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Advancing equity in healthcare systems: understanding implicit bias and infant mortality

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Abstract

Using data from the Centers for Disease Control and Prevention's Wide-ranging Online Data for Epidemiologic Research (CDC WONDER) and Project Implicit, this study examined whether anti-Black implicit racial biases predict infant mortality for Black Americans. We examined state-level mean Black-White Implicit Association Test (BW-IAT) Bias Scores and controlled for explicit bias scores and White infant mortality rates for over 1.7 million American participants across ten different ethnoracial groups between 2018–2020. Hierarchical linear regressions determined state-level anti-Black implicit bias significantly predicted state-level Black infant mortality rates, above and beyond explicit bias and White infant mortality, in 2018 ($b = .32$, $t(34) = 2.09$, $p < .05$), 2019 ($b = .30$, $t(34) = 2.09$, $p < .05$), and 2020 ($b = .32$, $t(34) = 2.18$, $p < .05$). State-level anti-Black implicit bias also explained a significant proportion of variance in state-level infant mortality rates, in 2018 ($R^2 = 0.30$, $F(3, 35) = 4.89$, $p < 0.01$), 2019 ($R^2 = .33$, $F(3, 36) = 5.95$, $p < .01$), and 2020 ($R^2 = .39$, $F(3, 35) = 7.58$, $p < .001$). Also, among healthcare professionals, there are similar levels of implicit biases compared to the general American population. Findings suggest that implicit racial bias is a risk factor for Black infant mortality. These findings also point to the ethical challenge implicit biases pose to equitable decision-making and patient-provider relationships in healthcare. By integrating these insights into interdisciplinary discussions, this study provides supporting data for systemic reforms and anti-bias training to create a healthcare system grounded in fairness and equity.

Keywords Implicit bias, Explicit bias, Black Americans, Infant mortality, Anti-Black racism

As of 2020, there were approximately 41.1 million Black Americans, making up 12.4% of the total population (U.S. [84]), where Black Americans refers to all Black people living in the United States, including immigrants. While smaller in number, Black communities face significantly higher rates of physical morbidity and mortality compared to their White counterparts [43]. A more contemporary illustration of this health disparity can be marked by the recent COVID-19 pandemic. This widespread and global virus made the already present social and economic inequities faced by racialized groups glaringly obvious. For instance, Black Americans in particular are more likely to live in crowded homes, work essential jobs requiring close contact with others (e.g., transportation, food services, home health care), have chronic health conditions associated with poor COVID-19 outcomes (e.g., type 2 diabetes), and be burdened by immunity compromising life stressors (e.g., racism, income inequality) as compared to their White counterparts [19, 22].

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Poor health outcomes are rarely due to a single cause, but often are the confluence of multiple inequities. To understand this more fully, it is necessary to consider the individual bias and systemic racism which feed such disparities and allow them to flourish. At the healthcare level, several studies found poorer patient-physician interactions, as well as decreased treatment and testing of COVID-19 symptoms in healthcare settings of Black Americans compared to other ethnoracial groups, all of which contribute to poor health outcomes [29, 73, 87]. Beyond COVID-19, barriers for ethnoracial groups such as a lack of cultural competency continue to penetrate health care systems in the United States [64, 77]. Moreover, the prevalence of poor health outcomes and disparities in Black communities can largely be attributed to subtle, potentially unconscious, negative attitudes, and prejudice, otherwise known as implicit bias, present within health providers themselves [17].

Implicit racial biases can have devastating and lasting impacts on the health of Black Americans, as illustrated by the case example of Brianna and Jayden described in Table 1. And yet to the untrained eye, the impacts of implicit biases are often difficult to detect. Using the gold standard indicator of infant mortality rate, this article aims to bring awareness to and characterize the potential impact of said bias on Black lives. This article will do so quantitatively by exploring the relationship between implicit racial biases as per the *Black-White Implicit Association Test* (BW-IAT) and state-level infant mortality rates among Black Americans, as well as qualitatively through further examination of Brianna and Jayden's case example. But first, to fully appreciate the role of implicit bias in this larger context, one must recognize how both implicit and explicit biases operate and affect our cognition and social behaviour.

Implicit vs. explicit biases/understanding biases

Prejudice is inherent in our thoughts, decisions, and interactions due to lifelong socialization in a biased culture [44]. This prejudice or bias can be separated into two categories based on an individual's awareness, insight into the presence, content, and impacts of such prejudices. The most known form is *explicit bias,* defined as a conscious and overt attitude about an individual or group of people. As such, explicit bias accounts for attitudes and beliefs that are voluntary, controllable, and readily available to our consciousness. Alternatively, *implicit biases* are automatic, involuntary attitudes and beliefs that operate at a largely unconscious level [35, 62]. People with implicit biases will engage in biased behaviors that are believed to occur outside of their conscious awareness or focus, which is different than simply realizing one has biases. As such, we conceptualize implicit bias as an individual trait and not simply a reflection of situational or systemic bias [20, 28].

More specifically, implicit bias can be characterized as positive or negative stereotypes that influence the way in which one interacts with other members of society, whether that is based on gender, age, ability, faith, race, or any other number of identities. Many studies have shown that negative implicit biases are correlated to prejudicial behaviors, including in medical contexts [21, 40, 58]. Despite the impact of explicit bias, implicit bias can be more severe due to a lack of awareness on the part of its host. Thus, measuring implicit bias is crucial.

Measuring implicit bias

Several tools measure implicit biases, but none are as well-known or used as the *Implicit Association Test* (IAT). The IAT is the most popular method with 3,300 peer-reviewed studies utilizing it (Greenwald et al., [33, 61]). Specifically, this test measures the strength between dichotomous concepts (i.e., young vs. old age) and

Table 1 Case example

Brianna (pseudonyms used) is a 27-year-old African American woman living in Boston. She's the kind of person everyone counts on—reliable, quick to laugh, and always willing to take an extra shift. After years of dedication at the local hardware store, she was recently promoted to manager. Around the same time, she and her husband, Jayden, a 30-year-old Black Caribbean man, found out they were expecting their first child. They were overjoyed. Jayden painted a mural on the nursery wall, and Brianna started keeping a journal for the baby.

Not long into the pregnancy, COVID-19 hit. Jayden was laid off, along with several others—mostly employees of color. Brianna picked up extra hours to help make ends meet, pushing through nausea and fatigue. When she eventually told her boss she was pregnant, his tone shifted. "I had high hopes for you," he said. "I took a chance making you manager." Brianna felt the sting of disappointment—not just in his words, but in what they implied. She chose not to respond, afraid of confirming the stereotype of the "angry Black woman." Instead, she worked harder.

At 22 weeks, Brianna finally secured an appointment with an obstetrician. The doctor, although seemingly professional, spoke mostly to Jayden, occasionally frowning when Brianna's braids brushed her arm during the exam. When Brianna admitted she had not been eating regularly or taking vitamins—things they couldn't always afford—the doctor responded with mild irritation. "That's not optional during pregnancy," she said. Brianna left feeling uneasy but said nothing. And a couple of weeks later, when symptoms emerged and worsened—shortness of breath, nausea/vomiting, pain close to her ribs, blurred vision—she did not call.

