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Exposure to Anti-Black Lives Matter Movement and Obesity of the Black Population

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Introduction

Black Lives Matter (BLM) is a social movement against systemic injustice and police violence toward Black people whose goal is to ensure the safety of Black people and safe expression of their culture and identity. As the BLM movement gained momentum, counter-movements such as All Lives Matter (ALM; advocating for the lives of all races), White Lives Matter (WLM; advocating for the lives of White people), and Blue Lives Matter (BlueLM; advocating for the lives of police) emerged (Pew Research Center, 2016). These counter-movements can be race-related stressors for Black people because they undermine support for their protection from police brutality (Gallagher et al., 2018) and suppress the expression of Black culture and identity (Tillery, 2019).

Experiencing race-related stressors is associated with negative health outcomes, including obesity (Cozier et al., 2009; Thorpe et al., 2017), diabetes (Bacon et al., 2017), cardiovascular disease (Chae et al., 2012), and mortality (Chae et al., 2015). Identifying how race-related stressors lead to obesity is important because obesity is often a gateway to other diseases (Steppan et al., 2001; Van Gaal et al., 2006).

In this study, we examined Twitter data to determine whether negative stances on BLM are associated with a higher body mass index (BMI) and the prevalence of obesity among Black people. Discussions about BLM on Twitter provide valuable data for research on the movement (Gallagher et al., 2018; Tillery, 2019). Stances on BLM may be accurately captured through Twitter data because race-related issues are often more explicitly stated online than in real-life interactions (Bartlett et al., 2014). We utilized geo-located tweets containing hashtags related to BLM and its counter-movements (i.e., #BlackLivesMatter, #AllLivesMatter, #WhiteLivesMatter, and #BlueLivesMatter) from 2014 to 2016 in metropolitan or micropolitan statistical areas and metropolitan divisions (i.e., some metropolitan statistical areas are divided into metropolitan divisions) (MMSAs) across the United States to capture stances on the BLM movement. We used machine learning algorithms to identify stances, and then explored whether stances were associated with BMI and obesity within the Black population in 2017. Living in areas high in racism can lead to negative health outcomes among minorities (Chae et al., 2018, 2015). If so, Blacks living in regions with more negative stances on the BLM movement may have a higher BMI and prevalence of obesity than those living in regions with fewer negative stances.

This research advances the literature in three ways. First, we propose a new way of capturing stances on race-related issues in online discussions, thus avoiding the social desirability bias inevitable in self-reported surveys (Krieger et al., 2005). Second, we incorporate machine learning algorithms to classify stances on BLM. This advance opens a new door for researchers to analyze social media data, whose vast size makes it unrealistic to manually code full datasets. Given the vast size of social media data, machine learning constitutes an alternative option for social scientists to classify data, other than manual coding. Third, we leverage geographic information to investigate whether people's health outcomes such as obesity are associated with regional negative stances on race-related social movements such as BLM. In particular, we investigate how social sentiments about race-related issues may affect the health outcomes of minorities, which we believe to be a new area of study.

Black Lives Matter Movement

The BLM movement started in 2013 after the acquittal of George Zimmerman, who killed an unarmed Black teenager, Trayvon Martin. The movement gained momentum on social media with the hashtag #BlackLivesMatter when 18-year-old Michael Brown was shot during an arrest in 2014. As the BLM movement grew, counter-movements such as ALM, WLM, and BlueLM emerged (Pew Research Center, 2016). ALM undermines BLM because ALM reflects a color-blind ideology that people matter over and above their race (Bonilla-Silva, 2017; Gallagher et al., 2018). A color-blind ideology masks and ignores systemic injustice (Bonilla-Silva, 2017) and understates the importance of race in discussions of police brutality (Langford and Speight, 2015). The WLM movement is explicitly against BLM. It supports White privilege, alleges reverse discrimination, and emphasizes negative stereotypes about Black people (Langford and Speight, 2015). BlueLM focuses on the importance of law enforcement and its positive influence in communities, which downplays the severity of police brutality. Because the anti-BLM movements are characterized by negative stances on BLM, studying all four movements (i.e., BLM and the three anti-BLM movements) may best capture discriminatory beliefs and opinions about minorities.

Counter-Movements to BLM as Race-Related Stressors for Blacks

Exposure to stances against BLM may be a salient race-related stressor for Blacks. Opposition to BLM can threaten the very existence of the ingroup (Stephan and Stephan, 2000) because it undermines the protection of Black people's physical safety from police brutality. Physical threat may lead to stress and negative health outcomes. For instance, just *vicariously* experiencing unfair treatment from police led to negative health outcomes for Black people (McFarland et al., 2018). Real-life counter-movements often involve protesters who brandish a Confederate flag or carry firearms (Miller, 2016), which pose physical threats. Because one major discourse around BLM is supporting the expression of Black culture (Tillery, 2019), expression of Black people's culture and identity can be undermined by counter-movements.

Black people may therefore perceive symbolic threats—as outgroups neglecting ingroup culture (Stephan and Stephan, 2000). As a form of symbolic threat, Black people who perceive negative stances on BLM may experience the restriction of collective autonomy—a feeling that the rights of one's ingroup to express identities are restricted (Anonymous, 2020). In turn, symbolic threats can negatively influence psychological well-being (Schmid and Muldoon, 2015).

Perception of Racism and Health

Race-related stressors are associated with negative health outcomes among minorities (Mays et al., 2007). One key pathway through which these stressors alter health outcomes is through the activation of the hypothalamic-pituitary-adrenal (HPA) axis, which secretes the hormone cortisol in reaction to stress (McEwen, 1998). Cortisol is associated with increased fat storage, which can lead to obesity, diabetes and cardiovascular disease (Björntorp and Rosmond, 2000). Investigating how race-related stressors lead to obesity is critical because obesity is a gateway to other diseases, such as diabetes (Steppan et al., 2001) and cardiovascular disease (Van Gaal et al., 2006).

