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# Structural Racism and Homophobia Evaluated Through Social Media Sentiment Combined with Activity Spaces and Associations with Mental Health Among Young Sexual Minority Men

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## Abstract

**Background:** Research suggests that structural racism and homophobia are associated with mental well-being. However, structural discrimination measures which are relevant to lived experiences and that evade self-report biases are needed. Social media and global-positioning systems (GPS) offer opportunity to measure place-based negative racial sentiment linked to relevant locations via precise geo-coding of activity spaces. This is vital for young sexual minority men (YSMM) of color who may experience both racial and sexual minority discrimination and subsequently poorer mental well-being.

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**Methods:** P18 Neighborhood Study (n=147) data were used. Measures of place-based negative racial and sexual-orientation sentiment were created using geo-located social media as a proxy for racial climate via socially-meaningfully-defined places. Exposure to place-based negative sentiment was computed as an average of discrimination by places frequented using activity space measures per person. Outcomes were number of days of reported poor mental health in last 30 days. Zero-inflated Poisson regression analyses were used to assess influence of and type of relationship between place-based negative racial or sexual-orientation sentiment exposure and mental well-being, including the moderating effect of race/ethnicity.

**Results:** We found evidence for a non-linear relationship between place-based negative racial sentiment and mental well-being among our racially and ethnically diverse sample of YSMM ($p<0.05$), and significant differences in the relationship for different race/ethnicity groups ($p<0.05$). The most pronounced differences were detected between Black and White non-Hispanic vs. Hispanic sexual minority men. At two standard deviations above the overall mean of negative racial sentiment exposure based on activity spaces, Black and White YSMM reported significantly more poor mental health days in comparison to Hispanic YSMM.

**Conclusions:** Effects of discrimination can vary by race/ethnicity and discrimination type. Experiencing place-based negative racial sentiment may have implications for mental well-being among YSMM regardless of race/ethnicity, which should be explored in future research including with larger samples sizes.

### Keywords

sexual minority men; structural racism; structural homophobia; Mental health; machine learning; social media; socio-spatial self-organizing maps; intersectionality

## 1. Introduction

Structural inequality, defined as a “system of structuring opportunity and assigning value based on race, that unfairly disadvantages some individuals and communities, and advantages others,” affects daily realities of marginalized communities, including communities of color and sexual minority individuals.[1, pg. 231] Much research has focused on structural racism and structural homophobia as the ways in which racism and homophobia are entrenched in structures such as laws, policies, institutional practices, and entrenched norms.[2–5] In addition to institutional forms of structural discrimination, research has also highlighted cultural racism and homophobia, composed of the ideologies spread through norms, rhetoric, and values about the inferiority of certain groups of people (e.g., racial minorities and sexual minorities).[6–8] In terms of the relationship between different forms of racism (i.e., cultural and structural), research has reported that structural forces act through and are mediated by the cultural milieu.[9] While cultural racism can be reflective of structures and norms, the other direction of influence has also been articulated; culture can produce an environment where institutional and individual-level discrimination can thrive.[8,10–12] Indeed, cultural racism and homophobia are associated with implicit biases that can influence behavior[13] and norms that inform racist and homophobic policies (e.g. the institutionalization of the Defence of Marriage Act (DOMA) was driven by homophobia ideologies).[8,14]

Researchers have clearly drawn the link between mental health and structural-level discrimination.[15–18] The predominant approach to measure discrimination at a structural level and assess its relation to health, focuses on discriminatory policies or neighborhood characteristics derived from information such as census data in administrative spatial units. Looking at other aspects of the structural process, sentiment is one way in which we can measure and understand the ways in which racist and homophobic norms are associated with health. Recently, several studies have shown that measures of negative racial sentiment by place from Twitter are associated with more traditional measures of structural discrimination such as residents' racial prejudice and hate crimes.[11,19] Although such work has successfully shown that such proxies for structural-level discrimination are associated with health at the state-level,[20] there is a paucity of research that specifically ascertains measures of discrimination relative to the lived experience of individuals, especially for sexual minority populations and considering the role of intersectionality. However, social media provides a promising way to assess highly localized measures of discrimination in relation to health of sexual minorities, especially those of color, and recent work has developed methods to address issues of noise (posts can be unclear in their content), sparsity at high-geographic resolution, and unrepresentativeness of Tweets, to create area-based measures which are socially-meaningful from this data.[21]

In the current study we seek to address the paucity of research examining how exposure to structural-level discrimination, specifically in terms of racial or sexual-orientation climate, impacts mental health among sexual minorities, through an intersectional lens. As this work focuses on how the cultural milieu is organized by place, it intertwines with institutional processes, and we frame this work in terms of the overarching term structural racism. We acknowledge that structural racism is multi-faceted and here provide a window into one aspect of structural forces that are understudied in relation to health. First, we use novel data (socio-spatial self-organizing maps [SS-SOMs]; generated from geo-located social media)[21] as a measure of place-based negative racial and sexual-orientation sentiment acting as a proxy for racial climate. Further, we use geo-positioning captured activity spaces, which is an innovation given that it enables ascertaining the lived experience of a diverse sample of young sexual minority men (YSMM) in relation to the place-based sentiment from social media measures.[22,23] Second, we seek to examine how race/ethnicity moderates the associations between place-based negative racial sentiment or place-based sexual-orientation sentiment and mental health; another unique contribution to the literature including via consideration of consistent measures of both structural racism and structural homophobia in one study.