At 27 weeks, while helping unload a shipment at work, Brianna collapsed. She was rushed to the hospital and underwent an emergency delivery. Her son, Marcus, was born early and struggled to breathe. Despite the medical team's best efforts, Marcus passed away three days later.

pleasant or unpleasant evaluations of the concept (i.e., bad vs. good) in alternating sequences [36]. In relation to race, the BW-IAT involves presenting participants with pleasant or unpleasant adjectives on their screen, which they are then asked to sort into categories: Black/Good or White/Bad, then Black/Bad or White/Good. To determine your IAT score, the test considers the time differentials taken to sort each word. Meaning, the less time you take to associate words into a certain category, the more likely you are to have an implicit preference for that group relative to the other. Other than race, there are different versions of the IAT that measure the effects of implicit attitudes on stereotypes about gender, age, body weight, sexual orientation, and more. This study focuses on the BW-IAT which measures the strength of respondents' automatic preferences for the Black race relative to the White race.

The role of implicit bias in the health outcomes of Black Americans

While implicit bias may not always result in discriminatory behaviors, it can have deleterious impacts when it does. One of the most important settings in which implicit racial bias is studied is within healthcare and clinical settings, where direct impacts of biases can be more easily measured and observed. Studies have revealed that on average, Black Americans face poorer psychosocial health outcomes and lower quality of care compared to White Americans due in part to healthcare providers' prejudice (e.g., [8, 42]). This can inform communication, treatment decisions, and overall attitude [40, 52, 58]. Implicit biases can lead to microaggressions in clinical care [89, 92]. Additionally, other research within healthcare has focused specifically on providers' implicit beliefs surrounding Black people's pain tolerance. Holmes et al. [48] suggest poor labor and delivery care is linked to false beliefs about Black American women's pain tolerance. Similarly, Hoffman et al. [47] found White clinicians share these beliefs, leading to delayed responses and poorer pain management. Moreover, Green et al. [32] discovered that medical residents with higher pro-White implicit bias were more likely to treat White patients with myocardial infarction appropriately, but not Black patients.

A recent study by our research team, examined levels of implicit biases within the general population, both White *and* non-White, and the role such biases play on mental health-related mortality within Black communities in the United States [31]. Using the BW-IAT implicit biases scores and national mortality data, they found that implicit biases held within the general population predicted poor mental health outcomes for Black Americans. For example, 40.7% of Black suicide rates were accounted for by explicit bias and White American suicide rates (i.e., the control variables) with an additional 11.0% variance in Black suicides being accounted for by implicit biases when BW-IAT scores were added to the analysis. Such results beg the question of what role implicit biases within the general population play in the poor health outcomes observed within Black communities.

Infant mortality as an indicator of Black Americans' health outcomes

One way to assess the health status of marginalized communities is by examining different indicators of health. These indicators help determine the state of a population's health and monitor the overall state of the health system of a community. Some examples include mortality by age and sex (i.e., stillbirth rate), mortality by cause (i.e., suicide rate), fertility rate, and morbidity [88]. Infant mortality rate (IMR) in particular is one of the most well-respected health indicators. Notably, it reflects the welfare and well-being of a community and consequently its socio-demographic status [30]. IMR is calculated per 1000 live births and shows the likelihood of a child dying before age one [71]. These rates vary due to socioeconomic, environmental, and political conditions.

Research shows that IMR is often highest within racialized groups, which can be attributed to factors such as racial discrimination and the related stressors that marginalized ethnoracial people experience [6]. In fact, non-Hispanic Black Americans were reported to have the highest IMR in 2018 [18]. As previously discussed, implicit bias contributes to discriminatory behaviors impacting infant health. Structural racism has been linked to greater infant mortality in Black but not White babies [67]. Orchard and Price [66] revealed that counties in the United States reporting higher levels of implicit racial prejudice were strongly positively correlated with adverse birth outcomes and explicit racial bias towards Black people. Although these are key findings that imply a relationship between infant mortality and racial biases, a few gaps remain. Said study evaluated implicit bias within a Black-White gap and IAT scores on a county-level basis, whereas the current study examines this at a state level. Additionally, their measure of explicit bias was a single item rather than a validated scale. Finally, Orchard and Price's data, from 2002–2012, only examined birthweight and preterm labor, not infant mortality.

Positionality statement

As diverse researchers working within the space of racism, racial inequities and mental health, we believe it is important to shine a light on the role we all play, regardless of race, in bringing awareness to and limiting the power of our racial prejudices to prevent harm to others.

We offer the following information about ourselves to help situate our motivations and identities in the context of the subject under investigation [72].

This article's first author is a White, first-generation Canadian, settler of European ancestry undertaking her doctorate in clinical psychology. She works primarily with racialized and marginalized groups on topics of racism, mental health disparities, and homelessness. The second author has completed an undergraduate degree in psychology and social work. They are a second-generation South Asian Canadian immigrant, and settler, and have an interest in cross-cultural psychology, mental health disparities, as well as anti-oppressive and intersectional approaches to mental health care. The third author is a Black-Indigenous woman and a doctoral student in clinical psychology. Their lived and community experience inspires her work towards anti-racism and equity for Black and Indigenous populations, and sexual and gender minorities populations. The fourth author is a Canadian Ashkenazi Jew who is completing her doctorate in clinical psychology. She has researched in the areas of microaggressions, racial bias, institutional racism, police violence, racial trauma, and psychedelics, and now focuses on antisemitism. The fifth author is an African American living in Germany and an experienced neuroscientist and pharmaceutical professional, specializing in clinical development and social justice. She researches in the areas of microaggressions, racial bias, institutional racism, police violence, racial trauma, and psychedelics. Finally, the senior author on this article is a registered clinical psychologist, professor at a large urban university, and research chair. She is also an African American woman with expertise in the mental health of communities of color, with over 200 publications.

The present study

Researchers have extensively studied the impact of anti-Black implicit bias in healthcare settings. However, there is a lack of research that explores anti-Black bias across ethnoracial groups and its consequences on the health and longevity of Black communities. Hence, the primary aim of this study is to explore and address the following: To what extent does implicit bias predict Black American IMR? It is hypothesized that there is a significant relationship between implicit bias towards Black Americans and infant mortality. While controlling for explicit anti-Black attitudes and White American infant mortality, we predict higher state-level mean scores on the BW-IAT will predict poorer state-based IMR within Black populations. But in so doing, this study does not wish to lose sight that Black individuals, families, and communities experience the direct and indirect impacts of anti-Black bias in their daily lives. As such, this article also strives to increase readers' awareness of the issue of implicit racial biases; compassion for those affected; and motivation for social change with the use of a case example.

Method

Data sources

The Black-White Implicit Association test

The BW-IAT is a computerized task aimed at ascertaining test-takers' implicit bias towards Black and White peoples. Underpinning this goal is the idea that race and evaluation pairings (e.g., "White" + "Bad", "Black" + "Good") that are easier and thus faster to make, are more aligned with the test-takers implicitly held biases. In other words, the less time it takes for someone to make the race and evaluation prompts a single unit, the stronger the association of that pairing in the individual's mind.

