4.1.1 A Short List of Racialized Data Harms

- Health care[71, 72] algorithms which reduce the number of Black patients identified for additional care by greater than 50% than equally ill white patients.
- Predictive policing[73] and smart cities[74,75] which led to reinforcement of racist policing despite ineffective broken windows policies[76]
- Recidivism risk models [25] that are twice as likely to misclassify Black offenders as re-offending compared to white ones [26,77]
- U.S. credit markets [78] which disproportionately negatively impact communities of color.
- Bias in image[79] and facial recognition[80] software including deep fakes[81] that mislabel dark skinned faces.
- Search engine optimization[82] engines which equate search terms for "girls" with pornography
- Bias in education where algorithms assign grades favoring students from private schools[83] and harming students from lower socioeconomic areas[84]

4.2 Viable Alternatives for Data Futures

The second task of emancipatory data science requires developing a theory of alternative social structures and institutions whose aim would be to help mitigate harms and injustices identified in the diagnosis and critique stage. These alternatives are reflected in the form of three criteria: 1) desirability (i.e., the utopian view of the world), 2) viability (i.e., potential alternatives) and 3) achievability (i.e., what can be accomplished). The evaluation of alternatives from this three-pronged perspective provides a powerful lens by which to approach alternatives in data science. Again, by knowing what you do not want (diagnosis and critique) makes it much easier to know what you do want (viable alternatives). However, when envisioning systemic change in data science, what is possible (or probable) is determined in large part by the imaginings of those with the power to propose and co-create alternatives. Data scientists as currently defined, consist of a primarily homogenous group of techno-centric white and Asian males whose lived experiences reflect a very narrow segment of the U.S. population despite the wide-ranging impact of their models on a global scale. The ideas that these groups conceptualize as potential viable alternatives to existing data science workflows will necessarily reflect a combination of their technical expertise as well as their lived experiences. However, their experiences will not mirror those of other marginalized, minoritized and vulnerable populations. This mismatch is what leads to the data harms described earlier.

In order for emancipatory data scientists to achieve their *desired* outcome (i.e., social justice), the *viable* alternative is a diverse community of data scientists that is reflective of the U.S. populace that takes into consideration long-term implications of data work above and beyond efficient code and elegant predictive models. Lastly, the practical *achievability* of this viable alternative requires the conscious and intentional pursuit of the intended outcome with full knowledge that this will vary in ways that are largely dependent on pre-existing social structures and "the *relative power* of key actors who both support and oppose the alternative in question.[28]" Subsequently by taking a passive, *Laissez faire* approach toward data science academic and workforce pathways we ensure the continuation of the harms and biases that have already been institutionalized and reinforced with today's models.

4.3 Transforming the Data Science Community

This is the final stage in the emancipatory data science framework. This stage describes how to move from point A (current state identified through diagnosis and critique) to point B (the desirable, viable and achievable alternative). It requires having a vision of the future, the courage to help to realize it, and can be accomplished via the following steps.

- *Social reproduction* states that in order for systems of oppression to exist in data science, there must be *active* means of social reproduction in place to maintain those systems (i.e., systematic oppression does not happen by happenstance or by "some law of social inertia." [28]). Transforming higher education and workforce pathways into data science will require intentional effort at a federal and institutional level [85].
- *Gaps and contradictions* within the process of reproduction, involves identifying where the system of reproduction is likely to "fail," and how to use these failures to enable emancipatory transformation. Public value failure theory (See [86]) can provide significant insight into the types of data failures likely to emerge from data generated products and processes.
- *Unintended social change* is particularly challenging as not all change is intentional. How can we plan or prepare for the unintended consequences of strategic actions? Answering this question requires having a long-time horizon[87] regarding data products (i.e., deployed algorithmic models) by which to evaluate the impact of data work..
- *Collective actors, shared strategies and struggles* are needed to help contend with the obstacles and opportunities facing the achievement of an emancipatory data science future. This requires having a system of accountability and a set of protections in place to shelter and support those who would otherwise call attention to and reveal these gaps (i.e., Wells, Gebru etc.); as they are often targeted and subject to attack by powerful opponents (most recently, Silicon Valley corporations, think Google and Amazon) whose profit margins stand to be affected in the face of these critiques.

Table 1 (below) summarizes the outcomes of this analysis using our three cases as an illustration.