### 1.1. Traditional Models of Structural Racism and Homophobia and Health in Large Administrative Units

Scholars have operationalized structural and environmental racism and homophobia using relevant measures such as policies,[24,25] political fragmentation,[26] neighborhood characteristics,[27] in order to study its effects on health across studies. For example, in initial work using census data Frye et al.[28] found, cisgender sexual minority men residing in neighborhoods with higher numbers of individuals from the lesbian, gay, bisexual, and transgender (LGBT) community had lower risk of engaging in HIV risk behaviors compared to men living in neighborhoods with lower numbers of individuals from the LGBT community. However, many of the data and techniques utilized in these studies have been criticized for not fully explicating structural racism or homophobia constructs.[5] One challenge is that laws and policies that inform structural racism can be different from those that inform structural homophobia, and thus this type of measure is hard to compare across forms of discrimination and their confluence thus structural racism and homophobia are rarely examined in the same study. Also, the use of census tracts or ZIP codes to measure neighborhood-level characteristics theoretically linked to structural racism (e.g., racial residential segregation) has been critiqued.[5]

This is, in part, because predetermined census tract or ZIP code bounded areas do not capture the lived experiences of an area – including macro-level forces (e.g., policies, social norms) that may reinforce structural racism and homophobia implicitly or explicitly.[5,29] Furthermore, the types of data available at such resolution may represent very indirect proxies for aspects of structural racism that are themselves confounded by the same forces (i.e., segregation does not actually represent structural racism, but is a consequence of it)[5] and may fail to capture covert forms of racism.[12] Further, racist and homophobic norms are a key aspect of structural racism and homophobia that have an entrenched association with place, to produce health inequities. As such, current measures that are based on administrative units are limited by spatial imprecision as they are usually measured at crude spatial levels such as census tracts, the area circumscribed by ZIP codes, and states[30,31] which lack spatial granularity and a true connection to racial and homophobic norms. Indeed, such spatial units are not directly relevant to the lived experiences of individuals in the spaces that they spend time in (e.g., activity spaces).[5,23,25,32] As such, Riley[5] argues both for shifting the focus of research from traditional area-based measures (e.g., ZIP codes) to those having more substantive meaning, as well as considering new data sources to better capture the forces of racism. Further motivating the use of new data sources, a recent systematic review it was found that self-reported measures of discrimination may not infer stress in a manner that influences health outcomes and recommends that work should consider alternative methods for measuring minority stress that do not rely upon self-report.[33] Other syntheses have highlighted that this can be due to numerous factors (e.g., personality traits, additional buffers).[34]

The use of new computational (e.g., natural language processing and machine learning) and statistical methods allows for geographically-linked measures from social media data, providing more geographically precise information while going beyond self-report, which suffers from recall and other information biases.[35] Indeed, social media has been used to create granular measures of sentiment by location on multiple topics such as vaccination[36] and psychological stress that can be reflective of climate vis-à-vis social structures and norms.[37]

### 1.2. Intersectionality Framework

With Intersectionality Theory, researchers attempt to map out the complex nature of privilege and oppression based on multiple, mutually reinforcing identities and positions that individuals occupy.[38] Intersectional identities and positions intertwine at the individual-level and reflect structural-level power inequities, influencing health behavior and outcomes.[38–40] Current conceptions of intersectionality posit that intersecting identities (e.g., sexual orientation and race/ethnicity) and processes (e.g., systems of homophobia and racism) are both vitally important to understanding the patterning of health and health behaviors.[41,42] However, the possession of intersecting identities, on the one hand, and the experience of intersectional discrimination related to these identities, on the other, serve fundamentally different purposes with respect to health and health behaviors.[41] The former positions differences in health outcomes based on the intersection of intractable identities, while the latter focuses on the complex interdependence of multiple forms of systematic inequality (e.g., racism, homophobia) at micro and macro levels.[43] There is a need to better understand the variance in interdependencies of identity and how systematic discrimination is linked to health among sexual minorities.[41,44,45] Indeed, emerging research shows differential effects of structural racism and structural homophobia among racial/ethnic sexual minority men as compared to White sexual minority men.[31]

### 1.3. Measuring Structural Racism and Structural Homophobia Using Social Media Data

With few exceptions, traditional data sources are limited in their ability to capture the relevant lived experiences of discrimination.[46,47] For example, the policies or census-level data used to represent structural racism versus structural homophobia are by nature not of the same form; different types of measures are used for each. Today, individuals spend more of their time online[19,48] and researchers have begun to think critically about how the online environment may mirror factors in the offline world.[29,49–51] In particular, online environments such as Twitter provide a window to passively assess sensitive topics such as discrimination that individuals may be hesitant to actively report through other data sources such as surveys. In addition, Twitter gives precise geo-located data (for a fraction of Tweets) that can help detect the discriminatory (e.g., racial) climate of an area.[12,52] For example, online discrimination from Tweets originating in a specific area relate to racial/ethnically motivated biases in the same physical area.[19,53,54]

Social media research has matured such that researchers have developed methods to address methodological challenges in using Twitter data due to the unstructured and noisy nature of the text in Tweets. Relevant to this work, Relia, Akbari, Duncan, and Chunara[29] designed a novel methodology called socio-spatial self-organizing maps (SS-SOMs) which uses data from Twitter to create contiguous, non-overlapping “clusters” (i.e., neighborhoods) characterized by consistent levels of racism and homophobia. This method specifically addresses common challenges highlighted in social media data. Tweets are not generated evenly by place, discerning a racist or homophobic post is challenging given colloquial language, and simply aggregating data over ZIP codes or census boundaries may obscure the sentiment particular to a place through spatial averaging (full details of this methodology are published elsewhere[29] and also summarized in the methods section). Through this work, Relia, Akbari, Duncan, and Chunara[29] showed that this approach leads to geographic clusters which have more internal consistency than ZIP code level aggregations. Further, evidence that the experience of structural racism and homophobia, ascertained from online racist and homophobia sentiment, measured through SS-SOMs and linked geographically to the activity spaces of a racially and ethnically diverse cohort of YSMM, provides a much different view of their experiences of structural inequality compared to Tweet sentiment averaged over ZIP codes.

### 1.4. The Present Study

The purpose of the current investigation is to utilize social media as a proxy for local racial and homophobic climate, along with activity space measures to generate measures of exposure to race- and sexual orientation-based structural discrimination based on spaces frequented and assess its relation to mental health of YSMM. As structural racism as well as structural homophobia can manifest in many different institutionalized practices and norms, our measure focuses on cultural racism and homophobia, via place-based sentiment on social media as a proxy.[55] Based on the extant literature,[56,57] we hypothesize that YSMM who spend more time in areas that are higher in structural racism or structural homophobia will experience more days of poor mental health as compared to YSMM who spend more time in areas lower in structural racism or structural homophobia, and that these effects will be stronger for YSMM of color compared to White YSMM.