In terms of reliability, Lane and colleagues [54] considered a handful of racial-attitude related IAT studies (BW-IAT included) and found test–retest correlations between 0.32 (tested two weeks apart) and 0.65 (tested 24 h apart). A more recent article by Greenwald and Lai [34] of IATs yielded a meta-analytic test–retest correlation of 0.50. While considered to be a low reliability coefficient by most, it is important to acknowledge the dynamic nature of the implicit bias construct, as implicit biases are heavily influenced by one's environment and experiences. Like an individual's blood pressure, acute factors such as stress and anxiety, room temperature, alcohol/caffeine consumption, etc., may cause substantial differences between readings. Similarly, one's BW-IAT performance is highly influenced by sleep quality, cognitive and emotional load, the presence of a third-party who may see one's score, etc. [7, 14, 23]. Researchers find that "despite its capriciousness at the individual level, implicit bias can be remarkably stable at the context level (such as city, county, or state level, [28], p. 110)." This is termed "emergent stability" because the aggregate stability is greater than the stability of the individual scores [28].

Implicit bias scores The BW-IAT consists of several different blocks, but only two blocks contribute to one's implicit bias score (note, IAT scores are commonly referred to within the literature as "D-scores", but within this text we will use "Bias Scores" for clarity). The response latency between the different sorting conditions in these two blocks (and/or error rates) results in a score on a continuum of -2 to + 2. Should a test-taker find themselves on the *positive* side of the continuum, they are believed to hold an implicit preference for White people over Black. Conversely, a Bias Score on the *negative* end suggests an implicit preference for Black people over White. A Bias Score of/near "zero" suggests neutrality

– the test taker does not have a preference for White or Black people over the other. Moreover, a test-taker's implicit preference strength can be gleaned by their position on their respective arm of the continuum: ± 0.15 is "slight," ± 0.35 "moderate" and ± 0.65 "strong" [41]. These are nominal categories where the cut-scores between them are determined by convention.

Explicit bias scores In addition to completing the IAT-related task, two indicators of explicit bias were also administered to some or all participants. The first was the *Modern Racism Scale* (MRS; [59]), a self-report measure designed to ascertain test-takers' covert contemporary anti-Black attitudes. There are seven MRS items, and responses are elicited on a 5-point scale (where 1 is "strongly disagree" and 5 is "strongly agree"). Sample items include "Black people should not push themselves where they are not wanted" and "Over the past few years, the government and news media have shown more respect for Black people than they deserve." Items are subsequently totaled, with the highest possible score being 35. Higher scores are reflective of greater explicit biases towards Black peoples. The MRS has been in use for many years, and in this time, scores have been correlated with related variables like anti-Black affect, political conservatism, a social dominance orientation, etc. [63]. Of note, only a subsample of BW-IAT participants were randomly assigned to complete the MRS (sample size or $n = 61{,}089$). Within this study, the MRS' Cronbach alpha was 0.83.

The second indicator is a thermology item offered to all participants completing the BW-IAT. It was a single item that asked, "Please rate how warm or cold you feel toward the following group – Black people." Responses were elicited on a 11-point scale where 0 is "extremely cold" and 10 is "extremely warm." While not used in the analyses below, participant thermology scores proved important as they were correlated with MRS scores to see if the MRS scores of the subsample could be generalized to the larger group. The correlation was small to moderate (Pearson correlation coefficient or r [61087] = -0.26, $p < 0.001$) and operated in the expected direction (i.e., as warmth ratings for Black people increase, MRS explicit bias scores decrease). MRS scores were used as a measure of explicit bias, as opposed to thermology scores, on account of thermology scores being determined by a single item, thus making it more difficult to establish reliability and construct validity [5].

BW-IAT study participants The current study accessed the original BW-IAT hosted by *Project Implicit* [96]. On a yearly basis, *Project Implicit* collects, cleans and makes available their IAT data, BW-IAT and otherwise, thus providing access to researchers interested in analyzing the data. As such, readers of this article are free to download and repeat/verify this study's analyses. Project Implicit is approved by the University of Virginia's Internal Review Board (IRB).

In completion of this study, we analyzed BW-IAT data files from 2018, 2019, and 2020. Therefore, participants are those that completed a BW-IAT online sometime between January 1, 2018 and December 31, 2020. In total, there were 3,492,257 participants included within these data files (859,472 in 2018; 875,209 in 2019; and 1,757,576 in 2020). However, additional data cleaning steps were undertaken by the authors (as per recommendations by [65]) including: (1) removing non-American residents,(2) removing participants with impossible values for race, explicit bias, or Bias Scores; (3) removing participants who completed the IAT task too quickly (i.e., > 10% of responses faster than 300 ms); (4) removing participants who completed the IAT with too many sorting errors (i.e., > 30% errors); and (5) removing participants with missing race, explicit bias (thermology only), and Bias Scores data.

A few points to note relating to the data cleaning process: first, BW-IAT Bias Score outliers were identified using z-scores of the Bias Score variable ("D_biep.White_Good_all"), for each ethnoracial group and year separately. Moreover, given the large sample size (i.e., sample size of more than 1000), an outlier was identified as having a z-score > ± 3.29 [78]. Considering those with Bias Scores on the positive side of the spectrum, 46 outlying participant Bias Scores were modified to represent the next most acceptable Bias Score within their ethnoracial group and year. On the negative side of the spectrum, 3034 outlying participant Bias Scores were similarly modified. Second, a new variable was created integrating race and ethnicity. As such, in addition to eight existing racial categories offered, "Hispanic and Latino" identities were added to create "White (Hispanic)" and "non-White (Hispanic)." This classification was possible as both race and Hispanic ethnicity were provided on infant death certificates, and these identifiers were also collected for the IAT.

Upon completion of the data cleaning steps described above, the study's final sample size was 1,706,566 participants. Majority of participants identified as being between the ages of 25 and 64 (46.7%), female (63.7%), and/or White (non-Hispanic/Latino; 64.3%). Nearly half reported having a bachelor's degree or higher education

