Article

Social Psychological and
Personality Science
2021, Vol. 12(2) 156-164

DOI: 10.1177/1948550620909775
journals.sagepub.com/home/spp
SAGE

Using Environmental Features to Maximize Prediction of Regional Intergroup Bias

Eric Hehman[1], Eugene K. Ofosu[1], and Jimmy Calanchini[2]

Abstract

The present research adopts a data-driven approach to identify how characteristics of the environment are related to different types of regional in-group biases. After consolidating a large data set of environmental attributes (*N* = 813), we used modern model selection techniques (i.e., elastic net regularization) to develop parsimonious models for regional implicit and explicit measures of race-, religious-, sexuality-, age-, and health-based in-group biases. Developed models generally predicted large amounts of variance in regional biases, up to 62%, and predicted significantly and substantially more variance in regional biases than basic regional demographics. Human features of the environment and events in the environment strongly and consistently predicted biases, but nonhuman features of the environment and population characteristics inconsistently predicted biases. Results implicate shared psychological causes of different regional intergroup biases, reveal distinctions between biases, and contribute to developing theoretical models of regional bias.

Keywords

intergroup relations, prejudice/stereotyping, racism

A new front to understanding intergroup biases has opened in the past 5 years. Traditionally, research has focused on individual variability in bias. In contrast, recent work has examined the intergroup biases of populations. By geolocating participants and examining shared biases of people within the same geographic area, this approach examines between-*region* variation in bias and its outcomes. For instance, this approach has revealed that in regions where White people are more implicitly biased against Black people, more Black people are killed by police (Hehman et al., 2018). Other research adopting a regional approach has found links between regional intergroup biases and health (Leitner et al., 2016a, 2016b; Orchard & Price, 2017), segregation (Rae et al., 2015), ethnic diversity (Sadler & Devos, 2018), education (Riddle & Sinclair, 2019), and federal policy (Leitner et al., 2018; Ofosu et al., 2019).

Research investigating the relationships between regional intergroup bias and its consequences is important for a variety of reasons. First, this approach allows social scientists to examine the role of bias in consequential, real-world events (i.e., being killed by police, disciplinary actions in school) that are almost impossible to study in the lab with any degree of ecological validity. Second, while the magnitude of relationship between individual-level bias and behavior has tended to be meaningful but small (Greenwald et al., 2009; Kurdi et al., 2019; Oswald et al., 2013; Schmidt & Nosek, 2010), relationships between regional aggregates of bias and behavior appear to be more robust (Hehman et al., 2019; Payne et al., 2017). Therefore, the continued exploration of regional bias and its potential predictors and correlates appears to be a worthwhile endeavor.

Yet with this new approach come new concerns, both methodological and theoretical. When studying individuals in a laboratory setting, a fixed amount of information is obtained throughout the data collection process, constrained by the accumulative time and effort of each measure. Researchers make theory-informed decisions regarding what information to collect, and this researcher-driven approach necessarily constrains the relationships that can be uncovered, as researchers can only explore the limited information collected.

In contrast, when geographic regions rather than individuals are the unit of analysis, a virtually unlimited number of variables can be considered. Any variable from any source that describes a region could be included in a model. This "kitchen-sink" approach allows for the bottom-up discovery of relationships that researchers may not have anticipated and therefore would be unable to find in a more researcher-constrained approach. Furthermore, this data-driven technique positions researchers to potentially explain a large percentage

[1] Department of Psychology, McGill University, Montreal, Quebec, Canada
[2] Department of Psychology, University of California, Riverside, CA, USA

Corresponding Author:
Eric Hehman, Department of Psychology, McGill University, Montreal, Quebec, Canada H3A 1G1.
Email: eric.hehman@mcgill.ca

of variance in the outcome of interest. The advantages inherent in such prediction-focused methods have been increasingly advocated for in social science research (Yarkoni & Westfall, 2017).

The Present Research

We began by collating a large data set ($N = 813$) of regional characteristics of the environmental context, with limited constraints on the features included. Because our ultimate aim was to inform causal theories of intergroup bias, we excluded variables that could plausibly be expected to be the direct or indirect by-products of intergroup biases. Following the compilation of the data sets, we used a modern model selection technique—elastic net regularization—to identify the environmental features to retain in parsimonious models of implicit and explicit intergroup bias in different domains. The resulting parsimonious models were then analyzed in a more traditional linear regression framework to estimate relationships with various biases. Finally, we interpreted results with a focus on the extent to which any relationships that emerged were consistent with modern theories of intergroup bias.

Method

Region of Analysis

We focused our analysis on core-based statistical areas (CBSAs), which are defined by the U.S. Office of Management and Budget as areas of at least 10,000 people and adjacent areas socioeconomically linked with an urban center by commuting. In contrast to smaller (e.g., counties) or larger (e.g., state, province) regions of analysis, CBSAs maximize spatial resolution while grouping qualitatively similar regions into units of analysis. We included Washington, DC, and excluded U.S. territories.

