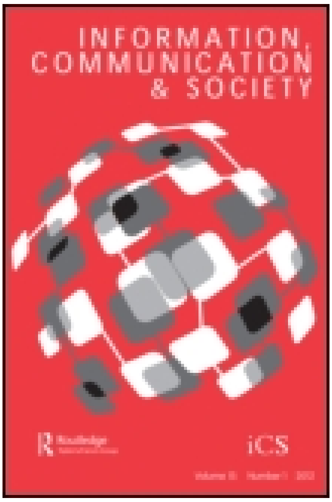

Information, Communication & Society
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/rics20

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Published online: 20 Dec 2013.

To cite this article: Jeannette Sutton, Emma S. Spiro, Britta Johnson, Sean Fitzhugh, Ben Gibson & Carter T. Butts (2014) Warning tweets: serial transmission of messages during the warning phase of a disaster event, Information, Communication & Society, 17:6, 765-787, DOI: 10.1080/1369118X.2013.862561

To link to this article: http://dx.doi.org/10.1080/1369118X.2013.862561

Information, Communication & Society, 2014
Vol. 17, No. 6, 765–787, http://dx.doi.org/10.1080/1369118X.2013.862561

Warning tweets: serial transmission of messages during the warning phase of a disaster event

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(*Received 23 January 2013; accepted 25 October 2013*)

Serial transmission – the passing on of information from one source to another – is a phenomenon of central interest in the study of informal communication in emergency settings. Microblogging services such as Twitter make it possible to study serial transmission on a large scale and to examine the factors that make retransmission of messages more or less likely. Here, we consider factors predicting serial transmission at the interface of formal and informal communication during disaster; specifically, we examine the retransmission by individuals of messages (tweets) issued by formal organizations on Twitter. Our central question is the following: *How do message content, message style, and public attention to tweets relate to the behavioral activity of retransmitting (i.e. retweeting) a message in disaster*? To answer this question, we collect all public tweets sent by a set of official government accounts during a 48-hour period of the Waldo Canyon wildfire. We manually code tweets for their thematic content and elements of message style. We then create predictive models to show how thematic content, message style, and changes in number of Followers affect retweeting behavior. From these predictive models, we identify the key elements that affect public retransmission of messages during the emergency phase of an unfolding disaster. Our findings suggest strategies for designing and disseminating messages through networked social media under periods of imminent threat.

Keywords: social media; online communication; disaster; Twitter; warning; networks

Introduction

Public warnings during times of high crisis and imminent threat have the potential to reduce harm and save lives of those who are at risk (Mileti, 1999). These messages' ability to alert individuals and provide protective action guidance has spurred the design of integrated systems of communication and the development of new alerting technologies (National Research Council, 2011). At the same time, public and official governmental use of social networking services for public communications has grown tremendously (Crowe, 2012). Some public officials have made efforts to utilize social networking services to broadcast messages to their online constituents, in order to reach those who are at risk.

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This is a study of messages from public officials that are delivered via short text on Twitter and their transmission across networks during a high-threat event. Previous research on Twitter in disaster has focused on the public and has been largely descriptive, providing details of how public individuals use Twitter during an event. By contrast, we focus on public officials and their Twitter messages posted during a high-threat disaster event. In this paper, we utilize the tweet content and Follower networks of public officials to generate models on how messages get passed on and under what circumstances. More specifically, this study explores how message exposure across social networks, and message content and style relate to patterns of retransmission. From this, we identify strategies to improve Twitter-based warnings under times of heightened crisis and stress.

In this paper, we address the following research question: *How do message content, message style, and public attention to tweets relate to the behavioral activity of retweeting a message in disaster?* To answer this question, we collected tweets from a sample of official government accounts over a 48-hour period during the Waldo Canyon wildfire in Colorado Springs. We manually conducted open-ended coding of tweets to identify their thematic content and elements of message style. We then developed predictive models to show how these message elements, along with changing numbers of Followers, affect public retweeting behavior. From these predictive models, we identify the key elements that affect the public behavior of retransmitting messages during a high-crisis period in disaster. Outcomes of this research are useful for guidance on strategies for designing and disseminating messages through networked social media under periods of imminent threat.

Background

Serial transmission – the passing on of received information from one party to another – is a phenomenon of central interest in the study of informal communication in emergency settings. When a formal message (i.e. one constructed and delivered by official response organizations) is introduced to a population, who then chooses to retransmit that message to others is of great importance: all other things being equal, retransmitted messages are likely to be seen by a larger number of persons, are likely to have been seen a larger number of times by any given person, and are more likely to have been received from a personally known and trusted source than messages that are not retransmitted. Serial transmission by members of the public can be seen as *amplifying* messages from formal sources, with the degree of amplification varying as a function of the probability that those receiving a given message elect to pass it on. Our goal here is to gain a better understanding of the factors that make such behavior more or less likely, in the context of terse (i.e. limited length) text messages transmitted by social media. In addition to helping us understand how informal communication during disasters (often called 'milling') operates in this new regime, identifying message characteristics that influence serial transmission may inform the strategies of emergency management organizations and others who need to quickly disseminate warnings or alerts in crisis situations.

In the past, the study of serial message transmission has required *post hoc* surveys (Lardry & Rogers, 1982; Rogers & Sorensen, 1988; Scanlon, 1977) or coding of after-action documents to identify patterns of communication (Butts, 2008; Butts, Petrescu-Prahova, & Cross, 2007). Although valuable, these studies are limited by informant mnemonic errors (Bernard, Killworth, Kronenfeld, & Sailer, 1984) and/or by being constrained to 'target of opportunity' studies on groups or organizations whose activities happen to have been documented. The rise of social media as a widely used platform for information dissemination by the public, combined with the prevalence of sites like Twitter that focus on open, publicly visible communication, allows us for the first time to examine the behavior of large populations in response to hazard events, with an accurate record of both actions taken and the time at which those actions take place. Our work exploits this opportunity, using data on user retransmission of official messages to model the dynamics of communication behavior during an unfolding hazard event. The detail, precision, and behavioral nature of our data allow us to test hypotheses regarding serial transmission behavior that would be difficult or impossible to examine using other approaches.

In the remainder of this section, we provide additional background on the use of Twitter in disaster situations and summarize relevant work on warning messages more generally. This is followed in the next section by a description of our methodology, after which we present our results.

Twitter in disaster

Twitter represents an important online venue for social interaction and information exchange in disasters for members of the public and public officials alike. Twitter is a social media platform that enables individuals to post terse (140 character) messages in real time. This platform is publicly searchable and enables networked communication between Friends and Followers in an open environment. Within this context, Twitter has been identified as a mechanism for resource mobilization and collaboration as well as a platform for sharing life-safety information (Starbird & Palen, 2010). Research on disaster response has indicated that rapid exchange of up-to-date information about a given situation, through mechanisms such as online social media (Sutton, Palen, & Shklovski, 2008), is a vital information resource that can affect life safety (Tierney, Lindell, & Perry, 2001).

Studies of online communication in disasters have shown that the public often utilizes social media to fill the information gap that occurs when emergency responders follow a traditional model for public information release (Sutton, Hansard, & Hewett, 2011). Disaster-specific Twitter research includes descriptive studies that focus on Twitter adoption and use in mass convergence events (Hughes & Palen, 2009); mechanisms of information production, distribution, and organization (Chew & Eysenbach, 2010; Starbird & Palen, 2010; Vieweg, Hughes, Starbird, & Palen, 2010); public participation and citizen reporting across a variety of hazard types (Sutton, 2010); and detailed description of thematic content related to disaster and crisis communications (Heverin & Zach, 2010).