Perceiving race-related stressors can impact obesity (Cozier et al., 2009; McFarland et al., 2018; Thorpe et al., 2017). In a longitudinal study among Black women, weight gain was positively associated with the perception of everyday and lifetime discrimination (Cozier et al., 2009). In a cross-sectional study among Black men, a perception of lifetime discrimination was associated with a higher probability of being obese (Thorpe et al., 2017). McFarland et al. (2018) found that *vicariously* experiencing police brutality explained the Black-White waist circumference disparity among women. Overall, perceived race-related stressors can lead to higher BMI and prevalence of obesity. Therefore, among Blacks, exposure to negative stances on BLM can be associated with higher BMI and being obese.

Capturing Stances on BLM

Stances on race-related topics might not be accurately captured using self-reported measures. Although stances on BLM can be directly queried, individuals may report favorable attitudes due to social desirability bias (Krieger et al., 2005). Alternatively, researchers can assess Black peoples' perception of stances against BLM. However, discussions about BLM may be avoided; thus, perceived stances against BLM may be underreported. Indeed, self-reported experiences of racial discrimination are often underreported (Nuru-Jeter et al., 2018), which may explain the counterintuitive negative or null relationship between discrimination and health outcomes (Alhusen et al., 2016).

Stances about BLM may be captured through social media, such as Twitter. Many online discussions around BLM started on Twitter; Twitter thus provides rich data to investigate stances on BLM (Gallagher et al., 2018; Tillery, 2019). Assessing stances on BLM through Twitter data can overcome the bias of self-reported measures. The anonymity of Twitter encourages people to express views on race-related issues avoided during real-life interactions (Bartlett et al., 2014).

Previous literature shows that Internet search history and social media data can reliably reflect *regional* racial attitudes in the real-life setting (Chae et al., 2015, 2018; Nguyen et al., 2018). For example, racism can be measured at a regional level by utilizing the proportion of Google searches that contained the "N-word" in designated market areas (DMAs) in the United States (Chae et al., 2015, 2018; Stephens-Davidowitz, 2014). This measure was associated with other indicators of racial bias (e.g., attitudes about interracial marriage) as well as behavioral intentions (e.g., not voting for Obama in elections) (Stephens-Davidowitz, 2014). This measure showed predictive validity: Black people who lived in DMAs with a higher proportion of "N-word" searches also had a higher mortality rate (Chae et al., 2015) and higher rate of pre-term births (Chae et al., 2018).

Attitudes toward minority populations can also be captured using Twitter. Nguyen et al. (2018) assessed regional racism by analyzing the sentiments of tweets that contained race-related slurs. Minority members living in areas high in racism (i.e., regions with more tweets that are negative in sentiment toward minorities) had a higher rate of pre-term births and gave birth to babies with lower weights.

Further, the above studies suggest that living in areas high in racism can be stressful, which leads to negative health outcomes (Chae et al., 2015, 2018; Nguyen et al., 2018). Indeed, the characteristics of local social environments can impact various health outcomes. For example, people living in counties prevalent in negatively valenced emotional words, as assessed through Twitter, were more likely to die from heart disease (Eichstaedt et.al., 2015). Therefore, living in areas with more negative stances on BLM could lead to negative health outcomes among Blacks.

Because stances on BLM can capture racism, such stances may be associated with other measures of regional racism, such as explicit or implicit racism (i.e., assessed using the implicit association test). However, stances against BLM may have a unique impact on health outcomes of Black people over and above other types of racism. In addition to regional racism, stances against the BLM movement may further aggravate a hostile regional social environment toward Blacks, in that social sentiments around race-related issues can be strengthened through social interactions (Paluck, 2009). In turn, this hostile social environment could be associated with worse health outcomes of Blacks. Indeed, individuals in same-sex relationships showed better health outcomes when they resided in states that had legalized same-sex marriage (i.e., states that have a positive social environment regarding same-sex relations) (Kail et al., 2015).

Current Study

To test whether Blacks who live in areas where negative stances on BLM prevail have a higher BMI and occurrence of obesity, we used geo-coded tweets containing hashtags related to the BLM movement (i.e., #BlackLivesMatter, #WhiteLivesMatter, #AllLivesMatter, and #BlueLivesMatter) from 2014 to 2016. Given the size of the corpus, we trained machine learning models to classify stances. We classified the stance of each tweet into two categories, *against* or *not against* (i.e., support for or neutral toward) BLM. We captured *stances* instead of *sentiments* because the stance represents the attitude of a tweet while sentiments are not necessarily consistent with the attitude. For example, a tweet that expresses anger about police brutality (e.g., "Let's be angry with purpose … #BlackLivesMatter") has a *negative* sentiment (i.e., anger) but shows a *supportive* attitude toward BLM.

We located the metropolitan area each tweet originated from and aggregated stances on BLM at the MMSA level (i.e., the percentage of tweets against BLM). Then controlling for covariates (described below), we tested whether aggregated stances against BLM are associated with Black people's BMI and the prevalence of obesity in the following year. Data for BMI and obesity are from the 2017 Behavioral Risk Factor Surveillance System (BRFSS) (Centers for Disease Control and Prevention [CDC], 2017).

During periods when BLM is active, negative stances on BLM may better capture acute race-related stances compared to racial attitudes. In addition to existing regional racism, negative stances on BLM may have further aggravated hostile social environment toward Black people and BLM. Thus, stances on BLM may have a salient influence on health outcomes over and above racism toward Blacks. To test this hypothesis, we also examined the impact of stances against BLM on health outcomes while controlling for explicit and implicit racism toward Blacks.

