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Hswen, Yulin
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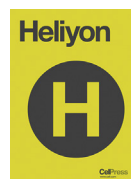Williams, David R
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Research article

Online negative sentiment towards Mexicans and Hispanics and impact on mental well-being: A time-series analysis of social media data during the 2016 United States presidential election

Yulin Hswen [a,b,c,d,h,*], Qiuyuan Qin [c], David R. Williams [a,e], K. Viswanath [a,f], S.V. Subramanian [a,g], John S. Brownstein [b,c]

[a] Department of Social and Behavioral Sciences, Harvard T.H. Chan School of Public Health, Boston, MA, USA
[b] Computational Epidemiology Lab, Harvard Medical School, Boston, MA, USA
[c] Innovation Program, Boston Children's Hospital, Boston, MA, USA
[d] Department of Epidemiology and Biostatistics, University of California San Francisco, San Francisco, USA
[e] Department of African and African American Studies, Harvard University, Cambridge, MA, USA
[f] Center for Community-Based Research, Dana-Farber Cancer Institute, Boston, MA, USA
[g] Harvard Center for Population and Development Studies, Harvard University, Cambridge, MA, USA
[h] Bakar Computational Health Science Institute, University of California San Francisco, San Francisco, USA

A B S T R A C T

Purpose: The purpose was to use Twitter to conduct online surveillance of negative sentiment towards Mexicans and Hispanics during the 2016 United States presidential election, and to examine its relationship with mental well-being in this targeted group at the population level.
Methods: Tweets containing the terms Mexican(s) and Hispanic(s) were collected within a 20-week period of the 2016 United States presidential election (November 9th 2016). Sentiment analysis was used to capture percent negative tweets. A time series lag regression model was used to examine the association between percent count of negative tweets mentioning Mexicans and Hispanics and percent count of worry among Hispanic Gallup poll respondents.
Results: Of 2,809,641 tweets containing terms Mexican(s) and Hispanic(s), 687,291 tweets were negative. Among 8,314 Hispanic Gallup respondents, a mean of 33.5% responded to be worried on a daily basis. A significant lead time of 1 week was observed, showing that negative tweets mentioning Mexicans and Hispanics appeared to forecast daily worry among Hispanics by 1 week.
Conclusion: Surveillance of online negative sentiment towards racially vulnerable population groups can be captured using social media. This has potential to identify early warning signals for symptoms of mental well-being among targeted groups at the population level.

1. Introduction

1.1. Racism and mental health

A sizeable body of research has documented the link between racism and adverse psychological and mental health symptoms [1, 2]. These studies have documented the substantial effect of racism on psychological distress and have shown that the experience from racism is a strong predictor of the number of poor mental health days indicating the relationship to poorer health outcomes [3]. In a meta-analysis with a pooled sample of 18,140 subjects across studies, a positive association between perceived racism and psychological distress was found [4, 5]. Additionally, it has been documented that certain minority groups such as immigrant populations are less likely to report acts of discrimination [6, 7, 8, 9]. This may result in observation of a dampened relationship between racism and mental health within these groups. However, research has yet to investigate the time period between negative public sentiment and its effect on the mental health of the targeted population.

1.2. 2016 United States presidential election

The 2016 United States presidential election provides a unique opportunity to examine the relationship between online discriminatory attitudes and mental well-being among vulnerable minority groups. When Donald Trump kicked off his campaign on June 16th, 2015 with a speech in which he labeled immigrants from Mexico as "rapists" and "criminals". "*When Mexico sends its people… They're sending people that have lots of problems, and they're bringing those problems with us. They're bringing drugs. They're bringing crime. They're rapists*" [10]. In his Super Tuesday victory speech in March 2016, Trump outwardly spoke about *"…countries like Mexico…killing us on the boarder…destroying us in terms of economic development*" and discussed building a wall during a press conference [10]. Donald Trump's negative speech towards Mexicans and Hispanics continued throughout his campaign in his speeches, interviews and were actively prominent on the social media network platform Twitter. Derogatory tweets from Donald Trump included "*El Chapo and the Mexican drug cartels use the border unimpeded like it was a vacuum cleaner, sucking drugs and death right into the US*" [10]. These negative tweets about Mexico perpetuated during the 2016 United States presidential election and may have generated widespread online racial animosity and hostility towards Mexicans and Hispanics that negatively impacted the mental well-being of Mexicans and Hispanics in the United States, as documented by previous studies [11].

