Evidence of Covariation Between Regional Implicit Bias and Socially Significant Outcomes in Healthcare, Education, and Law Enforcement

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Contents

Abstract

When viewing the state of the world today, social and behavioral scientists face a puzzling inconsistency: how can it be that evidence of discrimination persists in all significant aspects of life – from housing and jobs to healthcare and law enforcement – even though individuals and institutions adamantly stand for equality? Over the past two decades, research has demonstrated that at least

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part of the answer to this puzzle can be attributed to the *implicit* nature of biases – attitudes, beliefs, and identities that are less conscious and controllable but that nevertheless exist and shape behavior. Today, it is taken as a given that evidence is strong and substantial for the presence of implicit bias in the minds and behaviors of *individuals*. This chapter, however, reviews an emerging body of research that uses large-scale, aggregated data across millions of tests of implicit attitudes and beliefs to understand outcomes of socially significant *systemic* behaviors ranging from the police use of lethal force to infant healthcare to school suspensions and discipline. Methodologically, the studies quantify social and psychological processes acting in the real world and introduce data of unprecedented scope across geography and time. Theoretically, both the approach and findings of this research underscore a new meaning of the term *systemic discrimination* that recognizes how implicit bias both shapes and is shaped by broad structural systems and outcomes.

Keywords

Education · Discrimination · Healthcare · Implicit attitudes · Implicit bias · Implicit stereotypes · Policing · Systemic discrimination

For students of the social sciences, the term "bias" is commonly used to capture at least two distinct meanings. In one sense, a bias refers to a behavior or cognition that deviates from accuracy. If two individuals of differing ethnicity (e.g., Asian and White) are both US citizens, both born in the United States, and both live in the United States, then it is accurate to consider them both to be American. Yet measures of implicit beliefs indicate that one group is perceived to be more American: White Americans are more "American" than Asian Americans (Devos and Banaji 2005; Devos and Mohamed 2014). Such a belief can therefore be said to be biased in the sense that it deviates from accuracy. A second meaning of bias refers to thoughts or behavior that deviates from one's own consciously stated values. If a company's stated, conscious values dictate that the best candidate should be hired and yet the evidence shows that male candidates are repeatedly hired even when female candidates are equally qualified (Moss-Racusin et al. 2012), then that behavior is taken to be biased because it is inconsistent with stated ideals.

Both forms of bias – deviations from accuracy or from ideals – are known to be prevalent in shaping cognitions and behaviors (Pager 2007). First, evidence of bias can be found in experimental studies, in which researchers systematically manipulate some expected causal effect on behavior (e.g., the gender of a candidate) and then assign participants to one of several experimental conditions. As an example, participants (drawn from a population of scientists) were randomly assigned to see either a male or female applicant profile for a science lab manager position (Moss-Racusin et al. 2012). Systematically, participants were more likely to recommend that the male applicant be hired, given a higher salary, and given more mentorship compared to the identical and equally qualified female applicant. Similarly, participants in another study were more likely to hire a male candidate to complete an arithmetic task over an identical female candidate and, most surprisingly, even continued to select the male candidate after receiving evidence that women outperform men on the task (Reuben et al. 2014).

A complementary method – audit studies, also called "experimental field studies," in which real-world respondents do *not* know they are in a study and may therefore be less prone to experimenter demand effects (Pager 2007) – has also been used to reveal biased behavior toward targets differing on race, sexual orientation, criminal history, and more. For instance, counselling professionals were more likely to initiate further counselling treatment for a potential client if the hypothetical client was White rather than Black (Shin et al. 2016), and hiring managers were more likely to call back an applicant if the applicant was White rather than Black (Bertrand and Mullainathan 2004). Applications from ostensibly heterosexual job candidates sent to real hiring managers across 1,769 jobs were more successful than applications from identically qualified but openly gay candidates (Tilcsik 2011). And hypothetical job candidates that listed a previous criminal record were less likely to receive a call back than identical candidates without a criminal record, especially if the candidate with a criminal record was Black (Pager 2003).

Because experiments and audit studies control for all features of the hypothetical candidates except the candidate's salient identity (e.g., their race, gender, or sexual orientation), the evidence conclusively shows the existence of *biased* behaviors. That is, despite respondents stated ideals for equality or for accuracy, respondents in all studies were more likely to treat a candidate favorably (e.g., hire them, offer them medical treatment) when the candidate came from a typically preferred, high-status, or dominant social group (e.g., male, White, straight), relative to a typically dispreferred, low-status, or minority social group (e.g., female, Black, gay).

