

Using Big Data to Study the Impact of Mass Violence: Opportunities for the Traumatic Stress Field

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Studying the community impact of mass violence using a Big Data approach from social media data (e.g., Twitter) offers traumatic stress researchers an unprecedented opportunity to study and clarify theoretical assumptions using large-scale, observational, ecologically valid data. We describe challenges and benefits of working with Twitter data and briefly review studies that used Twitter data to explore community responses to mass violence. We then demonstrate the use of Twitter data to examine community responses to a specific event: the 2015 San Bernardino terrorist attack, in which 14 people were killed and 22 were wounded. In a 6-week time frame around this attack, we evaluated the time course of community-level negative emotion. We downloaded 1.16 million tweets, representing 25,894 users from San Bernardino, CA, and a matched control community, Stockton, CA. All tweets were coded in R using the Linguistic Inquiry and Word Count (LIWC) negative emotion dictionary. A piecewise regression technique with a discontinuity analysis was used to evaluate pre- and postevent trajectories of negative emotion across the study window. Controlling for within-user variability, negative emotion increased by 6.2%, $\beta = .182$, $SE = .014$, $p < .001$, in San Bernardino on the day of the attack and remained elevated for 5 days; no elevation was observed in Stockton. We discuss how data-driven text analytic techniques are useful for exploring Twitter content generated after collective traumas and describe challenges and opportunities accompanying analyses of social media data to understand the impact of mass violence on affected populations.

The rising interest in “Big Data” analytics among social scientists (National Research Council, 2013) has led to the development and refinement of computational tools for analyzing complex cross-sectional and longitudinal data. In particular, this has been the case for the analysis of large-scale corpora of social media text. Easy-to-use packages in open-source statistical programming languages (e.g., R, Python) now allow social scientists to engage with their data in ways that were once relegated to individuals such as computer scientists with extensive training in programming languages. Indeed, a quick Internet search yields many text- and video-based tutorials for extracting information embedded within social media data. Big,

archival data (especially those generated on social media platforms like Twitter) and the techniques used for analyzing them come in many shapes, sizes, and flavors. This variety translates to a robust toolkit with which trauma researchers can answer important questions relevant to the field. In gaining expertise with these tools, there is an opportunity for new and seasoned traumatic stress researchers to generate new knowledge about how people within affected communities respond to and cope with mass violence in its immediate aftermath and over time.

In this paper, we provide a brief introduction to methodological considerations of working with Twitter data. We highlight studies at the intersection of technology and traumatic stress across several disciplines to demonstrate the value of this approach for studying mass violence. We then describe how we employed this approach, using a strong quasi-experimental design, to study the December 2015 terrorist attack in San Bernardino, CA, an incident of mass violence. Finally, we end with a discussion of how big social media data can be used to develop a rich understanding of the impact of collective traumas (i.e., large-scale natural or anthropogenic negative events that affect many people) and advance knowledge and theory in the field.

As many traumatic stress researchers know, using rigorous study designs with traditional research methods to examine the

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impact of collective trauma can be challenging (Silver, 2004). Mass violence events are typically unexpected and occur without warning. This precludes a researcher's ability to collect pre-event data against which to compare postevent trends. Moreover, getting into the field quickly after an event can be difficult because of delays in ethics board approval or acquisition of funding and staff to conduct research (Silver, 2004; Steinberg, Brymer, Steinberg, & Pfefferbaum, 2006). Finally, studies of large-scale traumas do not typically allow for the formation of control groups, a hallmark of true experiments and an important feature of any strong quasi-experimental design (Shadish, Cook, & Campbell, 2002).

Recently, researchers in informatics, sociology, communications, and psychology have circumvented these challenges, tapping Twitter data across the globe to study the impact of collective traumas. The data analyzed in these studies are comprised of "tweets," which are short messages, written by Twitter users, that contain opinions, random thoughts, and emotions, all of which can be shared publicly if the user desires. The primary analytic units of tweets are the words people use when writing them, and many social scientists use an automated means of capturing the emotion, mood, and cognition expressed in these words. The most popular method to accomplish this goal is the Linguistic Inquiry and Word Count (LIWC; Pennebaker, Booth, Boyd, & Frances, 2015) program, which is comprised of empirically validated dictionaries that contain words related to several psychological constructs (e.g., emotion, cognition) and linguistic features related to psychological states (e.g., pronouns). Words in these dictionaries are then automatically compared to the words in individual tweets, and the software produces a count of word matches that can be analyzed in various ways, depending on the research question.

There are important features of Twitter data that make them ideally suited for studying collective trauma. First, tweets are free and relatively easy to retrieve with some technical understanding of how to work with Twitter's Application Programming Interface (API). The text data they contain allow for the extraction of psychological information generated naturally, without interference from a researcher. Researchers often achieve this extraction using the LIWC program, but they may also use other computational text-analytic techniques (e.g., word frequency, inverse frequency). This relatively straightforward method for capturing emotion in tweets is powerful, especially when coupled with the fact that tweets are archival by design; that is, each tweet has a timestamp that allows a researcher to compute pre-event trends of emotion expression that can serve as a baseline against which to compare postevent trends. Moreover, because tweets are rather easy to collect, it is also much easier to include tweets from a control group, a necessary but rare feature of collective-trauma studies.