1.3. Digital surveillance using Twitter

Widespread reach and penetration of online big data from social media has made it made it possible to capture real-time insights from a large number of individuals [12, 13, 14, 15, 16]. For instance, the social media platform Twitter has emerged as a highly promising approach for identifying population based trends. Twitter consists of an open forum where users "tweet" out short sentences of 280 characters (formerly 140 characters). Twitter facilitates discussion and debate by allowing users to cross-post, share their views, and connect with others outside of their traditional network to retrieve information. Twitter has become the "agora" marketplace for public discussion. With over 500 million tweets posted each day [17], Twitter yields a unique opportunity to capture in the moment daily thoughts, feelings and behaviors. It has been widely used to support the detection and understanding of infectious disease epidemics, from Zika [18], to Ebola [19] and Dengue [20]. Sentiment analysis of tweets has also been shown to be effective at reflecting mass public opinions and has been use to predict political elections around the world [21, 22, 23]. Therefore, Twitter may provide opportunities to monitor public racial perceptions in real-time.

In the past, racist graffiti, defamation of religious buildings and acts of vandalism were used to measure the amount of racial hostility and hate in society [24, 25]. Twitter's posts are today's forum for "writing on the walls" where people openly express their thoughts, opinions and beliefs. Unlike in-person conversations where individuals may be less inclined to use racial slurs, racial language is often used openly on social media platforms like Twitter [25]. Although Twitter is smaller relative to popular social media platforms like Facebook, Facebook is a closed social network, whereas Twitter is an open forum and exerts an outsize influence of conversation [26]. Twitter is also based on less in-person relationships and thus offers less personalization and greater anonymity. Thus, hidden derogatory perceptions can potentially be expressed on Twitter and the consequences of "viewing" the pain caused by these online "actions" may not be as easily apparent. This unfiltered content on Twitter may offer a public reflection of negative attitudes and discriminatory views towards certain demographic groups that would otherwise not be possible to capture using traditional survey instruments [15, 24, 25, 27]. Racist and discriminatory language on platforms like Twitter has become the "racist graffiti" of our time [25]. For example, a disgruntled waitress tweeted "*If we had a real life purge I would kill as many Mexicans as I could in one night*" because of the lack of tip she received from a Mexican patron at the restaurant [28]. Thus, we may be able to quantify the effects of negative attitudes and discriminatory views using social media data that will allow us to investigate the relationship of racism on health outcomes in real-time.

In this study we have two aims. The first aim is to evaluate the feasibility of using the social media platform Twitter to monitor negative social discussions about Mexicans and Hispanics on Twitter during the 2016 United States presidential election, as this was a time of heightened negativity towards this minority group. The second aim is to examine the relationship between negative online social discussions about Mexicans and Hispanics during the 2016 United States presidential election and the mental well-being of this targeted group at the population level.

2. Methods

2.1. Online big data

This study involved developing an online "big dataset" of relevant communication on Twitter, referred to as tweets, about Mexicans and Hispanics as this was a highly targeted ethnic minority group during Donald Trump's campaign during the 2016 United States presidential election. We experimentally queried online big data to capture discussions about Mexicans and Hispanics on Twitter. The corpus of terms included: Mexican(s) and Hispanic(s), with and without hashtags (#). Tweets containing the terms Mexican(s) and Hispanic(s) were collected using a data licensing-access agreement from Twitter that enabled us to acquire the full stream of tweets from Twitter over a 20-week period, 10 weeks before and 10 weeks after the 2016 United States presidential election (November 9th 2016). This included the following range of dates: August 29st, 2016 to January 16th, 2017. Our primary predictor variable was defined as the percent of negative sentiment of tweets mentioning Mexicans and Hispanics. This predictor variable was calculated by dividing the number of negative tweets mentioning Mexicans and Hispanics over the total number of tweets that mentioned Mexicans and Hispanics.

2.2. Sentiment analysis

Sentiment analysis identifies opinions and sentiments expressed in text. On social media platforms like Twitter, sentiment analysis on tweets have been shown to be used to understand the "masses" opinion and has been shown to be able to predict movie box office openings [29], stock market prices [30, 31] and political candidates [30, 32]. By analyzing sentiment in a specific domain on online big data derived from Twitter, it is possible to gain better insight on public opinion on the specific subject of interest [33].

To identify the sentiment of the tweet we used a natural language processing (NLP) system that is a widely accepted lexicon and rule-based sentiment classifier for microblogs, Valence Aware Dictionary for Sentiment Reasoning (VADER) [34]. VADER computes sentiment for each word and generates compound scores for the sentence by summing the sentiment score of each word. A sentiment score ranges from -1 (most extreme negative) and +1 (most extreme positive). Scores of exactly 0.0 are discarded as they indicate that there is not sufficient context. A sentiment score is positive if the mean compound score is greater than or equal to 0.5 and negative if the score is less than or equal to -0.5. Mean compound scores between -0.5 and 0.5 are considered neutral.

VADER is based on the pattern library, which is trained from human annotated words commonly found in product reviews. VADER is often used for product reviews and news articles and therefore does not always contain similar text-based characteristics as Twitter. Therefore we used a previously validated method to append VADER's dictionary and rules to provide broader representation for Twitter [35, 36]. For instance, Twitter allows a maximum of 280 characters per post, which can be difficult for sentiment analysis because of the presence of abbreviated terms and emojis. To account for this, we incorporated more than 110 emojis and

their respective sentiment scores, abbreviated terms, and acronyms frequently used on Twitter. To test the robustness of VADER, we collected a random sample of tweets by week and calculated their sentiment score using VADER and found that the distribution for different weeks was similar suggesting that the sentiment score from VADER robust to fluctuations over time. An example of a negative tweet about Mexicans and Hispancs is "white girls: mexicans are so annoying when they speak spanish all the time dumb beaners go back home". A positive tweet about Mexicans or Hispanics is "contrary to popular beliefs, Mexicans & americans can peacefully coexist".

2.3. Daily mental-well being

Our primary outcome variable was negative mental well-being as defined by experience of worry on a daily basis among Hispanics in the United States. Data on daily worry was collected from the Gallup-Sharecare Well-Being Index, which provides a nearly real-time view of Americans' well-being and has been previously used to measure Hispanic's mental well-being during the 2016 United States presidential election [11]. This emotional well-being index measures Americans' daily experiences and respondents categorize their responses as thriving, struggling, or suffering in the areas that measure wellbeing. Gallup interviews US adults aged 18 and older living in all 50 states and the District of Columbia using phone numbers through random-digit-dial methods. Gallup interviews at least 500 US adults aged 18 and older daily, with more than 175,000 respondents interviewed each year. Gallup weights the samples to correct for unequal selection probability, nonresponse, and double coverage. Gallup also weights its final samples to match the US population, which is based on data from the most recent US Census. Additionally, Gallup interviews respondents in Spanish to capture respondents who are not able to complete the interview in English. Research has also shown that about 9 in 10 Hispanics are interviewed by Gallup in Spanish, and were born in another country. This makes this a potentially representative population that is being targeted by these negative online discussions about Hispanics.

2.4. Descriptive analysis

We plotted the frequency of the percent of negative tweets weekly, over the 20-week period, 10 weeks before and 10 weeks after the 2016 United States presidential election. We plotted the percent of worry by week within the same time frame. These values were plotted on the same graph to provide a visual representation to view descriptively if there was an underlying trend and a visual lag time could be seen.

2.5. Stationarity and differentiation

We used cubic spline interpolation to fill in missing responses of percent worry. In order to perform the time series lag regression, the data must be stationary. A stationary process has the property because the mean, variance and autocorrelation structure do not change over time. To conduct statistical forecasting, the time series trend cannot have periodic fluctuations or seasonality. Therefore, time series data was tested for stationarity using an Augmented Dickey Fuller (ADF) test because it is the most robust and strict where the null hypothesis is the data is not stationary. The ADF test was non-significant for both the predictor and the outcome therefore we could not reject the null and determined both time series not to be stationary. Given our time series data is not stationary, the mathematical transformation of stationarizing the time series through differencing was used. Given the series Z_t we create the new series to differentiate the data:

$$Y_i = Z_i - Z_i - 1$$

After differentiating the time-series we retested it with the run sequence plot and found the differentiated data was stationary.