Crucially, this evidence for biased behavior and discrimination is not an isolated phenomenon among a few "bad apples" – a common explanation that suggests bias would be solved if the few "bad apples" were rooted out. Although individual differences no doubt exist in the frequency or severity of discriminatory behavior, the bulk of the evidence shows that such behavior is far more pervasive than explained by the "few bad apples" account. *Both* men and women favored the male over female candidate for a STEM job (Moss-Racusin et al. 2012); hiring managers across most US states favored a straight over gay job candidate (Tilcsik 2011); and hiring managers across most occupations favored a White over Black candidate, generally regardless of the job requirements (Bertrand and Mullainathan 2004).

The widespread pervasiveness of discriminatory behaviors becomes difficult to square with the finding (often from these very same studies) that *few people* explicitly endorse biased beliefs. For example, the very same individuals whose behavior reveals unequal medical decisions to Black and White patients most often express equitable explicit beliefs about Black and White patients (Green et al. 2007), and despite aforementioned evidence of gender discrimination in hiring, most people explicitly endorse the belief that women are *more* intelligent than men (Storage et al. 2020). Such discordant results prompt the question: if discriminatory behaviors cannot be entirely attributed to *explicit* attitudes and beliefs, *what is the source of such discrimination?* What explains this inconsistency between expressed beliefs and revealed biases?

Over the past two decades, research and theory on *implicit* attitudes and beliefs – attitudes and beliefs that are less accessible to conscious introspection and deliberate control (Greenwald and Banaji 1995) – have provided a compelling answer to the inconsistency between pervasive discrimination and low explicit biases. These discriminatory behaviors are being shaped and maintained, at least in part, by underlying *implicit* biases that exist and persist in the minds of individuals and in the culture. Indeed, as reviewed below, the evidence that implicit attitudes and beliefs predict individual behaviors (e.g., hiring decisions, seating distance) is substantial, today stemming from hundreds of studies reviewed in depth across major meta-analyses (Greenwald et al. 2009; Kurdi et al. 2019; Oswald et al. 2013).

But the role of implicit bias in behaviors does not stop with the individual decision-maker. In line with evidence showing the pervasiveness of discriminatory behaviors across most people, the social sciences have long recognized that bias and discrimination are widely embedded in the broader *systems* of society – systems of healthcare, policing, education, and more. Recently, using massive data of implicit attitudes and beliefs aggregated across millions of respondents, an emerging body of studies has begun to quantify the relationship between implicit bias and such socially significant *systemic* outcomes, whether racial gaps in infant health outcomes (Orchard and Price 2017) or the gender gap in science and math achievement (Nosek et al. 2009). These studies have not yet been summarized together. Thus, the goal of the current chapter is to provide an introduction to this new and growing empirical evidence that reveals the coupling between implicit cognition and systemic discriminatory outcomes.

A Brief Definition of Implicit and Explicit Attitudes and Beliefs

In 1995, building from a wealth of literature showing that humans' conscious, introspective minds are not the whole story of cognition (Nisbett and Wilson 1977), Greenwald and Banaji (1995) proposed a distinction between two forms of social attitudes and beliefs. On the one hand, there are *explicit* attitudes and beliefs – thoughts and feelings about social groups that are relatively more controlled, deliberate, and reflective of conscious, personal values. On the other hand, there are *implicit* attitudes and beliefs – thoughts and feelings about social groups that are relatively automatic, uncontrolled, and less accessible to introspective access. In short, one cannot easily look into one's own mind to understand or control these kinds of implicit cognitions.

The distinction in format between implicit and explicit attitudes and beliefs also requires a distinction in measurement. Explicit attitudes and beliefs, being controlled and accessible to cognitive awareness, can be self-reported through the typical tools of social surveys or Likert items. One can ask respondents "do you prefer elderly people or younger people?" or "to what extent do you think younger people are smarter than elderly people?" and receive answers that reflect explicit cognitions. Implicit attitudes and beliefs, however, being less accessible to conscious awareness and control, inherently cannot be measured in such direct ways. Instead, implicit attitudes and beliefs are measured through *indirect* measures, including response time tasks such as the widely used Implicit Association Test (Greenwald et al. 1998); for a recent review, see (Greenwald et al. 2020). Today, in the more than two decades that have followed Greenwald and Banaji's (1995) initial conceptualization, the evidence continues to be compelling for both explicit and implicit bias (Greenwald and Banaji 2017), revealing that they are related but distinct mental constructs (Bar-Anan and Vianello 2018; Cunningham et al. 2001; Nosek and Smyth 2007).