Source of Data

Implicit and explicit in-group bias. We operationalized bias at the CBSA level by aggregating individual-level data from Project Implicit. Project Implicit is a website measuring explicit and implicit bias regarding a variety of social groups and relationships. In the present work, we focus on six different types of biases: White–Black, notMuslim–Muslim, straight–gay, notObese–obese, abled–disabled, and young–old. We selected these biases because we expected them to have both some shared and unique predictors.

We included data from Project Implicit respondents who had completed measures of their implicit and explicit attitudes in one of these domains. Implicit bias was assessed with an implicit association test (IAT; Greenwald et al., 1998), a speeded dual-categorization task in which respondents simultaneously categorized social targets (e.g., pictures of Black and White people) and attributes (e.g., pleasant and unpleasant words) by timed computer-key press. The speed with which people respond to one set of target-attribute pairings (e.g., White-Good, Black-Bad) relative to the other set of pairings (e.g., White-Bad, Black-Good) is thought to reflect the strength with which the target categories are associated with one versus the other attribute category. For all IATs, the attribute stimuli were pleasant and unpleasant words, and the target stimuli varied across IATs depending on the bias being measured (e.g., White–Black, straight–gay). Implicit bias was calculated according to the recommended D scoring algorithm (Greenwald et al., 2003). For all analyses, we used data only from respondents who had geographic information available and who were in the United States. We additionally excluded respondents with response latencies faster than 300 ms on 10% or more of trials as recommended by Greenwald and colleagues (2003).

Table 1. Inclusion Criteria and Final n for Various Data Sets.

Bias	Final n	Inclusion Criteria
White–Black	2,729,570	Self-reported non-Hispanic Whites only
NotMuslim–Muslim	114,248	Self-reported non-Hispanic Whites only Excluded self-reported Arabic or Muslim respondents
Straight–gay	931,834	Self-reported heterosexual respondents only
NotObese–obese [a]	980,964	Self-reported 10 < body mass index < 30 Did not self-identify as “moderately overweight” or “very overweight”
Abled–disabled	287,296	Self-reported no disability
Young–old	814,351	Self-reported 15 < age < 45

[a] In this task, participants responded to the category labels “thin” versus “fat”; consequently, we are examining the extent to which nonobese individuals evaluate the categories thin versus fat.

Explicit attitudes were assessed using a single item asking about attitudes toward one group relative to the other. Recent research focusing on racial bias found this single-item measure to have the highest correlation with the IAT D, relative to other explicit measures (Axt, 2018). Both the explicit and implicit bias measures were calculated such that more positive values represent more positive attitudes toward the normatively higher status group (i.e., White people, non-Muslims, heterosexual people, thin people).

To increase the theoretical precision and interpretability of the present research, we focus only on *in-group* bias. Consequently, we included in analyses only respondents who belonged to in the normatively higher status group for each data set. See Table 1 for inclusion criteria and final n. These were aggregated into CBSAs for which data were available ($n = 338$). Responses were completed between 2002 and 2018 and are collapsed across time.

Environmental features. Our goal was to develop causal models of regional intergroup bias. Because temporal precedent is necessary for establishing causality, we excluded from our initial data set any environmental features that could plausibly be direct or indirect downstream consequences of intergroup bias as predicted by theory. For instance, such by-products might include racial or ethnic differences in crime rates, segregation, socioeconomic status, or disciplinary rates in school. Of course, whether a given variable is a cause or consequence of bias is a difficult question to answer definitively because it is likely that many have a bidirectional relationship with bias. Consequently, we adopted a conservative approach and culled from the initial data set any variables whose temporal precedence to bias could not be clearly established.

Based on these variables, we created a taxonomy of features included in the model: (1) human features of the environment (e.g., average number of mental health providers, population density), (2) nonhuman features of the environment (e.g., average daily precipitation, water area in square miles), (3) events in environment (e.g., average alcoholic impaired driving deaths, premature deaths), and (4) population characteristics (e.g., percentage of Hmong who self-report speaking English very well, men aged 30–34 in the armed forces). This taxonomy helps to organize our findings but is unavoidably subjective, and we acknowledge that some variables could reasonably belong to multiple categories (see Supplementary Materials for conceptual definitions).

Inclusion of environmental features was constrained by the availability of data. The techniques employed could not accommodate missing data, so included data contained a value for every CBSA for each variable. Ultimately 813 variables were integrated from the following sources: the 2016 American Community Survey 5-year estimates, the Web-based Injury Statistics Query and Reporting System, the Integrated Postsecondary Education Data System, the Center for Disease Control and Prevention WONDER database, the North America Land Data Assimilation System, the Moderate Resolution Imaging Spectroradiometer, the Federal Bureau of Investigation Uniform Crime Reporting database, and the National Occupational Respiratory Mortality System. Broadly, these sources provided information on population demographics, health care, health metrics, topographical features, weather, temperature, and crime. A full list of these variables, their origin, and description is available in the Supplementary Materials (https://osf.io/dcvq4/).

