EXPRESSIONS OF RESILIENCE PERSONAL RESPONSES TO AN EXTREME WEATHER EVENT

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1. INTRODUCTION

Communication guides individual and community responses to extreme weather events and is a critical part of how they develop resilience to adversity brought on by such events (Houston et al. 2015; Buzzanell 2010). There are a number of ways communication plays a role in building resilience. People turn to their networks — both face-to-face (i.e., people they know in their communities that they interact with in person) and mediated (e.g., reporting by local news organizations or social media discussions) — for information about the event itself, how the event is affecting others, and resources available to help them recover (Arneson et al. 2017; Houston and Buzzanell 2018). This information seeking helps people manage the uncertainty they face following such an event (Brashers et al. 2000). Communication during a disaster is also a means for expressing various emotional responses, the dynamics of which are a key part of understanding how individuals and communities are processing and coping during adverse situations (Buzzanell 2010; Garcia and Rimé 2019; Jin et al. 2016).

This study explores how people express resilience as part of their communication during a regional flooding event that occurred in the state of Colorado in 2013. Using tweets collected before, during, and after the flooding event (*N* = 210,303), it examines how and when individuals express resilience throughout the event using a dictionary-based approach to computer-aided content analysis. It finds that emotional responses increase during the event, with positive emotions prevailing a month following the event. Social responses spike at the start of the event, but continue in the month following the event. Individuals' discussion of life events, like work and home, also increase during the event, with both discussions lasting in the month following the event.

2. PERSONAL RESILIENCE

This section reviews the role of communication — and particularly expressions — in building resilience, known as communicative resilience (Buzzanell 2010). It also identifies research that has used dictionary-based textual analysis similar to the methods used here to explore responses — including responses of resilience — to disasters and extreme weather events.

2.1 THE ROLE OF COMMUNICATION

Resilience is a response that occurs following an adverse event (McGreavy 2016). While scholars have primarily examined it as the recovery following a stressful event back to normal, or whatever the new normal is, there is increasing attention paid to the mitigation of or preparation for such an event (Boin et al. 2010). Such approaches acknowledge that pre-disturbance structures are in place that shape the event itself, immediate responses to the event, as well as longer-term recovery. Individuals have existing communication frameworks similar to what engineers refer to as a pre-disturbance structure that shape how they experience and respond to an adverse event. For instance, they hold varying levels of social capital based on their level of participation in community-based organizations, workplace type and structure, and social networks (Houston 2018). These provide them points of contact for finding and distributing information once disaster hits. Information seeking and sharing are individual-level communicative responses during an event and immediately following event (Griffin et al. 2008). These activities guide individuals toward community resources that are available to help recover from an event (National Research Council 2012). They also help to reintegrate with family members and friends and others in the community also affected by the event (Liu et al. 2016). Ultimately, communicative activities, often through language expressed in mediated and interpersonal sources, help a community find its way back to normalcy during long-term recovery after an event.

The idea that resilience is communicatively constructed entails a couple of main perspectives (Buzzanell 2010). First, individuals rely on communication in their social networks to reintegrate with their family, friends, and neighbors in our communities (Houston 2018). Those social connections are critical for developing tolerance to risks such as floods and confidence in how one's community will adapt to such a risk (Wong-Parodi et al. 2016). The other main perspective is that people express resilience through language exchanged in various sources. How we talk to each other and how media represents issues cultivates our perceptions after a disaster (Cheng et al. 2016; Binder et al. 2011). For instance, language can help identify communities and individuals within them as capable of solving problems and responding to emergencies (National Research Council 2012). Language also helps us develop resilience through expressions of normalcy, or the idea that things have returned to normal, and displays of positive emotions while negative emotions take a backseat (Buzzanell 2010; Bean 2018). Thus, we can turn to language to understand how resilience is expressed. For instance, news media accounts following disasters frame flood responses in ways that foster community pride and develop individuals' capacities to share their experiences (Bohensky and Leitch 2014).

While there are many sources of expression of resilience, one area of focus has been on expressions of resilience in social media discourse.