However, despite the virtues of Twitter data, there are several methodological challenges researchers should keep in mind. In any study of the impact of a collective trauma, identifying users

in a target location is key, and there is marked variation in how researchers have sought to achieve this goal. Unsurprisingly, the majority of studies of collective traumas that use Twitter data rely on analyses of geocoded tweets; that is, tweets tied to a specific geographic location via geocoordinates (Lin, Margolin, & Wen, 2017). This method offers total certainty about where a tweet was generated and, in using this approach, a researcher can capture tweets from residents and visitors in a target location affected by a collective trauma. However, as some Twitter researchers have noted (e.g., Jones, Wojcik, Sweeting, & Silver, 2016), very few users "opt in" to having their tweets geocoded. In fact, estimates of the percentage of Twitter users who opt in to having their tweet location made public range between ~6% and ~8% (Jones et al., 2016; Lin et al., 2017), although the true number is only known by Twitter.

Other Twitter studies rely on hashtags and keywords related to a collective trauma to source Twitter data (De Choudhury, Monroy-Hernandez, & Mark, 2014). This approach is reasonable given that when mass violence occurs, communities tend to respond on social media with hashtags like #BostonStrong or #PrayForParis, in the cases of the 2013 Boston Marathon bombings and 2015 Paris terror attacks, respectively. Although this may result in downloading tweets relevant to a specific event, there is no guarantee that these tweets will represent users in the affected location, especially when the event under study garners national (or international) media attention. Importantly, using this strategy to source Twitter data (a) only allows researchers to access tweets generated 7 days before they initiate their search because of restrictions set by Twitter in the availability of data from their API, and (b) limits the search to a small but undetermined subset of all available Twitter data (Twitter, 2019).

Because of these limitations, some researchers have used other methods to approximate a user's location. For example, some researchers take advantage of the fact that downloaded Twitter data come with a variable called "location," a field that users can optionally complete as part of their Twitter profiles (Doré, Ort, Braverman, & Ochsner, 2015). This field can contain useful information like "Purdy, MO" (a real city in the United States) or unusable information like "New Berlin, Luna" (a location that does not exist). The advantage here is that users who provide a real location are likely to live there. The downside to this method is that it can be labor intensive for researchers to sift through each user's location to identify individuals to retain in a study. Moreover, individuals could forget to update this field, thus potentially including users no longer living in a target area in the sample. If automated means of identifying locations of interest are employed, misspelled locations may be excluded unless a human identifies them or the automated system is built to account for variations in spelling. It is also unclear whether users differ systematically in their propensity to provide this information.

Rather than relying solely on geocoded tweets, keywords, or the location field to source Twitter data for analysis, researchers can identify users in a community of interest in two other ways.

The first involves “scraping” (i.e., downloading) tweets generated in a geographic region by interfacing with the Twitter API and downloading tweets using a bounded geographic box that is defined by a set of geocoordinates that demarcate the box geospatially. This produces a data set of tweets generated in a geographic area and provides information about the users to whom those tweets belong. Researchers can then construct a computational focus group (Lin, Keegan, Margolin, & Lazer, 2014) composed of users with public accounts in the data set, and then download the most recent 3,200 tweets (the maximum number of tweets accessible for free through the Twitter API) from each user’s Twitter time line. Although this method provides researchers with a time line of data before and after the event in question for each user, the data are still derived from the very small subset of users who opt in to having their tweets geocoded. Moreover, this method has the potential to capture tweets from both residents and visitors of the geographic location under study, in which case community-based claims of an event’s impact may be overstated.

The second alternative method is community-specific. To target likely residents in a community that has been impacted by mass violence, researchers can first identify Twitter accounts of local organizations or agencies in that community and then download the list of users who follow those accounts (cf. Jones et al., 2016). The rationale is that users who follow the Twitter account of the Riverside, CA, City Hall, for example, are likely to be residents of Riverside, CA, and it is less likely that residents of New York City would follow this Twitter account.

After compiling lists of users who follow local accounts, researchers can download the most recent 3,200 tweets from each user who possesses a public account (9%–13% of users have private accounts; see Jones et al., 2016). An additional advantage of this method is that it lends itself to the inclusion of data from a closely matched control community, an important feature of any observational study attempting to make a strong inferential claim about the impact of a mass violence event. However, this method is not without error. It is possible that accounts belonging to users outside of the community may be included when downloading the list of users who follow local Twitter accounts. For example, residents who have moved away from an area may still follow local accounts from their former community.

Keeping the pros and cons of each approach in mind, we present findings from several studies that have leveraged the methodological flexibility of working with Twitter data to understand how communities are impacted by a variety of collective traumas. As an early example, De Choudhury and colleagues (2014) examined Twitter data, coupled with county-level homicide data, to study the impact of the Mexican drug war across several Mexican communities facing ongoing, protracted exposure to violence. These researchers used a keyword search to harvest approximately 3.1 million tweets over the course of 2 years. They found that negative affect expressed in tweets declined over time despite rising homicide rates in the communities under study. These authors suggested that this

trend is perhaps indicative of a desensitization effect, in which exposure to increasing violence numbs psychological responses to it. Importantly, this study demonstrated the value of triangulating on a community response by coupling Twitter data with related objective data (i.e., local homicide rates) to make a strong circumstantial case about the importance of the Twitter results obtained in the context under study.

