Social Media and Warning Response Impacts in Extreme Events: Results from a Naturally Occurring Experiment

Yulia Tyshchuk
Rensselaer Polytechnic Institute
tyshcy@rpi.edu

Cindy Hui
Rutgers University
huic@rpi.edu

Martha Grabowski
Le Moyne College,
Rensselaer Polytechnic Institute
grabowsk@lemoyne.edu

William A. Wallace
Rensselaer Polytechnic Institute
wallaw@rpi.edu

Abstract

Our understanding of the impacts of social media on individuals who receive warnings of extreme events is limited. There is to date no uniform approach to integrating social media as part of emergency management strategies. This research addresses the question of the role of social media in the effectiveness of the warning response process in the context of a naturally occurring experiment. The results of the experiment contribute to our understanding of how social media complements as well as facilitates the warning response process.

1. Introduction

Social media has become an integral part of the communications that support modern global society. Many government organizations, including the U.S. Federal Emergency Management Agency (FEMA), as well as corporate businesses, have an active presence on social media sites. In the context of emergency management, this presence is often constrained to dispensing relevant but limited emergency information to the public [11, 19, 26]. This is understandable since there is no clear understanding of how social media can be used to assist the public in making decisions that result in recommended actions, nor is there a uniform approach to integrating social media as part of emergency management strategies. This research addresses the question of the role of social media in the effectiveness of warning response and describes a methodology for identifying and extracting emergency-relevant information present in social media.

The paper begins by surveying the role of social media in emergency management, and past research on warnings in extreme events. It then describes a naturally occurring experiment that provides data for examining the role of social media in warning response processes. Qualitative content analysis and quantitative relationship analysis were used to analyze the data. The paper concludes with contributions of the results of the analysis to the warning response process.

1.1 Social Media and Emergency Management

The way we seek and provide information and data using social media is resulting in new behaviors of social interaction. The question we address in this research is: can we relate these behaviors to social science theory concerning human response to warnings?

A number of social media sites are currently available, including Twitter, Facebook, YouTube, Flickr, and LinkedIn. In this research, we focus on the use of Twitter in emergency management research and strategies. Many emergency management organizations employ social media, including the U.S. Federal Emergency Management Agency (FEMA); federal agencies such as the U.S. Department of Justice, the Department of Homeland Security, and the Federal Bureau of Investigation (FBI); local, state, regional and provincial emergency management agencies; a host of first responder organizations such as police and fire departments, as well as an international research community that focuses on emergency management, the Information Systems for Crisis Response and Management (ISCRAM) group [5, 7, 39].

A majority of emergency management personnel agree that on-line social networks are effective mechanisms for sharing information, and most social media is considered timely, accurate, and usable [44]. Social media provides new ways to interact with others outside the bounds of crisis [25], allowing for the rapid diffusion of locally relevant information, which can be particularly important when emergency management personnel are geographically distributed [30]. Social media postings connected with the Virginia Tech campus shooting on April 16, 2007 showed a number of novel uses for the technology: to notify others of students’ and staff members’ well-
being, to reach out to a wide audience in a short period of time, to detect student safety by observations of postings, as well as a variety of self-organizing and self-policing activities, including compiling online lists of victims that were found to be accurate, even if aggregations of independent lists were not developed [25].

1.1 Twitter as a Social Media Relevant to Warnings

Twitter (http://www.twitter.com) is a microblogging service that enables users to post text messages whose length is up to 140 characters (referred to as ‘tweets’) to their profile page. Each user can “follow” or subscribe to other users’ stream of tweets, which are publicly visible unless the user modifies their privacy settings. Users can send tweets through various platforms, such as the Twitter website, SMS, desktop applications and mobile applications such as Tweetdeck or Tweetie. In addition, content hosting sites, such as Twitpic, can attach pictures to a tweet, and location-based social networking sites, such as Foursquare and WHERE, can be linked to Twitter and allow users to share a “check-in” from their mobile devices and inform others of their location. The random sample of tweets provided by Twitter through an API search were utilized as a convenience sample in this study because the data are easily accessible, Twitter provides convenient tools for data collection and analysis, and because the data elements included in the data set facilitate efficient construction of relationship graphs.