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2.2 SOCIAL MEDIA DURING DISASTERS

Scholars consider social media engagement to be a component of how individuals develop resilience (Zhang and Shay 2019). This is grounded in the idea that disasters establish a need for information, in part to inform how individuals can respond to the threat, but also to reduce the uncertainty that develops during such events (Crijns et al. 2017; Brashers et al. 2000). Thus, information seeking is a critical part of disaster response, and individuals have a number of sources they can turn to in such situations. Social media is a key source, particularly for accessing social perspectives to complement more mainstream mediated information. As such, scholars have started to empirically examine the way people discuss disasters in social media discussions for evidence of resilience.

Empirical analyses of social media discussions following events have identified several components of resilience. For instance, one component of resiliency is the development of group identity (National Research Council 2012). A study of tweets following the Paris terrorist attacks in 2015 provides evidence that individuals refer to community solidarity as a response to the attacks (Garcia and Rimé 2019). Evidence from other textual sources written by non-expert or non-technical audiences (e.g., written essays or Wikipedia pages) indicates language used references components of resilience in a social environment that are similar to solidarity, such as family (Wong-Parodi et al. 2015; Ferron and Massa 2012). Another key aspect of resilience is the emotions that are invoked, with a productive response being one of foregrounding positive emotions but an acknowledgement that negative emotions play an important role to help individuals process their experiences (Buzzanell 2010; Zhang and Shay 2019). Evidence from Weibo, a Chinese social media platform, examined after a major flood event indicates emotional responses are prominent (Fang et al. 2019).

2.3 THE CASE OF COLORADO FLOODS IN 2013

This study examines a major flooding event that occurred along the front range of the Rocky Mountains in Colorado in 2013 as a case for analyzing expressions of resilience. Unprecedented rainfall began on September 9 and continued through September 20, 2013. A severe flood caused by heavy rains impacted multiple communities along the Colorado Front Range, affecting 17 counties and damaging thousands of homes and some oil wells (Smith and Hennen 2013). The impact of the flood may have been worsened in part by a period of drought and severe wildfires the area previously experienced. At least one mountain community was cut off by floodwaters and road damage. Many others experienced mandatory evacuations, and the National Guard was called in to assist in rescue efforts. This event, in part, has spurred a response to resilience around the state, with the development of the Colorado Office of Resilience.

2.4 STUDY GOALS

Resilience is reflected through emotional responses. Existing evidence shows that emotions run high during disaster events, with negative emotions prevailing at least in the short-term (Ferron and Massa 2012; Fang et al. 2019). Some evidence shows that over time people will express more positive emotions (Garcia and Rimé 2019). As such, this study explores the following:

> RQ_1: Does the presence of positive and negative emotional discussions change before, during, and after the flooding event?

Empirical evidence also suggests social, and particularly family-based, responses are evoked when exposed to a natural disaster event like a flood (Wong-Parodi et al. 2015). This supports the idea that communication among community members is an important component of building resilience (Buzzanell 2010). This study also explores the following question:

> RQ_2: Does the use of social language change before, during, and after the event?

Resilience is brought about by an upheaval in one's daily life, often due to a disaster. This indicates the potential for a greater presence of uncertainty around issues of home and work. Yet, little research has examined the presence of such expressions of resilience. This study examines the following research question:

> RQ_3: Does the use of language related to a) work and b) home change before, during, and after the event?

3. METHODS

3.1 SAMPLE SELECTION AND DESCRIPTION

A sample of 210,303 public tweets relating to the 2013 Colorado floods between the dates of September 1st, 2013 and October 31st, 2013 were collected by and purchased from Gnip for this project. Gnip is an authorized reseller real-time and historical public Twitter data (Gnip). Though it is now owned by Twitter itself, this change of ownership took place in April of 2014 after the data for this project was already collected (Moody 2014). This study analyzed the content of the tweets themselves, with the tweet being the unit of analysis. Data collected includes links, location of the twitter user, User ID, and other Gnip metadata such as the time the tweet was posted.