## 2. Methods

### 2.1. Participants

Participants in this study came from the Project 18 Neighborhood Study. The P18 Neighborhood Study was conducted from January 2017 to January 2018; 450 participants from the second phase of the P18 Cohort Study were randomly selected to receive an offer, via email, to participate in the study.[58,59] Those who were interested were screened for eligibility and the goal was to enroll 250 participants. Eligibility criteria included: identifying as cisgender male, self-reporting as HIV-negative, having no mobility restrictions, and being comfortable carrying the GPS device for two weeks. The GPS protocol used follows a prior pilot week-long study conducted among a sample of 75 participants in the cohort.[60] Participants came in for two study visits at our office in New York City (NYC). After consent participants were instructed to place the small QStarz BT-Q1000XT GPS device (QStarz International Co., Ltd., Taipei, Taiwan) in their pocket and to complete a GPS use diary.[60–63] The GPS devices were programmed prior to distribution to log locations in 10-second intervals, a high sampling frequency over one full day, with enough memory to store data over 14 days. Participants also completed the first of two computer surveys and were compensated with $35.

During the two weeks they carried the device, each participant received 3 text messages a week reminding them to charge and carry their device. At their second visit, participants returned the device and travel diary, completed the second survey, and received $75 in compensation. The Institutional Review Board at New York University School of Medicine (i16–00082) approved the research protocol and written informed consent from each participant was obtained prior to participation. The analyses reported here were determined to be exempt by the Columbia University Mailman School of Public Health Institutional Review Board. The focus in this study was limited to White, Black, and Hispanic YSMM due to low sample size in other racial/ethnic groups.

### 2.2. GPS Data and Activity Space Definition

The GPS protocol used to garner the data in this study was the same as that of a prior pilot study which showed feasibility and acceptability of the protocol.[60] GPS data extracted from the devices were cleaned to eliminate duplicate time stamps and isolated GPS points (400-meter or longer distance between two consecutive points corresponding to 10 second interval); likely data errors.

To define the activity spaces of participants, we employed daily path area (DPA) calculations. DPA is an advanced method in behavioral geography,[23,64–66] shown to accurately capture travel routes and destinations without overgeneralization.[67] The DPA was defined by creating a 200-meter dissolved buffering zones around participant GPS points, excluding any records outside of NYC due to limitation of data.[68,69] All GPS data processing and cleaning were conducted using ESRI ArcGIS 10.4 and Quantum QGIS 2.6.

### 2.3. Measures of Structural Homophobia and Racism Derived from Twitter

In order to assess how much time study participants spent in areas with different levels of discrimination, we created geographically-linked measures of racism and homophobia using Twitter, a popular online news and social networking service wherein users post and interact with short messages (“Tweets”).[29,36,50,51,70,71] To overcome issues of noise, sparsity at high-geographic resolution, and unrepresentativeness of Tweets for underlying sentiment of an area, we developed the measures of racism and homophobia using SS-SOMs to identify regions of collective, consistent sentiment from social media data. The overall pipeline for creating the spatial distribution of racism and homophobia on social media includes sourcing social media data from the region of interest (NYC), classifying the social media posts, and forming clusters that best represent consistent sentiment. Importantly, in contrast to averaging Tweets by arbitrary areas such as ZIP codes, this method identifies areas of consistent sentiment (individual Tweets are not representative of a neighborhood area, both by the nature of being generated by a small population as well as being point observations), as previously demonstrated.[29]

Readers are referred to previous work which details the full pipeline for processing the data including what is labeled as race-based discrimination and example texts, which are briefly summarized here.[21] Previous work also includes qualitative interpretation of the results based on spatial distribution as well as quantitative city-level relationships between discrimination online and other measures of discrimination, demonstrating validity of Twitter as a proxy for measuring discrimination by place.[19] Data from Twitter was used as it provides geo-located, freely available data, with sufficient data volume in the region of interest. The Twitter Application Programming Interface (API) was used to source geo-located Tweets having point coordinates within NYC boundaries. Tweets were selected from a time period precisely overlapping the time period of the YSMM cohort mobility data collection (January 25, 2017 to November 3, 2017), resulting in 6,234,765 Tweets. To classify Tweets as expressing racism or homophobia, a comprehensive set of training examples were first manually labeled as positive for racism (or homophobia), alongside control data labeled as negative. As the topic is nuanced, a combination of keyword filtering, labelling, and iterative learning was used to generate this training data.[29] Once a training set of ~10,000 Tweets was obtained, a machine learning algorithm was used to learn from the training data and classify new Tweets. The algorithm learns words, phrases, and general linguistic context that indicate racism or homophobia. For the algorithm, we used a neural learning module, which shows improved performance over other approaches, especially for short texts like Tweets.[29] Performance of the classifier was evaluated using area under the receiver operating characteristic curve.

To account for varying levels of Tweeting by location, the number of racist/homophobic Tweets was normalized by the total number of Tweets within a series of grids (spatial bins) that divide NYC; each approximately the area of one NYC block.[21] These grids, each with their normalized proportion of racism or homophobia, are grouped in a geographically linked self-organizing map to create contiguous and non-overlapping clusters. The resulting SS-SOM clusters partition the city into the regions that are most similar in each attitude. The number of clusters was chosen to create a reasonably local geographic area (the total number of resulting SS-SOM clusters is similar to the number of ZIP codes), while still including a high enough proportion of racist /homophobic Tweets per contained grid cells. The proportion of racism/homophobia for each cluster is then used for each of the grid cells contained within that cluster. It is not possible to use the grids themselves, due to low amounts of Tweets at this resolution; 68% of grid cells have less than the mean number of Tweets per grid (41.5).[29]

The proportion of discriminatory (racist or homophobic) Tweets by grid cell was computed using the SS-SOM method. An area-weighted mean discrimination exposure by place was computed based on averaging this discrimination over the grids in the activity space of each individual and normalized on a scale of zero to one. In this sense, the final measure indicates the relative spatial exposure to negative racial or sexual-orientation climate for each person based on the places they visit.

### 2.4. Sociodemographic Covariates

All variables were captured consistent with a previous study examining associations of spatial mobility with sexual risk behaviors in the P18 Neighborhood Study.[58] Participants self-reported their socio-demographic characteristics, including age (years), race/ethnicity (White, Black, Hispanic), current income level (0-$14,999, $15k-$34,999, $35k+), education (high school or less, associate's degree, college degree or graduate degree), sexual orientation (gay or bisexual), housing type (family apartment/house, own apartment/house, other), foreign-born status (inside the U.S. versus outside of the U.S.), and current school enrollment status (yes/no). Further, area-based exposures were computed from census-tract level socio-demographic characteristics in the 2017 U.S. Census American Community Survey (5 year estimates)[72] of percentage of Hispanic and non-Hispanic residents (% Hispanic), the percentage of Black and non-Black residents (% Black) and the percentage of people who lived under the federal poverty level (% Poverty). An area-weighted mean exposure to each of these variables was also computed by averaging respective values in the activity space of each individual. We excluded those who identified as Asian or another racial/ethnic category due to a small number of respondents in these categories (n=22 and n=18, respectively).

### 2.5. Mental Health

Mental health was measured using a 30-day timeline follow-back (TLFB) method. The TLFB is a calendar-based, semi-structured, interviewer-administered assessment that collects information on health behaviors during the 30 days preceding the study visit.[73,74] Participants were asked to report on how many days their mental health was not good (e.g., the number of days they felt stressed or depressed) over the preceding 30-day period. Responses to this item can range from 0 to 30 (days of poor mental health).

### 2.6. Analytical Plan

Due to overdispersion in the study outcome, zero-inflated Poisson regression models were utilized to identify associations between area-weighted discrimination exposure to negative racial climate or negative sexual-orientation climate and mental health.[75] We chose the zero-inflated Poisson over the Poisson, negative binomial, and zero-inflated negative binomial because it was the best fitting model according to the AIC, BIC, and likelihood ratio test.[76] We specified models for the outcome of mental health over the preceding 30 days (Models 1 and 2). Model 2 includes interaction terms between negative racial and sexual-orientation climate exposure and race/ethnicity to determine if there were differences in the association by race/ethnicity. We reported log odds and confidence intervals in the table and the incident rate ratios in-text. We also completed post hoc analyses to determine the simple slopes and identify differences by race/ethnicity for significant interactions. After exclusion of records with missing data on either the outcomes or covariates, 147 YSMM were included in the analyses. All statistical analyses were completed in Stata v17.

## 3. Results

### 3.1. Participant Summary

Table 1 includes descriptive statistics summarizing participant socio-demographic characteristics and race/ethnicity and sexual orientation-based discrimination experienced by race/ethnicity group. Mean age of the study sample was 27 years (range=26 to 29), with 35% identifying as White, non-Hispanic, 36% identifying as Hispanic, and the remaining identifying as Black, non-Hispanic. Regarding sexual orientation, 90% of the sample identified as gay and the remaining as bisexual. The majority of the sample (59%) reported having a college or graduate degree, while reported having an associate's degree (8%) or a high school diploma or less (33%). Twenty-three percent of the sample reported having an income between $0 and $14,999, the remaining reported an income of $15,000 to $34,999 (37%), or greater than $35,000 (40%). With respect to housing, 31% reported living in a family apartment or house, 29% reported living in their own apartment or house, while the remaining reported another housing type. Thirty-nine percent of participants reported zero days of poor mental health over the preceding 30-day period, while, on average, the sample reported a mean of 4.05 days of poor mental health in the last 30. The mean proportion of area-weighted discrimination experienced, as measured by the SS-SOM measures, on a scale of zero to 1, was 0.49 (racism) and 0.45 (homophobia).

### 3.2. Association between Structural Discrimination and Mental Health

Table 2 displays the results of the zero-inflated Poisson models examining mental health over the preceding 30-day period. The model without any interactions and with a quadratic specification for structural racism was statistically significant (see Table 2, Model 1; $\chi 2(22)=238.24$, $p<.001$). With respect to general health, those who reported worse overall general health had more days of poor mental health as compared to those who reported excellent general health (see Table 2, Model 1). Further, those born in the U.S., as compared to those who were born outside of the U.S., had less days of poor mental health (IRR=.67, $p<.05$; Table 2, Model 1). In addition, those who identified as bisexual had more days of poor mental health as compared to those who identified as gay (IRR=2.25, $p<.001$; Table 2, Model 1). In terms of housing, those who reported living in their own apartment/house (IRR=2.76, $p<.001$) or another housing category (IRR=1.37, $p<.05$) had more instances of poorer mental health as compared to those who lived in a family apartment/house (Table 2, Model 1). The squared term for racism experienced based on locations frequented was significantly associated with days of poor mental health (IRR=187.56, p=.001). Further, a one-unit increase in the percentage of Hispanics in a participant's activity space was associated with a decrease in the rate ratio of poor mental health by a factor of .28 (IRR=.28, $p<.05$).

The overall model with the interaction term (Model 2; $\chi^2(23) =254.48$, $p<.001$), as well as the interaction term itself for Hispanic and Black individuals, were significant, providing evidence that race/ethnicity was a moderator (see Table 2, Model 2). More specifically, there was a quadratic relationship between structural racism and mental health such that spending more time in areas higher in structural racism was associated with a flatter curve at first and then a steeper increase in terms of days of poor mental health for White and Black YSMM. For Hispanic YSMM, there was a slow increase at lower levels of structural racism and then a flatter curve and overall decrease in terms of days of poor mental health at higher levels of structural racism. Post-hoc analyses revealed that the quadratic curvature was statically significant ($X^2$ [2, N = 147] = 13.87, $p < .01$). Further, post hoc analyses demonstrated that the differences in the quadratic association between race-based location-specific social media sentiment and days of mental health for each of the race/ethnicity groups were statistically significant two standard deviations below the mean, at the mean, and two standard deviations above the mean of structural racism. The quadradic function was statistically significantly different between the White and Hispanic groups ($\Delta = 11.68$, SD = 3.55, $p < .01$) as well as between the Hispanic and Black groups ($\Delta = -14.65$, SD = 3.94, $p < .001$).

At two standard deviations below the overall mean of structural racism, Whites had about 1.74 less days of predicted poor mental health than Hispanics ($p < .05$) and Hispanics had about 2.36 more days of poor mental health compared to Blacks ($p < .05$). The difference disappeared between Whites and Hispanics at one standard deviation below the mean of structural racism; however, Hispanics had about 2.58 more days of predicted poor mental health at one standard deviation below the mean of structural racism compared to Blacks ($p < .05$). Further, at two standard deviations above the overall mean of structural racism, Whites had about 7.10 more days of poor predicted mental health compared to Hispanics (p

< .01) and Hispanics had about 9.46 less days of poor predicted mental health compared to Blacks (p < .01). At one standard deviation above the mean for structural racism, differences were still observed between Whites versus Hispanics and Hispanics versus Blacks such that Whites had about 4.25 more days of predicted poor mental health than Hispanics (p < .001) and Hispanics had about 3.93 less days of predicted poor mental health than Blacks (p <. 001). Differences between racial/ethnic groups were not observed for both comparison groups at the overall mean of structural racism. In sum, at one and two standard deviations above the overall mean of structural racism, the statistically significant disparity between the Black and White groups disappeared, while the differences between the Black and While groups versus the Hispanic groups became more pronounced (see Figure 1).

## 4. Discussion

We utilized social media and GPS data to derive measures of structural racism (racial climate) and structural homophobia (sexual orientation climate) relevant to the lived experiences of a sample of YSMM and examined how these measures are related to mental well-being for YSMM of different racial/ethnic groups, which provides a meaningful contribution to the literature. This study is guided by an intersectional framework and leverages natural language processing, machine learning, and spatial statistics to utilize social media as a proxy measure for structural discrimination via area-based climate.

We hypothesized that increased exposure to discrimination via area-level racial climate or sexual orientation climate as measures of structural discrimination would be associated with increased days of poor mental health among YSMM. Secondly, in line with intersectionality theory, we hypothesized this association would be moderated by race/ethnicity such that Black and Hispanic YSMM who experienced more structural racism or structural homophobia would have more days of poor mental health over the last 30 days than White YSMM due to these population subgroups having less privilege and power in society. Our hypotheses were partially supported. In our main effects model, spending time in more racist spaces was associated with significantly more days of poor mental health (quadratic relationship). Findings also suggest that Hispanic YSMM have lower days of poorer mental health compared to White and Black YSMM when spending moderate to heavy time in spaces of higher negative racial climate. However, when spending time in spaces lower in negative racial climate, Hispanic YSMM have slightly more days of poor mental health compared to White and Black YSMM.

Our hypothesis regarding structural racism and days of poor mental health was largely supported by the extant research literature showing that YSMM who experience discrimination such as racism and homophobia have poorer mental health.[77–80] Our findings extend this work by showing that structural racism, specifically racial climate, as measured by location-specific social media sentiment, is associated with more days of poorer mental health. However, we did not find that structural homophobia was associated with days of poor mental health. This finding is divergent from current literature which demonstrates that there are key linkages between structural homophobia and poorer mental health in lesbian, gay, and bisexual populations.[30] There are many potential explanations including the finer spatial granularity of structural homophobia measures used here, inclusion of multiple sexual-orientation groups here (bisexual and gay) which obscures subgroup differences,[81] and the idea that there are unexplored mechanisms or moderators that should be explored in future research.

Second, at lower levels of structural racism, Hispanic YSMM experienced a slight increase in the days of poor mental health reported in the last 30 days that decreased at moderate levels of spending time in spaces of higher racial animosity and then decreased and remained steady as time spent in racist spaces increased. This finding is contrary to our hypothesis, but cultural differences should be acknowledged. Some research has discussed denial of racism in Latino culture which is not present in Blacks.[82] Further, there may be habituation – the idea that increased exposure to racism desensitizes an individual to later experiences.[83] Given that the lived experiences of Hispanic individuals are heterogeneous, this finding could be due to variance within the Hispanic group, which future research should examine.

Measures of discrimination used in this study provide a local representation of discrimination. While previous work has shown that Twitter-derived sentiment correlates with hate crimes at the city level,[19] this study combines discrimination measures with activity space measures to created measures of racial climate pertinent to an individual based on places they frequent. In addition to providing local relevance, social media data can be obtained in a timely and cost-efficient manner, which can be relevant to changing climates. Few studies have explicitly examined the impact of structural homophobia on health behaviors of YSMM. This may be, in part, due to less availability of data and validated measures. Policies are often used, but these are generally limited to state and nation-level.[31,84–88] For example, in a study examining tobacco and alcohol use among YSMM, Pachankis, Hatzenbuehler, and Starks[84] measured structural homophobia utilizing state-level policies that affect lesbian, gay, and bisexual (LGB) individuals and state-aggregated attitudes towards LGBs, finding that YSMM residing in states higher in structural homophobia were more likely to engage in risky tobacco and alcohol use behaviors. While these studies provide valuable insights into the deleterious effects of structural homophobia on health outcomes and health behaviors of populations at the state-level, state-level policy data are relevant to but do not manifest in the lived experiences of individuals in the places they directly frequent.

Our findings also extend existing fields of inquiry. Findings suggest that there may be a non-linear relationship between the time spent in spaces of higher racial animosity and resultant mental health that varies by race/ethnicity. Indeed, Black and White YSMM had slower rising days of poor mental health when spending a smaller amount of time in spaces of higher racial animosity. However, we saw a steeper increase in days of poor mental health when they spent moderate or more time in spaces of higher racial animosity. It is acknowledged that there can be many factors intervening this relationship; for example, it may be that there are certain coping mechanisms, resilience factors, or other factors that mitigate the negative effects of spending time in spaces of higher racial animosity on mental health. However, once a critical point is reached, the mechanism(s) put in place to cope with this exposure may no longer be effective. In sum, future research should assess factors that specifically explain the non-linear relationships between time spent in spaces of higher racial animosity and mental health among White and Black YSMM.

This study is not without its limitations. First, we recruited from the larger P18 cohort which was already ongoing, so our study could have suffered from selection bias. Inclusion was limited to those in Black, White and Hispanic groups. There was no meaningful hypothesis that could be tested through creating an "Other" racial/ethnic group which combined multiple racial/ethnic categories, and thus the sample included was limited. In future research, more diverse groups of racial/ethnic YSMM should be proactively sampled to obtain a more robust picture of the ways in which structural racism and homophobia influence mental health. Accordingly, our study frame was small and more so this study will suffer from the same limitations as the parent study (and more generally the limitations associated with a convenience sample approach).[89] Included in the study frame limitations is the power of the study due to this existing sampling frame and size. Because our study consists of a relatively small sample size that tested a moderation model, it is underpowered. Thus, we can only consider these results to be preliminary. This analysis will need to be replicated with a larger sample size. Further, via the cross-sectional study design, mobility patterns assessed once over a two-week period may not be representative of one's typical travel patterns or spaces exposed to. However, the vast majority of GPS-based studies focus on a week or just a few days.[23] A seminal study showed that 2-weeks is an adequate time period to illustrate the typical activity space for an individual.[90] Participants may have changed their spatial patterns given our distribution of GPS devices (potential reactivity bias). However, past work suggests these issues are minimal.[60] This study also did not account for time spent in different places. While time has importance, detailed studies are needed to properly first identify the appropriate time length of discrimination exposure that are relevant to mental health outcomes. Moreover, an analysis that includes time could also consider if both the discrimination and health measures represent aberrations from an underlying relationship for each individual. As well, the role of residential self-selection based on sexual-orientation, race and/or ethnicity and other factors relevant to the relationship between discrimination and mental health should also be considered in future research to decrease possible residual confounding. Regarding specific measures, there can be recall bias on the mental health measure especially given the time frame of measurement (a period over 30 days). Further, this study was conducted in NYC and there are known GPS issues due to large buildings.[91] Additionally, individuals in NYC often travel via the subway system, and underground GPS receivers are unable to obtain signals from satellites, which may lead to additional data loss, though this would be for relatively short periods of time, and obtained data are still valuable in determining general activity spaces. Further, the structural discrimination data are within NYC though some participants travelled outside NYC during the study period. Much of these trips were not representative of their typical mobility pattern, so we do not believe that limiting our data to NYC significantly influenced findings. Regarding geo-located data from Twitter, though the data was selected to overlap in time with when the mobility study occurred, there can be temporal influences associated with place-based sentiments given, for example, different socio-political forces including the cultural context in New York City during the mobility study period. The Twitter data is also generated by a non-representative sample of the population. However, despite the data not wholly representing the underlying population, geo-located sentiment from Twitter has been shown to relate to the “surround” or racial climate of an area.[11] This area-level measure is relevant to poorer health outcomes as it has been thought to represent an environment that may harbor more racial prejudice and/or encourage the tolerance of racism.[11] The source population of the discrimination can vary and could be investigated in future work that seeks to better understand and develop interventions to address the source of discrimination. Indeed, sub-populations, such as those voicing discrimination online, can drive sentiment and norms and can be impactful even if they are not representative of the entire population.[92] However, we acknowledge we are unable to assess the validity of our discrimination measures against reference measurements of structural discrimination, such as those that would be obtained from an in-depth survey of residents of the corresponding areas or neighborhoods. Indeed, another limitation is that we do not explicitly compare different forms of discrimination measures or test the modifiable areal unit problem associated with discrimination measures aggregated to ZIP codes empirically. Instead, this study leverages measures that have been shown to better categorize areas by consistency of sentiment compared to those averaged over administrative boundaries.[21] Finally, although our study sample was particularly large for a study of this type, sample sizes were small overall for both race/ethnicity and sexual-orientation subgroups. Our results, especially given varying effects across race/ethnicity groups, endorse the need to support larger studies to understand these varied relationships.

## 5. Future Research and Conclusion

This study used geo-located social media sentiment combined with GPS activity spaces to assess hyper-local measures of area-based discrimination and its relationship to mental health among YSMM. Results indicated imperative areas of future research. Leveraging new forms of data can help researchers investigate associations between structural discrimination and risk behaviors in more nuanced and new ways (e.g., by capturing relevant discrimination experiences in both time and place). Going further, experience-sampling methods (also known as ecological momentary assessment [EMA]), which involve asking participants to report on their thoughts, feelings, behaviors, and/or environment on multiple occasions over time, can enable researchers to collect ongoing information about experiences and behaviors as they occur within the context of individuals’ everyday lives,[23,93,94] especially when combined with GPS methods, known as geographically-explicit ecological momentary assessment,[95] and are shown to be feasible among YSMM samples.[96] This could augment the ecological validity of the emerging associations between area-based measures of structural discrimination and behavior among YSMM in urban areas. Additionally, because experience-sampling methodologies can facilitate the examination of “microprocesses” between various social and behavioral phenomena among YSMM,[96,97] such research could demonstrate how fluctuations in YSMM’s sense of social discrimination relate to changes in health behaviors and conditions, such as mental health burdens over time (i.e., at the within-person level). The present work has highlighted online data and its contribution to area-based discrimination which offers an opportunity to think about how to mitigate such sentiment; for example, considering interventions or education in the online world. Finally, methods in this analysis can be used to study other outcomes in other populations with an intersectional perspective such as among Black transgender women.[62,98,99]

We utilized an intersectionality framework to contextualize the ways in which self-defined Black, Hispanic, and White YSMM identity intersects with race-based and homophobia-based location-specific social media sentiment to influence number of days of poor mental health. Intersectionality theory posits that multiple marginalized identities intertwine at the individual level, and this intertwining reflects structural-level power inequities and inequality, influencing health behavior and outcomes across the life course.[39] Current conceptions of intersectionality posit that intersecting identities (e.g. sex/gender and race/ethnicity) and intersectional processes (e.g. systems of sexism and racism) are both vital to understanding the patterning of health and health inequalities.[41] However, the possession of intersecting identities and the experience of intersectional discrimination related to these identities serve fundamentally different purposes with respect to health and health disparities.[41] The former positions differences in particular on health outcomes based on the intersection of coexisting identities, while the latter focuses on, "*simultaneous intersections between aspects of social difference and…forms of systematic oppression (racism, classism, sexism, ableism, homophobia) at micro and macro levels in ways that are complex and interdependent*."[43(p. 16)] Thus, although we have new ways of measuring intersectionality ,[100,101] we still have few ways to measure the ways in which intersectional structural and individual level features interact to influence health and health behaviors.

Thus, in addition to illuminating complex associations between structural racism and mental health among YSMM, we have expanded measures and theory in two ways. First, there has been a push to characterize online experiences of intersectional structural racism and discrimination;[102,103] however, research has not typically been based on public health theories (which help us ultimately inform social change). In this analysis, we were able to take a first step in merging two areas (i.e., measurement of discrimination via online data, and intersectionality theory) by utilizing our novel SS-SOMs and GPS-based measurements of the everyday experiences of individual YSMM combining multiple forms of data; social media, activity spaces and surveys. We extend the field related to online discrimination by showing evidence of the need to understand area-based and individual-level factors when understanding mental health. Indeed, Hancock[45] and others specify[43] that an intersectional approach must examine such differences at multiple levels (i.e., structural and individual level). It is only in such a space that we can meet the challenge of getting closer to understanding intersectional influences of structural discrimination on mental health among YSMM.

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- We study structural discrimination via place-based race/sexual-orientation climate
- Geo-located social media sentiment was a proxy for structural racism and homophobia
- Linking social media and activity spaces created negative climate exposure measures
- Negative racial climate exposure and mental health were related non-linearly
- Significant differences by race/ethnicity groups motivates larger sample studies

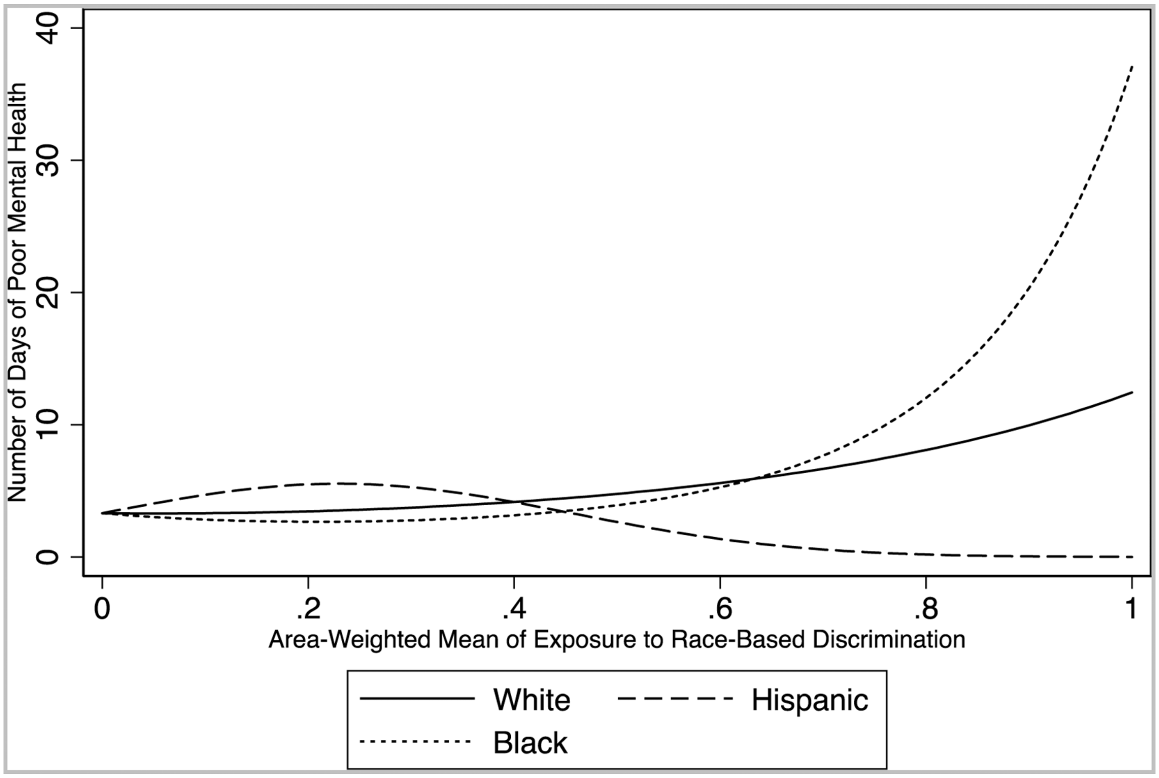


**Figure 1.**
Structural racism measured via the Twitter proxy for the racial climate of an area, and race/ethnicity in relation to the number of days in which individuals experienced poor mental health.

**Table 1.**

Sociodemographic characteristics, the P18 Neighborhood Study (n=147)

| | M(SD) / %(n) |
|---|---|
| Age | 27.36(.81) |
| Education | |
| High School or Less | 32.65(48) |
| Associate's Degree | 8.16(12) |
| College Degree or Graduate Degree | 59.18(87) |
| Income | |
| $0 – $14,999 | 23.13(34) |
| $15,000 – $34,999 | 36.73(54) |
| $35,000+ | 40.14(59) |
| Race/Ethnicity | |
| White, non-Hispanic | 34.69(51) |
| Hispanic | 36.05(53) |
| Black, non-Hispanic | 29.25(43) |
| Sexual Orientation | |
| Gay | 89.80(132) |
| Bisexual | 10.20(15) |
| Housing | |
| Family Apartment/House | 31.29(46) |
| Own Apartment/House | 29.25(43) |
| Other | 39.46(58) |
| Self-Reported General Health | |
| Excellent | 25.85(38) |
| Very Good | 44.90(66) |
| Good | 21.09(31) |
| Fair/Poor | 8.16(12) |
| % Black | 21.85 |
| % Hispanic | 34.92 |
| % Poverty | 33.52 |

| | M(SD) / %(n) |
|---|---|
| % Same Sex | 28.49 |
| Structural Racism | .45(.15) |
| Structural Racism – Race/Ethnicity | |
| White, non-Hispanic | .42(.17) |
| Hispanic | .42(.09) |
| Black, non-Hispanic | .52(.18) |
| Structural Homophobia | .49(.19) |
| Structural Homophobia – Race/Ethnicity | |
| White, non-Hispanic | .42(.16) |
| Hispanic | .52(.21) |
| Black, non-Hispanic | .52(.18) |
| Mean Mental Health[1] | 4.05(5.96) |
| Mean Mental Health[1] – Race/Ethnicity | |
| White, non-Hispanic | 5.31(5.85) |
| Hispanic | 3.25(3.74) |
| Black, non-Hispanic | 3.56(7.89) |

[1] Self-reported number of days with stress, depression or problems with emotions over preceding 30 days