Additional studies, both within and outside of the disaster research context, have focused on 'microstructure elements'. The term microstructure refers to elements of the message content that have specific social meaning such as mentioning others, including links to external resources, and signals of reported content (retweets). These include examinations of the primary function of the '@' within a tweet (also known as 'directed messages') (Honey & Herring, 2009) as well as the action of retweeting messages. The retweet function has been identified as an informal recommender system (Boyd, Golder, & Lotan, 2010) and a strategy to propagate information (Hui, Tyshchuk, Wallace, Magdon-Ismail, & Goldberg, 2012). One disaster-related study provided thematic analyses of individual tweets that received significant attention during a disaster event (Starbird & Palen, 2010), finding that widely retweeted messages are more likely to be about the event than non-retweets. Previous work has also looked at the association between microstructure elements, as well as other social and structural properties, and retweets (Petrovic, Osborne, & Lavrenko, 2011; Suh, Hong, Pirolli, & Chi, 2010). One disaster case study by Bruns, Burgess, Crawford, and Shaw (2012) examined the patterns and presence of different types of structural elements along with content features of tweets over a six-day flooding period in 2011 in Queensland, Australia. Content categories were generated in direct relation to the flood context, focusing on sense-making and collective memory along with emergency communication activities.

Individuals engage in information diffusion by retweeting messages, propagating information they have obtained by following other Twitter users to their own Followers (Starbird & Palen, 2010). Retweeting thus has important implications for message amplification as it provides organizations with a wider audience to share life-safety information. Not only are new audiences exposed to the tweet when others retransmit the message, but some users may be re-exposed to the tweet. Multiple exposures to messages have been linked to more confidence in its veracity (Arkes, Hackett, & Boehm, 1989; Hawkins, Hoch, & Meyers-Levy, 2001), which can lead to further sharing (Rosnow, Yost, & Esposito, 1986). Indeed, repeated exposures from multiple network ties are often a prerequisite for the spread of information through networks (Centola, & Macy, 2007; Starbird & Palen, 2012; Suh et al., 2010). This suggests that practitioners, who may endeavor to reach wide audiences with critical information, are likely to have an interest in tweeting messages that have both a high chance of being retweeted by others and reach a diverse set of other users who were not previously exposed directly to their initial message.

While much of the previous work in this area focuses on understanding *which* public tweets are being passed along, little attention has been dedicated to *why* these tweets have been passed along and how message content, style, or exposure might affect this public activity.

A focus on tweet exposure and how tweets might be amplified across a social network through serial transmission (i.e. reposting or retweeting) is missing from recent research. This is especially important during periods of high stress, such as during the warning phase of a disaster, when the diffusion of crisis information plays an essential role in reducing the loss of lives. To address this missing element, we turn to the empirical research on disaster warning messages and how message content and style affect human behavior in disaster.

Disaster warnings

Disasters are the 'defining events in a hazard cycle' that is commonly characterized by phases of mitigation, preparedness, response, and recovery (Tierney et al., 2001). Importantly, emergency response includes the actions taken a short period prior to, during, and after disaster impact to reduce casualties, damage, and disruption and to respond to the immediate needs of disaster victims. This includes detecting threats and disseminating alerts and warnings (Tierney et al., 2001). The alert and warning period may be very short, such as with a tornado, wildfire, or flood, or long and drawn out, such as with a hurricane. In some cases, there will be no warning period at all, such as with an earthquake.

Regardless of the type of hazard event or the length of forewarning, the goal of alerts and warnings is to get the attention of people who are at risk, to reduce the time taken to make sense of the warning, and to guide people to take appropriate protective actions (Mileti & Sorensen, 1990). This is achieved through a variety of channels from alarms and sirens to Emergency Alert System broadcasts to the more personalized alerts through desktop and mobile computing systems, with the intent to move people to action quickly. Irrespective of the warning system in place, because initial reactions to warnings are often marked by skepticism or disbelief (Drabek, 1969; Drabek & Stephenson, 1971) protective action will be delayed as individuals seek and confirm information about messages and the actions that they will take through sense-making or milling activities (Mileti & Sorensen, 1990).

Milling occurs following the initial warning message, where individuals search for additional and confirming information (Lindell & Perry, 2004) from other sources to help share and reaffirm what they understand, believe, personalize, and decide what to do or not to do about the warning message (Mileti & Sorensen, 1990). This is an intermediate step that occurs between message receipt and protective action taking. Warning messages received by members of the public via Twitter during a disaster event represent a simple form of milling due to the fact that Tweet messages are obtained via a purposeful search process in contrast with more traditional sirens or alarms

Table 1. Characteristics of effective warning message content.

Category	Characteristics of effective message content
Guidance	Tell people exactly what to do to maximize their health and safety and tell them how to do it
Time	Tell people by when they should begin their protective action and by when they should have it completed
Location	Say exactly who should and who should not do it in terms that the public can readily understand, e.g. the physical geographical boundaries for the location where people who need to take action are located
Hazard and consequence	Tell about the impending hazard by describing the event, the consequence of the hazard's impact, the threat posed, and how what they are being asked to do reduce consequences
Source	Say who is giving the message based on what constitutes the most credible/ believable source for the population as a whole

that are pushed out to individuals at risk. The decision to retweet a message during disaster also represents a purposeful action to pass along information, sharing with the online community.

Nearly six decades of empirical research on warning response have led to conclusions that the content and style of official messages are the strongest determinants motivating appropriate and timely public protective action taking (Mileti & Sorensen, 1990). Messages that include content about the hazard impact, time, location, guidance, and source (Table 1) and are delivered in a style that is clear, specific, certain, accurate, and consistent (Table 2) have a higher probability to positively affect protective action taking among persons at risk.

Prior research on warning messages has been focused primarily on broadcast media, without limits to message length (see for instance Sellnow, Sellnow, Lane, & Littlefield, 2012; Vihalemm, Kiisel, & Harro-Loit, 2012), where warnings have the potential to meet optimum characteristics by including all of the relevant content and style aspects identified above. In this research project, we apply prior research findings to terse messages that are limited to 140 characters, in order to identify the message characteristics that may be associated with serial transmission. We concentrate on initial message exposure, thematic message content, and stylistic features (e.g. the sentence function of each statement, the inclusion of @, RT, and #hashtags, or use of ALL CAPS as textual elements) that may provide insight into serial transmission of Twitter messages in

Table 2. Characteristics of effective message style factors.

Category	Characteristics of effective message style
Clear	Messages should be simply worded, free of jargon, and in words that people can understand
Specific	Provide messages that are precise and non-ambiguous about the area at risk, what people should do, the character of the hazard, how much time people have to engage in protective action before impact, and the source of the message
Accurate	Messages should provide timely, accurate, and complete information that is free from errors to the extent possible
Certain	Messages should be stated authoritatively, confidently, and with certainty even in circumstances in which there is ambiguity about message content factors and especially about the protective actions the public is being asked to take
Consistent	Messages should be externally consistent, for example, by explaining changes from past messages and also consistent internally, for example, by never saying things that conflict with each other such as 'radiation is in the air, but do not worry'

disaster. From this literature review, we have identified a set of research hypotheses that will be investigated through an empirical analysis of official tweets collected during a recent wildfire event.

H1: Tweets that include warning content features such as hazard guidance, impact, time, location, and source will have more retweets than those that do not.

H2: Tweets that deliver clear and specific warning messages will have more retweets than those that do not.

H3: Tweets that have greater direct exposure via numbers of Followers will have more retweets than those tweets that have less exposure.

We now turn to a discussion of our data collection and analysis methods.

Methods

The research context

The Waldo Canyon Fire was a forest fire that affected the El Paso and Teller counties of Colorado. Beginning on 23 June 2012, the fire ravaged the mountainous area four miles northwest of Colorado Springs, Colorado, resulting in the evacuation of over 32,000 residents. The devastation of the fire resulted in the loss of 2 lives, 346 buildings, and 18,247 acres of national forest and residential area. These damages made the Waldo Canyon Fire the most destructive fire in Colorado history at the time.