Table 2 Summary of 2018–2020 BW-IAT participant characteristics

Participant Characteristics	Number of Respondents (%) 2018	2019	2020
Total	433,934	443,270	829,362
Age [a] (in years)			
0–24	239,324 (55.2)	240,355 (54.2)	302,046 (36.4)
25–64	178,837 (41.2)	185,877 (41.9)	474,067 (57.2)
65 +	6,534 (1.5)	7,288 (1.6)	28,199 (3.4)
undisclosed	9,239 (2.1)	9,750 (2.2)	25,050 (3.0)
Gender Identities [b]			
male	155,707 (35.9)	156,609 (35.3)	273,883 (33.0)
female	271,728 (62.6)	280,092 (63.2)	542,293 (65.4)
trans	791 (0.2)	895 (0.2)	1,375 (0.2)
queer or gender nonconform	2,727 (0.6)	2,687 (0.6)	5,941 (0.7)
other/combination of two or more of the above	2,427 (0.6)	2,376 (0.5)	4,657 (0.6)
undisclosed	554 (0.1)	611 (0.1)	1,213 (0.1)
Race			
American Indian/Alaska Native	1,977 (0.5)	2,066 (0.5)	2,958 (0.4)
Black or African American	47,527 (11.0)	50,443 (11.4)	71,447 (8.6)
East Asian	14,293 (3.3)	14,250 (3.2)	28,560 (3.4)
Multiracial	16,351 (3.8)	16,527 (3.7)	26,872 (3.2)
Native Hawaiian or other Pacific Islander	2,408 (0.6)	2,362 (0.5)	3,746 (0.5)
non-White (Hispanic)	37,112 (8.6)	39,656 (8.9)	55,514 (6.7)
South Asian	11,629 (2.7)	12,225 (2.8)	23,013 (2.8)
White (non-Hispanic)	273,311 (63.0)	274,390 (61.9)	564,580 (68.1)
White (Hispanic)	23,296 (5.4)	25,388 (5.7)	42,489 (5.1)
other or unknown	6,030 (1.4)	5,963 (1.3)	10,183 (1.2)
Highest Level of Education			
elementary—some high school	70,972 (16.4)	74,790 (16.9)	76,537 (9.2)
high school graduate	44,269 (10.2)	44,745 (10.1)	58,725 (7.1)
some college / Associates degree	133,699 (30.8)	131,923 (29.8)	194,192 (23.4)
bachelors degree	67,340 (15.5)	68,490 (15.5)	192,448 (23.2)
medical degree	4,883 (1.1)	5,561 (1.3)	14,889 (1.8)
graduate school or other professional degrees	104,329 (24.0)	108,864 (24.6)	279,111 (33.7)
undisclosed	8,442 (1.9)	8,897 (2.0)	13,460 (1.6)
Occupation			
healthcare-related	17,268 (4.0)	38,078 (8.6)	82,654 (10.0)
not healthcare-related	416,666 (96)	405,192 (91.4)	746,708 (90.0)

[a] Participant age was estimated based on birth year (i.e., year they participated minus birth year) as exact birthdate was not collected

[b] The BW-IAT gender identity item response options conflate gender and sex. As a result, the above categories reflect these conflated constructs

level (48.7%). Detailed participant information can be found in Table 2.

CDC WONDER

Infant mortality The Centers for Disease Control and Prevention's Wide-ranging Online Data for Epidemiologic Research (CDC WONDER) stores online databases on several areas of public health in the United States. This includes data on natality, mortality, morbidity, AIDS, cancer statistics, tuberculosis, population estimates, and the environment. While the CDC is responsible for developing the programs within the system, a number of agencies are also responsible for populating these databases, including the U.S. Department of Health and Human Services (US

DHHS), the National Center for Health Statistics (NCHS), and the U.S. Census Bureau [85].

For the purposes of this study, we used information from the *Underlying Cause of Death* dataset based on U.S. resident death certificates from 50 states and the District of Columbia. Each individual is associated with a certificate that provides information regarding their demographic information (i.e., race, ethnicity, age, gender, etc.) and the single underlying cause of death. All the causes of infant death are included in this dataset, which currently spans the years 1999—2020, but excludes nonresidents and fetal deaths [86]. Within this dataset, we will be using the underlying cause of death for infants from the International Classification of Diseases 10 (ICD-10). The ICD-10 reports diseases, injuries and causes of death, and external injuries after 1999. There are 130 selected causes for infant deaths that are reported within the ICD-10. In CDC WONDER, "infant" is classified as persons less than 1 year of age.

As part of the analysis, we select "All Causes of Death" as our variable within the ICD-10 130 group. This category includes causes of infant death such as infectious and parasitic diseases, neoplasms, internal system diseases (i.e., respiratory, nervous, circulatory, digestive, genitourinary, endocrine, nutritional, metabolic, etc.), diseases of the blood and blood-forming organs, conditions originating in the perinatal period, congenital malformations, deformations, and chromosomal abnormalities, and external causes of mortality such as accidents, assaults, and other complications.

CDC WONDER study participants Participants included in this study are those identified as "Black or African American" or "White" infants from 2018, 2019, and 2020 state-level data categorized under the All Causes of Death. Participants' race and Hispanic origin is identified by demographics on their death certificate in accordance with standards set forth by the Office of Management and Budget [86]. No gender restrictions were included in the selection. In some cases, a state's mortality was excluded from the analysis as the mortality rate was fewer than ten persons (i.e., suppressed). Those deemed "unreliable" (i.e., the state death count was below 20) were calculated by hand.

Data analyses

The analyses described below were undertaken using SPSS Statistical Software, version 28.

Ethnoracial levels of implicit racial bias

Descriptive statistics of the BW-IAT Bias Scores were collected for the ten different ethnoracial groups. As such, the variable of interest included Bias Score and participants were split by ethnoracial identity.

Comparison of implicit Bias Scores between those working in healthcare and the general population

A one-way ANOVA main effect F-tests was used to determine whether listing one's occupation as "healthcare" had a significant effect on Bias Score. Therefore, variables of interest included BW-IAT Bias Scores and occupation. Comparisons were split by participant ethnoracial identity. *P* values less than 0.001 were considered to be statistically significant. Note, a smaller more conservative alpha of 0.001 was used for the analysis comparing Bias Scores between healthcare professionals and the general population as per the large sample sizes involved in this analysis. That is, there were over 1.7 million cases to consider in total. With such a large sample size even small/not meaningful differences between groups can be detected as significant. Therefore, in addition to minimizing the chances that any significant findings were found due to chance, we also reported effect sizes.

Implicit bias and Black infant mortality

State-level mean BW-IAT Bias Scores and MRS scores were obtained. Note that State was used as the regional metric within this study for practical reasons: (1) CDC WONDER infant mortality data was publicly available at the State level, and (2) BW-IAT respondents could be aggregated by State of residence. Hierarchical linear regressions were then performed to test if said implicit Bias Scores could predict state-level CDC WONDER's crude IMRs between 2018 and 2020 for Black Americans. As an element of this analysis, White American crude IMRs and explicit biases (using the MRS) were added as control variables. As such, predictor variables in this analysis were state-level: White IMR, MRS scores, and Bias Scores. No offsets were used. Of importance, the aforementioned control variables were selected in accordance with best practice recommendations in the field (i.e., [13]). Specifically, White American infant mortality was selected as a function of its moderate-large relation to both the dependent and independent variables. MRS test scores, or the validated measure of explicit racial bias towards Black people, was selected on the basis of its conceptual relevance to the predictive path tested in the hierarchical regression. *P* values less than 0.05 were considered to be statistically significant. In the case of the analysis with state averages of implicit Bias Scores and Black infant mortality, the sample size is much smaller (consider how many states there are). As such, there was no need to use such a conservative alpha (i.e., 5% error is acceptable).

Results

To what extent does implicit racial bias against Black peoples exist within various ethnoracial groups residing in the United States?

BW-IAT Bias Scores from 2018 to 2020 were accessed from within ten different ethnoracial groups of American residents (see Table 3). As seen in the table, nearly all ten ethnoracial groups tested held positive mean Bias Scores within the slight to near moderate range (i.e., between 0.15 and 0.33; recall Bias Scores range on a continuum of −2 to + 2) in terms of implicit judgements of White versus Black peoples. Black or African American participants were the sole exception, as they had Bias Scores within the neutral range. Black/African American participants, therefore, did not show a bias for White or Black peoples on average. See Fig. 1. for a visual representation.