Methods

Study Population

The sample population is Blacks who lived in MMSAs and participated in the CDC BRFSS survey in 2017. BRFSS is a nationwide survey that assesses the health conditions of U.S. residents. MMSAs with 500 or more respondents were selected to comprise the Selected Metropolitan/Micropolitan Area Risk Trends (BRFSS-SMART) dataset (CDC, 2017), resulting in 136 MMSAs and 23,215 Black participants. We further selected MMSAs with more than 50 tweets to ensure the area had a sufficient number for analysis. The pattern of results remained the same when we selected MMSAs having more than 10 or 100 tweets. As another robustness check, results remained if areas with more than 50 or 100 unique users were selected (Obschonka et al., 2020). This resulted in 76 MMSA areas with 20,530 participants (9 excluded due to missing BMI and sex variables). The 76 MMSA areas covered 179,224,292 residents (55% of the population in the United States) (see Table 1 for descriptive statistics of participants and MMSA areas).

Primary Measures

Stances on BLM

Stances on BLM were assessed with a corpus of geotagged tweets from 2014 to 2016 (*N* = 71,107). The tweets contained one or more of the following keywords: #BlackLivesMatter, #AllLivesMatter, #WhiteLivesMatter, and #BlueLivesMatter.

Data Preprocessing. To improve classification accuracy, we preprocessed our tweets following procedures from prior research (e.g., Rathi et al., 2018). First, duplicate or similar tweets from users were removed to eliminate potential spam activities. Second, to further limit the impact of spam accounts, we calculated the mean number of tweets within the corpus. Then from each user's tweets, we removed the tweets that exceeded three standard deviations above the mean. Third, we cleaned the text (i.e., removed URLs, @username, repeated spaces, emojis, stop words, numbers, and punctuation) and converted all words to lowercase. Our final dataset consisted of 51,020 tweets. Of that number, 79.2% contained #BlackLivesMatter, 9.4% contained #AllLivesMatter, 0.7% contained #WhiteLivesMatter, 3.3% contained #BlueLivesMatter, and 7.4% contained multiple movement hashtags.

Manually Coding Stances on BLM. We sampled 5,000 tweets from the dataset and manually coded their stances on BLM. This dataset was used to train and validate the stance classification algorithm for the entire dataset. Because a small number of tweets contained hashtags against BLM, tweets containing #AllLivesMatter (20% of dataset), #WhiteLivesMatter (6%), and #BlueLivesMatter (14%) were oversampled to increase classification accuracy.

We coded our data into two stances: against and not against the BLM movement. Stances that were "not against" included both neutral and positive attitudes toward the movement, as we aimed to capture the impact of negative stances on BLM. Positive attitudes included support for the movement or Black people, or criticisms of counter-movements. Neutral attitudes were tweets describing a phenomenon (i.e., the time and place of an event). A tweet was considered as showing a negative stance if it was clearly against BLM or Black people, or if it supported counter-movements (see Table 2 for examples).

Four researchers independently coded a set of 200 tweets and achieved a reliable intercoder reliability assessed by Fleiss's Kappa (Fleiss, 1971), $k = 0.77$, $z = 26.50$, $p < .001$, with the percentage agreement between raters being 83.5%. To further elaborate the coding scheme, the researchers together annotated an additional 300 tweets. After this process, each coder independently annotated 1125 tweets. Overall, the researchers coded 5000 tweets.

Classification Algorithms. Of the annotated 5000 tweets, 90% were randomly selected as the training set and 10% as the testing set (Vukovic et al., 2020). We trained models based on machine learning techniques to categorize the stances of tweets. Models were trained with the training set, which provided information about tweets that were against and not against BLM. We tested the performance and accuracy of the models on the testing dataset by comparing the results yielded by the models and the manual annotations. As described below, we applied five different machine learning techniques, and the best-performing model was used to classify stances for all unannotated tweets.

Lexicon-based Sentiment Analysis. Lexicon-based sentiment analysis has been used to examine Twitter activities related to racial issues (Nguyen et al., 2018). Sentiment analysis allows the detection of emotional valence within messages. However, emotional valence is not always equivalent to a stance towards a movement; thus, this method may fail in revealing opinions about BLM. Therefore, we used machine learning techniques to predict the stances.

Naïve Bayes. The naïve Bayes (NB) classifier is widely used in spam detection and stance classification (Mourad et al., 2018). NB can be easily implemented on small datasets, making it particularly useful in our study. To employ NB, we created a data term matrix (i.e., a mathematical matrix describing the frequency of terms that occur in a collection of tweets) and then trained the classifier using this matrix.

Support Vector Machine. Support vector machine (SVM) is a classifier that maximizes distances between categories. Similar to NB, the SVM process is started by creating a data term matrix to train the classifier. SVM performs well with relatively small datasets (Suthaharan, 2016).

Deep Learning (CNN and LSTM). In deep learning methods, inputs are fed into one or more hidden layers of neurons to predict outputs; thus, hidden layers in a neural network serve to discover representations of inputs through feature learning (LeCun et al., 2015). We used two deep learning methods: convolutional neural networks (CNN) (Kim, 2014) and long short-term memory (LSTM) (Hochreiter and Schmidhuber, 1997). CNN has the advantage of efficiently detecting important features from a complex structure. LSTM has the advantage of capturing dependencies of words in a document (e.g., a tweet).

For both CNN and LSTM, we created a vocabulary for the tokens in our corpus of tweets and transformed each tweet from text to the corresponding token indices, thus converting text to vectors. The input was then fed to hidden layers to predict the stance.

Classification Results. Accuracy, precision, recall, and F1 scores were used to compare model performance. An accuracy score represents the percentage of correct predictions over the total number of predictions. A precision score represents the proportion of true positives (TP) in cases that had been predicted as such. The recall score reveals the proportion of TP in a set of cases predicted as positive. Because there is a clear trade-off between precision and recall scores, the F1 score was calculated based on both scores.

As shown in Table 3, machine learning models showed better performance than lexicon-based sentiment analysis (accuracy: 61%). The NB model had an overall accuracy of 85%, slightly higher than the CNN model (83.80%); both had higher accuracy than the other models. However, NB had the highest recall and F1 for predicting the "against" stance, whereas CNN performed poorly on identifying the "against" stance. We additionally conducted 10-fold cross-validation to compare model performance. This method partitions the data into 10 subsamples, retains one subsample as the test set, uses the remaining data as the training set each time, and then repeats the process 10 times. NB still had the highest recall and F1 for predicting the "against" stance.