The Relationship of Implicit Bias and Individual Discriminatory Behavior

Implicit and explicit attitudes and beliefs don't sit idle in the mind but, rather, also reveal themselves in behaviors. When studies of the relationship between implicit bias and behaviors are well-powered and performed with precision, the correlation between an individual's IAT score and their discriminatory behavior is of moderate to large magnitude, $r \sim 0.40$ (Kurdi et al. 2019), a correlation above the majority of effect sizes in psychology (Funder and Ozer 2019). Moreover, though *both* implicit and explicit cognitions often relate to individual's behaviors, the two cognitions show incremental predictive validity, meaning that each explains variance above and beyond the other (Kurdi et al. 2019), lending confidence to the unique and complementary role played by implicit bias.

Notably, the majority of evidence for such relationships between implicit bias and behavior comes from studies of *individuals*. As an example of such a study, Green et al. (2007) assessed individuals' implicit pro-White/anti-Black attitudes and found that stronger implicit pro-White/anti-Black attitudes correlated with less treatment for hypothetical Black patients with cardiovascular disease ($B = -0.19$) but more treatment for White patients ($B = 0.17$). Over hundreds of such studies, reviewed across three meta-analyses (Greenwald et al. 2009; Kurdi et al. 2019; Oswald et al. 2013), implicit attitudes and beliefs help explain why some people act in more or less discriminatory ways. Recently, however, investigations have turned to a new type of discriminatory behavior that is revealed through socially significant behaviors *aggregated* across millions of people.

The Relationship of Implicit Bias and Systemic Discriminatory Behaviors: An Overview

Prompted, in part, by the new availability of big data documenting implicit bias across millions of people around the globe (through the Project Implicit demonstration website, https://implicit.harvard.edu), the past few years have seen more than a dozen studies testing the role of aggregated implicit bias in both shaping and being shaped by systemic outcomes. In addition to the theoretical implications elaborated throughout this chapter, the new focus on aggregated systems or behaviors offers methodological advantages to identify the role of implicit cognition in discrimination. Specifically, aggregation allows for greater precision in the estimates of both implicit cognition and systemic behaviors and can help reveal the underlying strong relationships that may previously have been obscured by imprecise and noisy estimates taken from single individuals (Payne et al. 2017, 2022). Additionally, big data allows for investigations of implicit cognition in real-world behaviors measured in vivo and at scale, greatly improving ecological validity and enabling more generalizable conclusions across broader samples and geographic locations.

Nearly all of the studies examining aggregate relationships between implicit cognition and behavior have adopted correlational designs: implicit attitudes or stereotypes are aggregated across geographic locations (counties, states, countries, etc.) and correlated with aggregated systemic outcomes (e.g., rates of lethal force by police, gender gaps in math tests) across those same geographic regions, while controlling for a variety of structural factors (e.g., demographic representation, GDP, etc.). Because such correlations are generally noncommittal regarding the *direction* of the relationship, the studies can be grouped into two complementary approaches in thinking about the meaning of the relationship. First, there is a set of studies (see Table 1) that take discriminatory systemic behavior as the dependent variable to be explained by measures of implicit bias. For instance, this sort of study may look at how country-level differences in implicit gender stereotypes help explain country-level differences in the outcome of gender gaps in standardized tests (Nosek et al. 2009). Because the goal in this chapter is to show how implicit cognition can illuminate systemic discrimination, this first set of studies constitutes the primary focus. Below, the studies are organized and reviewed according to the outcome across socially significant domains of (1) education, (2) healthcare, and (3) policing.

A second type of study in this area considers the relationship between implicit bias and discriminatory systemic behaviors by flipping the equation and identifying the sources of implicit bias itself as the outcome (i.e., IAT scores become the dependent variable). For instance, studies of this type may look at how country-level differences in the representation of fat people help explain the country-level differences in the implicit anti-fat/pro-thin attitudes (Marini et al. 2013) or how demographic and physical features of the environment (e.g., the number of mental healthcare providers or the number of lakes) predict the magnitude of implicit biases (Hehman et al. 2020). Although these studies primarily seek to understand the sources of implicit bias (rather than the contribution of implicit bias to behaviors), the correlational nature of the studies means that they can still provide complementary insight into the coupling of implicit cognition and specific discriminatory behaviors. This group of studies is reviewed in the final section.

Table 1 Selected studies using implicit cognition to explain systemic discriminatory behaviors