2.6. Lag time-series analysis

After differentiating the data, to test the predictive ability of percent count of negative tweets mentioning Mexicans and Hispanics on the percent count of worry on Hispanics we used a time series lag regression test. We denote $y_{neg\_tweets}(t)$ the percent count of negative tweets mentioning Mexicans and Hispanics at time t, and $y_{worry}(t)$ the percent count of worry on Hispanics, and consider a distributed lag model similar to [37]:

$$y_{worry}(t) = \mu_t + \sum_{l=1}^{n_\beta} \beta_l \, y_{neg\_tweets}(t-l) + \varepsilon(t)$$

$$\varepsilon(t) \sim N(0, \, \sigma^2)$$

where lag is measured weekly and is the lag in time between the percent count of worry on Hispanics. In this model, β_{lag} quantifies percent count of the negative tweets mentioning Mexicans and Hispanics at time $t – lag$ to predicting the percent count of worry on Hispanics at time t.

In order to formally test for the significant lag time between time trends of y_{worry} and y_{neg_tweets}, we make the observation that within the range of lags considered (3 weeks), β_l is non-increasing with respect to lag length, since the case count measurements becomes less correlated as the distance in time between them increases. This observation leads to a sequential hypothesis testing procedure that tests for relationship between $y_{worry}(t)$ and $y_{neg\_tweets}(t-l)$ in an incrementing manner. Specifically, starting from $lag = 1$, we test for the null and alternative hypothesis:

$$H_{0, \, lag} : \; \beta_i \neq 0, \, \beta_{lag} = 0, \, \beta_j = 0$$

where $i < lag < j < n\_\beta$

$$H_{1, \, lag} : \; \beta_i \neq 0, \, \beta_{lag} \neq 0, \, \beta_j = 0$$

where $i < lag < j < n\_\beta$

this hypothesis can be tested using a likelihood ratio test with small sample adjustments [38]:

$$LR_{lag} = (N - lag)\left[L_{lag} - L_{lag-1}\right]$$

where L_{lag} indicates the maximized log likelihood under the model:

$$y_{worry}(t) = \mu_t + \sum_{l=1}^{lag} \beta_l \, y_{neg\_tweets}(t-l) + \varepsilon(t)$$

If we fail to reject the null hypothesis $H_{0, \, lag=1}$, the procedure is then to proceed to test for the hypothesis $H_{0, \, lag=2}$ etc. The procedure stops when the lag-specific hypothesis $H_{0, \, lag}$ is rejected at certain lag (say, $lag = k$), and we conclude that the percent count of worry on Hispanics measurements during $(t-k, t)$ is significantly associated with percent count of worry on Hispanics measurements at time t. Sensitivity analyses were also performed to test the robustness of our modeling on our findings. We tested our model on the exclusion of retweets, exclusion of tweets from highly political users, defined by the having the term Democrat or Republican in their user name [39], and a longer period of time from August 1st 2016 to January 23rd 2017.

3. Results

From August 29th 2016 to January 16th 2017, a total of 2,809,641 tweets that contain the terms Mexican(s) and Hispanic(s) with hashtags with a mean sentiment of -0.088. In total, 687,291 tweets were deemed to be negative comprising 24.5% of all tweets with a mean sentiment of -0.680. The mean number of tweets per week was 93,654.70, the mean number of tweets per day was 16,055, the total number of users was

943,766 and the number of retweets was 1,594,845. The total number of Hispanic respondents that answered about their daily worry in this time period within the Gallup data was 8,314 with an average number of 362 respondents per week and a mean of 33.5% who responded to be worried on a daily basis. Table 1 provides a summary of the Twitter statistics.

Figure 1 shows the average weekly plot for the percent of negative tweets mentioning Mexicans and Hispanics and percent worry among Hispanics. For the negative tweets mentioning Mexicans and Hispanics the highest percent of negative tweets occurred in the week of November 7th 2016, the week of the 2016 United States presidential election, with 35% of tweets being negative. For percent worry we see the largest peak of an average response of daily worry in 40% of Hispanics on the week of November 11th 2016, a week after the presidential election.