Analytic Approach

Model selection. Model selection was completed using elastic net regularization (Hastie & Zou, 2005). Elastic net regularization seeks to balance two competing goals in model development: explanatory power and parsimony. Maximizing variance explained focuses the model on the factors most related to the phenomenon. All else equal, models with more variables will always explain more variance than models with fewer variables, yet highly complex models (i.e., large numbers of predictors) become unwieldily and less likely to generalize. Therefore, parsimonious models that predict the most variance from the fewest predictors are desirable. Regularization helps find an optimal balance of explanatory power and parsimony—that is, minimizing both error and complexity—by including an extra term in the regression equation (λ) reflecting the complexity of the model. This term "shrinks" coefficients in the model to zero as model complexity increases. When $\lambda = 0$, the model is the same as traditional linear regression (i.e., no shrinkage). When $\lambda = \infty$, there are no variables in the model (i.e., all coefficients shrunk to zero). Simple models will have higher overall error and lower complexity, while models with many predictors will have reduced error but higher complexity. The optimal value of λ balances error with complexity. Elastic net regularization is ideal for the present research, which includes highly correlated variables and more variables than units of analysis (i.e., regions; Hastie & Zou, 2005).

In the present research, the optimal value of λ was selected using cross-validation in the R package glmnet (Friedman et al., 2010). Specifically, we performed 10-fold cross-validation, randomly dividing the data set into 10 nonoverlapping subsets (i.e., folds) of roughly equal size. The model is fit on the first 9 folds, and validated on the remaining fold, repeatedly in an iterative fashion. This process reduces the possibility of developing a model so specific to our data that it would not generalize to other data (i.e., overfitting). We selected λ based on the values that minimized cross-validated 10-fold error (see Supplementary Figure 1). Code for reproducing this analytic pipeline is available at https://osf.io/dcvq4/

Parsimonious models. Variables with nonzero coefficients at the selected optimal levels of λ were subsequently entered into linear regression models to assess their coefficients and overall variance explained by each model.

Results

Total Variance Explained

The parsimonious models had, on average, 30.5 predictors ($SD = 13.5$), indicating that 3.8% of the variables in the original data set were ultimately retained. The 12 models varied substantially in how much total variance was explained by environmental features. For instance, the models explained $\sim$50%–60% of variance in regional explicit young–old bias, and implicit and explicit straight–gay, implicit and explicit White–Black biases; and $\sim$10%–40% of regional variance in implicit young–old bias, and implicit and explicit notMuslim–Muslim, notObese–obese, and abled–disabled biases (Table 2). Generally, the models explained similar amounts of variance in implicit and explicit bias, with the exception of young–old and notObese–obese, which both explained more variance in explicit than implicit bias.

Relationships Between Environmental Features and In-Group Biases

The large number of predictors in our models increases the likelihood that any specific relationship is spurious.

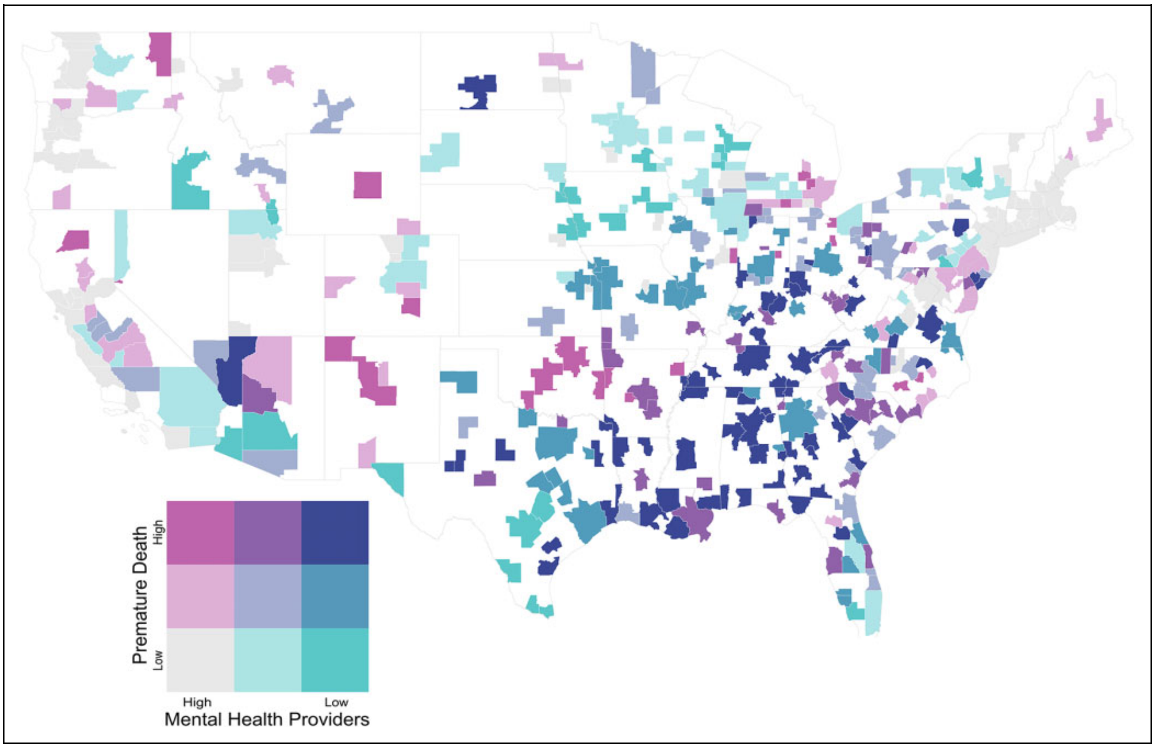

Figure 1. The core-based statistical areas included in our analyses. Colors are determined by the two largest and most consistent predictors in our analyses: the percentage of mental health providers (negatively related to many biases) and the rate of premature death (positively related to many biases). Darker colors are regions in which there are higher levels of bias as a function of these variables.