Authors	Geographic aggregation level	IAT topic	Societal outcome	Key result
Nosek et al. (2009)	Countries	Gender-science IAT (male-science/ female-arts)	Eighth grade standardized math/ science testing	Stronger male-science/female-arts associations correlated with larger gender gaps on 8th grade testing, $r = 0.60$
Riddle and Sinclair (2019)	US counties	Race attitude IAT (Black-bad/White-good)	Black-White gap in school discipline (i.e., out-of-school suspension, in-school suspension, law enforcement referrals, expulsions, and in-school arrests)	Stronger pro-White/ anti-Black implicit attitudes correlated with larger Black-White gaps in school discipline
Chin et al. (2020)	US counties	Race attitude IAT (Black-bad/White-good) among teachers	Black-White gap in standardized testing scores (3rd–8th grade for math and English) and school discipline	Stronger pro-White/ anti-black implicit attitudes among teachers correlated with larger Black-White gaps in standardized test scores. Counties with +1 SD attitudes had +0.037 SD in the Black/White gap or 6.7% of the test gap
Chetty et al. (2020)	US counties	Race attitude IAT (Black-bad/White-good)	Upward mobility among Black and White boys and girls (roughly defined as making more money than their parents)	Stronger pro-White/ anti-Black implicit attitudes correlated with less upward mobility among black boys and girls. Black boys and girls living in counties with +1 SD in implicit bias earn ~0.8 percentiles less income when they grow up
Hehman et al. (2018)	US community-based statistical area (CBSA)	Race attitude IAT (Black-bad/White-good) and stereotype IAT (Black-weapon/ White-object)	Police lethal force toward Black Americans versus White Americans	Stronger pro-White/ anti-black implicit attitudes correlated with greater disproportionate use of police lethal force, $B = 0.35$

(continued)

Table 1 (continued)

Authors	Geographic aggregation level	IAT topic	Societal outcome	Key result
Leitner et al. (2016)	US counties	Race attitude IAT (Black-bad/White-good)	Black American and White American death rates from circulatory diseases	Among black Americans, stronger pro-Black/anti-White implicit attitudes correlated with higher death rates from circulatory diseases, $B = 0.11$
Leitner et al. (2018)	US states	Race attitude IAT (Black-bad/White-good)	State spending on Medicaid disability programs (more likely to assist Black than White Americans)	Among White Americans, stronger pro-White/anti-Black implicit attitudes correlated with less spending on Medicaid, $B = -0.33$
Orchard and Price (2017)	US counties	Race attitude IAT (Black-bad/White-good)	Black-White gap in infant low birth weight and preterm births	Stronger pro-White/anti-black implicit attitudes correlated with larger Black-White gaps in infant birth weight and preterm births. Counties with +1 SD attitudes had 14% larger gap in low birth weight and 29% larger gap in preterm births
Giasson and Chopik (2020)	US states	Age attitude IAT (old-bad/young-good)	Health behaviors (e.g., smoking, diet) and health (e.g., self-reported physical and mental health) among adults aged 65+	Stronger pro-young/anti-old implicit attitudes correlated with worse health outcomes among elderly, $B = -0.29$
Stelter et al. (2022)	US counties	Race attitude IAT (Black-bad/White-good) and stereotype IAT (Black-weapon/White-object) among White respondents	Police traffic stop rates of Black drivers relative to Black population. Specifically, percentage of Black drivers stopped (from all drivers stopped) minus	Stronger pro-White/anti-Black implicit attitudes among White respondents correlated with greater racial disparities in the proportion of traffic stops, $r = 0.30$ (for

(continued)

Table 1 (continued)

Authors	Geographic aggregation level	IAT topic	Societal outcome	Key result
			percentage of Black people in population	counties with >150 respondents) to $r = 0.07$ (for all counties). No correlations between implicit race stereotypes and racial disparities in police traffic stops
Ekstrom et al. (2022)	US counties	Race attitude IAT (Black-bad/White-good)	Police traffic stop rates of Black versus White drivers. Difference in percentage of Black drivers stopped (from Black driving-aged population) versus percentage of White drivers stopped (from White driving-aged population)	Stronger pro-White/anti-Black implicit attitudes correlated with greater racial disparities in the proportion of traffic stops, $r = 0.31$
Johnson and Chopik (2019)	US states	Race stereotype IAT (Black-weapon/White-object)	Centers for Disease Control statistics on weapon-related deaths among Black and White Americans	Stronger Black-weapon/White-object implicit stereotypes were associated with greater rates of Black people dying by weapon violence, $B = 0.26$, and lower rates of White people dying by weapon violence, $B = -0.89$

Disparities in Education and Opportunity: Standardized Testing, School Discipline, and Economic Mobility

In the first paper to use aggregated Project Implicit data obtained from individual minds, Nosek et al. (2009) investigated whether country-level differences in implicit male-science/female-arts stereotypes correlated with gender gaps on 8th grade standardized mathematics achievement tests. The authors found that, across hundreds of thousands of respondents aggregated across 34 countries, those countries with higher implicit associations between male-science/female-arts also showed larger gender gaps (where boys outperformed girls) on standardized science and math tests ($r = 0.6$, or $R^2 = 0.36$). Additionally, this relationship persisted after controlling for country-level explicit associations, underscoring the incremental predictive validity of implicit cognitions in explaining a socially significant outcome of gender differences in performance.