3.1. Time-series regression

As illustrated in Figure 1, the autoregressive distributed lag model for testing the regression lag found a significant lag time of 1 week ($LR_{lag=1} = 0.314; p = 0.022$), in which negative tweets mentioning Mexicans and Hispanics appeared to predict daily worry among Hispanics 1 week earlier. Table 2 summarizes the forecasting performance for the autoregressive distributed lag model when lag 0 and lag 1 of the negative tweets mentioning Mexicans and Hispanics is used to predict percent worry of Hispanics. With the addition of lag 2 to the model with negative tweets mentioning Mexicans and Hispanics forecasting percent worry of Hispanics, lag 2 was not significant, and lag 1 still remained the only lag that was significant ($LR_{lag=1} = 0.291; p = 0.048$). Therefore, we selected the lag 0 and lag 1 model and conclude that, on average, negative tweets mentioning Mexicans and Hispanics significantly lead daily worry amongst Hispanics by 1 week. Our findings were robust to sensitivity analyses whereby a 1-week lag was seen with the exclusion of retweets ($p < 0.045$), the exclusion of tweets from highly political users ($p < 0.043$), and a longer period of time of 25 weeks, from August 1st 2016 to January 23rd 2017, ($p < .046$).

4. Discussion

Using the platform Twitter, we were able to capture the sentiment of public discussions about Mexicans and Hispanics. At the population level, the percent of negative tweets mentioning Mexicans and Hispanics had a lead-time of 1-week to the onset of percent of daily worry among Hispanics during the 20-week time period surrounding the 2016 United States presidential election (Figure 1). These findings contribute to a growing body of evidence on the use of online big data from Twitter for the detection of public racialized discourse [40, 41]. Our study highlights the feasibility of using Twitter to measure online attitudes towards race and its potential relationship to real-world mental health outcomes.

4.1. Online racial discussions

Since social media platforms have become a source of information and serve as a community in which people express and adopt ideas and ideologies, results from our study offer evidence for the ability of the online social media platform Twitter to potentially capture real-world negative sentiment directed towards racial minority groups. Moreover,

our findings support research has shown that racism can be derived from the culture of social media platforms because these platforms can act as the starting point and as amplifiers of racist discourse [42]. For instance, negative tweets about Mexicans include "Mexicans are rapist!" and "… mexicans are lazy…", and perpetuation of these negative online discussions can lead to negative mental health effects if viewed by these demographic groups who are active within this online environment. Additionally, these online sentiments may a proxy or spillover into real-world racist attitudes and propagate racist behaviors in offline contexts. We offer these insights as potential mechanisms but did not investigate or test these pathways in our study. The link between online racist discourse and impact on offline racist attitudes and behaviors is an important area to explore in future studies.

The ability to detect negative racial attitudes using online big data from social media advances the literature because in the past social desirability bias may have resulted in respondents withholding their socially unacceptable attitudes, such as negative racial sentiments [25, 43, 44, 45], or openly admitting racial or discriminatory bias in surveys [45, 46]. Therefore, people's responses are often not reflective of their actual behaviors when it pertains to negative attitudes or discrimination on the basis of race [45, 46, 47]. Online big data offers a valuable contribution to studying public perceptions related to race as it may be less susceptible to social desirability bias [43]. For instance, in the General Social Survey, the survey measure of support for a law banning interracial marriage is used as the state-level proxy for racial attitudes [48]. Using this survey measure, there was no evidence that racial attitudes affected Barack Obama's voting share during the 2008 United States presidential election [48]. However, when this same study was replicated using Google search queries that included racially charged language as a proxy for racial attitudes, these racially charged searches emerged as a large and robust negative predictor of Barack Obama's voting share [43, 49, 50]. There online racial sentiment may provide a greater capability for monitoring offline racial attitudes and norms, and could help to anticipate these incidents of hate faster, and could be used to inform and mobilize efforts aimed at mitigating the health consequences among targeted ethnic or racial minority groups.

4.2. 2016 United States presidential election and racial prejudice

The results of our study are based on a 20-week time period surrounding the 2016 United States presidential election and may be documenting the real-time shifts of racial prejudice and its consequences on the health of the target populations within this time period. Leading up to the 2016 presidential election, there was a rise in the proportion of negative tweets directed towards Mexicans and Hispanics. For instance, in the first month after Donald Trump won the presidency, the Southern Poverty Law Center catalogued 1064 incidences [51, 52]. These hate-fueled acts include acts of intimidation based on race, vandalism of places of worship, and racist graffiti at schools and public places [51]. Additionally, the Anti-Defamation League (ADL) reported spikes in reports of racist and anti-Semitic graffiti and vandalism, including the widespread use of swastikas and Nazi imagery, which have been linked to the outcome of the 2016 United States presidential election [53]. Although we only documented negative sentiment towards Mexicans and Hispanics, this may be a representation of the rise in racial animus in the United States and may give useful insights for monitoring these societal

Table 1. Description of tweets and percent worry.

Data Type	n	Percentage	Mean	SD
Total Tweets mentioning Mexicans and Hispanics	2,809,641	100%	-0.088	0.023
Negative Tweets mentioning Mexicans and Hispanics	687,291	24.5%	-0.680	0.017
Positive Tweets mentioning Mexicans and Hispanics	301,323	10.7%	0.656	0.046
Neutral Tweets mentioning Mexicans and Hispanics	1,821,027	64.8%	0.001	0.043
Worry amongst Hispanics	8,314	33.5%	361.48	25.22
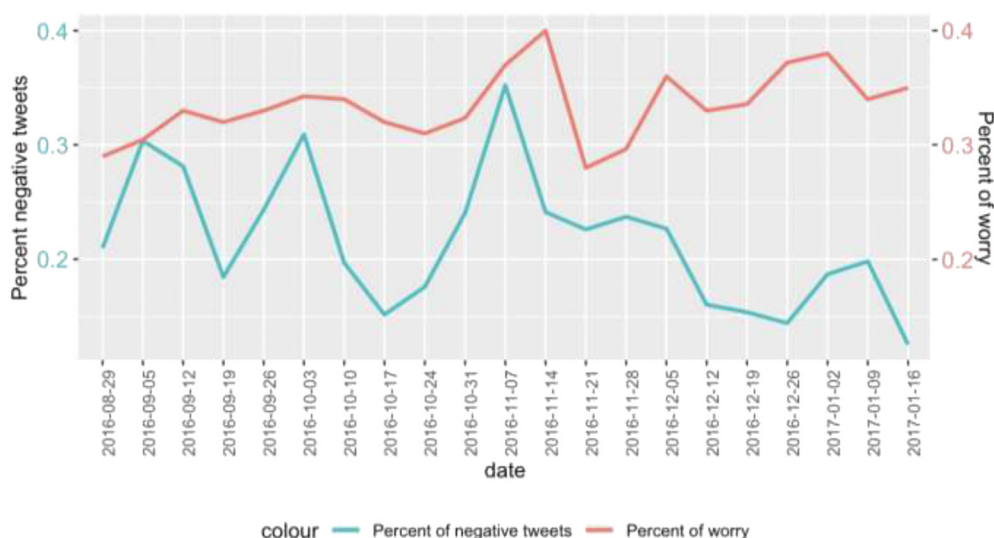
Figure 1. Percent negative tweets mentioning Mexicans and Hispancs and percent worry among Hispanics during the time period surrounding the 2016 United States presidential election.

Table 2. Performance for the autoregressive distributed lag time series regression model.

Time Lag	Overall
20-week	
Intercept	*ref (-0.0039)*
Lag 0 (t)	0.142
Lag 1 (t-1)	0.314*

*p < 0.05, **p < 0.01, ***p < 0.001.

shifts in racism earlier than traditional sources, such as documenting hate crimes or police reporting.

Additionally, threatening rhetoric from political leaders can increase the risk for mental health consequences for the targeted populations [54, 55]. It has been documented that after the 2016 United States presidential election, groups who were targeted by prejudiced expressions during Donald Trump's campaign experienced negative mental health effects [56, 57]. For example, the day after the election, lesbian, gay, bisexual and transgender (LGBT) persons reported the worsening of negative mental health symptoms [58]. A second study confirmed longer-lasting mental health impacts of the 2016 presidential election among those who identify as belonging to a sexual minority group [59]. Post-election mental distress was also experienced by Spanish-speaking Latinos and their mental distress lasted for a longer period of time compared to other demographic groups [60]. This is notable given that Hispanics and Mexican Americans were particularly targeted by negative campaign messages. These findings are consistent with our results that document the relationship between online negative sentiment towards Mexicans and Hispanics and the reduction of mental well-being in this group that occurred one week after.

4.3. Real-time digital surveillance

Results from our study showed that negative sentiment of discussions on Twitter about Mexicans and Hispanics was followed by an increase in reported daily symptoms of worry among Hispanics by 1 week. This suggests that the onset of symptoms from exposure to negative sentiment towards a group may have a 1-week lead time between racist exposure to the sentiment and the onset of symptoms of mental well-being. There is considerable evidence of a negative association between racial and ethnic discrimination and poor health, especially worsening mental health [49, 50]. In a systematic review of 53 studies documenting the

association between racism and poor health outcomes, 32 studies measured mental health, and mental health emerged as having the strongest negative association compared to all other outcomes [50].

Although there is a consistent finding that discrimination is associated with poorer health outcomes, there have been methodological limitations and questions that remain unanswered. Firstly, inadequate assessment of discrimination due to social desirability bias may have dampened findings. Secondly, the time period between racist sentiment and symptoms of mental well-being is not well-characterized. Findings from our study showed a 1-week lead time of negative sentiment of discussions about Mexicans and Hispanics and daily worry experienced by Hispanics in the United States. Using an online big data source potentially allows us to capture more authentic attitudes and a more discrete assessment of the window of time when this relationship between racial prejudice and mental well-being emerges.

4.4. Limitations

This study uses novel data to understand the relationship and time period between exposure to negative racial sentiment and mental health; however, there are limitations to carefully consider. The independent variable in our data was derived from Twitter. Only a certain segment of the United States population uses Twitter and these negative discussions towards Mexicans and Hispanics are within specific group of Twitter users. Therefore, the proportion of negative sentiment towards Mexicans and Hispanics are not generalizable to the entire United States population. However, it has been previously documented that Twitter has been effective at monitoring and influencing societal beliefs and behaviors [23, 61, 62]. With over 500 million tweets per day [17], Twitter has the potential to offer greater and more unfiltered insight about the population's thoughts, feelings and may act as a representation of social

norms and attitudes in real-time that would not be possible to measure using other approaches.

Our outcome measure of daily worry was collected by the Gallup survey, using population-based sample so it is representative of the United States population. However, this measure may not encompass the breadth of mental health symptoms associated with racial discrimination. Racism is associated largely with mental health outcomes of major depression and anxiety [2, 50, 63, 64]. Frequency of everyday discrimination has been associated with greater use of the emergency department and onset of one or more chronic diseases [65]. A meta-analytic review found that perceived discrimination was associated with smoking, overeating, excessive drinking and substance abuse [66, 67]. This review showed well-documented large epidemiological studies over long periods on the relationship between sustained negative emotional state and cardiovascular reactivity and other subclinical diseases, which can lead to more serious cardiovascular diseases [66]. These measures we not taken into account in the present study. In an effort to capture this early signal of the impacts of racism on symptoms of mental well-being, the use of daily percent worry was used.

Importantly, our study findings cannot be interpreted as causal. Although it is notable that we found a 1-week lag between negative discussions about Mexicans and Hispanics on Twitter and percent worry among Hispanics, variables were population aggregates and analyses were conducted at the ecological level. As such, our findings should be interpreted with caution. Additionally, because of the restraints of access to tweets from Twitter, we were unable to capture another time period to evaluate if these findings were robust to changes in time. Without this comparison, our findings may not be generalizable to periods outside of the strongly political period during the 2016 United States presidential election when Mexicans and Hispanics were targeted negatively. However, our findings were robust to sensitivity analyses with the extension of the time period to 25 weeks during the election and provide evidence of a 1-week lag outside the period of the election. Furthermore, differentiation of the data was conducted to remove periodic fluctuations and to ensure time trends were not contributing to this lagging effect and thus seasonal changes should not have an impact on the results of this study based on time. Finally, the lack of geolocation information in both datasets did not afford the opportunity to conduct geospatial analyses of the relationship between Twitter trends and mental well-being. Therefore, we were unable to identify how this relationship differs across areas of the United States. Future studies should investigate the distribution of racial animus on Twitter and its varying impacts on mental health across the United States.

5. Conclusion

Online social media platforms may offer a method of early detection of social norms surrounding prejudiced racial beliefs and attitudes. Identifying these events earlier can allow communities to collectively take action and to develop resources to prevent discriminatory acceptability. These online public big data sources may also allow us to understand the period of time between exposure to racist attacks and the onset of mental health symptoms and worsening mental well-being. Identifying the time window of onset can inform the development of targeted interventions that can be dispatched at a time when symptoms can be managed to reduce the harmful effects of negative attitudes and discrimination on the health of targeted minority groups.

Declarations

Author contribution statement

Y. Hswen: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Q. Qin: Performed the experiments; Analyzed and interpreted the data.

D. R. Williams, K. Viswanath, J. S. Brownstein, S. V. Subramanian: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data.

Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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