3.2 METHODS OF TEXTUAL ANALYSIS

This study relies on textual analysis using the software program Linguistic Inquiry Word Count, or

LIWC. The program uses established dictionaries of terms that reflect various themes or categories. These terms are counted, and each text is assigned a score for any given theme based on the proportion of theme in the total terms used in the unit of text. For example, a score of 5.6 for the category *family* indicates that 5.6% of the terms used in that text contain family-related terms. This software is widely used across disciplines, and has been used specifically to analyze responses to disasters and to understand how resilience is expressed (Wong-Parodi et al. 2015; Ferron and Massa 2012; Garcia and Rimé 2019).

This study relies on the most recent LIWC dictionary from 2015, which contains broad categories that each have subcategories. For instance, a researcher can analyze all emotions under the affective processes category, or can choose to focus on just negative emotions or narrow the analysis down even further to just examine anxiety or sadness within negative emotions. This study uses several pre-established dictionaries in the LIWC program, including *positive emotions* (e.g., “happy”) and *negative emotions* (e.g., “cried”), *social* (e.g., “daughter”), *home* (e.g., “kitchen”), and *work* (e.g., “job”) (Pennebaker et al. 2015).

3.3 DATA ANALYSIS

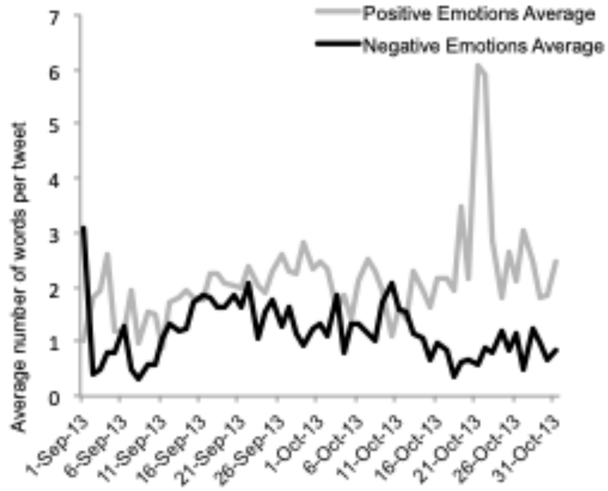
This study first examined frequencies of themes by date to ascertain broad descriptive categories over time. It then used chi-squared analyses to compare differences in terms used across three categories of tweets: before the event (September 1 - 9, 2013, N = 1,761), during the event (September 10 - 18, 2013, N = 168,719), and after the event (September 19 - October 31, 2013, N = 39,854).

4. RESULTS

4.1 EMOTIONS

An initial descriptive look at emotional language reveals that both positive and negative emotions increased during the event (see Fig. 1). After the event, negative emotions dipped closer to initial averages, while positive emotions remained higher than they were initially. On September 2 near the start of the data collection, the average for negative emotions was 0.40.[2] The average for negative emotions raised to 7.30 immediately after the start of the event on September 12, and was back down to 0.84 on October 31 at the end of the data collection. At the start of the data collection, the average for positive emotions was 1.02. After the start of the event, the average steadily grew to above 2 by the 17th of September, and it remained above 2 or close to 2 until the end of the data collection. The peak for positive emotions came in late October, with an average of 3.49 on October 19 and 6.09 on October 21.

[2] The negative emotions average (3.10) on September 1, the first date of the data collection, was much higher than the rest of the pre-event averages, which were nearly all below 1.



Analyses also compared how tweets before, during, and after the flood event portrayed negative and positive emotions. Tweets were significantly more likely to portray negative emotions during and after event, X^2 (2, *n* = 210,303) = 174.97, $p < .001$. Before the event, 13.3% of tweets contained negative emotions, while 22.8% and 24.9% of tweets during and after the event, respectively, contained negative emotions. Tweets were significantly more likely to portray positive emotions after the event than before or during the event, X^2 (2, *n* = 210,303) = 577.04, $p < .001$. Before the event, 26% of tweets contained positive emotions. During the event, a similar number -- 25.9% -- of tweets contained positive emotions. After the event, however, tweets were significantly more likely to contain positive emotions, with 31.9% of tweets containing positive emotional language.