A few years later, a similar analysis examined the correlation between country-level implicit male-science/female-arts stereotypes and the representation of women in the STEM workforce and STEM tertiary education (Miller et al. 2015). Although this study technically used the implicit stereotypes as the outcome rather than the predictor, we interpret the results alongside the study by Nosek and colleagues because of the correlational nature of the study and the fact that gender representation in STEM could theoretically be both a predictor and an outcome of bias (Charlesworth and Banaji 2019). Indeed, Miller and colleagues found that countries with higher representation of women in STEM tertiary education had weaker implicit male-science/female-arts stereotypes ($R^2 = 0.26$), with similar effects observed for explicit stereotypes ($R^2 = 0.21$). Additionally, women's representation in STEM appeared to be a key variable in the relationship between achievement and implicit stereotypes: in fact, when women's representation in STEM was controlled for, the relationship between achievement and implicit stereotypes was eliminated. Although there are individual bivariate correlations between country-level implicit bias and the outcomes of gender gaps in STEM achievement, the role of representation or prevalence of a minority group appears to be a mediating, explanatory variable.

Following these early studies on gender gaps in STEM achievement and representation, recent studies have looked to also explain *race* gaps in educational achievement and school discipline. Specifically, Chin et al. (2020) found that higher county-level pro-White/anti-Black implicit bias among *teachers* (a sufficient subsample of the Project Implicit data) correlated with larger Black/White gaps in standardized math and English testing for 3rd–8th grade students (see also Pearman 2021). Furthermore, county-level relationships also emerged between teacher's implicit bias and Black/White gaps in student *discipline*, such that high-bias counties had greater disproportionate discipline of Black students across K-12 (Chin et al. 2020; Riddle and Sinclair 2019).

How do these regression estimates (see Table 1) translate into real-word numbers of harm done to young people? Using the predicted probabilities from Chin et al. (2020), we see that in counties where teachers' IAT D scores are at the mean (D = 0.36), approximately 13% of Black students receive in-school suspensions, compared to only 5% of White students; in counties with lower IAT D scores (D = 0.15; a threshold typically used for denoting "no bias"), the race difference shrinks such that approximately 8% of Black students and 4% of White students receive in-school suspensions. Cook county in Illinois (one of the states that best represents the American electorate) has a population of 5.15 million, of which 22% are school-aged (1.13 million), 65% are White, and 24% are Black. If such a county had average IAT bias (D = 0.36), this means that approximately 35,100 Black school-aged children would receive in-school suspensions; if, on the other hand, such a county had lower IAT bias (D = 0.15), we would expect 21,600 Black children to receive in-school suspensions. In other words, nearly 13,500 Black children are likely to receive in-school discipline in a high IAT bias county than an average IAT bias county. Ultimately, such consequences of large racial disparities in school suspension and discipline among counties with high implicit race bias appear particularly poignant because early experiences of school discipline interrupt future opportunity and increase interactions with policing and prisons, creating the so-called "school-to-prison" pipeline (Smith 2009).

Finally, implicit Black/White race attitudes also have effects for future opportunity in income earning more broadly. That is, when implicit race attitudes are aggregated within US census tracts, greater aggregated county-level implicit biases are found to correlate with less upward social mobility (i.e., they are less likely to make more money than their parents) among historically disadvantaged groups (Chetty et al. 2020). Black American boys or girls living in a high implicit bias neighborhood have a lower chance of upward mobility and income earning than if they had, by luck or coincidence, grown up in a relatively low implicit bias neighborhood. In other words, the so-called American Dream of upward mobility appears to only be true for some types of children living in relatively unbiased contexts.

Why are these sorts of results interpreted as "discrimination"? Of course, an outcome such as the aggregated math testing gap between boys and girls in an entire country does not arise from any single actor producing discriminatory behavior (e.g., a specific biased examiner or teacher). Rather, the outcomes arise from the systemic presence of beliefs that are so pervasive that we refer to them as being "in the air." We use this analogy in the same way that Claude Steele referred to "a threat in the air" when explaining women's underperformance on mathematics tests after stereotypes were evoked (Steele 1997). This air reveals itself, for example, through ambient cues that signal who belongs in a certain field (Cheryan et al. 2009) or in the stereotypes revealed in the word associations across billions of words constituting humans' collective language (Caliskan et al. 2016; Charlesworth et al. 2021). In turn, such systemic cues may evoke stereotype threat among girls (Spencer et al. 1999) or stereotype lift among boys (Walton and Cohen 2003). These studies thus build an understanding that stereotypes are widely embedded in society and therefore have the potential to shape the discriminatory behaviors of all those interacting in that society. This spread may be especially true for *implicit* stereotypes (Payne et al. 2017) because such hidden, indirect beliefs can pervade and persist more easily in the face of conscious values and ideals against them. In this way, the results summarized above, and in the remainder of the chapter, give new meaning to the idea of systemic discrimination: they quantify how discriminatory outcomes arise from the "air" of implicit bias aggregated across thousands of people in a region.