Consequently, we interpret the patterns of results from the perspective of the taxonomy developed above, as a window into latent factors that might underlie these relationships, and focus especially on relationships that persist across multiple domains of bias (e.g., race, sexual orientation) and measurement types (i.e., implicit, explicit).

Human features of the environment. One cluster of significant predictors related to the availability of health care in a region. The most frequently predictive—mental health providers—was negatively related to bias in 7 of the 12 models (Figure 1). Overall, more health care is available in less biased regions, with the exception of dentists: More dentists are available in regions with more in-group bias.

Nonhuman features of environment. Regions in which White people demonstrate more implicit or explicit in-group bias are characterized by higher maximum heat indices. Similarly, regions with higher explicit White–Black or notMuslim–Muslim bias are characterized by more air pollution. No other relationships consistently emerged in this category of predictors, so we refrain from further interpreting these relationships.

Events in environment. Another cluster of significant predictors related to negative health outcomes, which were often related to increased levels of in-group bias. For instance, rate of premature death was positively correlated with increased preferences for the in-group in 6 of the 12 models and consistently predicted both implicit and explicit bias in these six models. It was descriptively the largest average standardized coefficient ($M_\beta = .28$, range $= .19$–$.42$). Total deaths due to injury, obesity rate, and smoking rate were all linked with increased implicit and explicit bias. Yet this potential link between negative health outcomes and in-group bias was not entirely consistent, as some were significantly associated with *less* in-group bias. For instance, teen birth rate and excessive drinking rate were significantly linked with less explicit straight–gay bias.

Population characteristics. No other relationships consistently emerged in this category of predictors, which are largely drawn from the U.S. census, so we refrain from further interpreting these possibly spurious relationships.

Addressing Alternative Explanations

When we selected data for inclusion in our models of environmental features that predict in-group bias, we sought to avoid circularity by excluding constructs that were likely direct consequences of in-group bias (e.g., residential segregation). That said, it is still possible that some of the data included are relatively more distal by-products or proxies for in-group bias. For instance, the proportion of health care providers in a region might reflect providers choosing locations based on the average income, education, politics, or other demographic characteristics of the population—and these choices might

Table 2. Variance Explained and Standardized Coefficients of all Significant Variables ($\alpha = .05$) in Parsimonious Linear Models, Sorted by Frequency Across Different Models and Organized by Our Taxonomy. [a]

	Straight–Gay		White–Black		Young–Old		NotMuslim–Muslim		NotObese–Obese		Abled–Disabled	
Type of Prejudice	Implicit	Explicit	Implicit	Explicit	Implicit	Explicit	Implicit	Explicit	Implicit	Explicit	Implicit	Explicit
Variance explained (adjusted R^2)	.62	.51	.48	.58	.29	.49	.25	.23	.12	.37	.14	.12
Human features of environment												
1. Percentage mental health providers	−0.30	−0.28	−0.22	−0.23	−0.12		−0.22	−0.21				0.17
2. Commute length	−0.20	−0.23		−0.15		−0.16						
3. Percentage primary care physicians	−0.19	−0.15		−0.20								
4. Total family therapists	−0.18											
5. Percentage dentists	0.12						0.21	0.19				
6. Other primary care providers				−0.09								
7. Total primary care physicians				−0.08								
Nonhuman features of environment												
8. Precipitation	−0.13											
9. Maximum heat index			0.22	0.23								
10. Water area			0.09									
11. Air pollution				0.15				0.15				
12. Minimum air temperature									0.18			
Events in environment												
13. Rate of premature death	0.27	0.21	0.35	0.42	0.19	0.24						
14. Rate of obesity	0.3	0.17										
15. Total injury deaths	0.11											
16. Rate of teenage births		−0.18										
17. Percentage excessive drinking		−0.26										
18. Total violent crimes			0.14		−0.09							
19. Rate of violent crimes			−0.17					−0.25				
20. Rate of injury deaths			−0.17									−0.12
21. Rate of homicides					−0.13						0.15	
22. Percentage smoking					0.22							
Population characteristics												
23. Black or African American	0.34										0.19	
24. Men, 20–21, armed forces		0.11										
25. Women, 18–24, associate's degree		0.21										
26. Women, 65–74, veteran		−0.29										
27. Women, 60–61, armed forces			0.13									
28. Hmong, speak English very well				0.30								
29. Men, 16–19, armed forces				0.16								
30. German, speak English less than very well					0.23							
31. American Indian and Alaska Native						−0.26						
32. Serbo-Croat, speak English less than very well							−0.13					
33. Gujarati, speak English less than very well							0.23					
34. Women, 45–54										0.13		
35. Navajo, speak English less than very well												−0.11