Researchers have also used Twitter data to explore temporal and geospatial psychological responses to school shootings. For example, Doré and colleagues (2015) explored how emotion expression changed after the 2012 Sandy Hook Elementary School shooting in Newtown, Connecticut, as a function of time and distance from this tragedy. The authors used Twitter’s Streaming API, a real-time data collection method that uses keywords, to source their data and relied on the location field to approximate a user’s location. They used the data to test two opposing theoretically based hypotheses about the expected pattern of sadness and anxiety. Specifically, they tested whether sadness and anxiety would decay at the same rate over time and distance from the school shooting (nonspecific distance hypothesis) or whether sadness and anxiety would change differentially across time and distance, based on appraisals of the event (construal-level hypothesis). Analyses revealed that expressions of sadness were most prominent around the Newtown, CT, area immediately after the shooting and that emotion expression shifted toward anxiety with time and geographic distance from the school. Consistent with the construal-level hypothesis, authors found that causal thinking mediated these associations.

Twitter data have also proven useful for understanding responses to international terrorist attacks. Lin and colleagues (2017) examined geo-located Twitter data from 6,514 users they had identified as part of their computational focus group in Paris during the attacks in November 2015. The authors found marked increases in sadness, anxiety, and anger among individuals in Paris and noted that the negative affect lingered for days following the attacks. Comparable patterns of negative emotion expression appeared among a similarly obtained sample of tweets in the aftermath of the terrorist attack at an airport in Brussels, Belgium, 4 months later, although the psychological response was not as strong.

The utility of Twitter data has also been demonstrated when examining community responses to college campus shootings. For example, Jones and colleagues (2016) sourced Twitter data by identifying Twitter accounts local to communities that experienced incidents of college campus violence (e.g., the Isla Vista killings near the University of California, Santa Barbara, campus in 2014) and downloading tweets from users who followed those accounts. The authors also sourced data from control communities to allow for a comparison of patterns between the target and control communities. Across three instances of violence on college campuses, they found that event-related negative emotion expression on Twitter increased sharply following each event and was sustained for several days before returning to baseline.

In another study, Jones, Thompson, Dunkel Schetter, and Silver (2017) employed a mixed-methods approach, coupling survey data collected from thousands of students at a large university with Twitter data scraped from followers of two of the university's Twitter accounts, to understand how distress was linked to rumor exposure during a protracted lockdown following an isolated shooting incident. They found that students who relied on critical updates from many social media channels (e.g., Facebook, Twitter), and trusted what they read, reported more distress than students who trusted those channels less. They also found that students who relied on Twitter for critical updates reported more exposure to distressing untrue rumors about the shooting (e.g., multiple shooters and victims). Patterns in the Twitter data collected revealed that (a) over three dozen rumors were generated during the 90-min period in which no updates from the university's emergency management officials were transmitted, (b) negative emotion increased dramatically during this time, and (c) rumor transmission during this period was widespread.

Many of these studies relied on LIWC dictionaries for coding tweets. Using this method to capture psychological information is a top-down approach that imposes an analytic frame onto the data. This is the most commonly used method in Twitter studies, and it is suitable for understanding emotion expressed in Twitter data over time. However, Twitter data are also rich with meaning that can be extracted to understand context-specific aspects of an event that may be important. From a natural language processing (NLP) perspective, the exercise of extracting meaning from a text corpus (i.e., a collection of text documents) is an automated, data-driven (or a bottom-up) approach. Several computational techniques have been developed for analyzing text data, and they vary considerably in technical sophistication depending on the problem at hand. However, simple NLP techniques used by computational linguists may be sufficient for traumatic stress researchers to quickly get a sense of tweet content over time.

One such technique is called an *n*-gram analysis (Silge & Robinson, 2018), in which a corpus is tokenized into words that comprise all documents in the text. The flexibility of the *n*-gram approach is that the "n" of *n*-gram refers to the number of co-occurring words a researcher chooses to identify in the corpus. The words are automatically counted to produce each word's frequency, and commonly used words (e.g., the, and) are stripped out. In a unigram (1-gram) analysis, the researcher can request a list of the most common words in the corpus. Unigrams can be presented in a variety of ways, including via "word clouds," which have gained popularity recently because of the ease with which they can be created and the rough overview of content they provide. If the interest is in identifying common pairs of words, this would be a bigram (2-gram) analysis. Thus, for example, if a document in a corpus contains the phrase "I went to the store," all possible adjacent word-pairings are extracted (e.g., I went, went to, to the, the store). These pairings are created and counted for all documents in the corpus to provide a frequency of the most commonly used pairs. This

technique has not yet been used in Twitter studies of collective traumas but may be particularly useful for the trauma field because (a) it is a relatively easy-to-employ automated process, and (b) it may reveal important themes generated on Twitter after a collective trauma that may be relevant for understanding context-specific aspects of an event that can help explain psychological responses.

