A Systematic Review of Techniques Employed for Determining Mental Health Using Social Media in Psychological Surveillance During Disasters

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ABSTRACT

During disasters, people share their thoughts and emotions on social media and also provide information about the event. Mining the social media messages and updates can be helpful in understanding the emotional state of people during such unforeseen events as they are real-time data. The objective of this review is to explore the feasibility of using social media data for mental health surveillance as well as the techniques used for determining mental health using social media data during disasters. PubMed, PsycINFO, and PsycARTICLES databases were searched from 2009 to November 2018 for primary research studies. After screening and analyzing the records, 18 studies were included in this review. Twitter was the widely researched social media platform for understanding the mental health of people during a disaster. Psychological surveillance was done by identifying the sentiments expressed by people or the emotions they displayed in their social media posts. Classification of sentiments and emotions were done using lexicon-based or machine learning methods. It is not possible to conclude that a particular technique is the best performing one, because the performance of any method depends upon factors such as the disaster size, the volume of data, disaster setting, and the disaster web environment.

Key Words: disasters, mental health, emotion, psychological surveillance, social media

Disaster results in loss of life, destruction of property, and degradation of the environment. At times, the magnitude of damage is so severe that it is beyond the coping capacity of the affected community. Disasters place the affected population under tremendous pressure to cope with and adjust mentally to a devastating situation. The World Health Organization (WHO) states that people suffer from a host of mental health problems during disasters and mental health is very vital for the overall well-being and resilience of the affected communities after disasters.[1] In the response and recovery phase that follows a disaster, mental health aspects are considered an integral component of the community's resilience.[2,3] Understanding and researching the psychological consequences of the disaster involve logical and methodological challenges as disasters shatter the lives of people unexpectedly.[4]

In the past decade, the usage of social networking sites in general has increased manifold.[5] Social media also has played a crucial role during emergencies and natural disasters.[6,7] Studies confirm that social media data have been used extensively in disaster management for preparedness,[8] situational awareness,[9-11] information dissemination,[12-14] relief and response coordination,[15-18] fund-raising,[19] damage assessment,[20,21] and relief and rescue activities.[20,22] Apart from information about the disaster, individual updates and posts having emotional content are also available from social media platforms.[23] It is also quite evident from the studies that the mental health of individuals and the affected population as a group can be predicted and analyzed from social media updates posted by the affected people.[24] Therefore, in emergency situations, the emotional content available in the social media platforms may aid in understating the psychological impact and overall well-being of the population as the data are real time and the updates are posted by the affected people. Our review aims to analyze the possibility, effectiveness, and procedures of using social media data to understand the emotional and psychological impact of an unforeseen disaster on the community. Specifically, this study tries to answer the following questions:

- Is it feasible to use social media data to understand individual/population's emotional characteristics during and after a natural disaster or a calamity?
- What are all the ways in which social media data can be leveraged to understand and analyze the mental health consequences of a disaster?

METHODS

The systematic review was conducted to examine how social media can be used to understand the emotions, well-being, or mood of the affected community or individuals during and after a disaster. We followed the guidelines of the preferred reporting items for systematic reviews and meta-analyses (PRISMA) for searching and assessing the published articles.[25]

Search Strategy

The electronic literature databases PubMed, PsycINFO, and PsycARTICLES were searched in November 2018 for collecting the relevant articles published between 2009 and November 2018. The databases were searched using the identified keywords as provided in Appendix 1. A manual search of the reference lists in the full-text articles considered for the study was also done.

Inclusion and Exclusion Criteria

Two independent reviewers screened the articles by reading the title and abstract and filtered the studies based on an inclusion and exclusion criteria. Primary research papers published in peer-reviewed journals or presented at international conferences in the English language were included. Studies that analyze or identify mental health, well-being, mood, emotions, or sentiments at the individual level or of the overall population in a disaster scenario using social media data were included for review. Studies with all types of study design were included in the review.

Studies were excluded if they used social media to choose the respondents for their survey or to fill up a questionnaire regarding disasters. Studies that analyze the social networks used by a population during disasters, which did not focus on the emotions of the individuals or a community, were excluded.