Given our focus on negative stances on BLM, we chose the model that best captured this negativity. Thus, the NB model was used to predict the stance of unannotated tweets. NB provides probabilities of tweets containing certain words classified as against or not against BLM. For example, the posterior probability of a tweet containing "#mikebrown" being categorized as "not against" was 95%. Also, #icantbreathe (94%) and #ericgarner (93%) contributed to predicting stances in support of BLM. In contrast, #whitelivesmattertoo (99%) and #thinblueline (98%) were the most predictive of the "against" stance.

Once all tweets were labeled, stances on BLM were aggregated on the MMSA level by calculating the percentage of tweets that were against BLM (i.e., [*N* of tweets against BLM / Total *N* of tweets about BLM] * 100). See Figure 1 for a map depicting the percentage of negative stances on BLM across MMSA areas. Our final dataset consisted of 40,314 tweets from the 76 MMSA areas that had over 50 tweets.

BMI and Obesity

BMI and obesity were assessed using 2017 BRFSS SMART data. Data on participant height and weight were used to calculate BMI. Obesity is a binary variable based on BMI: participants with a BMI less than 30 were coded as not obese (= 0), and those who had a BMI of 30 or higher were considered obese (= 1). Our results did not change if we used overweight as our dependent variable (i.e., BMI ≥ 25).

Control Variables

We introduced and controlled for individual- and regional-level covariates that may impact BMI and obesity (for a review see Hruby et.al., 2016).

Individual-Level Control Variables

Individual-level covariates were retrieved from BRFSS SMART 2017 data. Any missing values of a participant were imputed by the mean value of the MMSA in which the participant lived. We controlled for the following individual-level covariates (see Table 1 for the description of variables and coding schemes): age, sex, education level, income, no access to medical insurance, number of alcohol drinks consumed per week, smoking status, physical activity, number of times fruits and vegetables were consumed per day, and no internet access in past 30 days.

MMSA-Level Control Variables

All rate, ratio, and percentage variables were multiplied by 100 so they range from 0–100 (%). We controlled for MMSA-level Blacks' education (% of non-high school graduates), Blacks' income (median household income in dollars over the previous 12 months), Blacks' unemployment rate, Blacks' poverty rate (% poverty status over the previous 12 months), Blacks' inaccessibility to medical insurance (% of those who do *not* have access to medical insurance), Blacks' migration (% of Black people in each MMSA who moved there in the previous year from a different county in the same state, a different state, or abroad), and no internet access (% of population who lacks internet access). Data were retrieved from the 2013–2017 American Community Survey (ACS) 5-year estimates (US Census Bureau, 2017). Income was divided by 1,000 to increase the interpretability of the coefficient.

The variables of MMSA-level population and ratio of Black population in the area were controlled for and determined using the U.S. Census Bureau's 2010–2017 Annual Estimates of the Resident Population (U.S. Census Bureau, 2017). The population was divided by 10,000 to increase the interpretability of the coefficients. To capture the degree of urbanization, we controlled for population density for each MMSA (i.e., population per square mile) using the U.S. Census Bureau's 2010 Housing Units, Land Area, and Density report (U.S. Census Bureau, 2010). Seven MMSA areas lacked housing density values. Housing densities for those areas were imputed from the housing density value of the geographically most adjacent MMSA areas.

MMSA-Level of BMI from 2014

To better understand how BMI has changed since the onset of the BLM movement in 2014, we controlled for MMSA-level BMI as aggregated from BRFSS SMART 2014 data from 70 overlapping MMSAs with BRFSS SMART 2017 data with more than 50 tweets (6 areas were missing values) from 20,554 Black participants.

MMSA-Level Measures of Racism and Police Brutality Toward Blacks

Explicit and Implicit Racism. We controlled for other measures of racism that could impact BMI and obesity. Explicit and implicit racial bias measures were retrieved from Project Implicit (Xu et al., 2014), which operates a website where millions of people have reported explicit and implicit racism. Explicit racism toward Black people is assessed by asking participants' feelings about Black people on a scale from 0 (coldest feelings) to 10 (warmest feelings). The scale was reverse coded to make the higher value indicate higher levels of explicit racism. The implicit association test (IAT) assesses implicit racism. It evaluates the strength of associations between concepts (e.g., Black people, White people) and evaluations (e.g., bad, good). An IAT score was computed as the mean difference in response time between stereotypical (e.g., White – good association) and non-stereotypical (e.g., Black – good) associations toward White and Black people, divided by the overall standard deviation of response time (Greenwald et al., 2009). A higher IAT score represents more negative bias toward Blacks.

We used explicit and implicit racism measured from 2013 to 2017. From the 76 overlapping MMSAs with BRFSS SMART 2017 data and more than 50 tweets, we obtained 934,910 expressions of explicit racism and 885,808 of implicit racism. Explicit racism and IAT scores were aggregated on the MMSA level.

Police Brutality Toward Blacks. Because exposure to police brutality toward Black people (henceforth police brutality) can negatively impact Black people's health outcomes (McFarland et al., 2018), the MMSA-level rate of police brutality (i.e., fatality incidents of Black people involving police per 100,000) from 2013-2017 was controlled for (Schwartz & Jahn, 2020). For 14 areas, the estimate was available for the metropolitan area, but not available for the smaller divisions within the metropolitan area. For those areas, the values from the metropolitan areas were used.

Results

Preliminary Results

We tested the associations between negative stances on BLM, measures of racism, and police brutality (Table 4). Negative stances on BLM were positively associated with implicit racism (r = .42) and explicit racism (r = .15). Explicit and implicit racism measures were highly correlated with each other (r = .56). The rate of police brutality was *negatively* associated with negative stances on BLM (r = -.25).

Main Results

To account for the clustering of participants living in the same MMSAs, we conducted generalized estimating equation (GEE) analyses which is known to be robust against misspecification in large samples (Hubbard et al., 2010). We conducted GEE analyses using the "gee" package (Carey et al., 2012) in R (R Core Team, 2013).

For each outcome (i.e., BMI and obesity), we ran four models. Across all models, covariance structures were set as compound symmetric, which assumes a different covariance for each MMSA. In the first model, only negative stances on BLM were included as predictors. In the second model, the individual- and regional-level covariates were added to adjust for factors that might influence the outcomes. In the third model, measures of regional racism and police brutality were added. We explored whether stances against BLM predict health outcomes of Black people above other measures of racism and police brutality. In the fourth model, the average BMI in each MMSA in 2014 was included to better control for changes in regional BMI levels. In this model, six areas were missing 2014 BMI; thus, N_{MMSA} = 70.

All results were reported in Table 5 (BMI as the dependent variable) and Table 6 (obesity as the dependent variable). In the first set of models, Black people living in regions with higher levels of negative stances on BLM had marginally higher BMI levels (b = 0.020, p = .079) and were more likely to be obese (OR = 1.006, p = .033). In the second set of models, after controlling for covariates, Black people living in regions with higher levels of negative stances on BLM had higher BMI levels (b = 0.028, p = .007) and were more likely to be obese (OR = 1.009, p < .001). In the third set of models, explicit and implicit racism and police brutality were added. Black people living in regions with higher levels of negative stances on BLM had higher BMI levels (b = 0.031, p < .001) and were more likely to be obese (OR = 1.010, p < .001). Explicit racism did not significantly predict BMI or obesity. Implicit racism predicted higher BMI (b = 9.996, p = .003) and marginally higher likelihood of being obese (OR =7.117, p = .083). Black people living in areas with high police brutality rates had higher BMIs (b = 0.897, p < .001) and were more likely to be obese (OR =1.244, p = .002). In the fourth set of models, after controlling for covariates and 2014 regional BMI levels, Black people living in regions with higher levels of negative stances on BLM had higher BMI levels (b = 0.026, p = .003) and were more likely to be obese (OR =1.008, p = .003). Explicit racism still did not significantly predict BMI or obesity. Again, implicit racism predicted significantly higher BMI (b = 11.519, p = .004) and marginally higher likelihood of being obese (OR =11.627, p = .070). Black people living in areas with high police brutality rates had higher BMI (b = 0.901, p < .001) and were more likely to be obese (OR =1.245, p = .002).

In model 4, various individual-level factors were associated with BMI and obesity (see Tables 5 and 6). Age was positively associated with BMI and a higher likelihood of being obese. Compared to males, females had both a higher BMI and a higher likelihood of being obese. More education, higher income, no access to insurance, more alcohol consumption, smoking tobacco, more physical activity, and no access to the internet were all associated with a lower BMI and lower likelihood of being obese (alcohol consumption was the only individual-level factor that did not predict obesity). Among the regional-level variables, no access to insurance was associated with a lower BMI and lower likelihood of being obese. More regional mobility, a higher proportion of Black population, and higher regional BMI levels in 2014 were associated with a higher BMI and higher likelihood of being obese.

Discussion

This study showed a robust positive association between stances against BLM and indicators of obesity (i.e., BMI and prevalence of obesity) among Blacks. After controlling for individual- and regional-level covariates, regional measures of racism and police brutality rates, and baseline BMI in 2014 aggregated at the MMSA level, we found that Black people living in MMSAs that were higher in negative stances on BLM, as assessed with tweets from 2014 to 2016, had both a higher BMI and prevalence of obesity in 2017. An increase by one standard deviation (7.5%) in proportion of negative stances toward BLM predicted an increase of 0.20 in BMI and a 6% increase in the likelihood of being obese. Our effect sizes were larger than or similar to the effect sizes of studies that investigated the impact of regional racism on BMI and obesity (e.g., Chang, 2006). Why were stances against BLM associated with worse health outcomes of Blacks? In addition to existing regional racism, stances against BLM may have aggravated the hostile social environment toward Blacks and the BLM movement. In turn, the hostile social environment could have been salient race-related stressors for Blacks. During periods when the BLM movement was active, stances against BLM may have better captured race-related stressors than other racism measures. This finding is in line with previous literature showing an association between race-related stress and obesity (Cozier et al., 2009; McFarland et al., 2018).

The significant positive association of stances against BLM and implicit (but not explicit) racism toward Blacks further demonstrated that negative stances on BLM captured racism in a region. Compared to implicit racism, explicit racism may not accurately capture racism against minorities due to social desirability bias (Krieger et al., 2005). Also, implicit racism was associated with higher BMI and prevalence of obesity, replicating past findings that racism can undermine health outcomes (Chae et al., 2015). These results suggest that regions already high in racism toward Blacks can show high anti-BLM sentiments, which may further increase the probability of adverse health outcomes for Black people.

Interestingly, negative stances on BLM were negatively associated with regional rates of police brutality toward Blacks. It is possible that people living in regions with higher police violence rates were more likely to show support for BLM. Regardless of this association, stances against BLM and police brutality both predicted higher BMI and prevalence of obesity, replicating past findings that exposure to police brutality undermines health of Black peoples (McFarland et al., 2018).

Practical Implications

Our findings have several practical implications. First, legislation should promote policy changes to promote a more positive (and less toxic) social environment for minorities. In turn, a more positive social environment could promote better health outcomes for minorities (Kail et al., 2015). Second, as the stances of political leaders about race-related issues can influence popular stances (Park, 2013), politicians should express their support for minorities, which in turn can create a more inclusive social environment for the minorities. For example, former President Donald Trump calling COVID-19 virus as China Virus led to a surge in anti-Asian related tweets (Hswen et al., 2021). This incident demonstrates the detrimental effect of a politician negatively shaping popular stances about race-related issues. Lastly, social media platforms should foster a safer online community. Because hostile social sentiments on race-related issues can spread via social media, social media companies should expand their algorithms to better identify hateful conversations.

Limitations and Future Directions

This study has some limitations. First, our geo-coded tweet corpus is not a representative sample of the U.S. population, given that only 24% of online adults use Twitter. In addition, geotagged tweets are more commonly found in urban areas (Mislove et al., 2011). While we acknowledge these limitations, the characteristics of geo-coded Twitter data can be useful for our study, whose samples were people living in urban MMSAs. Second, we cannot make a causal inference about the effect of stances against BLM on health outcomes because our data were not longitudinal. Finally, we could not identify the pathways through which the perception of negative stances on BLM may have impacted the health outcomes of Blacks.

Future studies can continue to explore the relationships between stances about race-related issues and health outcomes. First, researchers can conduct longitudinal studies to better establish a causal effect of negative stances on the wellbeing of minorities. For example, one can examine how acute increases in negative stances may impact more temporally proximal health outcomes (e.g., sleeping patterns, mental health). Second, researchers can explore the pathways through which negative stances toward race-related issues influence the health outcomes of minorities, for example, how negative stances impact minorities' health outcomes through structural (e.g., discrimination in health care), regional (e.g., real-life protests against minorities), interpersonal (e.g., experiencing discrimination), behavioral (e.g., maladaptive coping), emotional, and physiological (e.g., stress responses) processes.

Conclusion

This study contributed to the literature in several ways. First, it captured stances on BLM through discussions on Twitter. It showed the utility of social media data in capturing stances towards sensitive race-related issues, which can reduce the social desirability bias in self-reported measures. Second, the study demonstrated the strengths of machine learning techniques in handling large datasets. Social scientists can use machine learning techniques to scale up traditional content analysis. Third, by aggregating stances to the MMSA level, we found that Black people had a higher BMI and prevalence of obesity in areas that showed higher negative stances on the BLM movement. Our findings suggest the detrimental effect of negative societal stances on race-related issues on the health outcomes of minorities. Our findings further highlight the importance of fostering a more inclusive environment for minorities through the efforts of members of society including policy makers, politicians, and social media platforms.

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Tables and Figures

Table 1
Descriptive Statistics for Primary Variables

	Variable Description	**M (*SD*)**
Individual level		
BMI	Body mass index (= weight (kg) / [height (m)]^2)	29.64 (*6.96*)
Obesity	Obese = 1; not obese = 0	40.40% (*49.07*)
Age	Age of participant	51.91 (*17.20*)
Sex	Female = 1; male = 0	60.68% (*48.85*)
Education	Measured on a scale from did not graduate high school = 1 to graduate from college or technical school = 4	2.84 (*0.97*)
Income	Measured on a scale from 1 = \$0-\$15,000 to 5 = \$50,000+	3.34(*1.41*)
No Insurance	No access to medical insurance =1; access = 0	9.90% (*29.79*)
Alcohol Consumption	Number of alcohol drinks consumed per week	1.99 (*7.64*)
Smoking Status	Smoke tobacco = 1; do not smoke = 0	16.78% (*36.75*)
Physical Activity	Measured on a scale from 1 = inactive to 4 = highly active	2.34 (*1.14*)
Fruit Consumption	Number of times fruits were consumed per day	1.12 (*2.31*)
Vegetable Consumption	Number of times vegetables were consumed per day	1.60 (*3.55*)
No Internet	No access to internet = 1; access = 0	25.85% (*43.74*)
MMSA level		
% Negative Stances	% of tweets that were against BLM	15.75% (*7.51*)
% Blacks with Less than High School Education	% of Blacks who were non-high school graduates	13.69% (*3.21*)
Blacks' Median Income	Blacks' median household income in dollars over the previous 12 months	\$40551.17 (*10100.94*)
% Blacks' Unemployment	Blacks' unemployment rate	11.26% (*2.33*)
% Blacks' Poverty	% of Blacks who were under poverty threshold over the previous 12 months	24.65% (*5.85*)
% Blacks' Insurance Inaccessibility	% of Blacks who do not have access to medical insurance	10.91% (*3.25*)
% Blacks' Migration	% of Blacks in each MMSA who moved there in the previous year from a different county in the same state, a different state, or abroad	6.70% (*2.51*)
% Internet Inaccessibility	% of population who lacks internet access	16.01% (*3.28*)
Population	Population of MMSA	2,358,214 (*2,476,674*)
% Black Population	% of Black population living in MMSA	15.62% (*10.54*)
Population Density	Population per square mile	749.07 (*958.01*)
Explicit Racism	Recoded to 0 (warm feelings) - 10 (cold feelings)	3.06 (*0.13*)
Implicit Racism	Mean difference in response time between stereotypical (e.g., White – good association) and non-stereotypical (e.g., Black – good) associations toward White and Black people divided by the overall standard deviation of response time	0.29 (*0.03*)
Police Brutality Rate Toward Blacks	Fatality incidents of Blacks involving police per 100,000	0.88 (*0.32*)
BMI 2014	Blacks' MMSA-level BMI from 2014	29.53 (*0.76*)

Table 2
Examples of positive, neutral, and negative attitudes toward the BLM movement.

Attitude	Tweets	Stance
Positive	#WhiteLivesMatter - The people who are legitimately using these hashtags are exactly what's wrong with this society	**Not Against**
	We have to start using our dollars to support and strengthen OUR poor communities that we have moved beyond #Justice4All #BlackLivesMatter	
Neutral	#MillionsMarchNYC #BlackLivesMatte	
	Black Lives Matter rally, #cambma City Hall #blacklivesmatter @ City of Cambridge (Official)	
Negative	#ferguson: if you can proudly say #BlackLivesMatter, why can I not freely say #WhiteLivesMatter? Same with #BlackPride and #WhitePride?	**Against**
	#BlueLivesMatter #foxandfriends We can NOT ask our officers to go where they are hated and shot at. It's worse than being sent to Iraq!	
	#AllLivesMatter, racism is a thing of the past, white supremacy? i can breathe, protesting does nothing	

Table 3
Stance classification results.

	Accuracy%	Precision%		Recall%		F1%	
		Not Against BLM	Against BLM	Not Against BLM	Against BLM	Not Against BLM	Against BLM
Sentiment Analysis	61.00	77.11	29.17	68.27	39.20	72.42	33.45
NB	**85.00**	**95.45**	64.71	84.00	**88.00**	**89.36**	**74.58**
SVM	83.60	87.47	**69.72**	**91.20**	60.80	89.30	64.96
CNN	83.80	88.68	68.33	89.87	65.60	89.27	66.94
LSTM	83.20	89.43	65.65	88.00	68.80	88.71	67.19

Note. The best-performing results are bolded. NB = naïve Bayes; SVM = support vector machine; CNN = convolutional neutral network; LSTM = long short-term memory.

Table 4

Correlations between negative stances on BLM, explicit/implicit racism, and police brutality.

Variable	1	2	3
% Negative Stances			
Explicit Racism	.15 [-.08, .36]		
Implicit Racism	$.42^{**}$ [.21, .59]	$.56^{***}$ [.38, .69]	
Police Brutality Rate Toward Blacks	$-.25^{*}$ [-.45, -.02]	.21 [-.02, .41]	-.07 [-.29, .16]

Note: Values in square brackets are the 95% confidence interval for each correlation.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 5
Results of the generalized estimating equation analysis predicting BMI.

	Dependent variable: BMI			
	Model 1 *b* (95% CI)	Model 2 *b* (95% CI)	Model 3 *b* (95% CI)	Model 4 *b* (95% CI)
% Negative Stances	0.020	0.028**	0.031***	0.026**
	(-0.002, 0.043)	(0.007, 0.048)	(0.014, 0.047)	(0.009, 0.043)
Individual level				
Age		0.019***	0.019***	0.018***
		(0.010, 0.029)	(0.010, 0.028)	(0.009, 0.028)
Sex		1.481***	1.482***	1.469***
		(1.285, 1.676)	(1.287, 1.677)	(1.270, 1.667)
Education		-0.266***	-0.264***	-0.263***
		(-0.385, -0.147)	(-0.383, -0.146)	(-0.384, -0.141)
Income		-0.242***	-0.239***	-0.242***
		(-0.322, -0.162)	(-0.320, -0.159)	(-0.323, -0.160)
No Insurance		-0.627***	-0.633***	-0.652***
		(-0.971, -0.282)	(-0.976, -0.290)	(-0.999, -0.304)
Alcohol Consumption		-0.017*	-0.017*	-0.017*
		(-0.030, -0.004)	(-0.030, -0.004)	(-0.030, -0.003)
Smoking Status		-1.260***	-1.256***	-1.258***
		(-1.559, -0.960)	(-1.557, -0.954)	(-1.566, -0.951)
Physical Activity		-0.555***	-0.556***	-0.552***
		(-0.625, -0.486)	(-0.626, -0.486)	(-0.622, -0.482)
Fruit Consumption		-0.017	-0.017	-0.017
		(-0.059, 0.024)	(-0.059, 0.025)	(-0.059, 0.025)
Vegetable Consumption		-0.005	-0.004	-0.005
		(-0.020, 0.011)	(-0.019, 0.012)	(-0.021, 0.011)
No Internet		-1.373***	-1.367***	-1.343***
		(-1.667, -1.078)	(-1.662, -1.071)	(-1.645, -1.041)
MMSA level				
% Blacks with Less than High School Education		-0.015	-0.018	-0.018
		(-0.081, 0.051)	(-0.080, 0.045)	(-0.082, 0.045)
Blacks' Median Income [1]		0.015	0.021	0.023
		(-0.020, 0.050)	(-0.009, 0.051)	(-0.009, 0.055)
% Blacks' Unemployment		0.019	0.001	0.011
		(-0.061, 0.099)	(-0.071, 0.073)	(-0.069, 0.091)
% Blacks' Poverty		0.066*	0.061*	0.060
		(0.005, 0.127)	(0.001, 0.121)	(-0.003, 0.124)
% Blacks' Insurance Inaccessibility		-0.027	-0.067**	-0.056*
		(-0.089, 0.036)	(-0.111, -0.024)	(-0.099, -0.013)
% Blacks' Migration		0.032	0.087**	0.106**
		(-0.053, 0.116)	(0.023, 0.150)	(0.039, 0.174)
% Internet Inaccessibility		0.021	0.020	0.009
		(-0.052, 0.094)	(-0.035, 0.076)	(-0.055, 0.072)
Population [2]		-0.001	-0.0001	-0.0002
		(-0.001, 0.0002)	(-0.001, 0.0005)	(-0.001, 0.0005)
% Black Population		0.026*	0.066***	0.064***
		(0.005, 0.047)	(0.048, 0.084)	(0.043, 0.085)

Population Density		-0.00002	0.00002	0.0001
		(-0.0002, 0.0001)	(-0.0001, 0.0001)	(-0.0001, 0.0002)
Explicit Racism			0.820	0.640
			(-0.680, 2.321)	(-0.913, 2.193)
Implicit Racism			9.996**	11.519**
			(3.293, 16.700)	(3.668, 19.370)
Police Brutality Rate Toward Blacks			0.897***	0.901***
			(0.445, 1.350)	(0.452, 1.350)
BMI 2014				0.189*
				(0.022, 0.356)
Constant	29.409***	28.183***	21.322***	15.698***
	(28.987, 29.832)	(23.802, 32.564)	(15.901, 26.743)	(8.671, 22.724)
Participants (Number of MMSAs)	20,530 (76)	20,530 (76)	20,530 (76)	19,984 (70)

Note: [1] Divided by 1000. [2] Divided by 10,000.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 6
Results of the generalized estimating equation analysis predicting the prevalence of obesity.

	Dependent variable: Obesity			
	Model 1 OR (95% CI)	Model 2 OR (95% CI)	Model 3 OR (95% CI)	Model 4 OR (95% CI)
% Negative Stances	1.006*	1.009***	1.010***	1.008**
	(1.000, 1.012)	(1.004, 1.013)	(1.005, 1.015)	(1.003, 1.014)
Individual level				
Age		1.006***	1.006***	1.005***
		(1.003, 1.008)	(1.003, 1.008)	(1.003, 1.008)
Sex		1.531***	1.532***	1.529***
		(1.443, 1.624)	(1.443, 1.625)	(1.439, 1.624)
Education		0.909***	0.910***	0.914***
		(0.878, 0.941)	(0.879, 0.942)	(0.881, 0.947)
Income		0.953***	0.954***	0.952***
		(0.931, 0.975)	(0.932, 0.976)	(0.929, 0.974)
No Insurance		0.865**	0.864**	0.862**
		(0.789, 0.949)	(0.788, 0.948)	(0.785, 0.946)
Alcohol Consumption		0.995	0.995	0.995
		(0.990, 1.001)	(0.990, 1.001)	(0.990, 1.001)
Smoking Status		0.715***	0.715***	0.708***
		(0.646, 0.791)	(0.646, 0.791)	(0.640, 0.784)
Physical Activity		0.864***	0.864***	0.862***
		(0.847, 0.881)	(0.846, 0.881)	(0.845, 0.880)
Fruit Consumption		0.993	0.993	0.993
		(0.980, 1.006)	(0.980, 1.006)	(0.980, 1.006)
Vegetable Consumption		0.997	0.997	0.996
		(0.990, 1.003)	(0.990, 1.003)	(0.989, 1.003)
No Internet		0.717***	0.718***	0.723***
		(0.663, 0.774)	(0.664, 0.776)	(0.668, 0.783)
MMSA level				
% Blacks with Less than High School Education		0.998	0.998	0.997
		(0.979, 1.018)	(0.978, 1.018)	(0.977, 1.019)
Blacks' Median Income [1]		1.004	1.004	1.005
		(0.995, 1.013)	(0.997, 1.012)	(0.996, 1.013)
% Blacks' Unemployment		1.005	1.003	1.007
		(0.978, 1.032)	(0.978, 1.030)	(0.978, 1.036)

% Blacks' Poverty		1.012	1.011	1.009
		(0.994, 1.031)	(0.993, 1.029)	(0.991, 1.028)
% Blacks' Insurance Inaccessibility		0.985	0.977***	0.981**
		(0.969, 1.002)	(0.964, 0.991)	(0.968, 0.994)
% Blacks' Migration		1.013	1.025*	1.031**
		(0.990, 1.037)	(1.006, 1.045)	(1.010, 1.053)
% Internet Inaccessibility		1.008	1.008	1.003
		(0.989, 1.029)	(0.990, 1.026)	(0.983, 1.024)
Population [2]		1.000	1.000	1.000
		(1.000, 1.000)	(1.000, 1.000)	(1.000, 1.000)
% Black Population		1.009***	1.017***	1.016***
		(1.004, 1.014)	(1.012, 1.022)	(1.009, 1.022)
Population Density		1.000	1.000	1.000
		(1.000, 1.000)	(1.000, 1.000)	(1.000, 1.000)
Explicit Racism			1.121	1.044
			(0.706, 1.780)	(0.659, 1.654)
Implicit Racism			7.117	11.627
			(0.764, 66.301)	(0.808, 167.292)
Police Brutality Rate Toward Blacks			1.244**	1.245**
			(1.085, 1.426)	(1.086, 1.427)
BMI 2014				1.078**
				(1.028, 1.131)
Constant	0.624***	0.464	0.135**	0.016***
	(0.562, 0.694)	(0.151, 1.428)	(0.034, 0.539)	(0.002, 0.114)
Participants (Number of MMSAs)	20,530 (76)	20,530 (76)	20,530 (76)	19,984 (70)

Note: [1] Divided by 1000. [2] Divided by 10,000.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

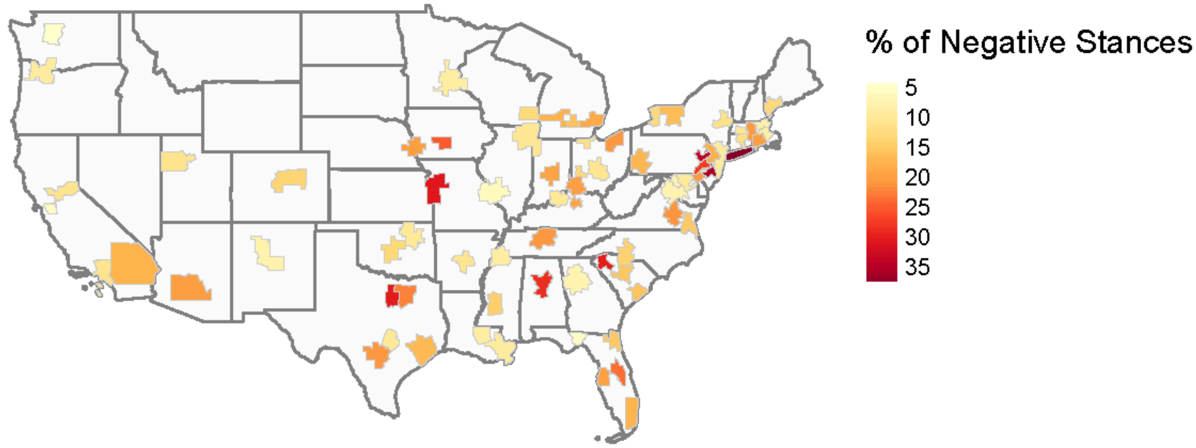

Fig 1 Negative stances on BLM by MMSA areas.

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Highlights

- Stances on the Black Lives Matter (BLM) movement captured through Twitter data
- Stances against BLM associated with higher BMI and prevalence of obesity for Blacks
- Stances against BLM associated with higher level of implicit racism against Blacks
- Negative stances on race-related issues can be detrimental to minorities' health