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Research Report

Racism hurts, can antiracism heal?: Positive mental health correlates of antiracist engagement

Tiffany N. Brannon [a,*]

[a]Department of Psychology, University of California, Los Angeles (UCLA), 1285 Franz Hall, Los Angeles, CA 90095, USA
*To whom correspondence should be addressed: Email: tbrannon@psych.ucla.edu
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Abstract

Racism can hurt by negatively impacting mental health. For instance, large-scale events tied to racism like the May 2020 police-involved murder of George Floyd have been linked to poor mental health indicators (e.g. depression and anxiety). Notably, racism can spark antiracist engagement—support for addressing systemic racism. For example, Floyd's murder sparked unprecedented antiracist engagement, including heightened Black Lives Matter (BLM) support and protest participation. The present research explored the potential that antiracist engagement can heal: be positively associated with well-being. First, study 1 found that state-level BLM engagement (i.e. protest numbers, antiracism information-seeking on Google/YouTube) during an 8-week period following Floyd's death was associated with positive mental health indicators (i.e. lower depression and anxiety, higher self-rated health). It found these effects among racial/ethnic minorities (e.g. Black/African Americans, Hispanics, $N = 161{,}359$) and Whites ($N = 516{,}002$). Then, study 2 examined social media data (i.e. tweets) and emotional well-being. It used a measure of happiness indexed across 144,649,285,571 tweets from 2019 through 2021. It found a positive correlation between the volume of tweets with antiracist engagement content (e.g. referenced efforts to address systemic racism) and the happiness measure. Finally, study 3 examined antiracism protest data/information-seeking and a sample of BLM tweets ($N = 100{,}321$) posted between April and July 2020. Conceptually replicating studies 1–2, study 3 found that antiracist engagement was associated with greater positive emotion/sentiment (e.g. happiness) relative to negative emotion/sentiment (e.g. anxiety). Relevant to theory and policy, the observed results suggest that antiracist engagement can be associated with benefits for well-being across racial/ethnic groups.

Keywords: antiracism, mental health, depression, anxiety

Significance Statement

The present research provides evidence that antiracist engagement can be associated with positive mental health consequences. Notably, the findings are observed across diverse indicators of well-being (e.g. screening assessments for anxiety/depression, emotional measures assessed through social media data). Given the focus on antiracist engagement at the state-level and using social media communication, the findings have implications for potential interventions that leverage policies and practices at such levels (e.g. state laws, social media campaigns). Further, relevant to theory and policy, the observed effects were found across racial/ethnic groups. Such findings, in particular across groups, contradict zero-sum beliefs in which engagement with or support for addressing systemic racism is assumed to advantage some groups (e.g. racial/ethnic minorities) at costs to other groups.

Introduction

Racism has been shown to hurt—inflicting painful decrements on health and well-being. Accordingly, experiences tied to racism can harm mental and physical health when they are directly experienced (e.g. daily experiences with discrimination). Even large-scale events tied to racism can negatively impact health. For instance, large-scale events such as police-involved shootings and immigration raids have been shown to negatively impact mental well-being (e.g. number of poor mental health days), and even intergenerational physical health (e.g. low birth weight in children) at community and state levels (1, 2). Notably, the May 2020 police-involved murder of George Floyd had a massive impact on mental health. It was associated with increased depression and anxiety among Black/African Americans and White Americans (3). Signaling an unprecedented global impact, research that has tracked daily emotional sentiments on Twitter since 2008 has found that the period following Floyd's murder was the "saddest" weeks on the platform (4). Importantly, while Floyd's murder placed a glaring global spotlight on racism, it also sparked unprecedented engagement with antiracist ideas and behaviors. That is, the period following Floyd's murder was

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marked by heightened support and historic volumes of protests for Black Lives Matter (BLM)—an antiracism movement that seeks to address systemic racism (5). The period was also associated with headline-making increases in antiracism book sales and the enactment of widespread antiracism practices and policies, including removing and renaming confederate symbols and passing police reforms across multiple states (6, 7). The present research explored the associated mental health consequences of such antiracist engagement. It asked whether antiracist engagement, enacted on a large scale, can help—by being linked to beneficial consequences for mental health. It investigated this prediction among US racial/ethnic minorities (e.g. Black/African Americans and Hispanics) and across social group lines (e.g. Whites, social media users that can represent a variety of racial/ethnic backgrounds).

The prediction that antiracist engagement can be related to positive mental health consequences for racial/ethnic minorities, especially Black/African Americans, is consistent with research examining individual behaviors and institutional diversity efforts (8). For example, at the individual level, BLM support is protective, a source of resilience that can buffer against depressive symptoms tied to racial discrimination (9). Similarly, research examining youth participation in BLM demonstrations has found that direct engagement, gauged as reported involvement with social media (e.g. posting, sharing) and marches/rallies, is associated with positive emotions (e.g. hope and inspiration; 10). This research among youth also highlights that the content of engagement matters, such that exposure to violence is associated with negative emotions. Also, underscoring the importance of content, research that has examined school mission statements has found that institutional support for antiracism, indexed as valuing diversity and multiculturalism, can benefit physiological health for adolescents from racial/ethnic minority backgrounds (11).

Moreover, research on individual-level engagement with antiracism efforts on college campuses, such as taking part in ethnic study courses or joining racial/ethnic minority cultural organizations, has found positive, longitudinal well-being effects. This research has revealed that individual-level engagement with antiracism efforts predicts lower depression yet higher self-rated health among Latino/a/x and Black/African American college students (12). Thus, integrating and building on such findings, the present research has the potential to illuminate whether large-scale antiracist engagement can be related to positive mental health consequences. Large-scale antiracist engagement is gauged as BLM protests and antiracism information-seeking through Google and YouTube searches in study 1. In study 2, it is indexed in the content of tweets. Finally, in study 3, antiracist engagement is gauged as *both* protests/information-seeking and tweet content.