Disparities in Healthcare: Medicaid Spending, Death Rates, and Infant Health Outcomes

A second group of outcomes in studies of aggregated implicit bias centers on the domain of health, including healthcare spending, rates of disease, and infant health. For instance, Leitner et al. (2018) used health data on US state-level Medicaid spending from across the United States to examine whether states that are lower in implicit anti-Black attitudes also had greater Medicaid spending. Because Medicaid spending is more likely to preferentially affect Black than White Americans due to persistent and significant racial gaps in income inequality and other health insurance coverage (Smedley et al. 2003), state investment in programs like Medicaid is, in part, a reflection of their intention to reduce racial inequality. In line with this perspective, states with higher implicit anti-Black attitudes were also found to be lower Medicaid spending states (Leitner et al. 2018), with a likely consequence of limiting equitable access to healthcare and thus compromising overall health. Indeed, implicit biases have recently been linked directly to health outcomes: Giasson and Chopik (2020) found that US states with higher implicit age bias (anti-old/pro-young) revealed worse health outcomes among elderly adults aged 65+. That is, states with higher implicit age biases were also those states in which elderly adults reported, among other indicators, having physical activity limitations, feeling physically unhealthy, experiencing mental distress, or engaging in unhealthy behaviors (e.g., insufficient sleep, smoking, binge drinking).

Perhaps even more consequential, implicit race bias has been shown to correlate directly with *death* rates, not only of the targets of bias (e.g., death rates among Black Americans in places where White Americans hold high bias) but also the holders of those biases (Leitner et al. 2016a, b; Zestcott et al. 2021). For instance, counties in which White respondents held stronger pro-White/anti-Black attitudes were also counties with higher death rates from cardiovascular disease among Black respondents ($B = 0.074$) and among White respondents ($B = 0.081$; Zestcott et al. 2021). The additional stressors that arise from living in areas "polluted" by bias thus appear to have consequences for health throughout the population.

Finally, looking at health outcomes earlier in the life span, researchers have investigated the relationship between county-level pro-White/anti-Black implicit attitudes and the persistent racial gap in infant health outcomes in the United States (Orchard and Price 2017). Because of a complex set of compounded stressors including lower prenatal healthcare and nutrition and repeated experiences of discrimination, Black American mothers in the United States are 1.6 times more likely to have preterm births and twice as likely to give birth to infants with low birth weight. Using aggregated county-level implicit race attitudes, Orchard and Price quantified bias that may shape these racial gaps in health outcomes. The authors showed that, in low-bias counties (those at -1 standard deviation below the mean), approximately 15% of births to Black mothers were preterm, while in high-bias counties (+1 SD above the mean) approximately 17% of births to Black mothers were preterm. For a representative county like Cook County, IL, with about 5,000 births to Black mothers in a given year, even this 2 percentage point difference would translate into *100 more preterm Black babies* born if that county had high versus low bias. Given the social and healthcare costs associated with preterm birth in the United States (Beam et al. 2020), the cost difference would be approximately 7.6 million dollars between a high- and low-bias county. Moreover, considering that early health consequences from aggregated race bias have also been demonstrated on outcomes ranging from the likelihood of Black foster children being adopted (Bell et al. 2021) to Black and Latinx youth's brain development (Hatzenbuehler et al. 2021), it becomes clear that region-level implicit biases play a powerful role in shaping and maintaining health outcomes from birth to death.

Disparities in Policing: Lethal Force and Traffic Stops

Perhaps one of the starkest displays of life-or-death consequences emerges in the relationship between pro-White/anti-Black implicit attitudes and the disproportionate use of police lethal force toward Black Americans (Hehman et al. 2018). First, using fact-checked data from the *Guardian*'s reports of US individuals killed by police, Hehman and colleagues observed that Black Americans constituted approximately 23% of all deaths from police lethal force but only 12% of the population, indicating disproportionate overrepresentation in deaths at the hands of police. The new result is that disproportionate overrepresentation in lethal force *can be explained by the strength of implicit bias in a region*: the greater the implicit anti-Black/pro-White attitudes and implicit Black-weapon stereotypes in a region, the greater the likelihood of lethal use of force by police toward Black Americans. For instance, a Black American who happened to be living in a region with relatively high implicit Black-weapon/White-object stereotypes was more likely to be killed by police than if they resided in a region with relatively lower implicit stereotypes (see also Correll et al. 2007; Johnson and Chopik 2019).