FEMA, the FBI, and various police stations and fire departments use Twitter for notification and posting status information, as do various Emergency Management Organizations (EMOs), who use Twitter primarily for keeping the public aware of current events, one example of which is: “Get your business prepared for spring floods with info from the FloodSmart Business Risk tips: http://go.usa.gov/gXs” [5]. Twitter is also used for disseminating useful information not related to an emergency event, such as “This channel provides FEMA mission-related information. For emergencies, call your local _re/EMS/police or 9-1-1. http://www.fema.gov” [7].

1.2 Use of Twitter During Disaster Events

In addition to status, current events and other information, Twitter has also become an important medium for information dissemination during disasters and crisis events, facilitating the spread of information and enhancing the public’s situation awareness [38], as public officials, emergency agencies, and news and media outlets post real time updates and announcements on Twitter. During the 2007 California Wildfires, emergency management personnel used Twitter to convey information about road closures, evacuations, and shelters. However, research showed that 0.2% of the affected public received their first evacuation warning via Twitter, either over the Internet or through text messaging, and consequently, only 4.9% used Twitter over the Internet for follow up information. [37] Twitter use has grown in recent disasters, however, as the public utilized Twitter to gather and share critical information during the 2009 Red River floods and the 2009 Oklahoma grass fires [8, 39, 40]. Previous studies have found that use of Twitter during emergencies differs from the general Twitter use, as during emergency events, activity on Twitter displays more signs of information sharing and broadcasting activities, with a higher percentage of tweets containing URLs and a lower percentage of directed or reply tweets when compared to general Twitter use [11].

1.2 Past Research on Warnings

Social science theory suggests that people’s response to warnings is a function of social, economic, and demographic factors [1], as well as physical environmental, technological and cultural factors [4, 9, 17, 33]. To be effective, warning messages and systems must consider individual and group perceptions, interpretations, and reactions to warnings. Effective warnings consider local population demographics, societal culture, and past events that have occurred in the location; message distortion, the level of detail in the message, and the completeness of the message, as well as whether the response interferes with normal activities, all play an important part in the recipients’ analysis of their situation and their willingness to respond to the warning [17, 18, 32, 34, 35]. People are more hesitant to comply with emergency recommendations when they are provided with incomplete information [26], and since they evaluate warning messages in relation to their own personal experiences and values, they often seek additional information and confirmation through observation and by querying others [21, 34, 35]. People are more likely to respond if they see others around them taking action in response to the warning [32].
Understanding how people respond to warnings is essential in designing effective warning systems. Theoretical models of warning systems describe a sequence of activities, from issue of an initial warning, through response and decision-making, to taking protective action [32, 34]. In general, the steps between receiving an initial warning and finally deciding to take protective action include milling, e.g. gathering information and seeking confirmation, assessing personal risk and determining appropriate response or protective measures [15]; during this process, social and informal networks often serve as a valuable resource for people to interact with each other and keep informed [22, 34]. Warning activities can be modeled as two components of a network, formal and informal. The formal network consists of official broadcasts made by warning sources, which are easily identifiable; the informal network, which consists of information from unofficial sources, is more diffuse and its elements are more difficult to identify [26, 28, 31]. Both formal and informal components of a warning network are essential elements of an effective warning system [3, 24]. Therefore, it is of interest to understand how people make use of social networks, and how to diffuse warning information through social networks in such a way that people will act and take protective actions [27, 36].

The general process of communicating emergency warnings, a derivative of classical persuasion models, can be thought of as a series of activities performed by various actors: a source (who) delivers a message (what) to a target audience (to whom) using a channel or medium in order to change behavior (effect) [13]. Sources can be government officials, public authorities, scientists, observers or the news media. The message informs the at-risk population, i.e. the target audience, of the potential risk and dangers, along with recommended actions to assure safety. The message can be relayed over many channels, not limited to television, radio, telephone, the Internet, social media, or in person. The effect of the message on recipients will depend on many factors, such as the recipients’ perception of the source credibility and understanding of the message. The desired effect of the message would be for recipients to perform the recommended actions, e.g. listen to media broadcasts covering the event, shelter in place, or evacuate their homes. Decision timing is affected by the time needed for recipients to effectively process the received information, acknowledge the threat and verify the warning information; in order to be effective, decisions taken must be made in a reasonable time [14].

### 1.2.1 Warning Mechanisms

Message characteristics also influence the effectiveness of emergency warning information and whether recipients take appropriate and timely action [7, 23]. In general, warning messages should contain details of what the threat is, what the recommended action should be, and who the source is [20]. The warning should be clear, consistent, easily understood and contain information about the potential impacts and risks of the threat, and include what action should be taken by the public at risk [20]. Messages are generally characterized along a continuum, with alerts indicating that a threat exists, while a warning message describes the hazard or danger and suggests protective actions [16].

Effective warnings come from trusted, reliable and credible sources [36], a consideration that is especially important when the warning message asks for actions to be taken. Classic warning mechanisms and channels include alarm systems such as loud speakers and sirens, authorities going door-to-door, and announcements on radio, television or on all-hazards broadcasts. In recent years, many communities, counties, businesses and organizations have adopted mass notification systems, such as Reverse 911, in order to rapidly disseminate information to target audiences in the community. In these systems, emergency managers call members of the community and inform them of a potential threat or hazard through prerecorded messages. New media such as the Internet, blogs, Twitter, Facebook, YouTube and other social media have expanded the ways that warning information reaches the population [19, 39], although our understanding of the impacts of social media on the public’s response to the warning information is limited. As a result, this study, one of several focused on understanding and framing our knowledge of the role of social media in extreme events, is of value to emergency managers and researchers responsible for the design and issuance of warnings. In the following section, a naturally occurring experiment that frames our understanding of the role of social media in extreme events is described.

### 2. Social Media in Extreme Events

#### 2.1 Research Questions

Data from a naturally occurring experiment were utilized to study the relationships in social media
that are formed after users receive warning information. The purpose of this research was to address two questions:

- How do social media information, e.g. Twitter, and official warnings complement each other?
- How does social media, e.g. Twitter, facilitate the social processes in warning response, particularly in terms of sharing information, directing people to information, and clarifying information?

The naturally occurring experiment that provides the research project data set is described in the following sections.

2.2 A Naturally Occurring Experiment

On April 6th, 2010, at 8:15 a.m., an armed perpetrator robbed Regina Check Cashing Corporation, located at 450 Hoosick Street in Troy, N.Y., which is about one mile away from the Rensselaer Polytechnic Institute (RPI) campus. Later on, the perpetrator was seen on campus, specifically, in the East Campus Athletic Village. The RPI Alert system was activated and the first ‘stay in shelter’ warning, via on campus loudspeakers, emails, phone calls, voice mails and text messages, was issued at 9:30 a.m. Two more ‘stay in shelter’ warnings were issued at 10:48 a.m. and 11:48 a.m. that day, before the ‘all clear’ message was issued at 12:52 p.m.

There were three sources of data in this study: an ‘After Action Report’ was obtained from RPI’s emergency management office, which included a detailed timeline of events that occurred on April 6th, 2010, starting when information was received by RPI’s emergency management office regarding the robbery, and ending with the all-clear message. The After Action report included times and information concerning the various warnings: texts for loudspeakers, texts for mobile phones, voice mails and email messages. The warnings and messages issued by the RPI emergency management office were also obtained. Following is an example of the warning issued by RPI emergency management office during April 6th, 2010 event:

“This is an RPI Alert. An armed robbery occurred on Hoosic St. The perpetrator reported near ECAV/LINAC. All should shelter-in-place, that is go indoors, lock windows & doors. An all clear will be sent via RPI Alert when the situation is deemed safe”

This message is characterized as a warning, as it not only states an existing threat but also prescribes protective action. [16]

Finally, Twitter data was also obtained by running a simple Java query using open source software. The query searched for the word/hash key RPI and date April 6th, 2010. The data includes tweets, or messages posted by users, user id, and user name. If a user directed his or her message to a specific person, the user name and id of this person were also identified in the data.

2.3 Method

Data were gathered from official reports and Twitter data, as just described. The data were categorized by the six stages of warning response (Section 2.4). A qualitative content analysis of the data and a quantitative relationship analysis of the data set were performed. The content of individual tweets was manually analyzed. The individual users were identified manually by accessing their information on Twitter. Relationship graphs were constructed based on the various ‘flags’ present in the data, which identified directed communication among Twitter users. A social network analysis, including analyses of centrality, group cohesiveness and blockmodeling, were undertaken to examine the relationships among Twitter users in this naturally occurring experiment.

2.4 Content Analysis: Twitter Data and the Warning Response Process

Lindell, et al. [16] as well as Mileti and Sorensen [23] suggest six stages of warning response:

1. receiving the warning (587 tweets);
2. understanding the contents of the warning message (521 messages);
3. trusting the credibility of the warning (360 tweets);
4. personalizing the warning (587 messages);
5. seeking and obtaining the confirmation (83 tweets); and
6. taking action (64 tweets).

Content analysis was performed to identify and categorize Twitter users who engaged in warning behaviors such as seeking information, obtaining confirmation and propagating information, as well as in order to understand the role of those users in the network. Those behaviors are strongly correlated with six stages of warning response process. Information
propagation behavior encompassed stages (1) through (4). This is evident because a Twitter user must first obtain, understand, trust the information and personalize it prior to the propagating it. Information seeking and obtaining confirmation behaviors are part of stage five of warning response process.

Twitter data obtained from this experiment confirms that Twitter users displayed the behaviors associated with those six stages in their messages. The number of messages associated with each of the six warning steps is provided above. Following are the tweets that serve as examples of those behaviors:

“Just received RPI Emergency text alert: armed robbery near Hoosic St. Perp reported near ECAV/LINAC @WNYT @WTEN @CBS6Albany @TroyRecord”

This tweet suggests that the user (1) received, (2) understood and (3) trusted the alert as the user proceeded to propagate it further through the network via directed messages.

“I heard there may be a gunman in Troy...and RPI in a lockdown? Any confirmations? #troy #albany”

This user was engaging in (5) information/confirmation seeking behavior on Twitter as suggested by the message’s content.

“Oh joy. #RPI campus on lockdown for an armed robbery nearby. Looks like I’m stuck in the office for a while.”

This tweet suggests the user took action prescribed by the warning based on his/her situation, which are stages (4) and (6) of warning response process.

2.5 Relationship Analysis of Twitter Data

The first step in the data analysis was to define the nodes and relationships in the social network of participating users. Nodes in this data are the unique users of Twitter that have posted a tweet during the event. 321 unique users were identified in this experiment. The relationships were defined by the presence of directed communication - directed tweets and/or re-tweets. A directed relationship was found to exist between two users if one user directed a message to another; in graphical representations, the user directing the message is shown at the head of the directed relationship and the user receiving the message is shown at the tail of the relationship.

This relationship is flagged in the data with the prefix ‘@username’.

Because the relationships have direction, the resulting graph is a directed graph. Since the relationships that are defined above require directed communication and there were a number of nodes that sent only broadcast messages, those nodes were designated ‘isolates.’ In this data set, 181 users were part of the directed graph, and 141 were isolates. The isolate data was not discarded, however, as isolates serve an important function in diffusing warnings, as discussed in a later section. There were 83 tweets and 129 re-tweets in the data set, resulting in 181 overall unique relationships, with re-tweet messages predominating in the data set. This may suggest that participants did not have direct knowledge of the unfolding events, but wished to pass on information. The data were not analyzed as tweets and re-tweets because the density of the resulting graphs would have been lower. A lower graph density would limit the group and blockmodeling analyses that could be performed.

Five graphs were constructed from the data set, based on the timeline of warnings. Each graph included all 181 users and the relationships that had developed up to the all-clear message. The graphs in Figures 3 through 7 show the change in network structure based on the warning timeline. The graphs also display evidence of the formation of a core and periphery structure when more warnings were issued. The graph after the last warning (Figure 7) shows the dynamics of the graph structure, with a core and
periphery structure. The core of the network is highly connected, while the periphery is less connected.

The next step was to study the different types of centrality exhibited by the nodes (which are Twitter users), specifically, the degree of centrality, closeness and betweenness of the nodes. Various centrality measures suggested an actor’s structural location in the graph. [41] In the directed graph that was constructed, inDegree and outDegree metrics were assessed. A high InDegree measure represents an actor’s prestige and prominence, which suggests higher trustworthiness. [2] On the other hand, a high outDegree measure represents actors who are exchanging with other actors more frequently and are generally regarded as influential actors. [10] Consequently, high inDegree nodes represent users who have the most users directing messages to them, as well as re-tweeting their messages; these users are thus the most information rich and are perceived by the network to be trustworthy. Accordingly, high outDegree nodes represent users who may have the most information and are dispensing it to other nodes. Closeness centrality values represent how close a node is to all other actors, which in turn represents an actor’s influence domain [12]; closeness centrality values aid in finding users with the most information available to them. The final centrality measure is betweenness; the node with the highest betweenness measure represents a user who controls the information flow. [29]
Cohesive groups were then identified. Friedkin [6] suggests that the existence of groups facilitates understanding the emergence of consensus among different members of the group; the existence of cohesive subgroups and their relationships to other groups reveal underlying communication patterns among the actors [6]. In the context of this data, cohesive groups suggested more frequent communication and therefore a higher exchange of emergency relevant information. An overlap of the groups revealed users who served as bridges and connected the groups. In order to study cohesive groups in this setting, a clique concept was utilized. A clique is a set of pairwise adjacent nodes [42], and in a clique, every node is connected to all other nodes.

Blockmodeling analysis examines the relationships among positions in the social network, rather than among individual actors. [43] Each position in the social network therefore includes actors who are structurally equivalent in the way they are embedded in the graph. Blockmodeling also reveals the core and periphery structure of the network. [41] In this data, the core contains the influential actors who tend to communicate the most and the periphery contains actors who communicate fairly infrequently.

2.6 Results

Centrality measures in the data and the resulting social network were assessed, and then the data were analyzed to find groups and cliques. The final result for the analysis was 17 cliques, with 11 cliques containing local media (TV, Radio, Newspaper) as a member and 7 out of the 11 cliques containing a student or staff member from RPI.

Analysis of these results showed that local media participated heavily in obtaining and dispensing information through Twitter, acting as central actors. Other central actors included RPI staff and students using Twitter to propagate the information. About 50% of the tweets posted by those RPI staff and students were re-tweets of tweets posted by the local media or other users propagating the information regarding the event. The isolates also displayed propagation behavior, as 79% of their tweets were broadcasting information about the event, 8% were confirmation seekers and 13% were information seekers.

The groups analysis suggested that as warnings were being issued, there were more and more groups emerging throughout the network: the number of cliques grew from 1 after the first warning, to 3 after the second warning, to 15 after the third warning, and 17 after the final warning. Note that these 17 cliques were formed in a local area in a three hour period, which supports the idea of emergent groups during emergency events. [38] Local media again played a central role in these groups, but interestingly, they formed cliques or groups with students, not with other local media. Other central actors, such as RPI staff and students, were part of a number of cliques and served as a bridge between the cliques, as the absence of those relationships would disconnect the cliques [39]. Hence, most of the cliques formed contained central actors with varying roles.

The block modeling analysis that followed the group analysis further supported the core and periphery trends observed. Throughout the event, there was one block that contained all the actors located in periphery that was tied to most of the central actors; however, most of the central actors were separate blocks and not part of the same block. This suggests that those actors were connected to different audiences. Since the actors were central and were connected to large audiences, they were able to reach even larger audiences than could a single actor. Egocentric network analyses show that many central actors in the network had large network sizes and were also minimally constrained, making it easy for central users to dispense information to wide audiences [41]. Thus, a key finding in the naturally occurring experiment was the presence of central actors in an emergency event that dispensed relevant emergency information to a wide audience. The finding was important, as it provides empirical evidence for central warning behavior in extreme events and suggests the importance of social media, specifically Twitter, in facilitating users seeking, receiving, confirming and understanding pertinent emergency information. In summary, the results of the naturally occurring experiment were the following:

1. Nodes with high betweenness values, e.g., local media, brokered information.
2. Nodes with high outDegree but lower inDegree engaged in information propagation.
3. Nodes with high inDegree brokered information and were regarded as trusted sources.
4. Nodes that were isolates (with no directed messages or re-tweets associated with them) engaged in all of the above activities, but were the only ones seeking confirmation.

Social network analysis of this limited but real data set demonstrated that graph theoretic measures can be used to guide data collection processes and identify relevant subsets of tweets to
code manually. Those tweets can then be analyzed to identify roles, behaviors and communications in the warning response process.

2.7 Contribution

In this study, Twitter was utilized by the affected general public and by the local media through all six stages of warning response. Local media in particular was found to facilitate the stages of the warning process by brokering and propagating emergency-relevant information using social media.

The results also showed role-specific uses of Twitter and warning behaviors when using Twitter. Key actors used social media to engage in various stages of the warning response process, and actors’ centralities such as betweenness, inDegree and outDegree identified those who brokered and propagated information. At the same time, inDegree centrality located those actors who were regarded as trusted sources of emergency-relevant information. Finally, actors who were isolates engaged in ‘seeking confirmation’ activities, the only actors to do so.

Analysis also revealed key actors identified through the centrality measures and the group structural analysis that were not connected to each other but had large outDegrees. This suggests that those actors were able to reach large audiences that didn’t overlap with emergency-relevant information.

Users were shown to be utilizing Twitter to obtain real-time updates of the emergency event as it related specifically to them. Users were also able to pose specific questions and have them answered. In this way, Twitter complemented the warning response process by providing emergency-relevant, but also audience-relevant, information to the affected public.

Twitter facilitated the warning response process, as actors were able to receive, understand, personalize and confirm emergency information through Twitter, as well as facilitate the warning process by brokering and disbursing information to other actors. In fact, key actors were able to engage in warning process activities more than others and to reach large audiences.

The results suggest that Twitter plays an important role in the warning response process, complementing the traditional official warning response process by providing a medium for real-time emergency-relevant information exchange that is ‘local’ or specific to the users, as well as providing the actors with a means for information exchange, allowing users to self-organize in groups and exchange information with large audiences affected by the emergency event.

3. Summary and Conclusions

This research contributes to our understanding of the role of social media in extreme events, specifically, the role of social media, e.g. Twitter, in a warning response process. The results of a data analysis undertaken with data gathered from a naturally occurring experiment suggest that users of social media such as Twitter engage in all six stages of the warning response process. Analysis showed that local media were heavily involved in those stages and were able to facilitate the stages through Twitter. Actors were shown to use Twitter to broker and provide information, as well as to obtain real-time emergency-relevant updates that were specific to them. Finally, actors were also able to self-organize in groups and exchange emergency-relevant information using Twitter.

This research provides insights on the role of social media in extreme events. However, it is limited to the study of one local university-based event. The results might differ greatly in settings where data were limited, or official/government data were incomplete. The event was able to generate relevant, however, limited data. To address this limitation, additional extreme events that can generate larger sets of data are now under study, allowing for the study of and deeper insights about and into the role of social media in extreme events. As larger sets of data are generated, a novel methodology for text mining will need to be developed, as currently, there is no algorithmic approach to reading social media data. Therefore, a methodology needs to be developed in order to extract emergency relevant data from large data sets. This is a next step for this research.

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4. References