After the first phase of screening, the full text of the screened articles was examined by 2 reviewers independently to decide whether to include or exclude that particular study in the review. Discrepancies between the 2 were resolved by the third reviewer through a discussion. Methodological quality assessment of the included studies was done using the Mixed Method Assessment Tool (MMAT).[26] MMAT is an efficient tool to evaluate the quality of studies with diverse designs.[27] However, based on the results of MMAT assessment, studies were not excluded, as methodologically poor articles also provided a few insights for the review.

Data Extraction

A standard template for data extraction was designed using Microsoft Excel based on the review objectives and content of the included studies. Data were extracted on disaster setting and period, study objective, the platform used for data collection, data collection and pre-processing methods, analyzing techniques, tools used, and findings/outcome of the study. Apart from these details, bibliographic information (author and year) was also extracted.

RESULTS

The initial search fetched 3326 articles on PubMed, 1316 articles on PsycINFO, and 57 articles on PsycARTICLES. After screening the title and the abstract, 21 articles from PubMed, 18 articles from PsycINFO, and 3 articles from PsycARTICLES were identified. Thirteen articles were selected through a manual search of the reference lists in the identified articles. After removing the duplicates, 37 articles were selected for full-article review. Among these, based on our inclusion and exclusion criteria, 18 articles were included for the review. The results of searching and screening articles using the PRISMA flowchart are provided in Figure 1.

We extracted the data from the 18 articles identified for the review. Table 1 shows the summary of the included articles,[28-45] and Appendix 2 gives the data extracted from the included studies in an Excel sheet. Appendix 3 shows the list of studies that were excluded after the full text of the articles was completely read.

Due to the heterogeneous nature of the included studies and also as they have varied objectives and outcomes, we chose to give the results in a descriptive manner. Studies can be categorized based on various characteristics such as disaster location, language used in the data, social network platform, and emotions extracted. Appendix 4 summarizes the number of studies based on their characteristics. Among the studies, 9 studies are from USA,[30,31,33,35,38-40,42,45] 2 each from France[37,41] and Japan,[29,43] and 1 each from Germany,[36] Mexico,[32] South Korea,[34] and the Netherlands.[44] Except 1 study,[28] all the other reviewed studies used data from Twitter, a widely used social media platform, for analysis. De Choudhury et al.[32], in their study, extracted posts from Blog del Narco (BDN) along with tweets. Khalid et al.[28] collected personal narratives and stories from blogs for emotional analysis. The maximum number of included studies[29,30,35,37,38,41,42,44,45] examined negative emotions (sad, anger, fear, confusion, disgust, shame) from the social media texts as an indicator of mental health problems. Three studies[33,40,43] observed sentiments (positive, negative, and neutral) from the social media texts to analyze the psychological state of the population. Apart from extracting the emotions and sentiments from the texts, 3 articles[28,34,36] analyzed the social media texts qualitatively based on their context.

A common framework of steps was formulated, based on the review in this study, to examine the psychological components from texts obtained from social media. Figure 2 shows the framework of the methodology that was applied in this review.

Data Collection Techniques

Articles that use updates and posts in social networking sites in their study were considered in this review. All the included

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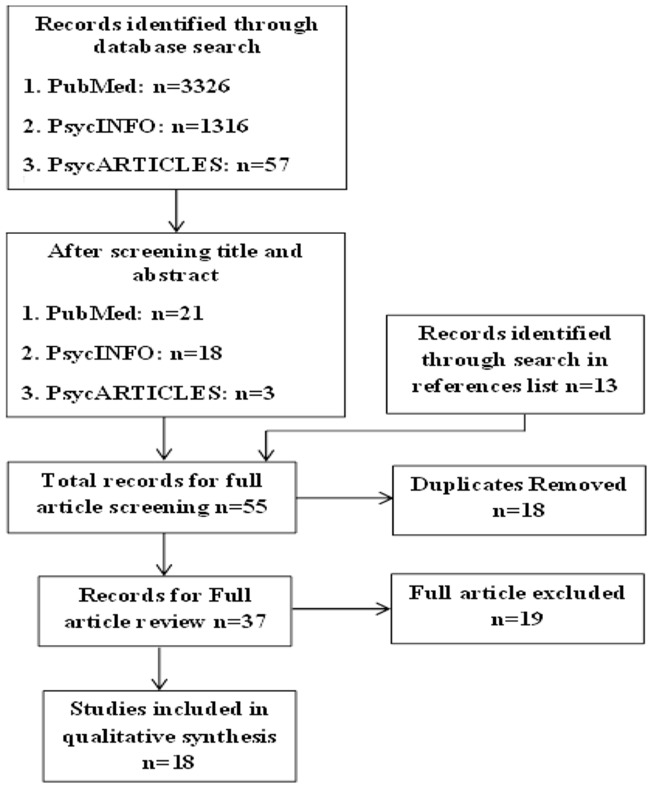
FIGURE 1

Flowchart of Review Selection process and Results.



studies collected tweets from the micro-blogging site, Twitter. The reason for the widespread use of Twitter may be because Twitter has a developer streaming and a search application programming interface (API) using which its data can be extracted by a third-party user. This gave researchers easy access to public tweets for their research.[46] Also, only a very few percentages of Twitter users apply privacy settings to hide their posts.[47] In the included studies, data were widely collected from the Twitter's search API[29-31,33,41] or streaming API.[35,40] Twitter's fire hose was used in 2 researches[32,43] for collecting the tweets. Tools like SOCIAL metrics™,[34] Radian 6,[36] Twitris,[39] Twitter package for R,[38] and TwiNL[44] was also used to harvest the tweets, but these tools also connect to Twitter API to extract data. In 3 studies, authors obtained tweets from the Harvard Centre for Geographical Analysis.[37,42,45] Data were gathered based on keywords, hash tags, and location information. Instead of using keywords to gather the tweets, 2 studies identified users to procure their posts on Twitter.[38,41] The data collection method in each study was decided based on the purpose of its research. For instance, if the objective of the research is to investigate emotions toward a particular event, then data were collected using keywords and hash tags. In the case of spatial analysis of emotions or sentiments, location-based data collection techniques were used. If the purpose was to study the psychology of people in a specific population, then data were collected from the users' updates.

Data Preprocessing

After collecting the tweets, some usual pre-processing steps need to be followed for extracting the needed information. Data preprocessing removes unwanted tweets, i.e., cleaning the data and preparing it for exploration. Preprocessing also involves removing the tweets that were not written in the language of interest. Eliminating retweets, duplicates, advertising tweets, automated tweets from the application, location check-in information tweets, and tweets that contain links to the external source were done before the analysis. This level of data filtering was done to eliminate tweets that do not have any emotional content. If the research was focusing on a particular location,[29,31,32,36,41] if the study's aim was to examine mental health with respect to space,[35,44,45] or if the study involved visualization of emotions or sentiments[33,37,40,42] in a geographical area, then tweets without geographical location were excluded. Preprocessing also involves handling negations

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TABLE 1

Summary of Included Studies

Reference	Objectives	Findings
Khalid et al., 2013 [28]	To understand people's attitudes and emotions during human-induced disasters by using text mining techniques and semantic visualization.	Mental health impacts after the terrorist attacks were much higher than just distress and vulnerability.Semantic maps and ontologies were effective in studying visually the community's feel and emotions during terrorist attacks.
Vo and Collier, 2013 [29]	To propose the classification method to identify earthquake-related tweets and to identify emotions as observed in Twitter feeds.To recognize emotions at the population level in various earthquake situations.	Multinomial naive Bayes model, combined with uni-gram, bi-gram, and tri-gram, gave the best emotion classification results.Fear and anxiety were the dominant emotions during big earthquakes.
Schulz et al., 2013 [30]	To present and evaluate an approach that detects seven emotions in Twitter posts.	For emotional classification, naive Bayes multinomial model performs well for large corpora. And naive Bayes binary model suits well for a small corpus size.
Glasgow et al., 2014 [31]	To devise a method that classifies death-related talks in tweets automatically	Analysis of social media data gives added information on a community's mind, in the aftermath of the disaster.
De Choudhury et al., 2014 [32]	To examine how social media data indicates desensitization of a community to violence when they experience it for a long period.	Quantified negative affect, activation, and dominance from Twitter posts as the measure of the population's psychology.
Lu et al., 2015 [33]	To propose a framework for sentiment modeling and visualization of sentiments geographically.	Sentiment distribution was analyzed in the geographical area to understand its distribution and identify hotspots.
Woo et al., 2015 [34]	To explore the change in public mood after the disaster	Keywords associated with suicide were more frequent after the disaster. Social media helps in understanding the population's mood change during disasters.
Doré et al., 2015 [35]	To identify and understand the emotional response of the community after a disaster, with respect to time and space.	With an increase in time and space, usage of sadness words declined, but anxiety increased.
Gaspar et al., 2016 [36]	To qualitatively analyze and present the emotional expressions from tweets.	Apart from the classification of social media data based on sentiments, it is also important to recognize the context of people's emotion at the time of a disaster.
Gruebner et al., 2016 [37]	To identify emotions from Twitter posts and to cluster the emotions in space and time.	Space–time surveillance of emotions in disaster scenarios with social media data was feasible.
Jones et al., 2016 [38]	To identify and examine the negative emotions before and after the violence.	Twitter is one of the apt tools that help to identify the emotions after violence on the college campus.
Hampton and Shalin, 2017 [39]	To identify the areas of need in disaster based on the lexical choice in Twitter posts.	Based on the lexical use at the time of disaster with reference to normal use, it is feasible to identify patterns of disruption in the population.
Neppalli et al., 2017 [40]	To classify the sentiments of tweets and map it.To analyze how sentiments change based on the distance from disaster.	Support vector machine (SVM) classifier was the best-performing sentiment classifier.The sentiment change was visualized on the geographical map.
Lin et al., 2017 [41]	To examine the expression of emotional distress of individuals before, during, and after the traumatic event from social media streams.	Social media data to analyze distress response will definitely complement traditional methods of distress analysis.
Gruebner et al., 2017 [42]	To identify emotions from tweets and to cluster the emotions in space and time.	Space–time surveillance of emotions in disaster scenarios with social media data was feasible.
Su et al., 2017 [43]	To study opinion expression aspects in Twitter before and after the disaster using a hybrid method and HK content analysis.	Combining of computational processing with human intelligence will give reliable and valid output for the analysis of social media content.
Van Lent et al., 2017 [44]	To study the relationship between sentiment, public attention in social media posts, and psychological distance from epidemics.	Public attention in social media does not coincide with the epidemics. In case of crisis situations, spatial and social distances are important factors to predict public attention.
Gruebner et al., 2018 [45]	To examine spatiotemporal variation of negative emotion before, during, and after a disaster.	Emotions and their concentrations were identified from social media in space and time.

and word normalization.[29] Negations were identified using the negation words and replacing it with NOT tagged with the word.[30] Word normalization means converting or transforming the texts into a uniform sequence and makes the words consistent in some way. Stemming was used in 1 of the studies[30] for word normalization. Translation of tweets to the required language or removing tweets that was not in the language of interest also is part of pre-processing. In general, as text analysis tools and lexicons were available in English, tweets were translated to English and non-English tweets were removed.[35,38,41-43,45]

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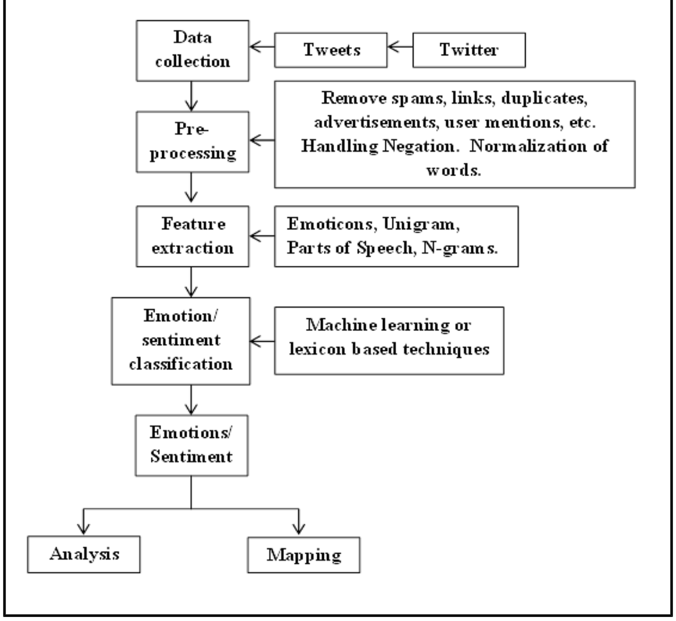
FIGURE 2

Framework to extract sentiments and emotions from social media texts.



In the included studies, German[36] and French[37] tweets were translated to English.

Feature Extraction and Data Analysis

After pre-processing the collected data, transferring the data into information and the requisite results were achieved by feature extraction and analysis of data. Features include emoticons, word unigram, parts of speech, sentiments, character trigram, and 4-gram.[29,30] These features were extracted before applying machine learning techniques to the data for their classification. Some studies used established systems and tools for analysis. In that case, feature extraction was done by an inbuilt module in the system itself. Natural language processing (NLP) methods were used for feature extraction in SOCIALmetrics™[34] and EMOTIVE systems.[37,42,45]

Extraction of emotions from the tweets was carried out using classification algorithms (machine learning algorithms, lexicon-based methods, or with tools that work based on the above-mentioned methods). Except 2 studies, other researchers used developed and evaluated systems or tools for extraction of context or theme and classification of emotions. In 2 studies,[29,30] dataset annotated with emotions by annotators was created for training the classifier. For classification, machine learning algorithm was used. The performance of the models was evaluated using human-annotated dataset. Both these articles concluded that multinomial naive Bayes (MNB) model performs well for classification of emotions from texts. Many studies used linguistic inquiry and word count (LIWC) for the detection of emotions in the Twitter posts.[31,32,35,38,41] LIWC is a validated computer program, developed to categorize the text into psychologically meaningful sections.[48] The LIWC tool extracts the emotional features from tweets and also is very user-friendly because it does not require any programming skills for its use.

The EMOTIVE system was used in studies to identify emotions in the tweets.[37,42,45] EMOTIVE was developed for the purpose of emotional analysis of informal text messages and it uses NLP pipelines for processing data and adopts an ontology approach to extract emotions.[49] Anger, unpleasantness, anxiety, sadness, fear, happy, inhibition, and calm are the basic emotions examined in the studies. There was little difference in the list of emotions studied based on the language of the tweets considered. Negative emotions such as anger, anxiety, sadness, and fear were correlated with psychological problems. To quantify the negative affect of the community exposed to long-term violence, negative emotional words (sad, anger, anxiety, and inhibition) identified by LIWC were considered.[32] The emotional categories of anxiety, sadness, and anger were considered as a distress response of the community to a disaster.[41] SOCIALmetrics™ was applied in one of the studies for processing and text analysis of Korean tweets.[34] SOCIALmetrics™ is a social media analysis tool that uses NLP and text mining techniques for processing and extracting information from social media texts. In this article, the related keywords to suicide and depression were identified by extracting the negative emotional words such as anger, anxiety, sad, hurt, suffering, and shock in the tweets, which were then analyzed by using SOCIALmetrics™.

Apart from examining emotions, 2 studies focused on sentiments (positive, negative, and neutral) in the social media data. In 1 study, the sentiments of the posts were studied using tools such as CoreNLP, SentiStrength, and SentiWordNet, and their uncertainty was measured by entropy.[33] In another study, initially SentiStrength was used, and then machine learning algorithms were used for classifying the sentiments. The models were validated using human-annotated dataset. Finally, support vector machine (SVM) was reported as best performing classifier of sentiments.[40] In both studies, sentiments were mapped in the geographical area and their variations with respect to space and time were studied.

Death-related talk tweets were automatically classified from the tweets by improving the DUALIST framework. DUALIST uses anMNB model. In 1 of the articles.[31] SVM was used to correct the false confidence of a naive Bayes model, and this model performs better than LIWC and DUALIST MNB model in classifying the death-related talk tweets.[31]

Other than extracting and classifying the emotions, the context in which the emotions and sentiments were expressed was also examined qualitatively in 3 articles.[28,36,43] In 1 study,[28] the

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authors used Leximancer, a text mining tool to extract themes and concepts from the narratives in the blogs after disasters. The concepts and their emotional relationship were analyzed with the help of semantic maps and ontologies. In the other 2 studies,[36,43] a small number of tweets were coded manually by the coders into several categories and themes, and then these coded tweets were used to extract concepts from a huge volume of posts. Finally, the results were presented qualitatively. In this way, the context in which the emotions are stated can be identified.

Hampton and Shalin,[39] in their study, examined the use of adjectives and their antonyms by the population during disasters. An antonym pair corpora was created based on tweets posted during disasters. By understanding the lexical choice in disaster situations with reference to a normative use, they proved that it was possible to recognize patterns of disruption among the population, thereby identifying the needy in disaster scenarios.