The *possibility* of police use of lethal force begins at the moment of police interaction; disproportionate rates of police and civilian encounters, such as racial differences in the rates of traffic stops, can give rise to later disparities in lethal force (such as in the cases of Dante Wright or Philando Castile). Indeed, two recent papers examined the role of aggregated implicit bias in accounting for the fact that Black drivers are stopped by police more often than White drivers in the United States (Ekstrom et al. 2022; Stelter et al. 2022). Both studies found an association such that regions with higher implicit pro-White/anti-Black attitudes also had higher rates of disproportionate traffic stops for Black drivers. For instance, inspecting the data reported by Ekstrom and colleagues, in a given county with high implicit race bias (at the maximum IAT D score), the predicted model estimates show a racial difference in stop rate scores of 79, which would translate, for example, as police stopping 179 Black drivers (per 100 Black driving-aged residents, i.e., many drivers are stopped more than once) but 100 White drivers (per 100 White driving-aged residents, i.e., drivers are stopped based on their population rate). In contrast, a representative low-bias county (at the minimum IAT D score) had a stop difference score that of −29, which can translate into 71 Black drivers being stopped (per

100 Black driving-aged residents, i.e., some drivers are never stopped) and 100 White drivers (per 100 White driving-aged residents). Ultimately, despite many analytical and theoretical differences between the two papers (e.g., how they operationalized traffic stop rates, how they controlled for demographics), the consistency of the link between regional racial attitudes and consequential police-civilian interactions highlights the robustness of the aggregate approach to understanding human behavior (Payne and Rucker 2022).

Examining Implicit Bias as the Outcome Explained by Systemic Predictors

Implicit bias not only shapes systemic outcomes across aforementioned domains of education, healthcare, and policing but is also *shaped by* the demographics and structural features of the environment. Indeed, knowing that the level of implicit biases varies meaningfully in magnitude across geography, the question naturally arises: where does such variation come from in the first place? A handful of recent studies have begun to shed light on the answer by using aggregated implicit attitudes and beliefs as the dependent variables predicted from a range of systemic predictors. The majority of these studies has focused on the role of regional *demographic representation* – the frequency or diversity of specific groups such as Black Americans or fat people – to explain geographic variation in implicit bias. In some cases, the relationship is intuitive and aligns with expectations of intergroup contact theories, in which greater intergroup contact will correlate with less bias (Allport 1954; Pettigrew and Tropp 2006). For instance, higher frequency of Asian Americans in US metropolitan areas was found to correlate with lower implicit stereotypes in the association of Asian American with "foreign" and European American with "American" (Devos and Sadler 2019); and, most compelling, temporal fluctuations in Asian American representation and diversity were found to correspond with fluctuations in implicit Asian American-foreign biases (Devos et al. 2021). Similarly, for implicit anti-gay/pro-straight attitudes, higher self-reported personal contact, as well as higher county-level frequencies of sexual minorities, correlated with lower implicit bias (MacInnis et al. 2017). And, finally, as noted above, higher country-level representations of women in STEM correlated with lower implicit male-science/female-arts stereotypes (Miller et al. 2015).

However, the relationship between demographic representation and implicit bias is not always straightforward. In fact, a higher representation of fat people in a country (presumably allowing for more outgroup exposure) was found to correlate with *higher* country-level implicit anti-fat/pro-thin attitudes (Marini et al. 2013). Additionally, greater frequency of Black Americans in a US state was found to correlate with higher state-level implicit pro-White/anti-Black attitudes among White Americans (Rae et al. 2015, 2022; but see O'Shea et al. 2019). Perhaps these counterintuitive findings could be explained by considering not just the quantity of intergroup contact but also the *quality* of that contact (Paluck et al. 2018). Indeed, areas with higher representations of a marginalized group may counterintuitively result in more *negative* intergroup interactions, thereby perpetuating negative implicit bias. More nuanced insights into the relationship of representation and aggregate implicit bias may therefore come from considering not only raw frequencies of minority representation but also the integration and variety of minority groups. For instance, when looking at multiple indicators of context racial diversity (e.g., integration, prevalence, and variety of groups), implicit stereotypes associating Black Americans with weapons were indeed found to be weaker in US metropolitan areas with greater integration and a larger variety of minority groups (Sadler and Devos 2020).

It is also notable that the relationships between demographic representation and implicit bias have deep and complex roots in the *historical* patterns of representation across the country. Recent data show that the greater the proportion of enslaved to free people in the southern states in the 1860s, the greater the implicit anti-Black/pro-White bias among White Americans in those areas today, 160 years later (Payne et al. 2019). In fact, the correlation between historical rates of slavery from 1860 and state-level implicit race bias today ($r = 0.87$) was nearly three times larger than the relationship between contemporary Black American representation and implicit race bias ($r = 0.32$). Studies like this suggest that, when one thinks about group-based discrimination, one must also think about their effects as extending forward in time, translated through the continuous presence of social structures and reminders of inequality (e.g., the presence of confederate monuments; Payne et al. 2019). The result also suggests that today's Americans who live in regions of greater historical legacies of slavery must be acquiring the particles embedded in the biased air. Systemic discrimination is a useful term in this case as it helps capture the pervasiveness of discriminatory treatment extending across space and time.