**Table 2.**

Zero-inflated Poisson Results for Self-reported Mental Health Over the Preceding 30 Days, the P18 Neighborhood Study (n=147)

| | | Model 1 | | Model 2 | |
|---|---|---|---|---|---|
| | | **Log Odds(SE)** | **95% CI** | **Log Odds(SE)** | **95% CI** |
| Poisson | Self-reported General Health | | | | |
| | Excellent | *Ref.* | -- | *Ref.* | -- |
| | Very good | .28(.14) * | .00, .56 | .39(.15) * | .09, .69 |
| | Good | .54(.16) ** | .22, .86 | .60(.18) ** | .25, .94 |
| | Fair/poor | 1.18(.19) *** | .82, 1.55 | 1.39(.20) *** | .99, 1.78 |
| | Age | .13(.07) † | −.01, .27 | .14(.07) † | −.00, .28 |
| | Education | | | | |
| | High school or less | *Ref.* | -- | *Ref* | -- |
| | Associate degree | −.52(.31) † | −1.12, .09 | −.50(.31) | −1.10, .10 |
| | College or graduate degree | .26(.16) † | −.04, .57 | .18(.16) | −.12, .49 |
| | Income | | | | |
| | $0 – 14999 | *Ref.* | -- | *Ref.* | -- |
| | $15000 – 34999 | .16(15) | −.14, .46 | .38(.16) * | .05, .70 |
| | $35000+ | .04(.16) | −.27, .35 | .08(.16) | −.24, .40 |
| | Race/Ethnicity | | | | |
| | White | *Ref.* | -- | -- | -- |
| | Hispanic | −.04(.13) | −.30, .22 | -- | -- |
| | Black | .10(.14) | −.18, .38 | -- | -- |
| | Foreign-Born Status | | | | |
| | Born outside the U.S. | *Ref.* | -- | *Ref.* | -- |
| | Born in the U.S. | −.41(18) * | −.76, −.05 | −.40(.18) * | −.75, −.05 |
| | Sexual Orientation | | | | |
| | Gay | *Ref.* | -- | *Ref.* | -- |
| | Bisexual | .81(.16) *** | .50, 1.12 | .95(.16) *** | .63, 1.27 |
| | Housing | | | | |

| | | Model 1 | | Model 2 | |
|---|---|---|---|---|---|
| | | Log Odds(SE) | 95% CI | Log Odds(SE) | 95% CI |
| | Family apartment/house | *Ref.* | -- | *Ref* | -- |
| | Own apartment/house | 1.01(.17) *** | .67, 1.36 | 1.00(.18) *** | .65, 1.36 |
| | Other | .31(.16) * | .01, .62 | .31(.16) † | −.00, .63 |
| | % Black | −.30(.61) | −1.50, .89 | −.77(.66) | −2.05, .52 |
| | % Hispanic | −1.27(.50) * | | −1.35(.54) * | −2.41, −.30 |
| | % Poverty | .38(.63) | −2.24, −.29 | .79(.66) | −.50, 2.08 |
| | % Same Sex | .69(.41) † | −.84, 1.61 | .33(.41) | −.50, 1.13 |
| | Structural – Hom | .62(1.10) | −1.53, 2.77 | .59(.46) | −.32, 1.49 |
| | Structural – $Hom^2$ | .37(1.22) | −2.02, 2.76 | -- | -- |
| | Structural – Race/Eth | −2.45(1.58) | −5.55, .65 | -- | -- |
| | Structural – $Race/Eth^2$ | 5.23(1.52) ** | 2.26, 8.21 | -- | -- |
| | Race/Eth* SSOM - Race/Eth | | | | |
| | White | -- | -- | .10(1.73) | −3.30, 3.49 |
| | Hispanic | -- | -- | 4.76(2.52)t | −.18, 9.69 |
| | Black | -- | -- | −1.79(1.79) | −5.29, 1.72 |
| | Race/Eth* $SSOM^2$ - Race/Eth | | | | |
| | White | -- | -- | 2.83(1.67) | −.45, 6.11 |
| | Hispanic | -- | -- | −8.84(4.18) * | −17.03, −.66 |
| | Black | -- | -- | 5.81(1.90) ** | 2.07, 9.54 |
| Logit | Self-reported General Health | | | | |
| | Excellent | *Ref.* | | *Ref* | |
| | Very good | −1.19(.60) * | −2.37, −.01 | −1.19(.62) † | −2.40, .02 |
| | Good | −1.39(.71) † | −2.78, .01 | −1.33(.73) † | −2.76, .09 |
| | Fair/poor | −3.05(1.08) ** | −5.17, −.95 | −2.90(1.09) ** | −5.04, −.76 |
| | Age | .18(.33) | −.45, .82 | .21(.34) | −.45, .87 |
| | Education | | | | |
| | High school or less | *Ref.* | -- | *Ref* | -- |
| | Associate degree | −.21(1.09) | −2.34, 1.92 | −.20(1.16) | −2.47, 2.07 |

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | Log Odds(SE) | 95% CI | Log Odds(SE) | 95% CI |
| College or graduate degree | −.52(.33) | −1.73, .68 | −.36(.64) | −1.61, .89 |
| Income | | | | |
| $ 0 – 14999 | *Ref.* | -- | *Ref.* | -- |
| $15000 – 34999 | −.33(.66) | −1.62, .96 | −.15(.68) | −1.49, 1.19 |
| $35000+ | −.91(.72) | −2.31, .50 | −.80(.74) | −2.26, .65 |
| Sexual Orientation | | | | |
| Gay | *Ref.* | -- | *Ref* | -- |
| Bisexual | .23(.76) | −1.26, 1.73 | .31(.79) | −1.23, 1.85 |
| Foreign-Born Status | | | | |
| Born outside the U.S. | *Ref.* | -- | *Ref* | -- |
| Born in the U.S. | −1.67(1.03) | −3.70, .34 | −1.67(1.04) | −3.71, .37 |
| Housing | | | | |
| Family apartment/house | *Ref.* | -- | *Ref* | -- |
| Own apartment/house | 1.51(.80) | −.04, 3.07 | 1.53(.82)† | −.07, 3.13 |
| Other | −.53(.76) | −2.02, .95 | −.56(.79) | −2.10, .99 |
| % Black | 8.32(2.67)** | 3.08, 13.57 | 8.30(2.74)** | 2.93, 13.68 |
| % Hispanic | 6.41(2.59)* | 1.34, 11.48 | 6.63(2.67)* | 1.40, 11.87 |
| % Poverty | −9.13(3.44) | −15.88, −2.38 | −9.55(3.62)** | −16.65, −2.46 |
| % Same Sex | 2.39(1.81) | −1.17, 5.95 | 2.31(1.85) | −1.31, 5.93 |
| Structural - Hom | .44(2.21) | −3.89, 4.77 | .32(2.23) | −4.06, 4.69 |
| Structural - Race/Eth | 5.46(1.77)** | 1.98, 8.93 | 5.41(1.81)** | 1.86, 8.96 |

† p<.10;

* p<.05;

** p<.01;

*** p<.0001