Table 3 BW-IAT mean Bias Scores by ethnoracial group and general population versus healthcare profession

Ethnoracial Group	All Participants				Participants Working in the Healthcare Field			
	N	Bias Score Mean	Std. Deviation	95% CI Lower, Upper	N	Bias Score Mean	Std. Deviation	95% CI Lower, Upper
American Indian/ Alaska Native	7,001	0.23	0.43	0.22, 0.24	512	0.23	0.42	0.19, 0.27
East Asian	57,103	0.29	0.42	0.29, 0.29	5,956	0.29	0.43	0.28, 0.30
South Asian	46,867	0.24	0.41	0.24, 0.24	5,549	0.24	0.42	0.23, 0.25
Native Hawaiian or other Pacific Islander	8,516	0.22	0.43	0.21, 0.23	753	0.25	0.41	0.22, 0.28
Black or African American	169,417	-0.03	0.42	-0.03, -0.03	13,785	-0.02	0.43	-0.03, -0.01
White (non-Hispanic)	1,112,281	0.33	0.42	0.33, 0.33	91,972	0.34	0.42	0.33, 0.34
other or unknown	22,176	0.19	0.44	0.18, 0.20	2,085	0.20	0.44	0.18, 0.22
Multiracial	59,750	0.15	0.44	0.15, 0.15	3,966	0.17	0.45	0.16, 0.18
White (Hispanic)	91,173	0.27	0.42	0.27, 0.27	6,300	0.29	0.41	0.28, 0.30
non-White (Hispanic)	132,282	0.16	0.42	0.16, 0.16	7,122	0.18	0.43	0.17, 0.19

CI confidence interval, *N* sample size, *Std*. Deviation standard deviation

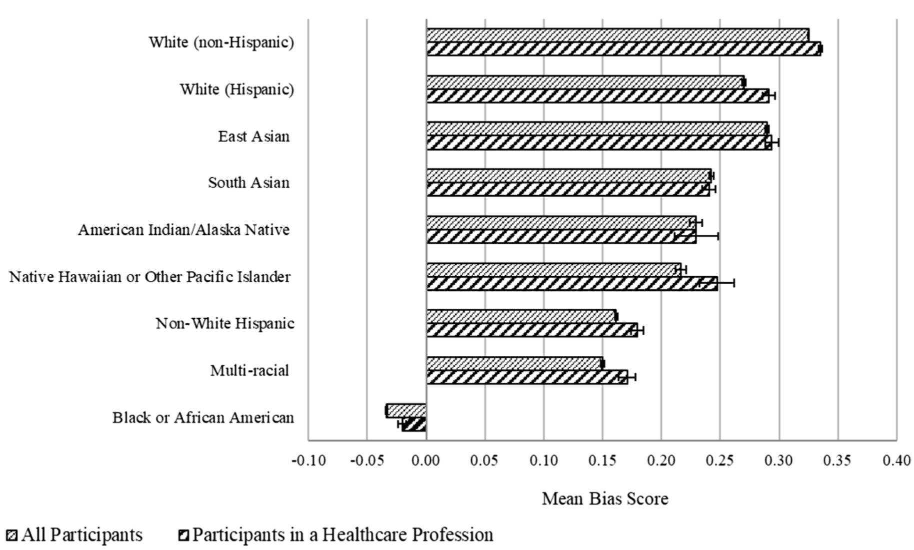

Fig. 1 Mean BW-IAT Bias Scores by ethnoracial group for the general population and those working in a healthcare profession. Caption. Bias Scores range on a continuum of −2 to + 2. Positive scores indicate a relative positive bias for White people, while negative scores indicate a relative positive bias for Black people. Bars represent standard error

Does implicit racial bias towards Black peoples differ among those working in the healthcare field compared to the general population?

Ethnoracial groups' BW-IAT Bias Scores within participants working within the healthcare field ($n = 138{,}000$) were compared against the general population (see Table 3). Of the ten ethnoracial groups assessed, four held significant Bias Score differences. The first was the Black or African American group, with those in the general population having a "neutral" but slightly more negative Bias Score than healthcare professionals ($F_{(1,\ 169{,}415)} = 15.30$, $p < 0.001$, partial eta squared or ${\eta_p}^2 = 0.00009$). The second was the non-White (Hispanic) group, with those working in healthcare remaining in the "slight" positive range, albeit with a higher Bias Score than the general population ($F_{(1,\ 132{,}280)} = 13.80$, $p < 0.001$, ${\eta_p}^2 = 0.00010$). Also, the White (Hispanic) general population and healthcare groups differed, with healthcare professionals having a higher, albeit still "slight" Bias Score ($F_{(1,\ 91{,}171)} = 17.66$, $p < 0.001$, ${\eta_p}^2 = 0.00019$). Lastly, the White (non-Hispanic) group's general population and healthcare profession Bias Scores significantly differed, with those in healthcare being more positive ($F_{(1,\ 1{,}112{,}279)} = 56.17$, $p < 0.001$, ${\eta_p}^2 = 0.00005$). However, note the low partial eta squared indicates a very small magnitude of effect between those in the general population and those working in the healthcare field. See Figs. 1 and 2 for a visual comparison.

To what extent does implicit bias predict Black American infant mortality rates?

BW-IAT Bias Scores and their relationship to infant mortality within Black communities in the United States was examined using state-level data. Note, the BW-IAT Bias score was only modestly correlated to MRS explicit bias (r [61,087] $= 0.19$, $p < 0.001$). After controlling for White American infant mortality and the MRS, the BW-IAT was found to significantly predict Black American infant mortality across all three years explored. Therefore, the higher the state-level BW-IAT Bias Score, the worse the infant mortality for Black communities. Specifically, in: 2018 (standardized beta or $b = 0.32$, $t(34) = 2.09$, $p < 0.05$); 2019 ($b = 0.30$, $t(34) = 2.09$, $p < 0.05$), and 2020 ($b = 0.32$, $t(34) = 2.18$, $p < 0.05$). State-level anti-Black implicit bias also explained a significant proportion of variance in state-level IMR, in 2018 (R-squared change or $R^2 = 0.30$, $F(3,\ 35) = 4.89$, $p < 0.01$), 2019 ($R^2 = 0.33$, $F(3,\ 36) = 5.95$, $p < 0.01$), and 2020 ($R^2 = 0.39$, $F(3,\ 35) = 7.58$, $p < 0.001$). All in all, 21–31% of the variation in Black infant mortality was accounted for by explicit bias and White IMRs. Moreover, implicit Bias Scores account for 8–9% of the additional variance seen in Black IMR, beyond explicit bias scores and White IMR. See Table 4 for details of the hierarchical regression analyses.

We hypothesized that these findings are due in part to differential treatment from healthcare providers due to implicit bias. To help determine this we conducted another regression for 2020 with the same dependent variables and predictors, including only those who identified as health care providers ($N = 82{,}654$).

We found this new model was even more predictive of outcomes than the 2020 model with all participants ($R^2 = 0.42$, $F(3,\ 35) = 8.30$, $p < 0.001$). See Supplementary Table S1 for details. Figure 2 provides a state map of healthcare provider implicit bias compared with implicit bias in general.