When the fire started on 23 June, weather conditions had left the area extremely dry, with winds causing a rapid spread of the fire to grow to 600 acres in a matter of a little over an hour. Mandatory evacuations were placed for 7000 residents of the Manitou Springs and Crystal Park areas, on 24 June 2013, but were lifted later that day and downgraded to a voluntary evacuation, allowing all residents back in their homes. Fire lines were maintained overnight and through the next day, with no structural damage reported. On afternoon of 26 June, however, winds shifted dramatically, causing the fire to spread toward its containment line, where it entered the Queen's Canyon area into Mountain Shadows, a neighborhood several miles north of the previously evacuated areas. Within 12 hours on 26 June, over 300 homes had burned to the ground. On 28 June, Mayor Steve Bach confirmed that 326 homes had been destroyed in the fire and that 2 people had been killed. The fire reached 100% containment on 10 July 2012, though no further structural damage occurred after 29 June.

Throughout the wildfire, public Twitter usage cycled through periods of increased attention as individuals posted tweets and joined following networks of public officials. In the early hours of the fire, local officials used Twitter to organize the use of #waldocanyonfire as the primary information-sharing hashtag. Between 25 June 2012 and 10 July 2012, over 100,000 messages from more than 25,000 unique Twitter users were posted using the #waldocanyonfire hashtag (Spiro, Sutton, Johnson, Fitzhugh, & Butts, 2012). Posting activity primarily occurred during the daytime hours and dropped off at night, demonstrating seasonal attention. However, a large spike in posting activity occurred around 9:00 pm MDT on 26 June 2012, coinciding with the time the fire moved toward residential areas. This time period of heightened danger is the focus of our analysis.

Data collection

We identified and enumerated a set of 16 Twitter accounts for the Waldo Canyon fire event. These targeted accounts were identified because they represent the population of public officials at the local, state, and federal levels who were serving in a public-safety capacity and who were actively tweeting about the wildfire when it first developed. The set of accounts satisfying these criteria were identified through two processes. First, we observed the tweets that were being posted on the #waldocanyonfire hashtag and identified all of the accounts that were linked to response organizations. Second, we manually sifted through the websites of local official organizations to identify additional accounts that may not routinely tweet, but could play a public information role. We did not choose to include local media as part of our targeted accounts because our hypotheses involve the exposure and diffusion of messages from public officials who provide public guidance to persons facing imminent threat. Our data set thus contains an approximate census of accounts in our target population; although it is possible that some accounts may exist that were not discovered by our collection procedure, such accounts would have to involve agencies that were neither advertised via government websites nor used the consensus hashtag employed by other responding organizations at any time during the study period. Should any such accounts exist, they are very unlikely to have been central in the response; likewise, we have no evidence to suggest that the mechanisms governing retransmission from such accounts would be fundamentally different from those governing retransmission for the accounts we have observed. We therefore regard the accounts employed here as strongly representative of the population of interest for this event.

For each of the enumerated targeted accounts, we retrieved their posting behavior history, including all of their messages posted to the public timeline for the entire month of June along with the timestamp for each post. We also obtained a count of the number of times that each such message was retweeted, the services used to post the message, and other features about the user (e.g. the number of Followers of that account at the time of collection). We queried each of these different data points daily over the period of observation. This data set was collected using the Twitter REST API. For the subsequent analysis, we consider all messages posted from 26 June 00:01 MST until 23:59 MST 27 June 2012. We restrict our analysis to this time period because it covers the period of imminent threat, when the winds shifted, pushing the fire into the Mountain Shadows neighborhood, which resulted in quick evacuations, and the destruction of more than 300 homes.

The targeted accounts vary in account-level characteristics and demonstrate a variety of posting activities. In Figure 1, we show the observed number of Followers and 'Friends' (accounts being followed, i.e. outgoing following relationships) for each targeted account on the two days of observation. In general, each targeted account has many more Followers than Friends. Importantly, none of these accounts added new Friends during the observation period (this would be seen in rightward movement of triangle-shaped points in the figure). In Figure 2, we show the number of Followers that each account gains over the observation period. From these two figures, we see that local organizations are the accounts gaining a large proportion of Followers relative to their initial Follower account, where @springsgov (the official account of Colorado Springs city government) gains the most Followers.

We also considered the number of messages posted by each account of interest. Focusing specifically on the 48-hour period of interest during the wildfire (26 June and 27 June), these accounts posted an average of 38 messages each, with a maximum of 126 by @springsgov and a minimum of 2 by @PSICC_NF (the Pike and San Isabel National Forests account). The targeted accounts had an average of 12,379 Followers, with a median of 2982 over the observation period. In Figure 3, we show the number of tweets posted for each account, along with the average number of times a message is retweeted. Recall that retweet count is our primary focus in the subsequent analysis.

As seen in Figure 3, the most active accounts were @springsgov (this was also the account that gained the most Followers), @EPCSheriff (El Paso County Sheriff), @CSFDPIO (Colorado

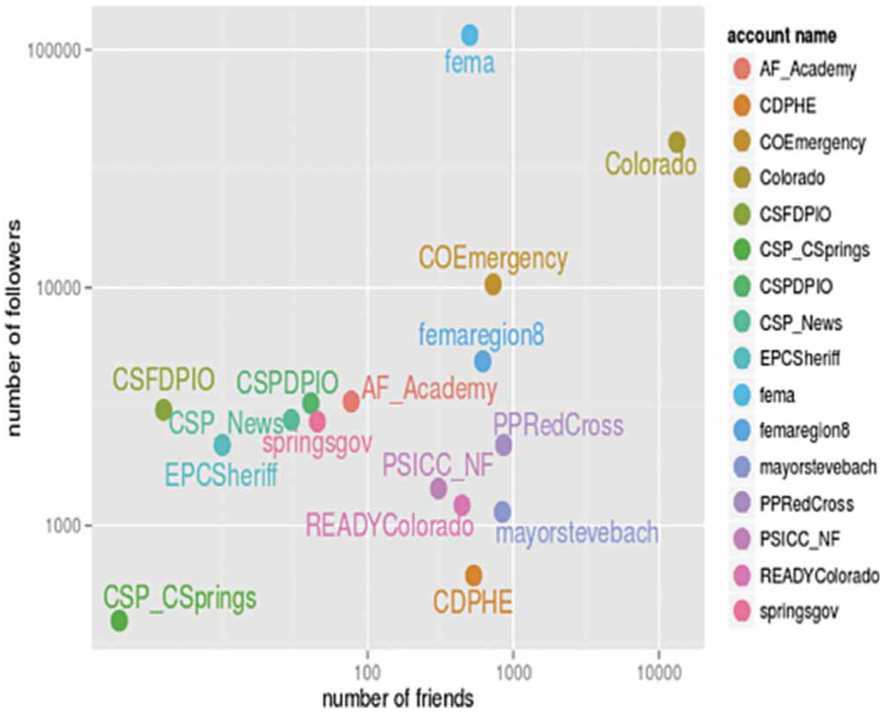

Figure 1. Friends and Followers of targeted accounts.