The present study employed the method described by Jones and colleagues (2016) to locate Twitter users in a community affected by mass violence, along with users in a matched control community. Using tweets from these samples, we sought to model negative emotion expression over time and explored the utility of using word clouds and *n*-grams to examine the community impact of the December 2, 2015, mass violence in San Bernardino, CA. On this date, 14 people were killed and 22 were wounded during a training event and holiday party for the San Bernardino Public Health Department. The perpetrators, who were husband and wife, fled the scene and were later killed in a shootout with police. At the time, this incident was considered the deadliest mass shooting in the United States since 2012.

We had two research aims. First, we looked to ascertain the time course of negative emotion expression in San Bernardino after a mass violence event compared to a matched control community. Second, we examined the informational efficacy of a word cloud and *n*-gram analysis of tweet content generated in the immediate aftermath of the attack.

Method

Participants and Procedure

Comparison community selection. Using procedures outlined by Wicke and Silver (2009), a list of potential mid-sized comparison communities on the West Coast of the United States ($n = 17$) was compiled. City size, whether the city was a county seat, ethnic distribution, and crime index were prioritized for selecting a community similar to San Bernardino. No community was an exact match. However, Stockton, CA, was selected as the comparison community primarily because the combination of its median household income (\$35,000 for San Bernardino vs. \$46,000 for Stockton), crime index (649.2 vs. 588.5), and Latino population (63% vs. 42%) was the most similar to San Bernardino. There were other communities that matched the ethnic distribution of San Bernardino more closely. However, they fell short on other metrics (e.g., in Santa Maria, the median household income was \$52,000, the crime index was 388, and the population was 103,000 compared to about 216,000 for San Bernardino).

Twitter data collection and cleaning procedure. Procedures outlined by Jones et al. (2016) were employed to source Twitter data generated by likely residents from each community. Twitter accounts owned by local government and commercial organizations (e.g., city hall, local radio stations) and likely

followed by residents of San Bernardino and Stockton, respectively, were identified. This list included 43 local accounts in San Bernardino and 18 accounts in Stockton. Next, the *twitteR* package (Gentry, 2015) for R (R Core Team, 2017) was used to interface with Twitter's API and scrape the most recent 4,000 followers (the average number of followers across San Bernardino accounts) of each San Bernardino account as well as 10,000 followers of each Stockton account. Given that we identified far fewer Stockton community accounts, we opted to download many more Stockton followers in an attempt to source a similar number of users across communities. After filtering out "verified" follower accounts (via a variable provided by Twitter) that likely belonged to businesses, celebrities, and other public figures (rather than local community members), a list of 47,962 user accounts in San Bernardino and 22,409 in Stockton was retained. Despite our efforts to equalize the user samples across communities, the number of Stockton users was nearly half that of San Bernardino. Nonetheless, we identified tens of thousands of users in each community.

This list was then read by an R script that interfaced with the Twitter API and downloaded the most recent 1,000 tweets generated by each user. Selecting the number of tweets to download from each user depends on how far back in time one wishes (or needs) to go to source tweets—the more tweets requested at this step will ensure that the data, in aggregate, will have been generated around the event in question. Moreover, the number of tweets one requests also depends on when data collection begins relative to the event. We began data collection roughly a year and a half after the attack and felt that moderate usage (two tweets per day for ~547 days, or 1,000 tweets), coupled with the large sample of users, was sufficient for the purposes of this study. If users had fewer than 1,000 tweets posted to their time line, all their tweets were downloaded. Computing limitations were also considered; requesting the maximum allowable number of tweets (3,200, set by Twitter) per user for over 47,000 users would have increased the number of users included in all analyses, but analyses would have been computationally prohibitive for a basic desktop computer.

In all, 1.16 million tweets representing 25,894 users who tweeted in a 12-week window around the attack (42 days before and after; cf. Jones et al., 2016) were downloaded (see Table 1 for details by community). On average, users tweeted approximately nine times per day (*Mdn* = 4.33 tweets) and generated at least one tweet an average of 6 days during the study period. Data collection procedures for this study were reviewed by the Institutional Review Board at the University of California, Irvine, and assessed not to constitute human subjects research.

Coding tweets for time. A primary study goal was to explore the time course of negative emotion expressed in the days and weeks before and after the event. To do so, the timestamp associated with each tweet was used to group tweets by hour. It is important to note that when downloading tweets from the Twitter API, the timestamp for each tweet is expressed in Uni-

versal Time, Coordinated (UTC) and should be converted to the local time of the communities under study for ease of analysis. In the present study, tweets were converted to Pacific Standard Time (PST) and then were automatically coded for their temporal distance from the event (i.e., December 2, 2015, around 11:00 a.m. PST) by subtracting the date and time the tweet was generated from the event date and time. For example, if a tweet was generated on November 29, 2015, at 11:00 a.m. PST, it was coded as -96 (4 days or 96 hr before the event). Likewise, a tweet generated on December 3, 2015, at 7:00 p.m. PST was coded as 20 (20 hr after the event). Converting timestamps, which are typically downloaded as a string variable, to a date and time format easily readable by R and other packages is important so that calculations can be conducted on these dates.

Measures

Negative emotion. A custom R script was used to compare the words in each tweet to a list of negative emotion words (e.g., sad, hate, tragedy) available in the LIWC program. Each tweet was then coded dichotomously such that if it contained at least one negative emotion word it was assigned a 1, and all others were coded 0. This allowed for a calculation of a proportion of tweets containing negative emotion in a given time frame (e.g., day, hour).

Data Analysis

Visualizations and statistical analyses. Data were manipulated using *tidytext* (Silge & Robinson, 2016), and descriptive visualizations were created in R using *ggplot2* (Wickham, 2009). We also employed the generalized additive model (GAM) smoothing function when creating plots with *ggplot2* to depict a nonlinear line-of-best-fit across time. To estimate linear trajectories over time and evaluate the significance of changes in negative emotion expression before and after the attack, a piecewise regression with a discontinuity analysis was conducted in Stata (Version 14.2; College Station, TX) using procedures outlined by others (Jones et al., 2016; Mitchell, 2012). This approach is well suited for statistically evaluating nonlinear changes in time-series data for which points of change are expected. First, a "knot" is placed at the moment of the event to signify a break in the time-series data. Doing so allows for an estimation of trends before and after the knot. A strength of this approach is that it provides a clear way to describe nonlinear trends in time-series data for which standard mathematical functions do not readily apply. Additionally, in this application of a piecewise regression, the use of a knot placed at the time of the event allows for a regression discontinuity analysis (Thistlethwaite & Campbell, 1960) in which a predicted value of negative emotion is calculated at the knot as if the event had not occurred. This value can then be statistically compared to a value representative of negative emotion that occurred at that knot point.

Many users tweeted multiple times each day throughout the 12-week time frame. If a user was more prolific than others

Table 1
Number of Users and Tweets

Community	12-Week Window				2-Week Window			
	Tweets		Users		Tweets		Users	
	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%
San Bernardino	784,479	67.5	17,980	69.4	150,481	68.9	12,611	69.2
Stockton	376,903	32.5	7,914	30.6	68,052	31.1	5,618	30.8
Total	1,161,382		25,894		218,533		18,229	

and expressed negative emotion across many of his or her tweets, that user could have undue influence on the results due to the correlated nature of the tweets. These dependencies violate the assumption of independence of residuals for an ordinary least squares regression analysis. To compensate, tweets were clustered within users in all regression analyses (Primo, Jacobsmeier, & Milyo, 2007; UCLA Statistical Consulting Group, 2015). In all contrasts, Stockton served as the reference group.

Tweet content analysis. To understand the content of tweets generated immediately after the attack, two text mining procedures in R were employed using tidytext (see Silge & Robinson, 2018, for a description of these techniques and the code to execute them). First, tweets were tokenized and common English-language words (e.g., the, and) were stripped out. Counts of remaining words generated the day of the attack were produced. A word cloud comprising the most commonly used words after the attack was then generated using the wordcloud (Fellows, 2013) package in R. A second word cloud—with positive and negative words differentiated—was produced using the Bing sentiment lexicon function in tidytext, which labels words based on their valence.

Next, a bigram analysis was conducted in each of the 12 hr after the attack to further extract tweet content as it unfolded in the immediate aftermath. Bigrams in each hour were assigned an importance weight using the term frequency–inverse document frequency (tf-idf) function in tidytext, a common technique that weights less commonly used words more heavily than commonly used words.

Results

Negative Emotion Trends

Raw proportions of negative emotion expression calculated each hour across the 12-week window are presented in Figure 1. There was marked variation in negative emotion expression in San Bernardino before the attack due to an unrelated event, the anniversary of the shooting of a young girl in the community. Also, relative to Stockton, this figure depicts a marked increase in negative emotion in San Bernardino on the day of the mass violence event.

Given the spike in negative emotion roughly 18 days before the attack, constructing a piecewise regression to evaluate the significance of emotion trends was problematic because the spike was not anticipated and would require an additional knot. However, the negative emotion trend exhibited by tweets in San Bernardino after the unexpected spike stabilized by the week before the attack, and negative emotion expression during this week appeared to be similar to the baseline negative emotion expressed before the anniversary of the young girl's death. Thus, we restricted the piecewise regression to the week before and after the attack (a 14-day window), aggregating tweets by day, to accurately model the trends in negative emotion expression in this time frame (see Figure 2).

Before the attack, no difference in negative emotion trajectories was observed between San Bernardino and Stockton, $\beta = -.001$, $SE = .001$, $p = .723$. In other words, both communities expressed negative emotion at the same rate before the mass violence event. Relative to baseline, negative emotion increased 6.2%, $\beta = .182$, $SE = .014$, $p < .001$, in San Bernardino on the day of the attack. No such increase was observed in Stockton (0.02%), $\beta = .007$, $SE = .017$, $p = .644$. In San Bernardino, negative emotion decreased 1.0% each day, $\beta = -.028$, $SE = .002$, $p < .001$, until returning to baseline roughly 6 days after the attack. In contrast, the postevent trend of negative emotion expression in Stockton remained stable after the attack, $\beta = -.001$, $SE = .002$, $p = .590$.

Tweet Content Surrounding the Attack

Results of the word clouds generated from tweets written by San Bernardino users are presented in Figure 3. The general word cloud reveals that “shooting” was the most commonly used word on the day of the attack. Ancillary words related to the attack also appear, although less prominently (e.g., “mass,” “victims,” “police,” “safe”). When differentiating the words by negative and positive valence, other dimensions of this event became clearer: This was a terror event, a massacre, and a bomb was involved. There was also much discussion about a suspect, and the word “dead” was very prominent, likely reflective of the shootout in which both suspects were killed. The word clouds appeared to converge on descriptive aspects of the attack.

Results from the bigram (2-gram) analysis of San Bernardino tweets are presented in Figure 4. Important word pairs identified

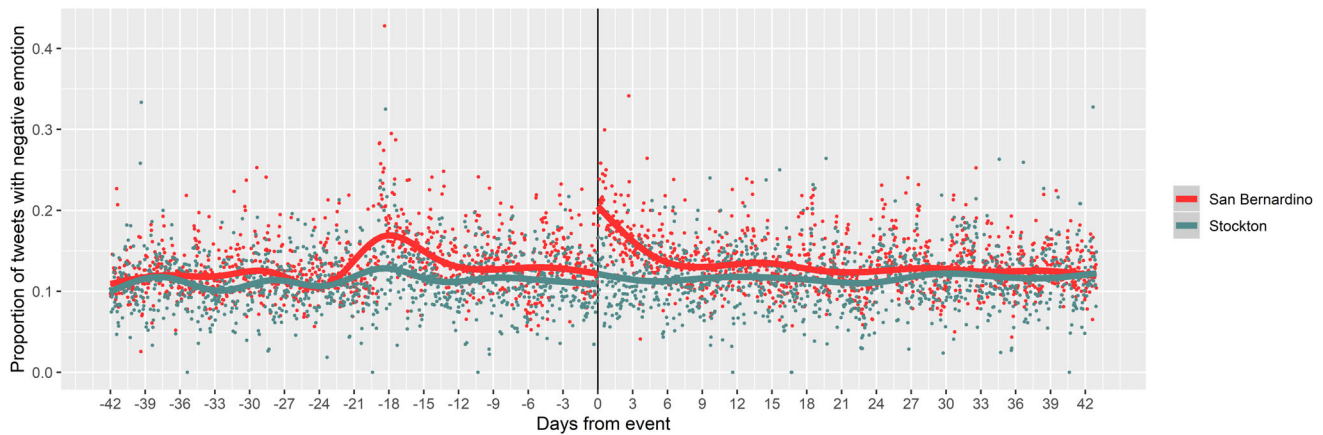


Figure 1. Hourly negative emotion expression among likely residents of San Bernardino and Stockton during the 6 weeks before and after the San Bernardino mass violence event ($n_{\text{tweets}} = 1,161,382$; $n_{\text{users}} = 25,894$).

in this analysis provide clearer detail about the timing of event-related content tweeted in the 12 hours following the attack. Less than an hour after the attack, users began tweeting about a “shooter situation.” As time unfolded, users tweeted about a “terrorist incident” (Hour 3), male and female suspects are dead (Hour 6), and then eventually used each shooter’s name (Hour 7). In Hour 11, a flurry of tweets was generated about the event, coinciding with a press conference held by the chief of police (Ortiz, 2015).

Discussion

The goal of this study was to source Twitter data in the context of a mass violence event using a method previously validated as efficacious in the context of school shootings on university campuses. Importantly, this method circumvented many of the drawbacks of other approaches (e.g., geotagged tweets and keyword searches), and the ease with which the data could be sourced allowed for the inclusion of a control community against which to compare trends in San Bernardino. Overall, the

results of the linguistic word count analyses revealed that after a mass violence event, negative emotion increased sharply and remained elevated for several days after the event; no such pattern was observed in Stockton, the matched control community. This pattern is consistent with what has been reported in past studies that have used Twitter data to explicate the impact of mass violence on communities (Doré et al., 2015; Jones et al., 2016; Lin et al., 2017). Although it is notable that the control community demonstrated no elevation in negative affect after the mass violence in San Bernardino—despite the fact that both communities were in California—the reason for this absence is not clear. Although we do not believe that the lack of an effect in Stockton necessarily reflects desensitization from repeated violence in society, it does provide strong circumstantial evidence that the effect we observed in San Bernardino was due to the shooting that occurred there.

We also used freely available standard text-mining tools to explore their efficacy in revealing thematic content of tweets not captured by coding for emotion using a top-down approach (i.e., LIWC dictionaries). The results of the word clouds and

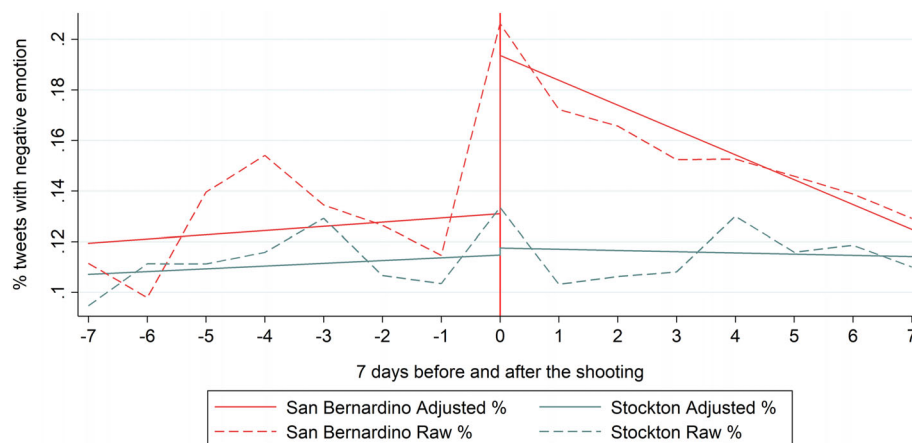
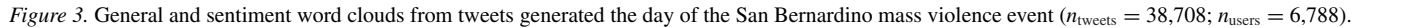


Figure 2. Daily negative emotion expression among likely residents of San Bernardino and Stockton in the 7 days before and after the mass violence event ($n_{\text{tweets}} = 218,533$; $n_{\text{users}} = 18,229$).



There were some limitations to our study that should be acknowledged. Past work has shown that Twitter users are not representative of the general population, as they are typically younger (age 18–29 years) and from urban communities (Pew Research Center, 2018). Although this does limit the extent to which the findings may generalize to a full community under study, the demographics of San Bernardino (e.g., lower median age relative to the nation) suggest that many residents may be Twitter users. Concerns about representativeness will always be woven into studies of individuals who use technologies that are not yet widely adopted by the general population. We also acknowledge that the sample in Stockton was smaller than that of San Bernardino. This occurred because of an error interfacing with the Twitter API. However, our analysis still comprised thousands of users who follow local accounts in Stockton.

As basic tools for extracting thematic content from a corpus, techniques such as word clouds and n -grams adequately revealed some aspects of the San Bernardino attack as the

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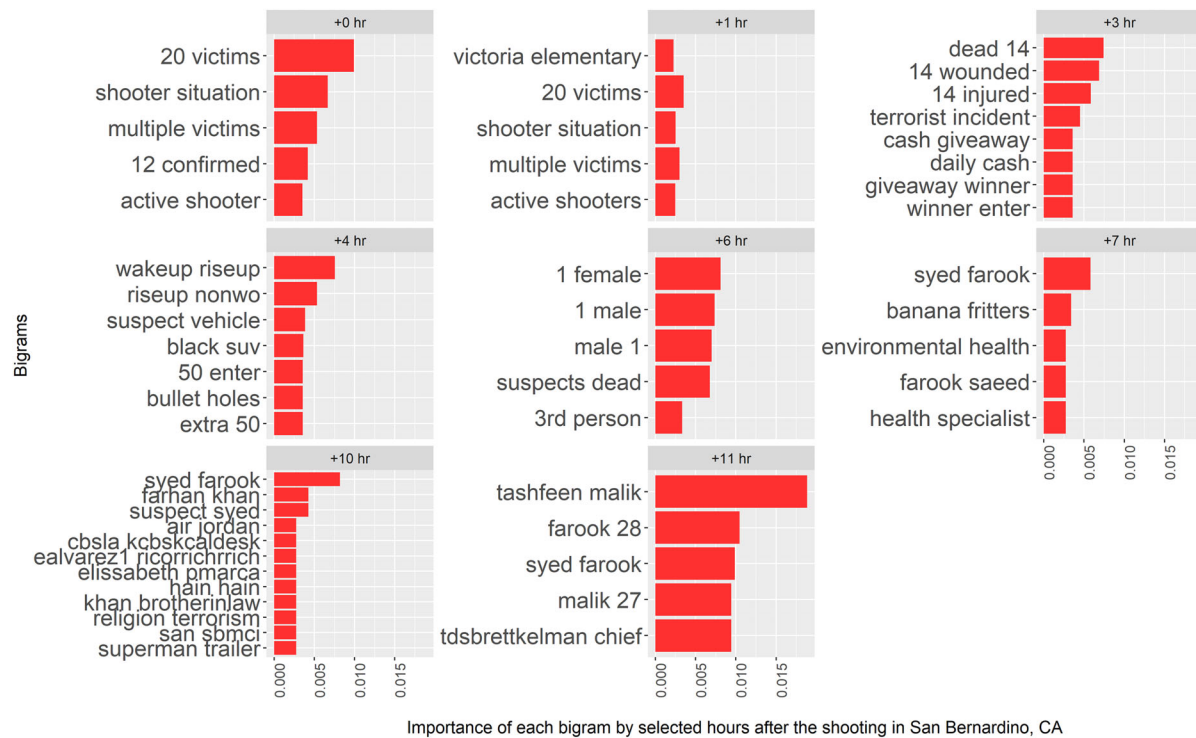


Figure 4. Top word pairs (bigrams) by selected hours that followed the San Bernardino mass violence event. Time blocks with uninformative bigrams were omitted. Importance weights were calculated using the term frequency–inverse document frequency (tf-idf) function in tidytext and represent the prevalence of that bigram in the time block.

event and its aftermath unfolded. However, they did not reveal any information about the neighborhood lockdown during the shootout between the perpetrators and police, a particularly tense time for some residents, coupled with live local news coverage via a helicopter over the area. Moreover, the bigrams did not identify any additional emotional content to shed more light on the community's response in the immediate aftermath. The utility of this method could be limited to assisting researchers in generating an event-related word list with which to tag event-related tweets for further qualitative examination. Future work should address this possibility to bring a mixed-methods frame to the analysis of large-scale Twitter data.