[a] Positive coefficients indicate a larger pro-in-group bias relative to the out-group. To identify actual variable name, link numbers in table (e.g., 20) with Supplementary Materials (https://osf.io/dcvq4/).

reasonably be influenced by in-group biases. To rule out such possibilities, we collated demographic variables typically controlled for in regional research (Hehman et al., 2018; Leitner et al., 2016a, 2018; Orchard & Price, 2017; Riddle & Sinclair, 2019). These consisted of 5-year estimates from the 2016 American Community Survey of regional socioeconomic status (i.e., income), education (i.e., percentage of population 25 and older with at least a bachelor's degree), employment (i.e., percentage of population 16 and older who were employed), and political orientation (i.e., average CBSA-level voteshare percentage difference between the primary Democratic candidates (Obama and Clinton) and Republican candidates (Romney and Trump) of the past two U.S. presidential elections. In addition, recent research has highlighted links between former slave statehood and regional White–Black bias (Payne et al., 2019), and we additionally included this information operationalized as a contrast-coded variable regarding whether or not a state considered slavery legal in 1846, when the maximum number of states ($N = 15$) had legalized slavery.

In a hierarchical regression approach, we first created a demographic base model including these variables. In a second step, we then entered the parsimonious models created above and examined variance explained above and beyond the base models. Statistical comparisons of the two models were done with ΔR^2 tests. Results are presented in Table 3.

All parsimonious models explained significantly and substantially more variance than the base model, which conceptually

Table 3. Differences in Variance Explained (ΔR^2) Between Base Demographic Model and Full Parsimonious Models for Each Type of In-Group Bias.

Models		Variance Explained		
		Base	Full	Δ
Straight–Gay	Explicit	.44	.68	.24
	Implicit	.38	.74	.36
White–Black	Explicit	.17	.62	.46
	Implicit	.15	.48	.32
Young–Old	Explicit	.21	.54	.33
	Implicit	.14	.41	.27
NotMuslim–Muslim	Explicit	.20	.34	.14
	Implicit	.12	.28	.16
NotObese–Obese	Explicit	.15	.39	.24
	Implicit	.07	.12	.05
Abled–Disabled	Explicit	.04	.12	.07
	Implicit	.06	.19	.13

Note. All Fs > 8, ps < .001.

demonstrates that the environmental features included in our models are independent from basic demographics.

Examining the Predictive Validity of Environmental Features

The models we have developed in the present research generally explain a substantial percentage of variance in regional implicit and explicit in-group bias and explain variance in bias above and beyond what is explained by demographics. Yet it is important to examine the validity of these models by predicting outcomes beyond that on which the models were trained. Consequently, we next examined the extent to which the environmental features in our models predicted other outcomes that previous research has identified as being related to intergroup bias.

We limited validation to four outcomes theoretically linked with White–Black bias: racially segregated housing, the number of Black individuals killed by police, disparities in education-related outcomes, and disparities in income.[1] Previous work has linked these outcomes with White–Black racial bias (Dovidio & Gaertner, 2000; Hehman et al., 2018; Rae et al., 2015; Riddle & Sinclair, 2019). Segregation was represented by the isolation index as calculated by Logan and Stults (2011), and disproportionate deaths from police as calculated by Hehman and colleagues (2018). White–Black differential high-school graduation rates and median incomes were obtained from 5-year estimates of the American Community Survey.

Eight separate models were run in a linear regression framework. Each dependent variable above was regressed on only the parsimonious models of White–Black implicit or explicit bias as identified by the elastic net regularization approach. Outputs from full models are available at https://osf.io/dcvq4/

All models explained significantly more variance than 0 (F-statistic ps < .05), yet varied in their predictive ability

Table 4. Variance in Outcomes Theoretically Linked to Racial Bias Explained by the Parsimonious Models.

	Variance Explained (Adjusted R^2)	
Outcomes	Implicit	Explicit
Residential segregation	.59	.57
Disproportionate deaths by police	.07	.10
High-school graduation disparities	.50	.50
Median income disparities	.28	.31

(Table 4). Environmental features most strongly explained regional variation in racial segregation, followed by high-school graduation rate disparities, and median income disparities. Environmental features explained relatively little regional variation in disproportionate deaths by police. There were no differences in the predictive ability of the parsimonious models trained on implicit and explicit bias. Taken together, models of environmental features that were built to maximize variance-explained in White–Black racial bias also predicted significant—and in most cases, substantial—variance in outcomes that are theoretically linked with racial bias.

General Discussion

The present research adopted a data-driven model-selection approach to maximize variance-explained in regional in-group biases. This approach removes researcher-based constraints, allowing for the discovery of new links with regional biases. The 12 models developed here generally have a high degree of explanatory power, are capturing meaningful variation beyond basic demographics, and have ecological validity in terms of predicting theorized downstream consequences of White–Black racial bias. Across models, a number of consistent patterns emerged, lending insight into theories of intergroup bias.

The present research examined a great deal of possible relationships and revealed a large number of associations with bias. Some of these relationships are almost certainly spurious, which is why we do not interpret every relationship identified but, instead, focus on relationships that persist across multiple domains of bias and measurement types.