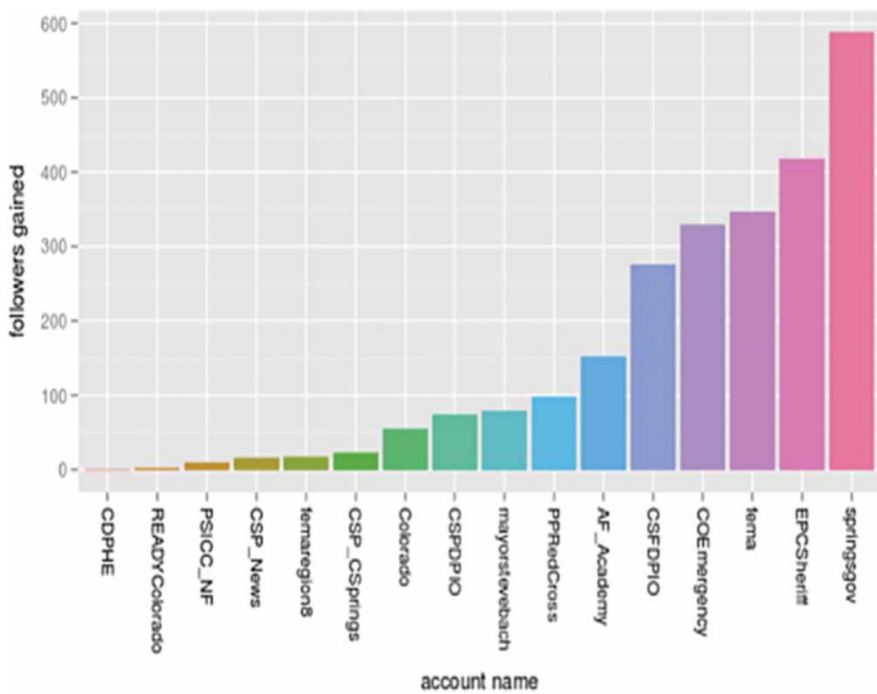

Figure 2. Followers gained by targeted accounts during the observation period.

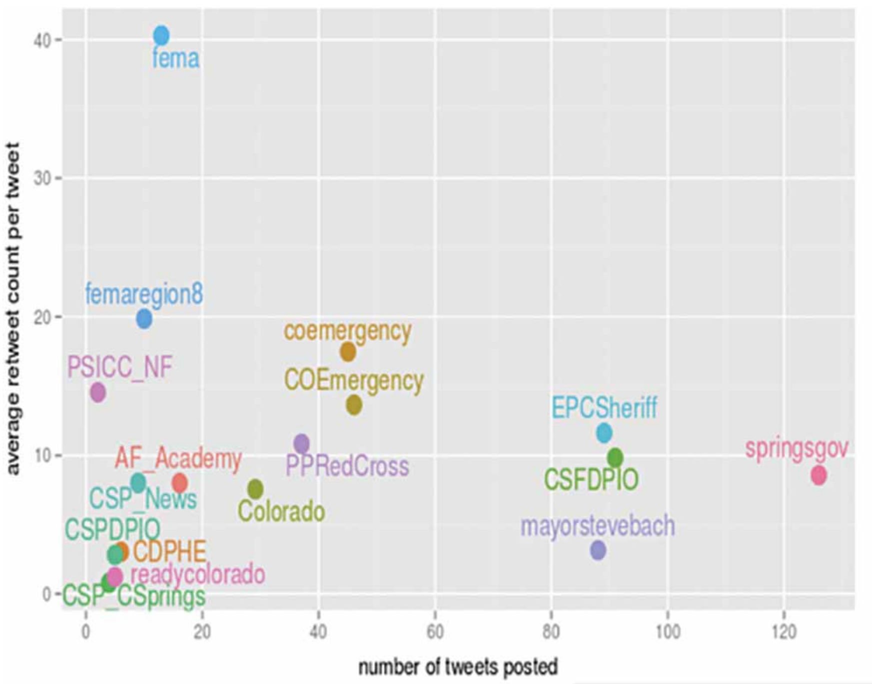

Figure 3. Messages posted by targeted accounts and their average retweet per tweet.

Springs Fire Department Public Information Officer), and @mayorstevebach (the official account for the Mayor of Colorado Springs). These four highly active accounts also tended to post tweets in a unified manner, where a single message was simultaneously pushed out through all four channels. One account, @FEMA (the national account for the Federal Emergency Management Agency), while not very active has a high average retweet count per message. In the following section, we build a predictive model of the retweet count allowing us to measure the relative influence of message content, message style, and structure.

Data analysis

Content coding

As discussed above, tweets are unlikely to conform to the five content categories or five style categories classically prescribed for effective disaster warnings due to their character limits. As pieces of information on a disaster continuum, they serve varying purposes and meet the needs of varying audiences at different points over time. However, we are interested in understanding how these tweets function as part of the larger warning milieu and how message content and style might affect milling behavior online in terms of message amplification via serial transmission. We do so by coding for thematic content (Gubrium & Holstein, 1997) found in each tweet and then examining aspects of the message style that contribute to message specificity and message clarity.

We began with the five content and five style categories identified by Mileti and Sorensen (1990) as normatively important for the design of effective warning messages. We quickly realized that the 140-character limitation of Twitter messages restricted the presentation of all five content areas within a single message, and that some categories of style (e.g. message consistency) were more relevant to continuous message *streams* than to single messages. In addition, content posted by our census of official accounts included information that had not been identified in prior empirical research on warning messages (Mileti & Sorensen, 1990). Therefore, we utilized the Mileti and Sorensen content and style categories as motivating concepts rather than as directly applicable categories, instead employing open-ended thematic coding to identify features of tweets that best reflected the properties of the Waldo Canyon corpus.

Two researchers manually coded the entire set of official tweets for the 48-hour time period, identifying emergent thematic content to identify *what* public officials were sharing with their Followers over time. The coders independently scanned all original tweets, identified thematic content patterns, and then met to discuss these 'candidate' categories. Throughout the coding process, researchers were blind to the number of times each original tweet was retweeted. This process continued through several iterations until the research team converged on a comprehensive set of categories and initial codes. The set of original tweets was then split recoded by the two researchers, with one-half being blind recoded by each researcher and then exchanged and checked for agreement. This comparison of codes within and across coders was used to verify reliability. We found nine primary themes (plus two additional categories: one for tweets that are not on-topic and one that did not fit into any category), ranging from evacuation guidance (including pre-evacuation and sheltering) to hazard information (such as phone numbers and resources) (Table 3). A description of key considerations in our coding process follows.

When coding content, we made an important distinction between two key warning themes that appear to be similar but function in very different ways. These themes are 'evacuation guidance' and 'advisory'. Evacuation messages are guidance messages oriented toward life-saving protective action. They tell the receiver what to do in order to remove themselves from harm's way (Drabek, 1999). Advisory messages are oriented toward public safety and merit caution from the receiver (Jacks, 2013), regardless of proximity to the hazard, but are not critical life-safety messages.

We also distinguished a series of thematic areas separate from the general theme of 'information'. These are hazard impact, closures, and re-entry. The 'information'-themed content area is broad and includes general updates about the fire response as well as phone numbers and tips for how to prepare for evacuation. In contrast, 'hazard impact' content provides specific information about the number of acres affected, the number of personnel mobilized, and the types and numbers of resources deployed. Messages about 'closures' discuss specific areas, events, and facilities that are either inaccessible for safety reasons, or canceled due to the ongoing fire response. 'Re-entry' messages provide updates specific to populations that have been evacuated and describe opportunities to return to their homes to retrieve belongings left behind.

In addition to thematic coding, we also coded each tweet for aspects of style. Here, we addressed the question of *how* officials share information via Twitter in ways that may provide greater clarity or specificity in their messages. Style aspects include sentence functions, the inclusion of words in ALL CAPS, and the use of conversational microstructure elements (Table 4).

We began with the question 'what kind of sentence is this?' (i.e. sentence function). Is it declarative (making a statement), imperative (commanding or making a request), exclamatory (attempting to convey powerful feelings or emotions), or interrogative (forming a question)? In particular, we were interested in the statements that provide guidance (imperative sentences that direct individuals to take protective action) versus those statements that do not tell people specifically what to do.

We also coded tweets based upon the use of All CAPS within each tweet, including its placement and perceived function. For instance, some ALL CAPS serve as a category signifier and include words or word phrases such as MANDATORY EVACUATION, PRE-EVACUATION,

Table 3. Thematic content identified and the definitions used to guide content coding.