4.2 SOCIAL LANGUAGE

References to social language were at an average of 3.41 at the start of the data collection on September 1 (see Fig. 2). After the event began, the average jumped to 7.29 on September 12, and remained in the 7 - 8 range until September 25. For the most part, social language averages remained above 4 for the rest of the data collection, with the final day of the data collection -- October 31 -- reflecting an average of 5.36.

Analyses also compared how tweets before, during, and after the event portrayed social language. Social language was significantly more likely to appear in tweets during or after the flooding event than before, X^2 (2, *n* = 210,303) = 1163.27, $p < .001$. Before the event, 58.5% of tweets contained social language. During the event, 81% of tweets contained social language. After the event, social language dipped, with 75.2% of tweets containing references to social aspects. Post-hoc standardized residuals showed that both of these categories -- during and after -- were significantly higher than before the event.

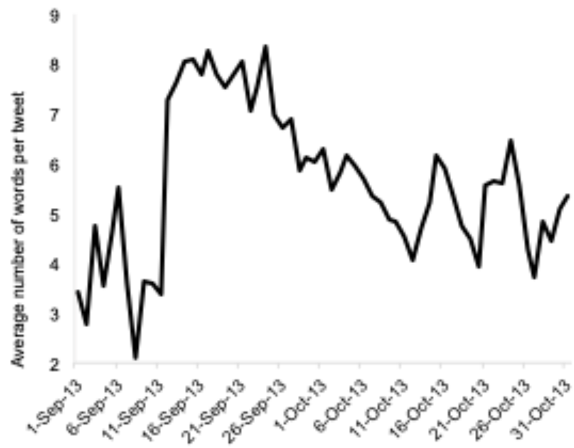


Figure 2. Social language used during tweets of the Colorado flood event in 2013.

4.3 LIFE EVENTS

This study also analyzed how life events were discussed in tweets throughout the time period of the flood event. References to work-related language were primarily at or below an average of 1 before the flooding started. Beginning with the date of September 12, work-related language averages rose above 1, where they stayed for the remainder of the study period with only 2 exceptions of dates where the average dipped below 1. References to home started quite low with an average of 0.09 on September 1. After the start of the flooding, the average for home-related language rose above 0.5, where it remained for most of the month of September. After September 29, the average of home-related language in tweets dipped below 0.5 -- closer to the initial average for the category -- for much of the remainder of the study period. There were a few dates in the month of October (October 22-27) during which the average raised above 0.5 again.

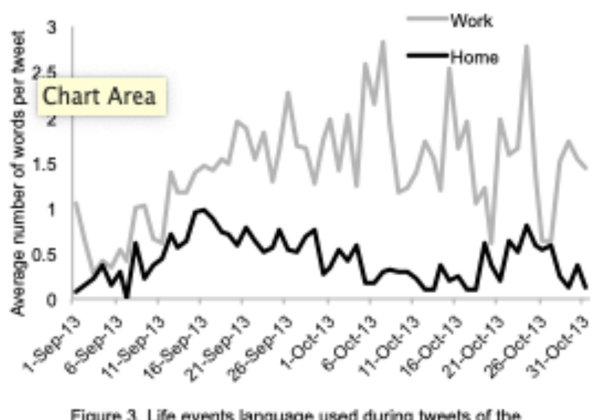


Figure 3. Life events language used during tweets of the Colorado flood event in 2013.

Follow-up analyses compared how life events -- or language related to work and the home -- changed over the course of the event. Work-related language was significantly higher during and after the event than before the flooding, X^2 (2, n = 210,303) = 822.75, $p < .001$. The percentage of work-related language in tweets that occurred before the flooding started was 11.7%, while the percentage of work language during the event reached 20.2%. After the event, tweets contained 26.4% of work language. