"With your help... we begin to heal": Social Media Expressions of Gratitude in the Aftermath of Disaster

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Abstract. In the aftermath of disasters, communities struggle to recover from the physical and emotional tolls of the event, often without needed social support. Social media may serve to bridge the distance between the affected community and those outside who are willing to offer support. This exploratory study uses Twitter as a lens for examining gratitude for support provisions in the aftermath of disasters. Gratitude for support is examined in the context of two significant U.S. disasters, a tornado that devastated Alabama and the mass shooting at Sandy Hook Elementary School. Observed expressions of gratitude for social support from each community differed from what would be expected based on established factors relating to social support in the aftermath of the disaster. These findings offer ways for social media – as a window into real-time community behaviors relating to response and healing after disaster – to contribute to the provision of mental health resources and monitoring community resilience and recovery.

Keywords: gratitude, social support, social media, disaster, machine learning, Twitter

1 Introduction

Disasters are serious disruptions of the functioning of a community or a society. They involve widespread human, material, economic, and/or environmental losses and impacts that exceed the coping capacity of the affected community or society. Their impacts are wide-ranging and may involve loss of life, injury, and other negative effects on human physical, mental, and social well-being; damage to property; destruction of assets; loss of services; social and economic disruption and environmental degradation [2]. Improved understanding of the processes of disaster response and recovery, including the role of social support, could contribute to improving the health and resiliency of communities coping with disaster.

Social support is critical to individual and community-level well-being and happiness, and it becomes more important when coping with disaster. Gratitude has been conceptualized as an emotion triggered in response to the supportive, helpful actions of others. Experiencing gratitude when coping with adversity, such as disasters, can contribute to healing, resilience, and growth [14].

There is a need for improvements to existing tools and procedures to support disaster behavioral health response and for additional research in the areas of risk, resilience, and recovery [29]. Current instruments rely on retrospective self-reports [11,16]. Social media such as Twitter could supplement this perspective by capturing the spontaneous expressiveness of a community as it experiences the event. Sharing emotional responses to a disaster, as well as offering and requesting support in networked publics, have become part of our collective response to crisis [5].

Relatively little research has explored the ongoing process of coping with a traumatic event as it progresses [26]. Successfully identifying social media discussions acknowledging social support could provide insight into how well a community is coping. This could help focus disaster mental health efforts or help monitor community resilience and recovery.

The present work explores expressions of gratitude for support on Twitter in the aftermath of two disasters. We demonstrate an automated method for detecting this important behavior which, while an imperfect proxy for actual social support received, is independently an important factor in resilience and healing after disaster [10]. We then measure this behavior in the context of two significant U.S. disasters, a tornado that devastated part of Alabama and a mass shooting at an elementary school in Connecticut.

2 Related Work

2.1 Characterizing Disasters

A traumatic event can be defined as one that involves exposure to death, threat of death, actual or threatened serious injury, or actual or threatened sexual violence [3]. Disasters are traumatic events that are collectively experienced, in contrast to personal tragedies.

While multiple typologies of disasters exist, we adopted a broadly applied approach that considers whether the disaster was natural or human-induced/technological [25], and if human-induced, whether it was intentional or accidental. These aspects of a disaster have been observed to shape offers of support, and the health, and influence recovery and resilience of affected individuals and communities [8,21].

In general, high levels of community distress after disaster are most likely when two or more of the following features exist: human perpetrators; intentional violence; high prevalence of injuries; threat to life; loss of life; severe, extensive property damage; and significant, ongoing financial difficulties for the community [16]. In our work, both disasters possess three or more of these features.

2.2 Disasters, social support, and gratitude

Social support has been demonstrated to be critical throughout one's life course, and is particularly valuable as a moderator of life stress [6]. Victims need social support to cope with and recover from disaster, and may experience a need for support that exceeds what their immediate environs and network can supply [12].

A number of factors influence the amount of support that disaster victims are offered. A primary factor is the severity of the event [9]. Psychological factors also play a role in the behavior of potential providers of support. Both *locus of causality* and *situational controllability* have been observed experimentally to influence provision of support in disaster contexts [15, 18]. Locus of causality involves the degree to which a person in need of help personally caused the negative event, while situational controllability considers if the negative event could have been foreseen, prevented or avoided.

Those who receive support or other benefits, particularly if the benefit was not anticipated, are likely to experience gratitude [4]. Gratitude has been found to be psychologically protective, notably in the context of human-induced disasters, such as the September 11th attacks [8] and in other types of events such as accidents, natural disasters, and personal experiences of violence [14].

2.3 Social media and disasters

Social media platforms such as Twitter have demonstrated utility in helping individuals cope with disasters [19], and enable collective response to crisis. The phenomenon of thanking others, or expressing gratitude via social media in the aftermath of a disaster has been identified as a significant portion of discourse, occurring across a wide range of disasters and spanning multiple continents, but this phenomenon is imperfectly understood [17]. This imperfect understanding has led to gaps in understanding disaster behavior and related communications [23]. Our work contributes new knowledge to help address this gap.

Olteanu [17] observed Twitter to more generally be a medium through which the "nuance of disaster events" is magnified, and a mechanism through which a disaster event is socially constructed. The scale and granularity of Twitter data provide a unique lens into the nature and dynamics of response to disaster, including social support and gratitude.

3 Current work: Comparing Expressions of Gratitude on Twitter Following Two Disasters

The full spectrum of emotions, intentions, and outcomes relating to social support following a disaster has provided fertile ground for theorizing and study. The current work draws from the literature on social support and gratitude, disaster response and recovery, and social media to examine aspects of the recovery of two communities struck by two typologically distinct disasters. It uses machine learning to help address the challenges posed by the scale of social media data, uncovering relevant tweets in datasets far too large to be easily annotated by humans. In this work, we focus on acknowledgments and expressions of gratitude for support after a disaster. We use social media as a lens through which to view the organic responses of the community.

This work contributes to an acknowledged gap in the literature regarding understanding expressions of gratitude in social media in the aftermath of disasters [23]. It extends work using Twitter to evaluate discussion of disasters using data from random 1% samples of Twitter data based on matching disaster key terms [17] with analysis based upon a much more complete and geographically relevant sample of tweets from members of the disaster stricken community.

In this work, we examined two disasters. One was a massive tornado, a natural disaster that tore apart Tuscaloosa and Birmingham, Alabama in 2011. The second was a brutal human-induced disaster and the deadliest elementary school shooting in US history, the Sandy Hook Elementary School shooting in Newtown, Connecticut. The current work examines disasters that differ with respect to severity, measured in terms of associated deaths, injuries, and damage. Previous work has identified severity of a disaster as increasing both willingness to help, and the amount of support offered to victims of a disaster in experimental settings [15, 18]. Severity of loss has been associated with greater support from non-kin after devastating flooding [13].

4 Background on disasters studied

Tuscaloosa Alabama tornado: The tornado that struck Jefferson and Tuscaloosa counties in Alabama on April 27, 2011 was the most devastating tornado in terms of damage that the United States had experienced, causing an estimated $2.4 billion in damage. The tornado sustained wind speeds up to 190mph, and left an 80-mile long swath of destruction. It killed 64 people and injured an additional 1500 [1]. Afterwards, the President visited the region and a federal state of emergency was declared.

Newtown school shootings: On December 14, 2012, 20 school children and six faculty members were shot and killed at Sandy Hook Elementary School in Newtown, Connecticut. This was the deadliest primary school shooting in US history. Most victims were six years old. In the days following this disaster, the President visited Newtown, spoke at a vigil, and met with families and first responders.

Assessed by typical quantitative measures, the tornado was the far more destructive event (see Table 1). Over twice as many people were killed, and orders of magnitude more were injured. The Alabama communities sustained over 50 times as much property damage. Thousands were left homeless by this natural disaster, and many saw their workplaces destroyed as well. The most fundamental difference between these two events – and one much harder to quantify – is the type of disaster. The tornado that devastated Alabama is a *natural disaster*. The school shooting was a *human-induced disaster*, a deliberate act of commission, not a consequence of error or negligence.

Table 1. Scale and destructiveness of Alabama tornado and Newtown school shooting

	Alabama tornado	*Newtown school shooting*
Number of victims killed	64	26
Number of children killed	19	20
Number of persons injured	1500	2
Estimated property damage	$2.4 billion	$42 million (replace school)
Displaced households	6k homes destroyed, 15k damaged	0

5 Methods and results

One challenge posed in working with Twitter content is identifying relevant tweets in large corpora. Social media discussions relating to the disasters and their aftermath are varied – providing information, describing volunteering opportunities, soliciting contributions, etc. Tweets acknowledging or expressing gratitude for support are a fraction of the general discussion relating to the disasters, which itself is a small fraction of the total data.

For both events, we used Twitter’s geo API to collect tweets from the affected counties. We analyzed data covering an 11-day span, beginning the day after the event. This helped eliminate potential effects of time of day variance. We retrieve 2.8 million tweets from 74,819 user from April 28-May 9 from Jefferson and Tuscaloosa counties, and 119,651 tweets from 3648 users from 15-26 December for Fairfield county. We collected many more tweets from Alabama than Connecticut. This may be attributable to changes in Twitter’s rate limit policy enacted in 2012, before the Newtown school shooting, though we cannot be certain.

Machine learning methods were used to help identify relevant tweets. Only a small percentage of the tweets were relevant to the topic of acknowledgement of social support following the tornado or the shooting. We estimated that less than about 1% of tweets were relevant to our task, based on random samples from each dataset. Table 2 provides examples.

Thus, we face a common challenge seen in real-world classification tasks. The classes we are interested in are only a small percentage of the actual data. To address this, we queried the dataset for tweets containing terms likely to indicate expressions acknowledging social support relating to each respective disaster. For Alabama, these included terms relating to thanks or support (*thank, help, support, aid*), and terms relating to the tornado (*tornado, twister, storm*). For Newtown, we queried the Twitter data for tweets containing terms likely to indicate expressions acknowledging social support relating to the school shooting. These included the previous terms relating to thanks or support, and terms relating to the shooting (*shoot, loss, kill, grief*). For each event, we further queried for tweets containing terms from both classes, support-related and event-related.

We randomly sampled from each of these sets of tweets, in addition to a random sample of tweets from the full dataset, to ensure sufficient positive tweets in the dataset and address class imbalance [28]. The dataset for the Alabama tornado contained 705 tweets annotated for ground truth, drawn from the sets described above. The equivalent dataset for Newtown consisted of 670 annotated tweets. Each dataset contained 15% gratitude tweets. We used a semi-supervised active learning framework that incorporates Twitter-specific features for building classifiers [22]. We used two classes to distinguish between tweets expressing gratitude for social support relating to disaster, and all others. The highest-scoring class (>.50) can be considered the label generated by the model for that tweet. We created a separate model for each dataset. Both models performed well at classifying tweets in the relevant class, achieving 96% recall on the Alabama test data and 94% for Newtown. However they produced a substantial proportion of false positives. One technique demonstrated to help reduce false positives rates is cascading classifiers, or using the output of an initial classifier as input for a second classifier [24]. The cascade can alternately be considered a focus-of-attention mechanism that discards regions unlikely to contain objects of interest. We developed a second classifier employing Linguistic Inquiry and Word Count (LIWC).

Table 2. Example positive and negative tweets for expressions of gratitude for social support

	Alabama tornado	*Newtown school shooting*
Positive	@A we are thankful for your help in our time of need from the #tornado #BhamSalvArmy	@B i know.thank you, a lot of people are making me feel better by just sending condolences. it's hard, but we're #203strong
Negative	Locked my keys in the house for the 2nd time in maybe 12 hours...?	@C baby your the best girlfriend ever I would never trade you for anything your perfect

Table 3. Confusion matrices for Newtown and Alabama classifiers

	Predicted Class			
Actual Class	*Newtown*		*Alabama*	
	Not Gratitude	Gratitude	Not Gratitude	Gratitude
Not Gratitude	0.74	0.07	0.58	0.09
Gratitude	0.07	0.13	0.09	0.24

LIWC is a widely used text analysis program [20, 27]. Its central premise is that the words people use can reveal their mental, social, or emotional state. LIWC incorporates a number of psychologically relevant variables that might pertain to this research, such as positive emotion, first person plural (we), money, and work. This final model incorporates LIWC features and the previous classifier score.

We created our training, validation, and testing data sets from an additional 1000 annotated tweets from the 34,600 Alabama tweets and 506 tweets from the 5,400 Newtown tweets output as positive by their respective classifiers. We used Rattle [30], which implements a number of R's machine learning libraries, to build our final classifiers.

For the Alabama data, the best performing final model, an SVM, achieved 82% accuracy on test data. For the Newtown data, the final SVM had 87% accuracy on test data. A confusion matrix for both models is provided in Table 3. Our task involves comparing relative percentages of gratitude tweeting for each disaster. The total gratitude tweets predicted by the models mirror the number of true positives in the data.

Findings from previous work suggest we should observe a higher percentage of tweets from Alabama in the positive class, since that was the more severe event [9, 13]. The tornado killed more than twice as many people, injured thousands more, caused over $2.3 billion more in damage, and physically devastated a far greater geographic area. Both events are similar in having an external locus of causality and minimal situational controllability.

However, when we compare data gathered from Newtown and Alabama in the days following their respective disasters, a different picture emerges. The community that experienced the quantitatively less severe disaster, Newtown, generated proportionally more support acknowledgments (1.1% vs. 0.15% of tweets, p <.001). A far larger percentage of their population expressed gratitude for support received (13.33% vs. 3.43%, also p <.001). and per capita gratitude tweeting is 6.33 times higher (Table 4).

Table 4. Tweets and users expressing gratitude in the Tuscaloosa tornado and Newtown school shooting

	Events	
	Alabama tornado	*Newtown shooting*
Population of affected counties	852k	917k
Unique Twitter users	74,819	3542
Gratitude tweets (final model)	4289	1330
Percent of gratitude tweets	0.15	1.11
Users with gratitude tweets	2564	472
Percent of users with gratitude tweets	3.43	13.33
Per capita gratitude tweets	0.06	0.38

Because rates of tweeting show daily variability, and Alabama suffered interruptions to power and Internet access immediately after the disaster, it is preferably to normalize daily rates of gratitude tweets as a percentage of total tweets per day. The two communities have the highest percentage of gratitude tweets in the days following the disaster. Both communities show about a 60% drop in the first week. Over the entire timeframe, the minimum rate for expressing gratitude in Newtown exceeds the maximum measured in Alabama, as shown in Figure 1.

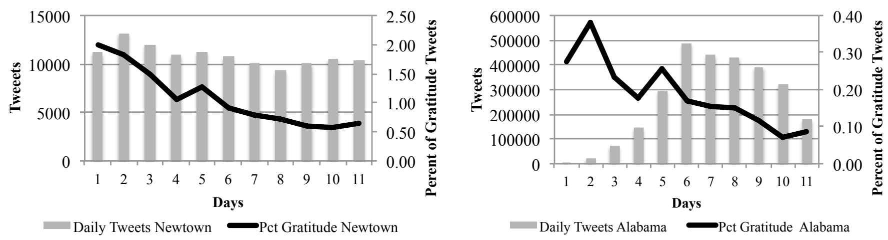

Fig. 1. Tweet activity and expressions of gratitude in the 11 days following the Newtown school shooting and Alabama tornado

6 Discussion

This study examines social media expressions of gratitude for social support received in the wake of two large-scale, traumatic events. Both events had deep impacts on their respective communities. The support provided to these communities after their disasters would be essential to any recovery process.

Yet, judging from patterns observed in Twitter data from these communities, their experiences and response to support differed markedly, and in ways not always anticipated by theory. In Alabama, the community that suffered the more quantitatively severe disaster, there were proportionally fewer expressions of gratitude for support received. This stands in contrast to theoretical predictions that support should be related to the severity of the event [13].

This work makes contributions in two primary areas: (1) it presents an approach and methodology for studying gratitude in response to support, (2) it suggests that additional social and psychological factors should be considered in theorizing about social support and disaster response.

Leveraging affordances of social media to focus on affected communities, rather than global discussion of disaster, provides unique insight into community-level phenomenon. Data collection over an extended time period has advantages over snapshots taken at one or a few points in time, and helps cope with disruptions of utility service or access to social media platforms.

Given the quantity of data that may be produced by a community after a disaster, automated text processing and machine learning approaches may be essential. While identifying expressions of gratitude across many types of disasters will not be amenable to a single cookie-cutter approach, bootstrapping off the language commonly used to express thanks and gratitude, and to describe the disaster should aid development of classifiers for gratitude for social support received after disasters.

Beyond the severity of a disaster, how bystanders view a disaster and the victims is known to affect how much support given. While the two disasters were similar in many of the ways disasters can engender different psychological responses, such as locus of causality and situational controllability, there must be other factors that explain the dramatic differences seen our analyses. The shooting at Sandy Hook Elementary School may have triggered more support because it was an intentional, human-induced disaster intended to produce mass casualties. It specifically targeted young children as victims. This emotional aspect of the disaster may have trumped the counts of dead and injured, and the physical devastation wrought by the Tuscaloosa tornado to evoke a larger amount of support that, in turn, earned the thanks of a grieving community. Further study of more, and more varied, disasters may help systematically examine which factors are most important in explaining real-world reactions to disasters.

6.1 Limitations and future work

We observe only acknowledgments of social support transmitted in Twitter by users who had provided geolocational data indicating they lived in the studied counties. Because we chose to focus on the response of community members to the disasters, and must rely on Twitter's affordances for representing location, the social media discussions of users who had associated themselves with different geographic locations, or no location, but actually were members of the community, are not captured.

Further, social media usage is not universal or representative within the US population. Thus we may be privileging the voices and responses of those who are active on social media, and underrepresenting those who are not.

This work compares social media data from two disasters, a natural and human-induced disaster, and finds the human-induced disaster produced expressions of gratitude more than an order of magnitude more frequently than the natural disaster. But human-induced disasters are not a unitary phenomenon. Comparison of the Newtown school shooting data expressing gratitude with expressions of gratitude in other, more similar events would likely be informative.

7 Conclusions

We presented findings of an exploratory study that treated social media as lens for examining gratitude for social support in the aftermath of disaster. Gratitude is an important factor in resilience and healing after disaster, and because it was triggered by receipt of support, may provide some insight into the dynamics of support itself. We then measured this behavior in the context of two significant U.S. disasters, a tornado and a mass shooting. The health and resilience of our communities after traumatic events is not easy to measure and monitor. Analyses of user activity in the aftermath of a disaster may prove an important adjunct to existing survey methods, providing more data and more temporal detail than would otherwise be obtainable [7], and enabling triangulation of data sources. The organic expressions and responses to events by community members, if closely examined, may advance our understanding of the complex linkages between the experience of disaster, support, gratitude, and post-traumatic growth.

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