Content theme	Theme definition and tweet example
Off-topic	Refers to tweets that are not directly related to the Waldo Canyon fire
Advisory	Refers to tweets containing advisory information, such as suggestions to the public and organizations on how to respond, what actions to take, and what to refrain from doing during the disaster "Please reserve cell phone use for emergencies only to keep the networks free for emergency personnel use (#waldocanyonfire)"
Closures	Refers to tweets containing information on closures of events, facilities, or roads "RT @ColoradoDOT: CO 71 Limon to Brush and US 36 Byers to Last Chance have reopened following wildfire activity. No wide loads allowed" "New Closures: Pulpit Rock Park, Ute Valley Park, Section 16, & Stratton Open space all closed (#WaldoCanyonFire)"
Corrections	Refers to tweets containing corrections to previously posted information "@ConnectColorado there is no hashtag change. Old tweet from 3 days ago"
Evacuation	Refers to tweets containing information on pre-evacuations, mandatory evacuations, voluntary evacuations, refraining from entering or staying in certain areas, sheltering information, and evacuation information "Crystal Park only: Evacuation downgraded from mandatory to VOLUNTARY. Evacuation recommended but not enforced (#WaldoCanyonFire)" "NEW #REDCROSS #SHELTER: #loc YMCA Southeast Family Center 2190 Jetwing Dr. Colorado Springs, CO 80916. (#WaldoCanyonFire)"
Hazard impact	Refers to tweets containing descriptions of the hazard itself, such as location, containment, etc., and descriptions of the hazard impact, such as fire bans, damaged areas, and results of the hazard hitting the area "Fire size is 5168 acres w/5% containment. More info to come. (#waldocanyonfire)"
Information	Refers to tweets containing information including disaster-related phone numbers, new information and updates, safety and preparedness tips and information, and links to resources

and HOW YOU CAN HELP. Such signifiers may indicate an intention to call out and specify tweet content by the message writer. These tend to be placed at the beginning of the tweet and are followed by a colon, as in this example:

> MANDATORY EVACUATION: Crystola, both El Paso and Teller County. Take animals with you – you will NOT be allowed back in. (#WaldoCanyonFire)

In contrast, we also find a second style of ALL CAPS use to emphasize specific words such as NOT (seen in the previous example), PLEASE, THANK YOU, and ANYTHING, and phrases such as 'DON'T LEAVE YOUR PETS IN UR CAR' (sic). Placing emphasis on words within a tweet via capitalization may serve to clarify portions of messages. These tend to be placed at various positions within the tweet and can also be akin to 'shouting' (Shipley & Schwalbe, 2008) at the reader in order to draw attention to a part of the message.

Third, we coded for conversational microstructure elements within the tweet. These include whether the tweet was directed at or responding to another Twitter user (demonstrated by the inclusion of @name), whether it was a retweet (a message which includes the characters RT), if it includes a mention of another user (but is not directed to a specific user), and the presence of a hashtag keyword (symbolized by #waldocanyonfire) or a reference to further information available online in the form of links to URLs (usually shortened by using bit.ly or another short URL service).

After we coded for thematic content and message style elements, we conducted statistical analyses on tweet transmission volume and dissemination via retweeting. We turn to these analytical methods next.

Quantitative analysis

One important aspect of information propagation is the number of times a particular message is passed between contacts – what is referred to as *serial transmission*. As noted previously, our focus is on serial transmission that occurs at the interface of formal and informal communication; specifically, we are interested in the extent to which messages from formal organizations sent via Twitter will be retransmitted (retweeted) by members of the public. To measure this transmission activity, we consider the number of times each message posted by our set of accounts of interest was retweeted. We build a predictive model to evaluate the relative importance of the message content, style, and exposure on the resulting count of serial transmission occurrences. We use the previously discussed content and style coding as well as the number of Followers of the user as potential features that influenced the subsequent retweet count to address our research question and the previously identified hypotheses.

Our model (described in detail below) can be conceptualized as follows. Each original message sent by a targeted account is broadcast to the public stream, and by design is directed to the #waldocanyonfire audience. The messages may vary in style and content (coded as described above), by the characteristics of the sender, and by the context in which the message was sent (e.g. the number of Followers of the sending organization at the time of posting, and by whether the message was simultaneously posted by multiple organizations as a deliberate dissemination strategy). Given these characteristics, the message is then retransmitted some number (possibly zero) of times by members of the public. Because this *retweet count* depends upon many complex, unobserved social processes, we cannot predict it exactly; nevertheless, certain style, content, or sender characteristics will on average produce messages that are more often retweeted, while others will tend to suppress retweeting. We thus model the retweet count for any given message as a random variable whose expectation is a function of the aforementioned characteristics (as inferred from the observed data). Specifically, we employ a negative binomial regression model for the retweet count data, a form that accounts for unobserved heterogeneity in the underlying retransmission process (manifesting empirically as overdispersion relative to a Poisson process); Poisson and geometric models were also considered and were found to produce inferior models as selected by the corrected Akaike information criterion (AICc). Details regarding modeling process, and our associated findings, are provided below.

Results

As discussed in the methods section above, we built a model of message transmission to assess the relative influence of content and style elements, as well as message exposure, on the number of times a message is retweeted. We use the R statistical computing platform to fit a negative binomial regression model for this data. The negative binomial family was chosen to account for observed overdispersion in the retweet rates relative to either a Poisson or geometric family; this is consistent with a process in which there are many sources of heterogeneity in the retweet process, only some of which can be captured via observed covariates.

In Table 5, we show the results of the model selection process. Each of the content codes for capitalization (ALL CAPS), linguistic features (sentence type), themes, conversational microstructure elements, and structural characteristics (e.g. the number of Followers of the account posting the message) of the accounts are considered as potential predictors in the model. In

Table 4. Descriptive statistics for targeted tweets based on theme content and style.

Theme	Number of tweets	Percent imperative	Percent with signifier	Percent with hashtag	Percent with URL	Percent directed	Percent retweets
Off-topic	102	0	0	0.6	0.61	0.07	0.46
Advisories	7	1	0	1	0	0	0
Closures	51	0	0.1	0.59	0.22	0.04	0.16
Corrections	3	0	0	0.67	0	1	0
Evacuation	157	0.27	0.32	0.88	0.36	0.04	0.07
Hazard impact	44	0	0	0.84	0.55	0	0.11
Information	123	0.22	0.01	0.89	0.57	0.02	0.11
Re-entry	33	0.24	0.12	0.91	0.48	0.03	0.03
Thank yous	18	0.06	0	0.44	0.11	0.61	0.11
Volunteering	69	0.3	0.23	0.84	0.74	0.09	0.12
Unsure	14	0.21	0	0	0.64	0.5	0.21

Table 5. Top five best fit models, according to AICc are shown. Top model (Model 1) will be used in subsequent analysis.

	Sentence Style				Capitalization		Microstructure				Organizational				Thematic Content		
	Declarative	Exclamatory	Imperative	Interrogative	EMPHASIS	SIGNIFIER	directed	flagged third party	hashtag	URL	username	log(friends)	log(followers)	log(tweets)		df	AICc
Model 1			✔			✔	✔		✔	✔	✔	✔	✔		✔	24	3029.293
Model 2			✔			✔	✔	✔	✔	✔	✔	✔	✔		✔	35	3029.737
Model 3			✔			✔	✔		✔	✔	✔	✔		✔	✔	34	3030.502
Model 4	✔		✔			✔	✔		✔	✔	✔	✔	✔		✔	35	3030.836
Model 5			✔			✔	✔		✔	✔	✔	✔	✔	✔	✔	35	3030.992

Table 5, we show the top five models chosen based on the small sample size-adjusted AICc, a model selection index that considers both goodness of fit to the observed data and model parsimony (in particular, the risk of overfitting). This criterion is minimized for the best-fit model (i.e. lower AICc values indicate models that fit better given the number of parameters they employ). The top five models are very similar both in terms of predictors included and AICc scores, differing only by the inclusion of one potential predictor. The simplest model is preferred and will be used in subsequent analysis; however, we note that inclusion of additional model terms did not result in qualitatively different results.