5 Discussion

In this paper I argue that the data scientists who are best equipped to undertake emancipatory data science are more often than not, vocal and conscientious members of the marginalized groups (i.e., race, ethnicity, sexual orientation, immigrant status etc.) that the

Table 1. Characteristics of Emancipatory Data Science

Concept	As Applied to…	Emancipatory Data Science Expression
Diagnosis and Critique	Data Harms	*Wells*: Falsified justifications of lynchings *Buolamwini & Gebru*: Biased facial recognition software *Noble*: Racist and sexist search engine models
Viable Alternatives	Data Futures	*Wells*: An end to the terrorization of Black people in the U.S. *Buolamwini & Gebru*: Unbiased facial recognition software and algorithms *Noble*: Anti-racist and anti-sexist search engine results
Transformation	Data Science Community	*Gebru's* Black in AI: creating community for Black AI experts *Buolamwini's* Algorithmic Justice League: calling for greater transparency and accountability *Noble:* Co-Founder and Co-Director of the UCLA Center for Critical Internet Inquiry (C2i2)

developers of these algorithms (knowingly or unknowingly) harm. That is to say, the data workers with the greatest capacity to challenge the design, development and deployment of algorithms with the potential to negatively affect marginalized groups, and subsequently devise solutions to rectify data harms, are those who self-identify as members of those groups.

This conceptualization, however, does not offer a predictive model for determining under which conditions a particular bias or harm is likely to occur. Attempts to imagine all of the ways that an algorithm can go wrong, or inflict harm is to willingly enter the realm of *unknown unknowns* which is not the contribution that this framing offers us. Instead, an emancipatory data science framework places an emphasis on answering the same two fundamental questions for any social change initiative, namely: *"how did we get here?"* and *"what can we do about it?"*

Ultimately, answers to these questions will vary from one context to another; however, what is shared is the fact that without a data literate and data capable stakeholder base that is reflective of the diverse public that data products ultimately aim to serve, the institutions behind these models risk reproducing and exacerbating data harms, particularly and most severely against minoritized groups.

5.1 Implications and Agenda for Future Research

The proposed analysis provides a preliminary framework to understand the value of minoritized, marginalized and vulnerable populations perspectives and contributions to data science. In the cases explored here, these scholar-activists not only identified biases in data, they attempted to change conditions that created these biases. This is; however, not an exhaustive list. Additional research is needed to identify the many different expressions of emancipatory data science efforts and identify the ways in which it is being (or can be) realized. The following preliminary research questions related to each dimension of emancipatory data science are worth exploring:

5.1.1 Diagnosis and Critique: What are the data harms that currently affect our society? How do/should data scientists mitigate data harms post- or pre-deployment at various units of analysis (i.e., organizational, state, federal, multinational)?

5.1.2 Viable Data Futures: In what ways do data scientists imagine their work serving a justice orientation? What are the characteristics of data scientists who seek to pursue justice through their work? What practical guidance do Black, Indigenous and other marginalized data scientists of color have for diversifying the field?

5.1.3 Transforming the Data Science Community: What types of institutions are actively training, recruiting and retaining Black, Indigenous and marginalized data scientists of color and what can we learn from them? What are the primary sources of support needed (personal, professional, financial etc.) for emancipatory data scientists to thrive?

6 Conclusion

Data science continues to have an unprecedented [59] influence on our social institutions.[82, 88] A lack of diversity in data science limits the range of perspectives needed to address the sociotechnical complexities of "biased" (i.e., harms associated with the deployment of models that are trained on datasets that reflect broader structural inequalities) datasets and analytical processes, leading to a profound negative impact on members of marginalized communities [89]. Diverse data scientists are able to leverage the power of data to counter *"white logic"* which consists of "both the foundation of the techniques used in analyzing empirical reality, and the reasoning used by researchers in their efforts to understand society."[90] Counter-examples highlight the work of scholars who through their data expertise challenged the notion of algorithmic neutrality and objectivity, holding the people and organizations accountable for their data harms.

In 2020, one hundred and twenty-five years after Wells' *The Red Record*; renewed support for the Black Lives Matter (BLM) movement, due to anti-Black policing and the killings of Ahmaud Arbery, Breonna Taylor, and George Floyd, and numerous other instances of police violence and systemic racism, and interest in race/ethnicity disparities in public health resulting from COVID-19's disproportionate impact on Black communities[91] both point to ongoing public harms caused by systemic structural racism. Structural racism is not a new concept, and neither are anti-Black police shootings or race/ethnicity disparities in public health. However, these topics have never been of greater importance and relevance to marginalized communities, and never before has the impact of these data harms been felt by such

a large segment of the U.S. populace. As members of the information systems community, we are responsible for preparing members of the data science workforce to intelligently contend with the socio-technical complexities of their work, create liberatory data science education pedagogy and curricula[92,93] as well as defend the data scientists who choose to use their expertise for data uplift and empowerment.

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