The strategy for coding emotion in tweets, as outlined in this paper, is just one way to model negative emotion in a community after a mass violence event. As others have noted (Jones et al., 2016), when dealing with social media data, how the data are coded depends on the research question. Twitter data coded for emotion are flexible in that they can be manipulated and modeled several ways. For example, rather than calculating the proportion of tweets with negative emotion over time, it is possible instead to analyze the proportion of users who expressed negative emotion across time. It is also possible to examine only the raw counts of negative emotion words used each hour or day across the study period, although patterns of raw counts may be difficult to interpret.

An example of an analysis afforded by this coding flexibility would be an examination of differential emotion expression in

a community based on pre-event tweet patterns of the users in a sample. For example, perhaps individuals who tweet less negative emotion than others before a collective trauma exhibit a stronger reaction to the event both immediately and over time. Such an analysis would go a long way in clarifying theoretical assumptions of reactions to collective trauma using large-scale, ecologically valid data from many thousands of users. Social media user behavior might also be important to consider. For example, users who share more news links in the aftermath of an event may display differential negative emotion relative to those who share fewer news stories. These types of analyses are possible and worthy of exploration to fully capture psychological and behavioral underpinnings of the overall trends observed in longitudinal Twitter studies.

The public forum Twitter provides for its users is also amenable to more sophisticated analyses of the ways in which the platform itself may be responsible for emotion contagion in a collective-trauma context. For example, after a terrorist attack, users in the immediate area might post a tweet with negative emotion, and this tweet may be seen by 20 other users who express a similar sentiment as they find out about the event. Such dynamics inherent in the platform could be examined using network analyses that would explicate clustering of users around specific emotions in the aftermath of a collective trauma. Moreover, these networks could be mapped over time to explore clusters of users for whom the negative psychological impact persists.

Extracting content from tweets, as we have outlined in this paper, is relatively simple to do. There are, however, more statistically sophisticated methods for analyzing corpora. For example, latent Dirichlet allocation (LDA) is a topic-modeling technique that algorithmically accounts for the fact that a corpus of text is made up of many documents, each containing many topics, and that each topic is made up of many words. Importantly, words can overlap in topics and topics can overlap in documents. This technique has proven useful for delineating topics in book chapters, but it is not clear whether it can surmount the “noise” in Twitter data. To mitigate this noise, it may be prudent to use the techniques discussed earlier to identify and filter down to event-related tweets and then use LDA to extract their thematic content. As topic modeling can be used to extract thematic content from Twitter data, it would also be useful to analyze this content over time. Indeed, there is an R package that does this (i.e., the “tm” package). Future work might explore how Twitter content generated after a mass violence event can reveal information about how communities mobilize material and social resources when a trauma occurs and elucidate long-term impact and recovery efforts.

As demonstrated by De Choudhury et al. (2015), there is immense value in pairing Twitter data with other data sources to triangulate on explanatory factors that may elucidate longitudinal trends in Twitter studies. These authors found, for example, that over the course of 2 years, negative affect in tweets generated by users in communities impacted by the Mexican drug war decreased over time. To understand this trend, they folded in community-level rates of death due to violence to provide evidence of affective desensitization. Likewise, Jones et al. (2017) used surveys and Twitter data to triangulate on how distressing aspects of a university lockdown context can be examined by harnessing the strengths of both traditional and Big Data methods. Although linking Twitter data with other relevant data sources may not always be possible, it is important that researchers interested in using Twitter data attempt to do so to strengthen their explanations of patterns they find.

In this paper, we described the challenges and benefits of working with Twitter data to highlight the important contribution data like these can make to the field of traumatic stress. The considerations and analytic techniques we have highlighted can also be applied to big social media data sourced from other platforms with text-based data (e.g., Facebook, Reddit). Despite Facebook’s recent policy change that limits access to its users’ data through the platform’s API, it has created opportunities for researchers to apply for access to its data to conduct social science research. Until other data sources become available, Twitter is the only widely used social media platform that offers researchers free access to public data generated by its users. Although Twitter studies have been ongoing since the platform was launched over a decade ago, the potential these data have for elucidating psychological processes on a large scale is far from exhausted. We hope that by introducing a selection of studies that highlight the different approaches with

which researchers have sourced local Twitter data and demonstrating how these data can be analyzed, trauma researchers will be energized to answer their own research questions by incorporating a Big Data approach.

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