Some of the variables identified as potential predictors are *not* retained by the best-fitting models, allowing us to reject the hypothesis that these are critical for explaining retweet behavior. For example, the indicator for declarative sentences is only a predictor in one model, Model 4. A few factors of interest are not chosen into any of the top five models, including log of prior activity (number of prior messages posted), exclamatory content, and the indicator for whether a message used capitalization for emphasis. This indicates that these features do not seem to be powerful predictors of the retweet count of a message, given the observed data. The best-fit model is Model 1, which we will use for the subsequent analysis. For the top model, we show the regression coefcient estimates for each variable, along with the standard error estimate and p-value (Table 6). The residual deviance of the top model is 564.85 on 492 degrees of freedom, a substantial improvement over the null deviance of 1091.66 on 524 degrees of freedom. Each of the content elements has been discussed in detail in previous sections. We also include structural elements – the number of incoming and outgoing following relationship – termed Followers and Friends, respectively. The coefficients here can be somewhat deceptive because they rely on the structural characteristics of the accounts themselves. Both, however, have a positive impact on the number of retweets. The individual terms for the organizations aid in accounting for unobserved heterogeneity. The reference organization here is the ‘Colorado’ account. Each of the content themes is also included; here, the reference category is ‘not on-topic’, i.e. not related to the Waldo Canyon wildfire. The negative binomial coefficients are interpreted as affecting the expected log count of the number of retweets. For example, a message containing an imperative increases the expected log count of the number of retweets by 0.339, i.e. increasing the expected retweet rate by about 140% compared to a tweet that does not contain an imperative (all else held constant). To aid in interpretation of these effects (especially in the context of multiple predictors), we find it helpful to consider the predicted retweet count for various predictor combinations of interest. We discuss some of these cases presently as they correspond to the primary question: what makes a difference in the behavioral outcome of retweeting; content, style, or network exposure?

We first address our question from a ‘content’ perspective, addressing H1, and ask the question ‘does tweeting on a particular topic affect the predicted number of retweets?’ Our results demonstrate that for the observed data, on-topic tweets (regardless of theme) produce more retweets on average than off-topic tweets, all else held constant. We show the predicted retweet count for on-topic and off-topic messages posted by each organization; this allows us to incorporate individual and network differences such as the number of Followers of any given organization. In Figure 4, we see that tweets that include content that is hazard-related are likely to be retweeted more in comparison with tweets that are not on-topic during the fire response. This is especially so for tweets sent from organizational accounts with a large number of Followers, such as FEMA, but holds consistent for all of the other accounts in our data set. Next, we asked whether specific on-topic content themes are more likely to produce larger numbers of retweets during the response period (Figure 4). Again, referencing H1, and our review of message content effects, we expect to find messages that include information about protective action guidance, hazard impact, and hazard location to be most frequently retweeted. These themes in particular are closely related to warning message

Table 6. Coefficient estimates and standard errors for the top negative binomial model for retweet count.

Coefficient	Estimate	Std. Error	p-value
Intercept	−1144	413.9e	0.005 **
Imperative	0.339	0.122	0.005 **
SIGNIFIER	0.343	0.139	0.014 *
Theme - Advisories	2.124	0.452	<0.001 ***
Theme - Closures	0.935	0.292	0.001 **
Theme - Corrections	0.326	0.819	0.690
Theme - Evacuation	1.651	0.262	<0.001 ***
Theme - Hazard Impact	2.312	0.283	<0.001 ***
Theme - Information	0.910	0.258	<0.001 ***
Theme - Re-entry	0.755	0.325	0.020 *
Theme - Thank yous	−0.079	0.458	0.862
Theme - Volunteering	1.191	0.265	<0.001 ***
Theme - Unknown	1.804	0.422	<0.001 ***
Directed	−1.651	0.251	<0.001 ***
Hashtag	0.757	0.153	<0.001 ***
External link	−0.243	0.104	0.019 *
log(Followers)	2.322	0.719	0.001 **
log(Friends)	118.1	43.64	0.006 **
AF Academy	612.9	224.3	0.006 **
CDPHE	386.6	140.2	0.005 **
COEmergency	346.0	126.7	0.006 **
CSFDPIO	961.3	353.5	0.006 **
CSP CSprings	104.7	383.7	0.006 **
CSPDPIO	686.3	252.0	0.006 **
CSP News	723.1	265.6	0.006 **
EPCSheriff	854.0	313.5	0.006 **
fema	385.0	142.6	0.006 **
femaregion8	368.1	134.1	0.006 **
mayorstevebach	332.4	120.6	0.005 **
PPRedCross	329.4	119.3	0.005 **
PSICC NF	452.0	164.4	0.005 **
READYColorado	405.9	147.6	0.005 **
springsgov	675.9	247.9	0.006 **

Coefficient estimates and standard errors for the top negative binomial model for retweet count.

content identified in Mileti and Sorensen (1990), compared with themes such as volunteering or thank yous. While there are no large, significant differences between the message content themes, the ordering of these effects is consistent across all accounts. In Figure 4, we compare off-topic tweets with the advisory and evacuation-themed messages, demonstrating that tweets with warning-related content are more salient during the warning period than those that are not. Overall, the guidance and impact themes are more likely to have higher numbers of retweets, holding additional message style characteristics constant.

We then investigated the effect of tweet style factors on retweeting (Figure 5), addressing H2, and issues of message clarity and specificity. We began by looking at the inclusion of a weblink (URL). Here, we find that the predicted number of retweets for the theme of evacuation guidance, with the inclusion of a weblink (URL), does *not* increase the predicted number of tweets. Importantly, the inclusion of an external link does not appear to increase the predicted retweet count for any of the content themes.

Next, we considered the effect of sentence style on predicted number of retweets (Figure 6). Here, we find that the use of an imperative sentence (using an active voice and telling people what

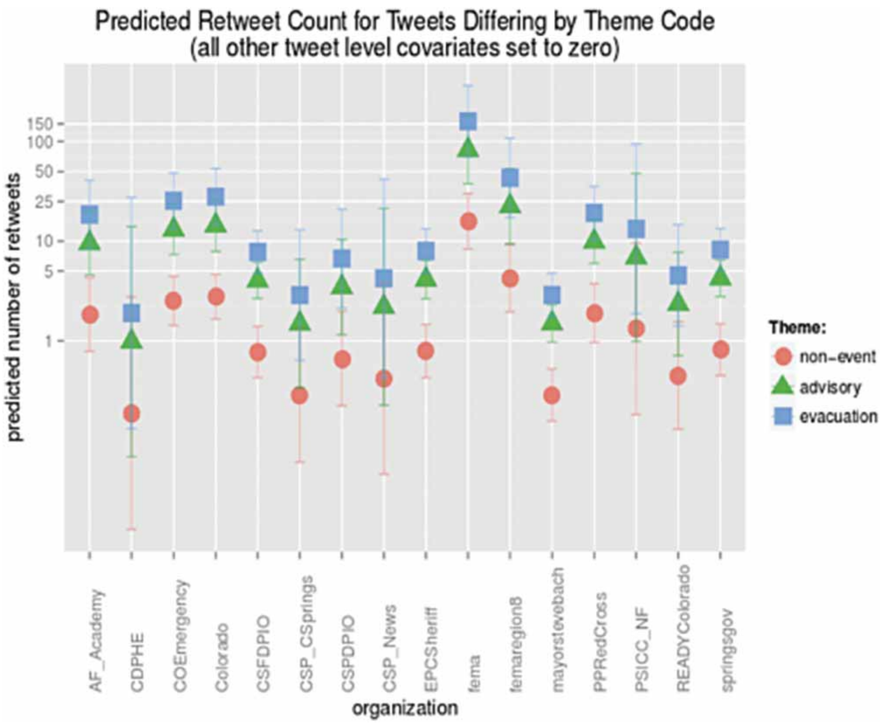

Figure 4. Predicted number of retweets for on-topic versus not on-topic tweets during the Waldo Canyon Fire.

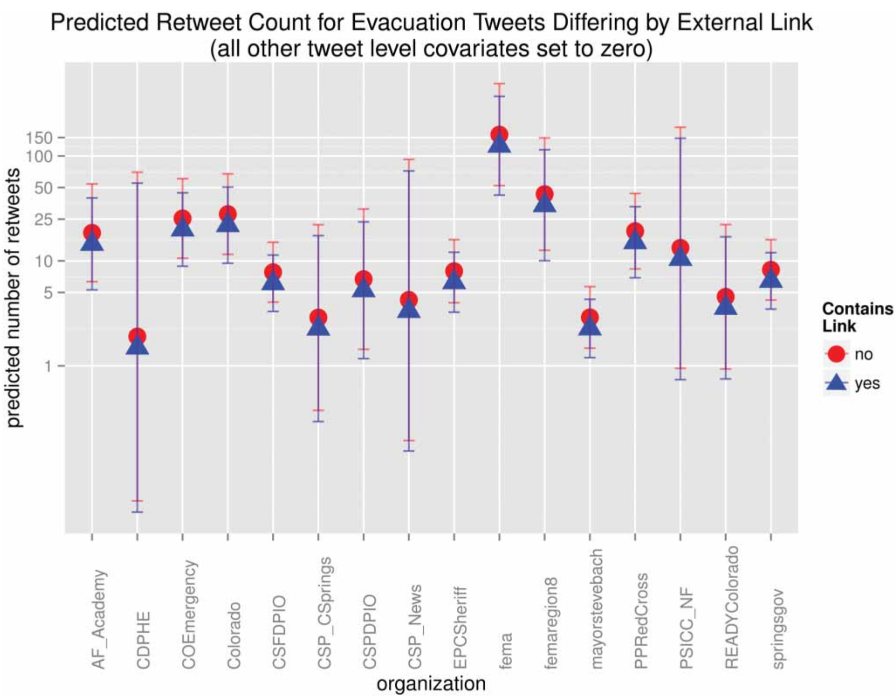

Figure 5. Predicted number of retweets for evacuation-themed tweets that include a weblink.

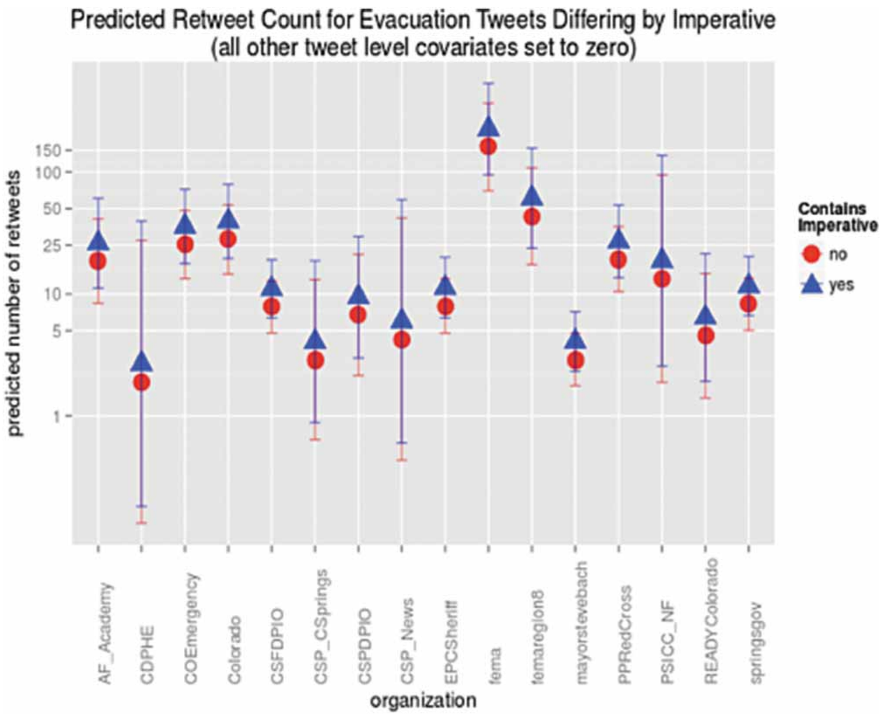

Figure 6. Predicted number of retweets for evacuation-themed content using an imperative sentence.

to do) is predicted to increase the number of evacuation-themed retweets. The use of an imperative sentence is also predicted to increase the number of retweets across all of the other identified themes.

To address the third aspect of our research question, we investigated the effect of tweet exposure on the predicted number of retweets, H3. We find that exposure matters (Figure 7). We demonstrate this by adding 1000 new Followers to each of our targeted accounts. Across all of the accounts, holding message content and style factors constant, their predicted number of retweets will increase. In other words, the more direct (first-order) exposure a message has, the more that message will be reposted (retweeted) leading to amplification of the message along social contacts. This turns out to be particularly important for local actors. For example, for the Mayor of Colorado Springs (mayorstevebach), the addition of 1000 new Followers has large, significant effects on the predicted retweet count – in fact, this effect is orders of magnitude different. For FEMA, on the other hand, 1000 new Followers is not a large change relative to their normal, everyday audience and does not have a large effect on the predicted retweet count.

From these predictive models, we find that all three aspects, message content, message style, and message exposure, make a difference in retweet rates. Importantly, in relation to our three hypotheses, we find serial transmission among public Twitter Followers can be predicted based upon specific message themes and key style factors.

One interesting observation that underscores the importance of the modeling approach used here is that simply examining the official tweets receiving the most retweets throughout our 48-hour observation period does not paint an accurate picture of the factors predicting retweet rates more generally. Consider the tweet that garnered the highest retransmission rate:

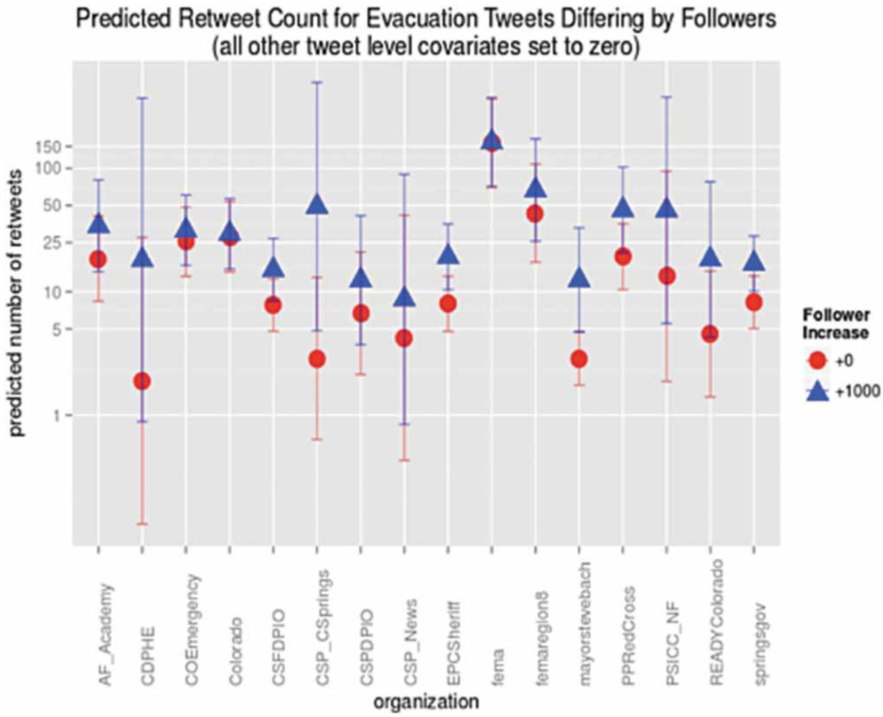

Figure 7. Predicted retweet count for thematic content differing by the number of Followers.

> PLEASE don't return to evacuated areas or drive in front of fire trucks. This creates a dangerous situation. #WaldoCanyonFire Pls RT!

This specific message focuses on evacuation guidance, uses ALL CAPS for emphasis, and even makes a request for Followers to retweet the message. The popularity of this single tweet, however, does not generalize to the entire population of tweets posted during the Waldo Canyon event. Indeed, our analysis shows that the thematic content most often retweeted in general does not conform to previously identified normative guidelines on messaging (that which is inclusive of time, location, protective guidance, hazard impact, and source), and the style characteristics that might increase specificity and clarity, especially the use of ALL CAPS or a weblink (URL), do not increase retweet probability. Because of the high variability in retweet rates, focusing only on individual tweets that are highly retweeted is not likely to lead to conclusions that are generalizable to the broader time spectrum or online population.

We also note, perhaps less surprisingly, that an increase in Followers is directly linked to predicted retweet rates; thus, building a larger network of Followers will result in message diffusion beyond first-order Friends in a network which increases the exposed population. How these results on message content, style, and network factors might be related to the broader context of disaster communications is discussed next.

Discussion

Serial message transmission, via retweeting following the initial receipt of a warning message, is characterized here as a form of online milling where individuals employ sense-making activities before taking protective action. Most specifically, message receivers engage in steps to understand, trust, personalize, and confirm information as they determine whether or not to act on the received warning (Lindell, 1987; Mileti & Fitzpatrick, 1991; Mileti & Sorensen, 1990). Milling encompasses all of these actions and inherently includes activities of following, obtaining, and passing along information as one strategy of engagement with disaster communication content. Retweeting is a visible sign of this online milling activity, demonstrating public exposure to messages, resulting in a decision to transmit information to a broader online network.

Previous research has shown that message content and style factors contribute to decisions to take protective action and milling activity, in the form of information search and sharing, occurs from the point at which a message is received until action is taken. Most importantly, guidance messages delivered in a clear and specific style contribute strongly to any at-risk populations' decisions to take action. Interestingly, while our research supports the findings from previous research (Lindell, 1987; Sellnow et al., 2012), it also raises some questions. The first is related to our first hypothesis and the thematic content of warning messages.

Complete warning messages include protective action guidance along with hazard impact, hazard location, time to impact, and message source. Due to their extreme brevity and character limits, Twitter warning messages are incomplete and tend to be posted in response to unfolding events. Therefore, we find that warning tweets are likely to focus on one or two themes at a time, rather than being complete messages. Furthermore, few messages (in this disaster situation) include 'guidance' information, such as recommendations to evacuate, but instead provide ongoing situational updates and what might be considered 'advisories' to a broader population that is not at risk. In response to H1, we found that the content of the messages predicted to be most highly retweeted do not focus on protective action guidance, but instead relay information about 'hazard impact' and are more 'advisory' in nature. Interestingly, both of these themes, as well as our fourth highest retweeted theme on 'volunteering', are meant for a broad audience with populations that may or may not be under imminent threat.

Two things stand out related to this finding on thematic content. The first relates to whose needs messages are designed to meet. The majority of messages posted by our targeted accounts during the 48 hours of interest were not centered on protective action guidance that would likely be directed to those under imminent threat. Instead, they spanned a variety of content areas that would meet the needs of locals and non-locals alike, including those who are online observers or others with an interest in helping in some form. The second item that stands out, related to findings on thematic content, centers on individual decisions to retweet specific messages as part of their online milling activities. Predictive models show that 'hazard impact' tweets will be retweeted the most and we discern that these tweets are relevant to populations that are both at risk and not. However, predictive models for serial transmissions of 'advisory'-type messages also suggests that during this event public Twitter users were most concerned with general public-safety messages (such as 'please drive slowly' and 'please do not use cell phones except in emergency') rather than life-safety critical messages. These two concepts taken together, for whom messages are designed and which messages the online public choose to pass along, leads to conclusions that during this disaster, and taken as a whole, officials utilized Twitter to relay information that is broadly applicable to the entire local public rather than using Twitter to post timely, focused, warning guidance for populations under imminent threat. Furthermore, the milling activities of Twitter users demonstrated their perceptions of message saliency in high-crisis periods by more frequently passing along broadly applicable messages that were public-safety focused.

Our research findings also support H2 that messages that are clear and specific are likely to be retweeted more often than those that are not. We found that the use of imperative sentences to provide direct guidance was infrequent (about 25% of the time), but was a predictor of retweets for all of content themes. Messages that used declarative statements were less clear in their directives and required interpretation from the reader. Interestingly, many tweets using declarative statements about evacuation were often preceded with an ALL CAPS signifier category, which would imply that a specific set of information was to follow. However, the use of ALL CAPS to signify this specific message content was not a predictor of retweets for any of the thematic areas. Therefore, we note that a clear and specific sentence style, rather than the use of ALL CAPS as a stylistic feature, is a greater predictor of retweets in this case.

Perhaps most interesting stylistically is the effect of the inclusion of a link (URL) within protective action guidance tweets, specifically those related to 'evacuation'. Prior research on warning messages indicates that incomplete information will result in additional milling activity (Mileti & Fitzpatrick, 1991) as people attempt to make sense of crisis information. Warning tweets are incomplete primarily due to message length. While stylistically clear, many of the tweets we analyzed lacked specific information about where evacuees should go, for how long, and what to expect after being evacuated. Without this additional information, persons facing imminent threat are likely to engage in milling behavior in order to understand and confirm the message content and its implications. Including a link to additional information is a logical strategy to direct people to accurate and specific instructions, reducing the time that might be spent searching online or offline. However, the inclusion of a link was not a predictor for serial transmission of evacuation tweets. There are a number of potential reasons for this including the likelihood that individuals see messages with links as being inherently 'noisy', and that they will require additional bandwidth and attention or time to open a link. But perhaps most obvious reason is that Twitter reduces risk communication to 140-character sound bytes. With this comes a growing expectation that a message should be complete even when extremely brief, especially under conditions of extreme duress.

Conclusions

In this paper, we examined the use of Twitter by public officials during the Waldo Canyon fire in Colorado Springs during the summer of 2012. We looked at tweet content, style, and network properties in order to predict the milling activity of retweeting warning messages under imminent threat. We identified a number of factors that influence predicted retweeting behavior, showing that content, style, and networks matter when tweeting to a public at risk.

This research has shown that serial transmission of warning messages resulted from online milling activities post-receipt of warning phase messages during a wildfire event. Serial transmission of messages will result in message amplification, by processes of message repetition that leads to diffusion across broader networks of users. Online information seeking results in one small sense-making step as a Twitter user chooses to pass over or pass on critical disaster information. In the future, repetitive research needs to be done on more events to provide additional evidence on factors affecting online milling and serial transmission of messages in disaster.

If the goal of a warning is to reduce the time it takes for someone to take a protective action, then it is important that a message be specific and clear in order to reduce the need for additional information search. However, we know that people mill about in disaster situations. Therefore, it becomes imperative to induce *favorable milling*, which will increase protective action, and reduce *unfavorable milling*, which will increase the time spent looking for useful information. The social network on Twitter can help to facilitate these things by building an informal information dissemination channel to amplify the message, by reinforcing messages, and by motivating behavior via structured effective message content.

Many public communication practitioners have adopted Twitter as an additional communication channel that is responsive to changing conditions and is redundant when communication infrastructure is threatened or compromised. Effective messages are key to influencing public protective action behavior, thus it becomes imperative for risk communicators to identify content that will be useful to promote life safety and to meet public-safety needs within a limited number of characters. Furthermore, public communicators must become aware of the multiple audiences that are attuned to Twitter, those who are both local and at risk, as well as distant observers who aspire to aid and assist. Focusing on content that is most salient to disaster-affected audiences and delivering clear and specific messages will most strongly influence retweeting behaviors, affecting message amplification, and ultimately reducing losses and saving lives.

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Acknowledgements

This research us supported by the National Science Foundation awards CMMI-1031853 and CMMI-1031779. Any opinions, findings and conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of NSF.

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