After the extraction of emotions, statistical analysis like clustering of emotions[37,42,45] and regression[38] to ascertain the change in emotions with time and multivariate regression to examine proximity, gender, interpersonal communication, media exposure, and their association with distress intensity changes[41] were done. Association between pre- and peri-disaster with postdisaster discomfort rates were examined by spatial regression techniques.[45] The mapping of sentiments and emotions was done to examine the spatial distribution of mental health of the population and to understand how emotions vary based on the distance from the disaster.

DISCUSSION

The language use and emotions expressed in the social media posts were predictors of various mental health problems.[52-55] There are several existing methodologies that can be used for ascertaining mental health from social media data.[24] But these methods or techniques are minimally used in a disaster context. Application of these techniques and broadening its use in a disaster context will help the respondents (e.g., the government, social service organizations, disaster management bodies) to the disaster understand the population's mental health.

Facebook is one of the widely used social networking sites globally and in a recent study, it was rated as the appropriate public social networking site for negative emotional expression.[56] But Facebook was scarcely used in disaster mental health studies, to the best of our knowledge. The reason may be that updates on Facebook are restricted by the users for public access and the data can be collected only after consent by the users. All the included studies used Twitter posts as the source of information for research, as Twitter itself provides streaming and rest APIs for developers to collect tweets for research.

The classification of emotions and sentiments from the texts is done either by machine learning models or by using lexicons. From the included studies, it is not possible to conclude that the best performing technique or lexicon depends on the situation and also factors such as size and volume of the social media texts, lexicon size, and the Web environment.

The traditional method of studying mental health during a disaster was by carrying out surveys and interviews of the affected population.[57-59] Surveys were always carried out after the disasters, and it was not possible to ascertain the mood of the population before and during the emergency situation. This limitation can be overcome by using social media data for mental health research as posts or update on social media networking sites are done in real time by the affected people at the time of the disaster. Furthermore, social media updates from the population before the disaster are also accessible.[42] Temporal analysis of the emotional state of the affected population before, during, and after the disasters can be studied from the social media data. Due to the financial and time restrictions, traditional surveys are limited in scope in a disaster situation. In such cases, social media data will help the researchers, decision makers, and the disaster response teams to get insights into the psychological characteristics of the affected population.

All the included studies analyzed only the updates posted by the public. Researches confirm that images or photos posted by the people can be used to identify and predict their emotional state and mood.[60-62] In the future, text and image analysis can be done together to study and understand mental health of a population during a disaster in an efficient way. There is evidence to show that online social network analysis plays a significant role in predicting and identifying the mental state of people in social networks.[63-65] Hence, incorporating online social network analysis with posts from social media would aid in understanding the emotional impact the disaster on the population during and after disasters.

CONCLUSION

As disaster strikes the population unexpectedly, information from traditional sources may not be available and it is advisable to get information from multiple sources. Social media is one of the sources for data gathering during a disaster. From the studies, it is very clear that information extracted from social media data provides valuable information about the emotions of the population during and after disasters and definitely augments the traditional methods of information gathering at the time of a disaster. The collected data also aid the public health professionals in the response team in decision making. Further research that incorporates image and social network analysis along with social media texts would provide more reliable results. These research improvements should be incorporated into practice during disasters to provide psychological support to people as a part of disaster response for building resilience of the affected population.

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Limitations

Based on the included studies, we summarized some of the limitations of using social media data for psychological analysis in a disaster scenario. The first limitation is that social media data do not represent the entire population, because social network users mostly constitute younger adults within the age range of 18 to 29 years and the socioeconomically privileged.[50] Therefore, the results obtained will not be a representation of the community. Second, the Twitter API service allows users to collect only the sample of the tweets[51] and so the data are not the representative of the entire Twitter activity. Third, there is a possibility that there is no connection between the disaster location and the person who tweets. There is no confirmation that all the tweets collected are obtained from only the concerned location of the study. Fourth, generally while pre-processing, only particular language tweets were considered and tweets with links were eliminated. This may lead to loss of some important information from the filtered tweets.

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Conflict of Interest

The authors declare that there is no conflict of interest.

Supplementary material

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