Indeed, *time* has featured as an important variable in several recent studies examining the temporal relationships between implicit bias and macrolevel societal variables. For instance, although the implicit Asian American = foreign stereotype had been slowly decreasing over the past decade, racial slurs tweeted during the beginning of the Covid-19 pandemic were found to have reversed the trend and coincided with sharp spikes in implicit bias (Darling-Hammond et al. 2020). Other data similarly suggest that levels of implicit bias fluctuate in response to the actions and events in the world – whether legislation (Ofosu et al. 2019), social movements (Sawyer and Gampa 2017), pathogens such as Ebola (Inbar et al. 2016), fat-shaming tweets (Ravary et al. 2019), or other group-targeting rhetoric (Charlesworth and Banaji 2022). These studies contribute to an understanding of the link between implicit bias and societal structures by showing that macrolevel events can shape the thoughts and feelings of respondents which, in turn, reshape the state of society.

Implications for Understanding Implicit Bias and Systemic Behaviors

The studies reviewed in this chapter belong to a new generation of research that holds the potential to develop a more robust understanding of the sources and consequences of *systemic* discrimination. Across more than a dozen studies, the evidence reveals relationships between aggregated implicit cognition across millions of individuals and socially significant outcomes ranging from academic performance to upward mobility to health and mortality. In the process, the findings also encourage an emerging perspective on implicit cognition as perhaps best understood as social representations that paradoxically are hidden from conscious awareness, yet pervasively embedded in the structures that surround us (Charlesworth and Banaji 2021; Payne et al. 2017). Recently, Payne et al. (2017) have summarized this new perspective in the "bias of crowds" model to suggest that individual measures of implicit bias are a noisy indicator of the true signal of bias embedded in the broader culture, and by aggregating across people, one can better capture that signal. Such a structural perspective of implicit cognition stands in contrast to the early notions that implicit measures can reveal a bona fide pipeline (Fazio et al. 1995) to an individual's trait-like personality or permanent individual inclinations (Greenwald et al. 1998). Instead, the mounting evidence reviewed here points more clearly toward the notion that implicit cognition reflects the thumbprint of the *culture* on the mind. While theorizing about implicit attitudes and beliefs as reflecting culture is not altogether unprecedented, what *is* new is the availability of large-scale data and analytic methods to *quantify* evidence for the operation of implicit bias in socially significant outcomes.

Concluding Remarks

The concept and measurement of implicit bias began in psychology but has since permeated many disciplines, from medicine (Green et al. 2007) to computer science (Caliskan et al. 2016) to business (Banaji et al. 2003) to law (Kang and Banaji 2006). Today, a particularly fruitful interdisciplinary approach has arisen from the intersection of psychology and those social sciences such as economics that are typically focused on larger units of society (Carlana 2019; Chetty et al. 2020). At this intersection, new combinations of variables are being studied that interweave measures of the thoughts and feelings inside individual minds with broader outcomes such as the opportunity of upward mobility, the likelihood of police shootings, or the health of infants. Evidence has also accumulated for the reverse relationships, in which structural variables, such as the frequency and diversity of demographic representations (e.g., of women, Black Americans), help shed light on the magnitude of implicit bias as an outcome itself.

Together, this emerging body of work shows the tight coupling between implicit bias at the level of the individual and socially significant outcomes at the level of society. The strength of relationships being what it is – with at least small-to-moderate effect sizes compounded over millions of people that experience hundreds of such interactions (Greenwald et al. 2015) – this evidence cannot be set aside. We, as researchers and as citizens, must take seriously the clear link between implicit bias and systemic discrimination. Moreover, these new studies remind us that discrimination is not always a simple person-to-person act but arises throughout the systems that shape the lives that inhabit these systems such as education, healthcare, or policing. Tackling discrimination therefore requires that one not only address individual decisions but also societal practices, systems, policies, and laws. With such goals, it is clearly an exciting and pressing time for social and behavioral scientists to collaborate in the study of implicit bias and discrimination. Such collaborations will consolidate the joint expertise in theory and methods to better understand the nature of the mind, socpety, and the way that each reflects and reinforces the other.

Cross-References

► Gender Based Discrimination in Health: Evidence from Cross Country
► Insights from Social Psychology: Racial Norms, Stereotypes, and Discrimination

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