Research that has examined geographic state and city-level correlations between BLM tweets and protest activity in 2020 further supports the predictions of the present research. That is, such research has found that BLM tweets are associated with negative emotions like anger yet also positive emotions like hope and optimism (13). Thus, the present research builds on such findings in several ways. First, it further examines the type of content that might allow BLM tweets to be associated with positive emotions; it examines content tied to antiracism—operationally defined as ideas and practices tied to addressing systemic racism (see Supplementary Material). Second, it investigates multiple assessments of emotions and well-being. That is, study 2 examines a measure of happiness. And, study 3 examines positive emotion/sentiment (e.g. happiness) relative to negative emotion/sentiment (e.g. anxiety). Together, these varied outcomes are leveraged to test conceptual replications of study 1 which examines screening assessments for anxiety and depression as well as a measure of self-rated health.

To examine potential confounds tied to the COVID-19 pandemic, studies 1 and 3 included additional measures. Specifically, study 1 included CDC data on US COVID-19 cases and study 3 included references to the COVID-19 pandemic in the content of tweets. These covariates are included in the noted analyses, and additional information about the covariates is given in Supplementary Material.

Study 1 tested associations between state-level BLM engagement (indexed as protest numbers, antiracism information-seeking through Google and YouTube searches) and US Census data, Household Pulse Survey Phase 1 (administered 2020 April 23 to 2020 July 21), that included measures of depression, anxiety, and self-rated health (14; Supplementary Material). To be consistent with past research that has used the Household Pulse Survey to examine mental health effects after Floyd's murder we defined the post period as starting on 2020 May 27 (3). The primary analyses focused on data from 2020 May 27 to 2020 July 21, an 8-week period following the death of Floyd. Given the heightened national engagement with antiracism practices and behaviors, this period was the focus of analyses. It was hypothesized that state-level BLM engagement would be associated with positive mental health indicators—lower depression and anxiety, higher self-rated health—among, racial/ethnic minorities (e.g. Black/African Americans, Hispanics; $N = 161{,}359$). The analyses related to non-Hispanic, Whites ($N = 516{,}002$) were exploratory. The analyses included covariates for respondents' age, gender, and educational attainment and state-level measures: US presidential election returns, racial/ethnic diversity, and COVID-19 cases. Additional analyses tested interactions between BLM engagement and Presidential Returns (Democratic). The analyses confirmed the effects of BLM engagement on the mental health outcomes held across Democratic and Republican voting states (see Supplementary Material).

Study 2 examined a measure of happiness, the "hedonometer" which through text analysis tracks daily happiness in English-language tweets (15). It also examined Twitter data that gauged the daily volume of tweets that contained particular search terms (16); these data were used to create an antiracist engagement measure that used analogous terms as the Google information-seeking measure in study 1 (Supplementary Material). Associations between the antiracist engagement measure (i.e. the volume of tweets with antiracism content) and the happiness measure (which was indexed using a sample of 144,649,285,571 tweets) were examined across a 731-day period between 2019 and 2021. It was hypothesized that the volume of antiracism content in daily tweets would be positively associated with the daily happiness measure.

Study 3 examined BLM tweets ($N = 100{,}321$) posted from 2020 April 1 to 2020 July 20. It also investigated antiracism protests/information-seeking that matched the same period (summary data on the volume of daily tweets and information-seeking through Google/YouTube are provided in Supplementary Material). Text analyses were performed using Linguistic Inquiry Word Count (LIWC-22; 17) software that assessed the prevalence of words that referenced positive emotions, negative emotions, positive tone, and negative tone. Consistent with past research (18), an emotional positivity index was created by computing a difference score between the prevalence of words referencing positive and negative emotions. A positive emotional sentiment

index was computed as a difference score between the prevalence of references to positive and negative tones. The LIWC-22 dictionaries that capture emotions are restricted to expressed affect.

In contrast, the LIWC-22 dictionaries that capture tone are more expansive in that they include references to emotions and words related to expressed emotions (18). Thus, the tone measure is broader yet the emotion measure is narrower. The tweets were also analyzed for antiracist engagement content using similar terms as those used in studies 1–2 (Supplementary Material). Study 3 examined associations between antiracist engagement (i.e. tweet content and protests/information-seeking; see Supplementary Material) and emotional positivity and positive emotional sentiment in the tweets. It was predicted that antiracist engagement would be positively associated with the outcome measures. Study 3 also included a covariate for references to COVID-19. Models were also tested on a "text-filtered" sample in which tweets containing references to counter-movements (i.e. All Lives Matter and Blue Lives Matter) were removed (text-filtered sample, $N = 97{,}712$). Additional analyses in which references to counter-movements (i.e. All Lives Matter and Blue Lives Matter) are tested, as covariates are included in Supplementary Material. The primary findings held across all analyses.

Results

For study 1, generalized linear mixed modeling (GLMM) was conducted to test the stated predictions for racial/ethnic minorities and Whites separately. BLM engagement (i.e. protest numbers, antiracism information-seeking on Google/YouTube) and covariates for respondents' age, gender, and educational attainment were added as fixed effects. For analyses among racial/ethnic minorities, covariates for Black/African American and Hispanic self-identification were added. MIT Election Data and Science Lab data on 2020 presidential election returns, US Census data on state-level diversity, and CDC data on COVID-19 case numbers were also added as covariates (19, 20). Geographic state ($n = 51$) and weeks ($n = 8$) were added as a random effect. As predicted and shown in Table 1, among racial/ethnic minority respondents, each BLM engagement measure was a negative predictor of depression (protest numbers, $P = 0.021$; YouTube searches $P \leq 0.001$; Google searches, $P = 0.028$) and anxiety (protest numbers, $P = 0.004$; YouTube searches $P \leq 0.001$; Google searches, $P = 0.002$). However, as hypothesized, among racial/ethnic minority respondents, each BLM engagement measure was a positive predictor of self-rated health ($P \leq 0.001$). Moreover, as shown in Table 2, the same pattern of results held among White respondents. That is, BLM engagement was a negative predictor of depression (protest numbers, $P = 0.006$; YouTube searches, $P \leq 0.001$; Google searches, $P \leq 0.001$) and anxiety ($P \leq 0.001$); yet, it was a positive predictor of self-rated health ($P \leq 0.001$).

For the purpose of comparing model fit, the Akaike Corrected Information Criterion (AIC) for a model that included a standardized composite of the BLM engagement variables and the noted covariates was compared with a model with only the noted covariates. The models were compared separately for racial/ethnic minority and White respondents. Among racial/ethnic minority respondents, the model that included the composite BLM engagement variable (full model) consistently had a lower AIC, which is an indicator of better model fit (21), than the model with only the noted covariates (covariates only model) for the tested outcomes: depression ($AIC_{full\_model} = 644{,}767.71$ compared with $AIC_{cov\_only\_model} = 644{,}777.53$; 9.82 AIC points lower), anxiety ($AIC_{full\_model} = 669{,}988.30$ compared with $AIC_{cov\_only\_model} = 670{,}018.30$; 30.00 AIC points lower), and self-rated health ($AIC_{full\_model} = 459{,}716.28$ compared with $AIC_{cov\_only\_model} = 459{,}774.65$; 58.37 AIC points lower). Similarly, among White respondents, the model that included the composite BLM engagement variable consistently had a lower AIC, which is an indicator of better model fit, than the model with only the noted covariates for the tested outcomes: depression ($AIC_{full\_model} = 2{,}010{,}128.37$ compared with $AIC_{cov\_only\_model} = 2{,}010{,}194.26$; 65.90 AIC points lower), anxiety ($AIC_{full\_model} = 2{,}099{,}005.79$ compared with $AIC_{cov\_only\_model} = 2{,}099{,}156.45$; 150.66 AIC points lower), and self-rated health ($AIC_{full\_model} = 1{,}435{,}225.77$ compared with $AIC_{cov\_only\_model} = 1{,}435{,}486.42$; 260.66 AIC points lower).

For study 2, hierarchical linear regressions were conducted to examine whether the volume of antiracist engagement content in daily tweets positively predicted the happiness measure. The regression models also include time (measured as days) and frequency of daily tweets. As shown in Table 3, and consistent with the hypothesis, antiracist engagement content in tweets positively and significantly predicted the daily happiness measure, $P = 0.033$. Accordingly, the F-change statistic (4.55, $P = 0.033$) provides some evidence that adding the antiracist engagement variable to the model contributes significantly to explaining the variance in the happiness measure.

For study 3, GLMM was conducted to test whether antiracist engagement (i.e. tweet content and protests/information-seeking) positively predicts emotional positivity and positive emotional sentiment. Date (day) was added as a random effect. As shown in Table 4, and aligned with predictions, antiracist engagement content in tweets ($P \leq 0.001$) and antiracist engagement as protests/information-seeking ($P = 0.028$) positively and significantly predict emotional positivity. Also, tweet content ($P \leq 0.001$) and protests/information-seeking data ($P \leq 0.001$) positively and significantly predict emotional sentiment. Table 4 also shows that the patterns of results remain significant and in the predicted direction using the text-filtered sample.

For the purpose of comparing model fit, the AIC for the nontext-filtered models that included the antiracist engagement variables and the noted covariate were compared with models with only the noted covariate. The comparisons provided evidence that the full models with the variables of interest are better fitting than the covariate-only models. That is, the models that included antiracist engagement content in tweets had lower AICs than the models with only the noted covariate for emotional positivity ($AIC_{full\_model} = 503{,}019.995$ compared with $AIC_{cov\_only\_model} = 503{,}053.89$; 33.89 AIC points lower) and emotional sentiment ($AIC_{full\_model} = 650{,}751.61$ compared with $AIC_{cov\_only\_model} = 657{,}328.72$; 6577.11 AIC points lower). Similarly, the models that included antiracist engagement as protests/information-seeking had lower AICs than the models with only the noted covariate for emotional positivity ($AIC_{full\_model} = 503{,}052.63$ compared with $AIC_{cov\_only\_model} = 503{,}053.89$; 1.26 AIC points lower) and emotional sentiment ($AIC_{full\_model} = 657{,}309.75$ compared with $AIC_{cov\_only\_model} = 657{,}328.72$; 18.97 AIC points lower).

Discussion

Taken together, the results of studies 1–3 provide evidence that large-scale antiracist engagement, indexed using ecologically valid measures including protest data, Google/YouTube searches, and tweets, can be associated with positive impacts on mental health. These findings were observed using diverse well-being indicators including screening assessments for anxiety/depression, self-rated health, and emotions expressed in social media data.

Table 1. Fixed-effect coefficients: model predicting mental health indicators from BLM engagement (racial/ethnic minority respondents).

	Depression (PHQ-2) (N = 160,362)			Anxiety (GAD-2) (N = 160,497)			Self-rated health[a] (N = 160,535)		
Model: BLM protest numbers	**Pseudo R^2 = 3.4%**			**Pseudo R^2 = 4.2%**			**Pseudo R^2 = 8.6%**		
Model term	**Coefficient (SE)**	**t**	**95% (CI)**	**Coefficient (SE)**	**t**	**95% (CI)**	**Coefficient (SE)**	**t**	**95% (CI)**
Intercept	2.93 (0.056)[b]	52.40	(2.82, 3.04)	2.94 (0.06)[b]	51.61	(2.83, 3.06)	3.25 (0.036)[b]	90.79	(3.18, 3.32)
Age	−0.014 (0.0003)[b]	−43.38	(−0.014, −0.013)	−0.014 (0.0003)[b]	−43.37	(−0.014, −0.013)	−0.011 (0.0002)[b]	−61.77	(−0.011, −0.010)
Gender (female)	0.21 (0.009)[b]	21.99	(0.19, 0.23)	0.21 (0.009)[b]	21.98	(0.19, 0.23)	−0.17 (0.005)[b]	−31.54	(−0.18, −0.16)
Educational attainment	−0.13 (0.003)[b]	−42.85	(−0.13, −0.12)	−0.13 (0.003)[b]	−42.83	(−0.13, −0.12)	0.15 (0.002)[b]	91.29	(0.15, 0.16)
2020 Presidential returns (democratic)	−0.059 (0.028)[c]	−2.08	(−0.11, −0.003)	−0.054 (0.029)	−1.83	(−0.11, 0.004)	0.085 (0.019)[b]	4.53	(0.05, 0.12)
Diversity index	0.00 (0.001)	−0.34	(−0.002, 0.002)	−0.001 (0.001)	−0.57	(−0.003, 0.001)	0.001 (0.0007)	1.03	(−0.001, 0.002)
COVID-19 cases	1.15e−7 (1.60e−8)[b]	7.23	(8.4e−8, 1.5e−7)	1.23e−7 (1.50e−8)[b]	8.17	(9.3e−8, 1.5e−7)	−5.20e−8 (9.33e−9)[b]	−5.57	(−7.0e−8, −3.4e−8)
Race/ethnicity: Black/African American	−0.016 (0.012)	−1.36	(−0.039, 0.007)	−0.016 (0.012)	−1.36	(−0.039, 0.007)	−0.15 (0.007)[b]	−22.17	(−0.16, −0.13)
Race/ethnicity: Hispanic	0.02 (0.011)	1.82	(−0.002, 0.042)	0.02 (0.01)	1.81	(−0.002, 0.042)	−0.013 (0.006)[c]	−2.12	(−0.03, −0.001)
BLM protest numbers	−0.012 (0.005)[c]	−2.30	(−0.022, −0.002)	−0.013 (0.006)[c]	−2.20	(−0.024, −0.001)	0.013 (0.003)[b]	4.54	(0.007, 0.019)
Model: YouTube searches (protests)	**Pseudo R^2 = 3.4%**			**Pseudo R^2 = 4.3%**			**Pseudo R^2 = 8.6%**		
Intercept	2.93 (0.057)[b]	51.67	(2.82, 3.05)	3.09 (0.06)[b]	48.33	(2.97, 3.22)	3.25 (0.035)[b]	92.92	(3.18, 3.32)
Age	−0.014 (0.0003)[b]	−43.40	(−0.014, −0.013)	−0.017 (0.0003)[b]	−50.45	(−0.018, −0.016)	−0.011 (0.0002)[b]	−61.75	(−0.011, −0.010)
Gender (female)	0.21 (0.009)[b]	22.01	(0.19, 0.23)	0.47 (0.01)[b]	46.14	(0.45, 0.49)	−0.17 (0.0053)[b]	−31.58	(−0.18, −0.16)
Educational attainment	−0.13 (0.003)[b]	−42.82	(−0.13, −0.12)	−0.069 (0.003)[b]	−21.42	(−0.075, −0.062)	0.15 (0.002)[b]	91.28	(0.15, 0.16)
2020 Presidential returns (democratic)	−0.052 (0.029)	−1.80	(−0.11, 0.005)	−0.048 (0.032)	−1.45	(−0.11, 0.017)	0.079 (0.018)[b]	4.32	(0.043, 0.12)
Diversity index	0.00 (0.001)	−0.28	(−0.002, 0.002)	0.002 (0.001)	−1.45	(−0.004, 0.001)	0.001 (0.0007)	1.05	(−0.001, 0.002)
COVID-19 cases	9.79e−8 (1.56e−8)[b]	6.29	(6.7e−8, 1.3e−7)	1.71e−7 (1.76e−8)[b]	9.75	(1.4e−7, 2.06e−7)	−3.7e−8 (8.9e−9)[b]	−4.18	(−5.5e−8, −1.98e−8)
Race/ethnicity: Black/African American	−0.017 (0.012)	−1.42	(−0.04, 0.006)	−0.019 (0.013)	−1.51	(−0.044, 0.006)	−0.15 (0.007)[b]	−22.11	(−0.16, −0.13)
Race/ethnicity: Hispanic	0.02 (0.011)	1.79	(−0.002, 0.042)	0.11 (0.01)[b]	9.01	(0.085, 0.13)	−0.013 (0.006)[c]	−2.08	(−0.025, −0.001)
YouTube searches (protests)	−0.03 (0.006)[b]	−5.57	(−0.041, −0.02)	−0.016 (0.006)[d]	−2.88	(−0.03, −0.005)	0.029 (0.0031)[b]	9.40	(0.023, 0.035)
Model: antiracism Google searches	**Pseudo R^2 = 3.5%**			**Pseudo R^2 = 4.3%**			**Pseudo R^2 = 8.6%**		
Intercept	2.94 (0.057)[b]	51.61	(2.83, 3.06)	3.11 (0.066)[b]	46.89	(2.98, 3.24)	3.24 (0.035)[b]	92.28	(3.17, 3.31)
Age	−0.014 (0.0003)[b]	−43.37	(−0.014, −0.013)	−0.017 (0.0003)[b]	−50.44	(−0.018, −0.016)	−0.011 (0.0002)[b]	−61.80	(−0.011, −0.011)
Gender (female)	0.21 (0.009)[b]	21.98	(0.19, 0.23)	0.47 (0.01)[b]	46.13	(0.45, 0.49)	−0.17 (0.005)[b]	−31.53	(−0.18, −0.16)
Educational attainment	−0.13 (0.003)[b]	−42.83	(−0.13, −0.12)	−0.069 (0.003)[b]	−21.40	(−0.075, −0.062)	0.15 (0.002)[b]	91.28	(0.15, 0.16)
2020 Presidential returns (democratic)	−0.054 (0.029)	−1.83	(−0.11, 0.004)	−0.039 (0.035)	−1.12	(−0.11, 0.03)	0.08 (0.019)[b]	4.14	(0.04, 0.11)
Diversity index	−0.001 (0.001)	−0.57	(−0.003, 0.001)	−0.002 (0.001)	−1.69	(−0.005, 0.00)	0.00 (0.0007)	1.45	(0.00, 0.002)
COVID-19 cases	1.23e−7 (1.50e−8)[b]	8.17	(9.3e−8, 1.5e−7)	1.8e−7 (1.6e−8)[b]	10.96	(1.5e−7, 2.1e−7)	−5.66e−8 (8.60e−9)[b]	−6.58	(−7.3e−8, −3.97e−8)
Race/ethnicity: Black/African American	−0.016 (0.012)	−1.36	(−0.039, 0.007)	−0.019 (0.013)	−1.50	(−0.044, 0.006)	−0.15 (0.007)[b]	−22.17	(−0.16, −0.13)
Race/ethnicity: Hispanic	0.02 (0.011)	1.81	(−0.002, 0.042)	0.11 (0.01)[b]	8.99	(0.084, 0.13)	−0.013 (0.006)[c]	−2.10	(−0.025, −0.001)
Antiracism Google searches	−0.013(0.006)[c]	−2.20	(−0.024, −0.001)	−0.020 (0.006)[d]	−3.14	(−0.032, −0.007)	0.018 (0.0033)[b]	5.60	(0.012, 0.025)

[a]Higher score indicate better self-rated health.
[b]$P \leq 0.001$.
[c]$P \leq 0.05$.
[d]$P \leq 0.01$.

Table 2. Fixed-effect coefficients: model predicting mental health indicators from BLM engagement (white respondents).

	Depression (PHQ-2) (N = 513,867)			Anxiety (GAD-2) (N = 514,071)			Self-rated health[a] (N = 513,983)		
Model: BLM protest numbers	**Pseudo R^2 = 5.5%**			**Pseudo R^2 = 8.7%**			**Pseudo R^2 = 8.5%**		
Model term	**Coefficient (SE)**	**t**	**95% (CI)**	**Coefficient (SE)**	**t**	**95% (CI)**	**Coefficient (SE)**	**t**	**95% (CI)**
Intercept	2.95 (0.06)[b]	49.62	(2.83, 3.06)	3.48 (0.068)[b]	51.45	(3.35, 3.61)	3.03 (0.037)[b]	82.64	(2.96, 3.10)
Age	−0.018 (0.0002)[b]	−118.33	(−0.019, −0.018)	−0.028 (0.0002)[b]	−168.64	(−0.029, −0.028)	−0.007 (8.81e−5)[b]	−79.78	(−0.007, −0.007)
Gender (female)	0.22 (0.005)[b]	45.91	(0.21, 0.23)	0.51 (0.05)[b]	95.32	(0.49, 0.52)	−0.073 (0.003)[b]	−26.32	(−0.08, −0.07)
Educational attainment	−0.16 (0.002)[b]	−91.57	(−0.16, −0.15)	−0.11 (0.002)[b]	−58.14	(−0.11, −0.105)	0.18 (0.001)[b]	185.71	(0.18, 0.184)
2020 Presidential returns (democratic)	−0.03 (0.034)	−0.85	(−0.095, 0.04)	−0.003 (0.039)	−0.08	(−0.08, 0.07)	0.099 (0.02)[b]	4.69	(0.06, 0.14)
Diversity index	0.003 (0.001)[c]	2.83	(0.001, 0.006)	0.00 (0.001)	−0.34	(−0.002, 0.002)	0.00 (0.0007)	0.67	(−0.001, 0.002)
COVID-19 cases	1.8e−7 (1.25e−8)[b]	14.41	(1.6e−7, 2.0e−7)	2.56e−7 (1.37e−8)[b]	18.73	(2.3e−7, 2.8e−7)	−6.10e−8 (7.19e−9)[b]	−8.48	(−7.5e−8, −4.7e−8)
BLM protest numbers	−0.01 (0.004)[c]	−2.77	(−0.018, −0.003)	−0.021 (0.004)[b]	−5.18	(−0.03, −0.013)	0.023 (0.002)[b]	10.63	(0.018, 0.027)
Model: YouTube searches (protests)	**Pseudo R^2 = 5.5%**			**Pseudo R^2 = 8.7%**			**Pseudo R^2 = 8.5%**		
Intercept	2.94 (0.06)[b]	49.52	(2.83, 3.06)	3.48 (0.069)[b]	50.69	(3.35, 3.62)	3.02 (0.038)[b]	80.60	(2.95, 3.09)
Age	−0.018 (0.0002)[b]	−118.31	(−0.019, −0.018)	−0.028 (0.0002)[b]	−168.63	(−0.029, −0.028)	−0.007 (8.81e−5)[b]	−79.84	(−0.007, −0.007)
Gender (female)	0.22 (0.005)[b]	45.91	(0.21, 0.23)	0.51 (0.005)[b]	95.34	(0.49, 0.52)	−0.07 (0.0028)[b]	−26.33	(−0.08, −0.07)
Educational attainment	−0.16 (0.002)[b]	−91.55	(−0.16, −0.15)	−0.11 (0.002)[b]	−58.10	(−0.11, −0.105)	0.18 (0.001)[b]	185.70	(0.18, 0.184)
2020 Presidential returns (democratic)	−0.021 (0.034)	−0.62	(−0.09, 0.05)	0.008 (0.04)	0.21	(−0.07, 0.09)	0.096 (0.022)[b]	4.46	(0.054, 0.14)
Diversity index	0.004 (0.001)[c]	2.98	(0.001, 0.006)	0.003 (0.001)[d]	2.24	(0.00, 0.006)	0.001 (0.0007)	0.94	(−0.001, 0.002)
COVID-19 cases	1.54e−7 (1.16e−8)[b]	13.25	(1.3e−7, 1.8e−7)	2.21e−7 (1.27e−8)[b]	17.39	(1.96e−7, 2.5e−7)	−6.03e−8 (6.70e−9)[b]	−9.04	(−7.3e−8, −4.72e−8)
YouTube searches (protests)	−0.03 (0.003)[b]	−10.87	(−0.035, −0.024)	−0.048 (0.003)[b]	−16.15	(−0.054, −0.04)	0.026 (0.0016)[b]	16.82	(0.023, 0.030)
Model: antiracism Google searches	**Pseudo R^2 = 5.6%**			**Pseudo R^2 = 8.9%**			**Pseudo R^2 = 8.6%**		
Intercept	2.96 (0.06)[b]	48.93	(2.84, 3.07)	3.5 (0.072)[b]	48.34	(3.36, 3.64)	3.00 (0.038)[b]	78.73	(2.94, 3.08)
Age	−0.018 (0.0002)[b]	−118.32	(−0.019, −0.018)	−0.028 (0.0002)[b]	−168.63	(−0.029, −0.028)	−0.007 (8.81e−5)[b]	−79.80	(−0.007, −0.007)
Gender (female)	0.22 (0.005)[b]	45.90	(0.21, 0.23)	0.51 (0.005)[b]	95.32	(0.49, 0.52)	−0.073 (0.003)[b]	−26.32	(−0.08, −0.068)
Educational attainment	−0.16 (0.002)[b]	−91.57	(−0.16, −0.15)	−0.11 (0.002)[b]	−58.13	(−0.11, −0.105)	0.18 (0.001)[b]	185.70	(0.18, 0.184)
2020 Presidential returns (democratic)	−0.022 (0.035)	−0.63	(−0.09, 0.05)	0.004 (0.042)	0.084	(−0.08, 0.085)	0.095 (0.02)[b]	4.32	(0.05, 0.14)
Diversity index	0.003 (0.0012)[c]	2.62	(0.001, 0.005)	0.002 (0.0014)	1.67	(0.00, 0.005)	0.001 (0.0008)	1.34	(0.00, 0.003)
COVID-19 cases	1.84e−7 (1.13e−8)[b]	16.33	(1.6e−7, 2.06e−7)	2.75e−7 (1.23e−8)[b]	22.23	(2.5e−7, 2.99e−7)	−8.47e−8 (6.47e−9)[b]	−13.09	(−9.7e−8, −7.2e−8)
Antiracism Google Searches	−0.014 (0.003)[b]	−4.82	(−0.02, −0.009)	−0.019 (0.003)[b]	−5.81	(−0.025, −0.013)	0.015 (0.0017)[b]	8.99	(0.012, 0.019)

[a]Higher score indicate better self-rated health.
[b]$P \leq 0.001$.
[c]$P \leq 0.01$.
[d]$P \leq 0.05$.

Table 3. Hierarchical regression model: antiracist engagement content predicting happiness.

	Model 1			Model 2			Model 3		
	Adjusted R^2 = 57.4% F change (984.18, $P \leq 0.001$)			Adjusted R^2 = 60.4% F change (57.00, $P \leq 0.001$)			Adjusted R^2 = 60.6% F change (4.55, $P = 0.033$)		
Model term	**Standardized coefficient**	**t**	**Sig.**	**Standardized coefficient**	**t**	**Sig.**	**Standardized coefficient**	**t**	**Sig.**
Constant		794.07	≤0.001		777.02	≤0.001		613.69	≤0.001
Frequency of tweets	−0.76	−31.37	≤0.001	−0.90	−30.04	≤0.001	−0.95	−24.67	≤0.001
Time (days)	—	—	—	0.23	7.55	≤0.001	0.24	7.82	≤0.001
Antiracist engagement content	—	—	—	—	—	—	0.068	2.13	0.033

Table 4. Fixed-effect coefficients: models predicting emotion outcomes from antiracist engagement (tweet content and protests/information-seeking).

	Emotional positivity			Positive emotional sentiment		
	Pseudo R^2 = 2.3% (N = 100,321)			Pseudo R^2 = 8.3% (N = 100,321)		
Model term	**Coefficient (SE)**	**t**	**95% (CI)**	**Coefficient (SE)**	**t**	**95% (CI)**
Intercept	−0.34 (0.053)[a]	−6.27	(−0.44, −0.23)	−0.19 (0.11)	−1.85	(−0.40, 0.011)
COVID-19	−0.031 (0.019)	−1.62	(−0.067, 0.006)	−0.48 (0.039)[a]	−12.25	(−0.56, −0.40)
Antiracist engagement (tweet content)	0.028 (0.0043)[a]	6.55	(0.02, 0.037)	0.75 (0.009)[a]	82.50	(0.73, 0.76)
	Pseudo R^2 = 2.3% (N = 100,321)			Pseudo R^2 = 2.0% (N = 100,321)		
Intercept	−0.27 (0.058)[a]	−4.60	(−0.38, −0.15)	0.31 (0.099)[b]	3.12	(0.11, 0.50)
COVID-19	−0.031 (0.019)	−1.69	(−0.068, 0.005)	−0.51 (0.04)[a]	−12.78	(−0.59, −0.43)
Antiracist engagement (protests/information-seeking)	0.15 (0.068)[c]	2.20	(0.02, 0.28)	0.57 (0.12)[a]	4.85	(0.34, 0.79)
	Text-filtering (references to counter-movement removed) Pseudo R^2 = 2.3% (N = 97,712)			Text-filtering (references to counter-movement removed) Pseudo R^2 = 8.4% (N = 97,712)		
Intercept	−0.32(.055)[a]	−5.93	(−0.43, −0.22)	−0.13(.11)	−1.20	(−0.34,.081)
COVID-19	−0.031(.019)	−1.64	(−0.068,.006)	−0.48(.039)[a]	−12.30	(−0.56, −0.41)
Antiracist engagement (tweet content)	.028(.0044)[a]	6.46	(.02,.037)	.75(.009)[a]	81.75	(.73,.76)
	Text-filtering (References to Counter-Movement Removed) Pseudo R^2 = 2.3% (N = 97,712)			Text-filtering (References to Counter-Movement Removed) Pseudo R^2 = 201% (N = 97,712)		
Model term	**Coefficient (S.E.)**	**t**	**95% (C.I.)**	**Coefficient (S.E.)**	**t**	**95% (C.I.)**
Intercept	−0.26 (0.059)[a]	−4.34	(−0.37, −0.14)	−0.37 (0.10)[a]	3.66	(0.17, 0.56)
COVID-19	−0.032 (0.019)	−1.71	(−0.069, 0.005)	−0.52 (0.041)[a]	−12.84	(−0.60, −0.44)
Antiracist engagement (protests/information-seeking)	0.15 (0.07)[c]	2.13	(0.012, 0.28)	0.54 (0.12)[a]	4.59	(0.31, 0.77)

[a]$P \leq 0.001$.
[b]$P \leq 0.01$.
[c]$P \leq 0.05$.

They were also observed in analyses that included covariates for other important, large-scale events such as the COVID-19 pandemic (studies 1 and 3), counter-movements to antiracism efforts (e.g. All Lives Matter, study 3), and state-level political orientation (e.g. Democratic/Republican voting states). Notably, study 1 found some evidence of positive mental health correlates among racial/ethnic minority and White respondents. Studies 2 and 3 used Twitter data that can represent individuals from various racial/ethnic backgrounds. Such findings across groups and using social media data suggest that the potential mental health benefits of antiracist engagement are not zero-sum. That is, the observed results suggest that antiracist engagement may not benefit some groups (e.g. historically marginalized groups) at a cost to other groups (e.g. historically dominant groups; 22). Rather, the results suggest that antiracist engagement can be associated with positive consequences across groups.

The present studies complement and extend research that has examined the harmful effects of large-scale events tied to racism, as well as vicarious racism, on health and well-being (1–3, 23, 24). Combined with such past findings, the present studies highlight the potential for large-scale events to have complex impacts on mental health. That is, past research has shown impacts tied to

hurt, such that racism has been shown to harm well-being (9, 10). The present research highlighted impacts related to *help* by promoting thriving and resilience when linked to antiracism. While the observed effects are encouraging and they extend findings observed tied to individual-level experiences with antiracism, it is important to note that the effect sizes for the present studies were small and modest. Research conducted using real-world data has observed small and modest effects that are socially meaningful at the population level (25, 26). Another limitation of the observed findings is that they are not experimental or casual. The present research also does not examine mechanisms; for instance, what psychological, affective, cognitive, and/or behavioral processes allow large-scale antiracist engagement to foster positive mental health correlates (e.g. does antiracist engagement foster hope for change or fuel a sense of personal meaning/purpose). However, and importantly, the observed findings are consistent with and underscore the efficacy of public health calls to move beyond merely documenting the *harmful* effects of racism. Instead, the observed findings answer the call to move toward examining the potential for antiracism to *help* eliminate negative health outcomes (27).

Materials and methods

Study 1: overview

Primary statistical analyses were conducted on data from weeks 5 to 12 of the US Census Pulse Household Survey, phase 1, which corresponded to 2020 May 28 to 2020 July 21 (14). This period corresponds to post the murder of George Floyd, a period of heightened BLM support and actions that reflected support for antiracism (e.g. increased antiracism book sales, enactment of legal reforms, Juneteenth recognized as a national holiday in the United States, removal of Confederate symbols; 7). The Pulse Household Survey provided respondent-level measures of depression, anxiety, and self-rated health and respondent-level demographic covariates including age, gender, and educational attainment. To examine political orientation and diversity exposure as additional covariates, since they were not available at the respondent level, the tested analyses included state-level measures of political orientation and a diversity index. Data on political orientation were obtained using 2020 presidential election returns from MIT Election Data and Science Lab (28). The 2020 US Census diversity index which indicates the likelihood that two randomly chosen individuals will be from different racial/ethnic groups was used as a measure of state-level diversity (19). Given the tested time period, weekly COVID-19 cases for each state were also added as a covariate (20). To index state-level BLM engagement, three measures were used. The measures included protest numbers ($M = 7.09$, $SD = 13.64$) and antiracism information-seeking through YouTube ($M = 24.80$, $SD = 22.02$) and Google searches ($M = 233.48$, $SD = 75.20$). The state-level BLM engagement data were selected to match the time period of the Pulse Household Survey data (2020 May 28 to July 21). The state-level BLM engagement measures were tested as a predictor of depression, anxiety, and self-rated health. Models for racial/ethnic minority and White respondents were examined separately.

Study 1: methods (respondents)

Racial/ethnic minority respondents

The sample included 161,359 self-identified, racial/ethnic minorities who responded during the noted period. The average age of respondents was 46.99 ($SD = 14.63$). The sample self-identified as Black/African American = 52,782; Hispanic (of any racial background) = 58,986; Mixed/Other = 32,834; and Asian = 30,297. The majority of the sample self-identified as female ($n = 100$; 62%). Educational attainment was recorded as 1 = *Less than high school*, 2 = *Some high school*, 3 = *High school graduate or equivalent (for example GED)*, 4 = *Some college, but degree not received or is in progress*, 5 = *Associate's degree (for example, AA and AS)*, 6 = *Bachelor's degree (for example, BA, BS, and AB)*, and 7 = *Graduate degree (for example master's, professional, and doctorate)*. The mean for educational attainment was 5.01 ($SD = 1.57$). Respondents lived in states with 2020 presidential election returns that were Democratic ($n = 96,902$ or 60.1% of the sample) and Republican ($n = 64,457$ or 39.9%). The mean diversity index (which represents the odds that two individuals chosen randomly will be from different racial/ethnic backgrounds) was 58.74 (11.70). A summary of the number of weekly COVID-19 cases for each state is shown in Supplementary Material.

White respondents

The sample included 516,002 self-identified, non-Hispanic, Whites who responded during the noted period. The average age of respondents was 53.25 ($SD = 15.62$). The majority of the sample self-identified as female ($n = 303,515$; 58.8%). The mean for educational attainment was 5.39 ($SD = 1.41$). Respondents lived in states where the mean 2020 presidential election returns were Democratic ($n = 272,199$ or 52.8%) and Republican ($n = 243,803$ or 47.2%). Respondents lived in states with an average diversity index of 50.57 ($SD = 14.08$).

Study 1: materials (outcome measures)

BLM engagement

State-level BLM engagement was measured as protest numbers, as well as searches performed on YouTube and Google from the noted time period, 2020 May 28 to 2020 July 21. The data used for analyses indexed these outcomes for each week of the 8-week time period, matching the Pulse Household Survey, phase 1, for every state.

BLM protest data were obtained from Open Science Framework repository materials (16) shared in relation to published research by Dunivin et al. (29). The repository materials were sourced from "Elephrame" and the Armed Conflict Location and Event Data Project. The number of protests for each state for the noted time periods is shown in Supplementary Material.

Google Trends data that assessed the volume of Google searches performed for antiracism terms (e.g. "Black Lives Matter," "antiracism," and "social justice"; see Supplementary Material) were obtained for the noted time period for each state. Google search data have been used as a behavioral indicator of attitudes and interests (e.g. efforts to learn about or gain more information about a topic; 30, 31). Past research has specifically linked Google searches to interest in and involvement with the goals and mission of BLM (29). Google Trends data index search behavior as a score in which 100 represents the geographic location (i.e. state) with the highest frequency of searches and subsequent locations receive a score in descending order based on the frequency of the search behavior within the given state. The Google Trends scores for the antiracism terms were summed. The summed Google Trends score for each state for the noted time periods is shown in Supplementary Material.

Google Trends data were also assessed for YouTube searches for the term "protest." That is, related to information-seeking, given that the observed time period was also during the COVID-19

pandemic, one way that people watched the protests was through videos posted or live streamed on YouTube. To capture information-seeking on YouTube data for searches tied to the word "protest" were recorded. Google Trends makes available information on related searches. For the 8-week period for which data were obtained, the topic most related to searches for "protest" was "George Floyd protests." YouTube search data for each state for the noted time periods are shown in Supplementary Material.

The BLM engagement measures were standardized and tested separately as predictors for the mental health outcomes.

Depression

Depression was assessed using the Patient Health Questionnaire-2 (PHQ-2). It is a two-item measure to detect and monitor depression (32). Respondents were asked the following two items, "Over the last 7 days, how often have you been bothered by … having little interest or pleasure in doing things? Would you say not at all, several days, more than half the days, or nearly every day?" and "Over the last 7 days, how often have you been bothered by … feeling down, depressed, or hopeless? Would you say not at all, several days, more than half the days, or nearly every day?" The items were answered using the following scale: 1 = *Not at all*, 2 = *Several days*, 3 = *More than half the days*, and 4 = *Nearly every day*. To be consistent with PHQ-2 scoring, responses were recoded from 0 to 3 and then summed to create a composite. The correlation between the two items, for racial/ethnic minority respondents, was $r = 0.74$, $P \leq 0.001$, and for White respondents was $r = 0.79$, $P \leq 0.001$. The summed composite for racial/ethnic minority respondents was 1.79 (SD = 1.84) and for White respondents was 1.48 (SD = 1.76).

Anxiety

Anxiety was measured using the Generalized Anxiety Disorder 2-item (GAD-2) instrument. It is a two-item screening measure for anxiety disorders (33). Respondents were asked the following two items, "Over the last 7 days, how often have you been bothered by the following problems … Feeling nervous, anxious, or on edge? Would you say not at all, several days, more than half the days, or nearly every day?" and "Over the last 7 days, how often have you been bothered by the following problems … Not being able to stop or control worrying? Would you say not at all, several days, more than half the days, or nearly every day?" The items were answered using the following scale: 1 = *Not at all*, 2 = *Several days*, 3 = *More than half the days*, and 4 = *Nearly every day*. To be consistent with GAD-2 scoring, responses were recoded from 0 to 3 and then summed to create a composite. The correlation between the two items, for racial/ethnic minority respondents, was $r = 0.80$, $P \leq 0.001$, and for White respondents was $r = 0.81$, $P \leq 0.001$. The summed composite for racial/ethnic minority respondents was 2.23 (SD = 1.99) and for White respondents was 1.93 (SD = 1.95).

Self-reported health

Self-reported health was measured using a single item. Respondents were asked, "Would you say your health in general is excellent, very good, good, fair, or poor?" The item was answered using the following scale: 1 = *Excellent*, 2 = *Very good*, 3 = *Good*, 4 = *Fair*, and 5 = *Poor*. The item was reverse coded to capture positive self-rated health so that higher scores represent better reported health. The average self-reported health for racial/ethnic minority respondents was 3.42 (SD = 1.06) and for White respondents was 3.65 (SD = 1.02).

Weighting

Consistent with past research that has used the Pulse Household Survey data to examine state-level effects weighting was not applied to the multilevel analyses (3). That is, design weights are not available at the state level. Such past research has noted that "unweighted multilevel models tend not to lead to different inferential conclusions when compared with weighted estimates (Carle, 2009)" (34, 35).

Study 2: overview

Publicly available data sources were used to gauge the content of Twitter data (16). Analogous to study 1 terms tied to antiracist engagement content (e.g. Black Lives Matter and antiracism; Supplementary Material) were selected and averaged to create a composite, alpha = 0.71. A factor analysis confirmed that the terms represented a single construct, eigenvalue = 5.73, that explained 63.69% of the variance. Publicly available data were also used to assess happiness (16; $M = 5.94$, SD = 0.06). The data sources for the Twitter content and the happiness measure overlapped across 731 days from 2019 to 2021. Thus, all of the available data that overlapped in dates were used. The frequency count of tweets tied to the happiness measure for the 731 days was 144,649,285,571. The antiracist engagement content in daily tweets ranged from 2830.56 to 440,995.56.

Study 3: overview

Analyses were conducted on Twitter data obtained from an online research repository for BLM tweets (36). Primary analyses were conducted on Twitter data identified as nonretweets (N = 100,321) posted between (2020 April 1 to 2020 July 20; see Supplementary Material). The tweets were analyzed using LIWC-22 (17) software. LIWC-22 software uses internal dictionaries that measure the prevalence of words associated with a specific linguistic category. For analyses, the following categories were used to test predictions related to emotional well-being: positive emotion, negative emotion, positive tone, and negative tone. As noted emotional positivity ($M = -0.26$, SD = 3.00) and positive emotional sentiment ($M = 0.27$, SD = 6.46) indexes were created by computing difference scores. Analogous to studies 1 and 2, references to specific terms associated with antiracist engagement (M = 0.49, SD = 2.19; see Supplementary Material) were coded using LIWC-22 software. Antiracist engagement as protests/information-seeking was assessed using the same sources cited for study 1. The protests/information-seeking measures were matched to the dates of each tweet (see Supplementary Material). The average number of BLM protests was 49.87 (SD = 53.76); the average YouTube information-seeking score for protest searches was 15.56 (SD = 18.93); and the average of the summed Google Trends information-seeking score for antiracism searches was 307.10 (SD = 170.26). The protests/information-seeking measures were standardized and averaged to create a composite, alpha = 0.86. A factor analysis confirmed that the measures were tied to a single construct, eigenvalue = 2.35, that accounted for 78.23% of the variance. As covariates, terms tied to the COVID-19 pandemic ($M = 0.047$, SD = 0.50) were also assessed. References to countermovements were text-filtered (i.e. All Lives Matter $M = 0.27$, SD = 2.11; Blue Lives Matter $M = 0.03$, $SD = 0.64$). Following recommendations that have been shown to improve the accuracy of using Twitter data to estimate subjective well-being the following three words were removed from tweets: "lol," "love," and "good" (37).

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Supplementary material

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Data availability

All data are publicly available and/or shared in Supplementary Material.

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