Discussion

Most groups possess an implicit preference for White over Black individuals

Among the ten ethnoracial groups analyzed in this study, our findings suggest that most possess an implicit preference for White over Black individuals in the United States. In particular, White (non-Hispanic), and White (Hispanic) anti-Black Bias Scores were among the highest. These findings are consistent with existing research that has found anti-Black biases across ethnic communities [31, 79]. Negative representations of people of color in the media contributes to the development of pathological anti-Black stereotypes and pro-White bias (e.g., [81]). In our society people can plainly observe or experience the unearned privileges afforded those with White status, also contributing biases [56].

Black American respondents in contrast reported neutral Bias Scores, indicating that they do not demonstrate implicit judgements for White or Black people over the other. This finding suggests that despite prejudice in this country, Black communities are not swayed significantly by anti-Black bias. Although some have conceptualized this as internalized racism, we believe that neutral mean bias scores should be interpreted as a positive trait, insomuch as low racial bias of any sort should be considered a goal for an equitable and just society. Notably, Black people tend to receive more anti-racism related socialization from their families growing up than White people to counter societal pervasive racist messages [1, 2, 90]. As such, this could explain why they harbor less implicit racial bias.

The deep-seated nature of anti-Black bias is evident in the fact that implicit anti-Black biases are present across most ethnoracial groups (e.g., [91]). As all persons can play a role in perpetrating racism, there is a pressing need for everyone to recognize the high prevalence of anti-Black implicit bias and take the necessary steps in their professional and personal lives to address this issue.

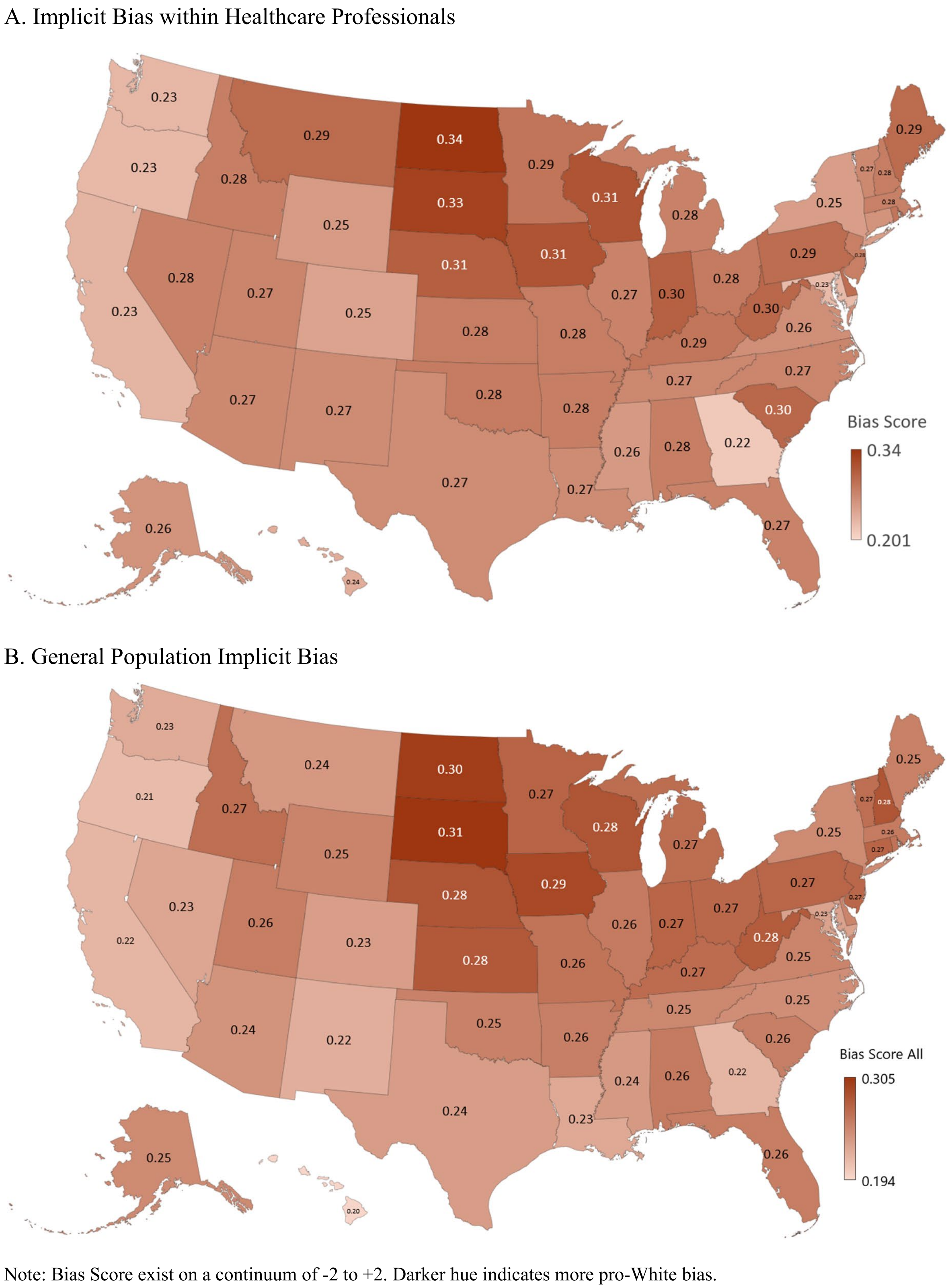

Fig. 2 Implicit Bias Score by state and healthcare profession status for 2020. **A**. Implicit Bias within Healthcare Professionals. **B**. General Population Implicit Bias. Note: Bias Score exist on a continuum of -2 to + 2. Darker hue indicates more pro-White bias

Table 4 Summary of hierarchical linear regressions for variables predicting Black infant mortality

Dependent Variable	Step	Independent Variables	B	t	R	R^2	ΔR^2	df	p
2020 Black Infant Mortality									
	1				0.55	0.30	0.30	1, 37	0.000
		2020 White Infant Mortality	1.24	4.00					0.000
	2				0.56	0.31	0.01	1, 36	0.478
		2020 White Infant Mortality	1.02	2.30					0.027
		2020 MRS Score	41.49	0.72					0.478
	3				0.63	0.39	0.08	1, 35	0.036
		2020 White Infant Mortality	0.98	2.32					0.026
		2020 MRS Score	4.44	0.08					0.939
		2020 BW-IAT Bias Score	3096.08	2.18					0.036
2019 Black Infant Mortality									
	1				0.47	0.22	0.22	1, 38	0.002
		2019 White Infant Mortality	1.24	3.24					0.002
	2				0.50	0.25	0.03	1, 37	0.205
		2019 White Infant Mortality	1.02	2.44					0.020
		2019 MRS Score	67.19	1.29					0.205
	3				0.58	0.33	0.08	1, 36	0.043
		2019 White Infant Mortality	1.24	2.96					0.005
		2019 MRS Score	44.67	0.88					0.387
		2019 BW-IAT Bias Score	2362.65	2.09					0.043
2018 Black Infant Mortality									
	1				0.42	0.17	0.17	1, 37	0.008
		2018 White Infant Mortality	1.32	2.78					0.008
	2				0.45	0.21	0.03	1, 36	0.221
		2018 White Infant Mortality	0.94	1.69					0.099
		2018 MRS Score	89.82	1.25					0.221
	3				0.54	0.30	0.09	1, 35	0.044
		2018 White Infant Mortality	0.95	1.78					0.084
		2018 MRS Score	43.30	0.60					0.554
		2018 BW-IAT Bias Score	3214.15	2.09					0.044