Implications of Shared Predictors

Classic research on intergroup bias at the individual level has generally concluded that when a person is biased against one group (e.g., Black people), they are likely also biased against others (e.g., Asian people; Altemeyer, 1988). The present research suggests a similar clustering effect at the regional level, in that different types of in-group biases are comorbid with others: White–Black, young–old, notMuslim–Muslim, and straight–gay biases are all related to some similar environmental features, such as health care providers and negative health outcomes (see Supplementary Table 1 for correlation matrix of all biases). The presence of shared predictors is consistent with the perspective that intergroup biases have a common root. The exception to this tendency is notObese–obese biases, which did not share many predictors with the other biases. Together, this pattern tentatively suggests regional notObese–obese biases are distinct from the others in the present research.

Implications of Variance Explained

The models of environmental features developed here explain high percentages of variance in both implicit and explicit measures of regional White–Black, young–old, and straight–gay biases. These findings are consistent with the "Bias of Crowds" model, which posits that implicit biases are largely a product of contexts (Payne et al., 2017). Yet the present research represents an extension of the Bias of Crowds model, which limits its claims to implicit bias. Recent research has found that regional aggregates of implicit and explicit bias are more strongly correlated ($r = .6–.8$) than is typically observed at the individual level ($r = .1–.3$), and the size of this correlation increases as the size of the regional aggregate increases (Hehman et al., 2019). Previously, relationships between implicit and explicit biases at the regional level had only been examined for straight–gay and White–Black attitudes (Hehman et al., 2018; Leitner et al., 2016a; Ofosu et al., 2019; Orchard & Price, 2017; Riddle & Sinclair, 2019), and the present research extends these findings to four additional intergroup domains. Together, these results suggest a large role of environmental context in both implicit *and* explicit measures of regional bias.

In comparison to White–Black, Young–Old, and Straight–Gay biases, our models of environmental features explained relatively less variance in notMuslim–Muslim, notObese–obese, and abled–disabled biases. One explanation for this disparity is that we may not have included the variables related to these biases. Other research has demonstrated that media-related fat-shaming events are associated with spikes in notObese–obese biases (Ravary et al., 2019). Such events are not included in the present data set, and we may be missing other important predictors. Alternatively, these biases may be better understood to reflect individual differences (e.g., personality, experience) rather than as products of environmental features. The Bias of Crowds model (Payne et al., 2017) makes a similar point about political attitudes. Taken together, these results highlight that some of these biases are distinct, potentially indicating diverse psychological sources.

Integrating Results With Modern Theory

The extent to which environmental features relate to in-group biases can be interpreted through the lens of existing intergroup dynamics theory. First, the finding that negative health outcomes are generally linked with increased levels of in-group biases is consistent with multiple theoretical frameworks. To the extent that negative health outcomes in a region threaten the in-group's status, social identity theory (Tajfel & Turner, 1986) predicts that in-group bias can buffer group status and thereby preserve self-esteem. Social identity theory posits a causal health → bias relationship, but the reverse is also consistent with our findings. Biopsychosocial challenge and threat models (Mendes et al., 2002; Tomaka et al., 1993) argue that living in prejudiced environments is stressful for both targets of prejudice and prejudiced people, and this stress is associated with a host of negative health outcomes (Pascoe & Richman, 2009). Our data cannot speak to causality and are consistent with both perspectives.

That said, the strong negative relationship between availability of health care providers and bias does not appear to be consistent with any prominent theories of in-group bias. This relationship is not simply a function of demographics, as demonstrated in the "Addressing Alternative Explanations" subsection. Previous research has found a relationship between the White–Black bias of White people and state-level Medicaid spending in the United States (Leitner et al., 2018): Because Black people in the United States disproportionately benefit from Medicaid, discrimination might manifest in limited funds to public-health networks. Yet the present research finds this same pattern across all types of biases examined (with the exception of the two biases actually related to health: notObese–obese and abled–disabled) indicating that the relationship between in-group bias and access to health care may be more general.

Ultimately, the results of the present research might be used in several ways. Practically, the developed models can help predict when and where bias and bias-related outcomes might be most likely to occur. Theoretically, the novel associations with different types and clusters of variables identified here might be fruitfully pursued by either confirmatory or hypothesis-driven research. Furthermore, the results of this research have important implications for future statistical modeling of regional bias. Depending on the questions being pursued, some of these identified clusters of variables with consistent relationships with bias might be considered important covariates in future models.

Limitations

The present research is limited in several ways. The "third-variable problem" may be particularly evident here. To the extent that important variables were not included in the original data set prior to model selection, they could not emerge in the results. We adopted a kitchen-sink approach to minimize the third-variable problem, but it can never be ruled out. Although the present research included orders of magnitude more variables than are typically examined in psychological research, future work might repeat our approach with additional variables included to hone the predictive ability of the models. Relatedly, we have identified variables that are consistently associated with different types of biases, but they may be indirect proxies of other variables more directly causally responsible for these biases. Additionally, our models do not account for curvilinear effects or interactions.

Individuals visiting Project Implicit are not representative of the general North American population, so any conclusions drawn from these data do not necessarily generalize to the population at large. That said, previous published research examining disparities in health care (Orchard & Price, 2017), policing (Hehman et al., 2018), mortality (Leitner et al., 2016b, 2016a), and other outcomes indicate that the biases of Project Implicit respondents predict important real-world outcomes. In the present research, our models built on Project Implicit data also predict a high percentage of variance in real-world outcomes, which bolsters their validity. Recent research has found strong correspondence between biases as measured by Project Implicit with those measured in representative samples (Hehman et al., 2019; Ofosu et al., 2019). These findings indicate that data from Project Implicit perform like representative data at least in some contexts. Future research should continue to carefully examine this issue of representativeness, or collect data enabling them to weight Project Implicit data (Hoover & Dehghani, in press), making it more representative.

Conclusion

Testing psychological hypotheses at a regional level is a relatively new approach to studying intergroup biases, and it comes with unique challenges and opportunities. The present data-driven research reveals distinctions between different types of in-group bias and how well they can be explained by environmental features. Implicit and explicit measures of in-group biases were consistently and equally explained by environmental features. Furthermore, results reveal support for existing models of bias (i.e., negative health outcomes) while uncovering novel relationships (i.e., health care providers). Future researchers dealing with regional data might employ similar techniques to develop parsimonious models and further our understanding of environmental contributors to in-group bias.

Author Contributions

The followings are the contributions by authors: conceived research (E.H.), methodology (all authors), data curation (E.H. and E.K.O.), analysis (E.H.), and writing (original draft [E.H.], review and editing [all authors]).

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This research was supported by the Fonds de Recherche (FRQ-SC NP-267701) to Eric Hehman.

ORCID iD

Eric Hehman https://orcid.org/0000-0003-2227-1517

Supplemental Material

The supplemental material is available in the online version of the article.

Note

1. Here, we focus only White–Black bias because outcomes associated with the other biases examined have not been clearly delineated by previous research and theory.

References

Altemeyer, B. (1988). *Enemies of freedom: Understanding right-wing authoritarianism*. Jossey-Bass.

Axt, J. R. (2018). The best way to measure explicit racial attitudes is to ask about them. *Social Psychological and Personality Science*, *9*(8), 896–906. https://doi.org/10.1177/1948550617728995

Dovidio, J. F., & Gaertner, S. L. (2000). Aversive racism and selection decisions: 1989 and 1999. *Psychological Science*, *11*(4), 315–319. https://doi.org/10.1111/1467-9280.00262

Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization paths for generalized linear models via coordinate descent. *Journal of Statistical Software*, *33*(1), 1–22.

Greenwald, A. G., McGhee, D. E., & Schwartz, J. L. (1998). Measuring individual differences in implicit cognition: The implicit association test. *Journal of Personality and Social Psychology*, *74*(6), 1464–1480. https://doi.org/10.1037/0022-3514.74.6.1464

Greenwald, A. G., Nosek, B. A., & Banaji, M. R. (2003). Understanding and using the implicit association test: I. An improved scoring algorithm. *Journal of Personality and Social Psychology*, *85*(2), 197–216. https://doi.org/10.1037/0022-3514.85.2.197

Greenwald, A. G., Poehlman, T. A., Uhlmann, E. L., & Banaji, M. R. (2009). Understanding and using the implicit association test: III. Meta-analysis of predictive validity. *Journal of Personality and Social Psychology*, *97*(1), 17–41. https://doi.org/10.1037/a0015575

Hastie, T., & Zou, H. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *67*(2), 301–320. https://doi.org/10.1111/j.1467-9868.2005.00503.x

Hehman, E., Calanchini, J., Flake, J. K., & Leitner, J. B. (2019). Establishing construct validity evidence for regional measures of explicit and implicit racial bias. *Journal of Experimental Psychology: General*, *148*(6), 1022–1040. https://doi.org/10.1037/xge0000623

Hehman, E., Flake, J. K., & Calanchini, J. (2018). Disproportionate use of lethal force in policing is associated with regional racial biases of residents. *Social Psychological and Personality Science*, *9*(4), 393–401. https://doi.org/10.1177/1948550617711229

Hoover, J., & Dehghani, M. (in press). The big, the bad, and the ugly: Geographic estimation with flawed psychological data. *Psychological Methods*.

Kurdi, B., Seitchik, A. E., Axt, J. R., Carroll, T. J., Karapetyan, A., Kaushik, N., Kaushik, N., Tomezsko, T., Greenwald, A. G., & Banaji, M. R. (2019). Relationship between the implicit association test and intergroup behavior: A meta-analysis. *American Psychologist*, *74*(5), 569–586. https://doi.org/10.1037/amp0000364

Leitner, J. B., Hehman, E., Ayduk, O., & Mendoza-Denton, R. (2016a). Blacks' death rate due to circulatory diseases is positively related to Whites' explicit racial bias: A nationwide investigation using Project Implicit. *Psychological Science*, *27*(10), 1299–1311. https://doi.org/10.1177/0956797616658450

Leitner, J. B., Hehman, E., Ayduk, O., & Mendoza-Denton, R. (2016b). Racial bias is associated with ingroup death rate for Blacks and Whites: Insights from Project Implicit. *Social Science and Medicine*, *170*, 220–227. https://doi.org/10.1016/j.socscimed.2016.10.007

Leitner, J. B., Hehman, E., & Snowden, L. R. (2018). States higher in racial bias spend less on disabled Medicaid enrollees. *Social Science and Medicine*, *208*(April 2017), 150–157. https://doi.org/10.1016/j.socscimed.2018.01.013

Logan, J. R., & Stults, B. J. (2011). *The persistence of segregation in the metropolis: New findings from the 2010 census*. Census brief prepared for Project US2010, 24.

Mendes, W. B., Blascovich, J., Lickel, B., & Hunter, S. (2002). Challenge and threat during social interaction with white and black men. *Personality and Social Psychology Bulletin*, *28*, 939–952. https://doi.org/10.1177/01467202028007007

Ofosu, E. K., Chambers, M. K., Chen, J. M., & Hehman, E. (2019). Same-sex marriage legalization associated with reduced implicit and explicit antigay bias. *Proceedings of the National Academy of Sciences*, *116*(18), 8846–8851. https://doi.org/10.1073/pnas.1806000116

Orchard, J., & Price, J. (2017). County-level racial prejudice and the black-white gap in infant health outcomes. *Social Science and Medicine*, *181*, 191–198. https://doi.org/10.1016/j.socscimed.2017.03.036

Oswald, F. L., Mitchell, G., Blanton, H., Jaccard, J., & Tetlock, P. E. (2013). Predicting ethnic and racial discrimination: A meta-analysis of IAT criterion studies. *Journal of Personality and Social Psychology*, *105*(2), 171–192. https://doi.org/10.1037/a0032734

Pascoe, E. A., & Richman, L. S. (2009). Perceived discrimination and health: A meta-analytic review. *Psychological Bulletin*, *135*(4), 531–554. https://doi.org/10.1037/a0016059

Payne, B. K., Vuletich, H. A., & Brown-Iannuzzi, J. L. (2019). Historical roots of implicit bias in slavery. *Proceedings of the National Academy of Sciences*, *116*(24), 11693–11698. https://doi.org/10.1073/pnas.1818816116

Payne, B. K., Vuletich, H. A., & Lundberg, K. B. (2017). The bias of crowds: How implicit bias bridges personal and systemic prejudice. *Psychological Inquiry*, *28*(4), 233–248. https://doi.org/10.1080/1047840X.2017.1335568

Rae, J. R., Newheiser, A. K., & Olson, K. R. (2015). Exposure to racial out-groups and implicit race bias in the United States. *Social Psychological and Personality Science*, *6*(5), 535–543. https://doi.org/10.1177/1948550614567357

Ravary, A., Baldwin, M. W., & Bartz, J. A. (2019). Shaping the body politic: Mass media fat-shaming affects implicit anti-fat attitudes. *Personality and Social Psychology Bulletin*, *45*(11), 1580–1589. https://doi.org/10.1177/0146167219838550

Riddle, T., & Sinclair, S. (2019). Racial disparities in school-based disciplinary actions are associated with county-level rates of racial bias. *Proceedings of the National Academy of Sciences*, *116*(17), 8255–8260. https://doi.org/10.1073/pnas.1808307116

Sadler, M., & Devos, T. (2018). Ethnic diversity matters: Putting implicit associations between weapons and ethnicity in context. *Group Processes and Intergroup Relations*, 1–16. https://doi.org/10.1177/1368430218796933

Schmidt, K., & Nosek, B. A. (2010). Implicit (and explicit) racial attitudes barely changed during Barack Obama's presidential campaign and early presidency. *Journal of Experimental Social Psychology*, *46*(2), 308–314. https://doi.org/10.1016/j.jesp.2009.12.003

Tajfel, H., & Turner, J. C. (1986). The social identity theory of intergroup behavior. *Psychology of Intergroup Relations*, 7–24. https://doi.org/papers3://publication/uuid/D2BDCF87-F446-49DA-8698-DD4EF14AECAA

Tomaka, J., Blascovich, J., Kelsey, R. M., & Leitten, C. L. (1993). Subjective, physiological, and behavioral effects of threat and challenge appraisal. *Journal of Personality and Social Psychology*, *65*(2), 248–260. https://doi.org/10.1037/0022-3514.65.2.248

Yarkoni, T., & Westfall, J. (2017). Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspectives on Psychological Science*, *12*(6), 1100–1122. https://doi.org/10.1177/1745691617693393

Author Biographies

Eric Hehman is an assistant professor at McGill University. His research examines how individuals perceive and evaluate one another across group boundaries (e.g., race, gender, sexual-orientation, occupation, etc), and the downstream consequences of such perceptions.

Eugene Ofosu is a graduate student working with Eric Hehman at McGill University. Broadly, he is fascinated by the intersectionality of identities (race, sexual orientation, SES, and others), how it affects ambiguous perceptions, and how these perceptions manifest in the context of competitive settings and institutional authority.

Jimmy Calanchini is an assistant professor at the University of California Riverside. He studies cognitive processes related to the formation and change of intergroup biases.

Handling Editor: Robyn Mallett