MRS Modern Racism Scale, *BW-IAT* Black-White Implicit Association Test, *B* unstandardized beta, *df* degrees of freedom, *p* p-value, *R* coefficient of determination, R^2 R-squared, ΔR^2 R-squared change, *t* test statistic

How individual actions impact maternal health – the role of implicit bias

In Brianna and Jayden's case example (see Table 1.), we see how individual biased actions impact maternal health, and how implicit biases play a role in negative health outcomes in infants (e.g., [3]). The obstetrician's implicit biases resulted in the commission of microaggressions towards Brianna that tarnished the therapeutic relationship between patient and caregiver (e.g., [39, 92]). This represents a lack of due diligence, which has been noted for Black female intersectionalities [46, 60].

It has further been documented that pain management remains an issue for Black people due in part because of false unconscious beliefs that Black people's pain levels and nerve ending sensitivity differ from White patients. As a result, physicians are more likely to underestimate the pain of Black patients compared to their non-Black counterparts [47]. This lack of diligence caused the obstetrician to miss the early signs of preeclampsia and the poor therapeutic relationship made it less likely that Brianna would reach out for support when her symptoms worsened. Notably, a national study found Black women were 2.7 times more likely than White women to die from preeclampsia, which is attributed in part to a lower quality of care [80]. Moreover, a recent poll of Black American women, between the ages of 18 and 49, found 71% have had at least one negative interaction with a healthcare provider [27]. As a result, 45% prefer to see a Black health provider over that of a different race.

In terms of infant health, a study of 1.8 million births in Florida hospitals between 1992 and 2015 found that the mortality rate of Black newborns is three-fold greater than White newborns [37]. The same study also found the Black infant mortality rate was reduced by 50% when the attending physician was Black. Although implicit bias was named as a major driver of these outcomes, Greenwood and team did not go into detail about how specifically physician implicit biases may result in greater Black infant mortality. However, some possible considerations include: a greater prescription for riskier Caesarean sections in Black mothers compared with other ethnoracial groups, even in low-risk pregnancies, overlooking Black mothers' concerns or complaints before, during, or after giving birth; and poorly communicated/inaccessible information on infant care post-delivery (e.g., [15, 24]).

One must also consider the several-week delay experienced by Brianna and Jayden when searching for an obstetrician. Black Americans are also discriminated against at the level of seeking and obtaining healthcare services. For instance, Kugelmass [53] examined response rate differences when Black and White callers based in New York City left voicemails seeking mental health services from psychotherapists. They found White middle-class women callers received an appointment offer from one in five therapists called. Black working-class men, however, had to call 80 therapists on average before receiving a single positive response. Similarly, many medical offices are transitioning to using machine learning as a means of assisting with medical appointment scheduling. Such software aims to identify patient risk for not showing up to appointments to schedule high risk patients into/immediately following overbooked appointment slots. Samorani and team [75] have found that these systems cause Black patients to wait 30% longer than non-Black patients for their appointment. Had Brianna and Jayden been able to access prenatal care earlier, perhaps more could have been done to ensure a healthy pregnancy.

There are also more indirect factors present that contribute to infant mortality, as seen in Brianna and Jayden's case. Consider that Brianna's pregnancy complications were in part a result of having to work longer and harder at her place of employment [12]. She was forced to take extra shifts when her husband was laid off as a result of COVID. In this example, only employees of color were laid off. Notably, research shows that implicitly held attitudes and stereotypes play a role in who is selected for an interview, who is hired, and who is promoted [16, 38, 70]. By the same token, implicit bias can also influence who is laid off.

Further, Brianna's boss' comments may have contributed to the loss of her infant. Recall, when sharing her pregnancy news with her employer, negative comments were made insinuating Brianna's promotion to manager was not necessarily due to her hard work and dedication, but instead a result of the owner's goodwill. Such opportunity shaming is not an uncommon message pushed onto Black women in the workplace. The underlying message is that the employee is not deserving of their position. When such messages are communicated, it is not uncommon for the targeted person to behave as Brianna did and work harder and longer than is healthy to prove their worth (e.g., "John Henryism"; [50]).

This case example and the research findings described herein focus on infant mortality, but there are likely many other health outcomes that, if explored in a similar way, are likely to yield a comparable relationship. As such, it is important for researchers to consider implicit racial biases present in all people, as there are many distal contributors to poor health.

Healthcare professionals carry similar levels of implicit biases as the general American population

In this study, two-thirds (66.6%) of those working in healthcare identified as White (non-Hispanic/Latinx), which is not far from the percentage of White physicians and registered nurses currently practicing in the United States (56.2% and 80.0%, respectively; [9,10]). Moreover, while one would hope that those responsible for caring for people in their most vulnerable moments would be without bias, the reality is that they are not [4, 26]. In fact, this study finds that individuals working in the healthcare field hold near identical levels of anti-Black implicit biases to those in the general population, White and non-White alike, however we found interesting differences in statewide comparisons which we address below. Further, when examining the biases of health care providers broadly, we find this is more predictive of Black infant mortality than regional biases alone.

It has been observed that medical trainees learn material that centers White patients and minimizes the needs of people of color (e.g., [57, 68]). This contributes to inadequate healthcare experienced by marginalized populations, especially Black women [46, 49]. In medical education, it is essential to ensure that the tools and knowledge used do not reinforce implicit biases but instead reflect and serve the diverse backgrounds of patients. Our study found implicit racial biases among individuals working in the healthcare field across various ethnoracial groups, emphasizing an urgent need for anti-racism training throughout the healthcare sector, with particular attention to addressing anti-Black racism [25].

Researchers have developed effective implicit bias training workshops for medical students and recent graduates (e.g., [52]). Kanter and colleagues describe an effective intervention emphasizing the role of mindfulness and the value of interracial interactions grounded in mutual vulnerability and responsiveness to effectively address and mitigate harmful implicit biases. Participants evidenced significant improvements in interracial patient-provider emotional rapport and working alliance, and provider explicit attitudes towards patients of color.

To facilitate a safe environment and address healthcare disparities, anti-racism action is critical at all levels of the medical system, not only on individual biases [55]. Efforts must be made at the institutional level (i.e., policy, organizational structure, community) to embed these values and create systemic change [45]. Potentially helpful actions include, but are not limited to, the adoption of non-Eurocentric ways of knowing, curriculum that is informed by and serves non-White patients, and a trainee pool more representative of the country's diversity.

Representation is a deciding factor in patient outcomes and bias scores

It is also important that Black people specifically are represented in the medical field. While White physician representation is on par with demographics in the United States, only 5.0% of active physicians and 6.3% of registered nurses are Black [9, 10]. This percentage is misaligned with the 12.4% of Black people living in the United States (U.S. [84]. Physicians and nurses of color are furthermore more likely to work in underserved areas than White health providers which magnifies their impact in these communities [95]). Indeed, research has found that Black infant mortality is sharply reduced when at-risk infants are cared for by Black doctors [37].

In terms of the state specific data shown in Fig. 2, Washington DC and Georgia serve as case-in-point outliers. Here, we found that Georgia and the District of Columbia had the lowest levels of healthcare worker bias among all states analyzed (the four lowest being, District of Columbia, Georgia, Maryland and Oregon). A recent report by the Association of American Medical Colleges [11] provides additional context, highlighting that Black physicians make up 10% or more of the practicing workforce in the same 3 states with the top 4 being the District of Columbia, Georgia, Mississippi, and Maryland. Georgia, in particular, stands out among southern states, where Black individuals comprise 31% of the population and 16.3% of the physician workforce—a significantly better ratio compared to many other states in the region.

This representation has profound implications. Snyder and colleagues [76] demonstrate that greater Black workforce representation is linked to higher life expectancy, lower all-cause Black mortality, and reduced mortality disparities between Black and White individuals. In summary, our findings indicate that lower BW-IAT Bias Scores among healthcare professionals are consistently observed in states with higher numbers of Black physicians and better health outcomes among Black individuals. Importantly, these bias scores correlate directly with the IAT results of healthcare professionals rather than the general population [76].

Implicit racial biases predict Black infant mortality

Our findings show that state-level implicit racial bias does indeed predict higher infant mortality rates for Black communities. These findings are consistent with previous research on the relationship between implicit bias and Black infant mortality. As previously mentioned, Orchard and Price [66] found that county-level implicit bias was correlated with negative birth outcomes for Black communities, with lower birth weight and higher preterm births in counties with higher rates of implicit bias, though they did not examine infant mortality.

Importantly, our findings corroborate previous literature on the impact of implicit bias on other health indicators within Black communities in the United States. Our team found that higher state-level implicit bias accounted for worse mental health outcomes for Black Americans. More specifically, we found that implicit bias contributes to increased suicide rates and drug-induced mortality for Black Americans [31, 77]. Further, implicit bias has been suggested to be a contributing factor in maternal mortality and morbidity; according to the *Centers for Disease Control and Prevention National Pregnancy Mortality Surveillance System*, between 2007–2016, Black women were more than three times as likely to die during pregnancy than White women, and many studies have identified implicit bias as a factor (e.g., [69, 74]. However, much of the effects of implicit biases are felt outside of the institution of healthcare as well and should be considered.

Implications: Our ethical duty

The findings point out the urgent need for systemic changes within healthcare to address bias and improve patient outcomes. Increasing the admission of physicians of color, particularly Black physicians, into medical schools and other healthcare disciplines is essential to bridging the representation gap and fostering trust in underserved communities. Additionally, culturally-informed training should become a cornerstone of medical education, equipping providers with the skills to recognize how conditions manifest across different skin tones and to navigate the cultural nuances that influence patient care [33]. Comprehensive anti-racist training must also be prioritized, with a focus on addressing microaggressions, which often serve as barriers to care and exacerbate health inequities [61, 91–94, 96]. Beyond individual education, professional healthcare organizations must actively prioritize social justice, embedding equity in their policies and practices while holding institutions accountable for combating discrimination within the field. Together, these measures represent a path toward reducing disparities and achieving equitable, high-quality healthcare for all.

Limitations

The limitations of the BW-IAT have been discussed by the authors previously (i.e., [31]). More specifically, limitations include the comparative nature of the BW-IAT, and thus an inability to speak with certainty about test takers' biases towards White or Black groups as a single ethnoracial category, and potential issues surrounding the representativeness of the BW-IAT sample to the national US population.

In addition, while White infant mortality and explicit racial biases were controlled for in our analysis, there may be extraneous/third variables associated with both implicit/explicit bias as well as infant mortality that are not. For example, it has been suggested that health insurance coverage, rurality of residence, and medical service availability, among others, could play a role in the observed associations. To address concerns that the relationship between anti-Black implicit bias and infant mortality rate is better accounted for by socioeconomic status, this article's authors ran a supplementary analysis. Specifically, we examined a similar hierarchical linear model for the sample year 2019, in which we accounted for per capita state median income differences between Black and White households (U.S. [82, 83]). This supplementary model suggested median income difference accounted for only an additional variance of 2% in Black infant mortality rate (see Supplementary Materials Table S2 for details). However, differential access to income, education. and lucrative jobs is not independent from racism, and is arguably a result of it [51]. Nonetheless, future researchers might identify third variables that could account for these differences that are not racism-related.

Conclusion

This article explored anti-Black bias within the United States among the general public and health care professionals. Our findings show that not only do most ethnoracial groups possess an implicit preference for White over Black individuals in the United States, but that healthcare professionals carry similar levels of implicit biases compared to the general American population. We also examined the connection between anti-Black implicit biases on the health and longevity of Black communities. Using infant mortality rate as an indicator of health, we found implicit racial biases predict poor health outcomes in Black American infants. Said findings speak to the need for awareness of and interventions targeting implicit biases, across all ethnoracial groups. Moreover, these findings highlight a need for additional work characterizing the ripple effect of harm within Black communities originating from healthcare professionals and the systems that maintain inequities.

Lower BW-IAT Bias Scores among healthcare professionals are found specifically in states with the highest representation of Black physicians and better health outcomes among Black individuals. Importantly, these scores are more strongly correlated with the IAT results of healthcare professionals rather than the general population, underscoring the pivotal role of physician attitudes in shaping patient care. These findings suggest that state-level policies or initiatives—such as recruitment efforts for Black medical students, targeted anti-bias training, or community engagement programs—may contribute to these outcomes and offer a roadmap for reducing disparities in other regions.

Abbreviations

ANOVA	Analysis of Variance
BW-IAT	Black-White Implicit Association Test
CDC	Centers for Disease Control and Prevention
CI	Confidence interval
COVID-19	Coronavirus disease 2019
IAT	Implicit Association Test
IMR	Infant mortality rate
IRB	Internal Review Board
MRS	Modern Racism Scale
N	Sample size
PI	Principal investigator
Std. Deviation	Standard deviation
WONDER	Wide-ranging Online Data for Epidemiologic Research

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12910-025-01228-y.

Supplementary Material 1.

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Authors' contributions

SGR, SM, MMM, and DS drafted the Introduction, Method, Results, and Discussion. SGR & SF prepared the Figures. SGR and MTW did the analyses. SF and MTW finalized the Discussion. All authors contributed to the main manuscript text and reviewed the manuscript.

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Data availability

The data is freely available from the Centers for Disease Control and Prevention's Wide-ranging Online Data for Epidemiologic Research (CDC WONDER) and Project Implicit (https://osf.io/52qxl/).

Declarations

Ethics approval and consent to participate

Participants from Project Implicit received informed consent prior to participation, and the study was approved by the University of Virginia IRB (PI: Dr. Bethany Teachman). This study complied with the Declaration of Helsinki.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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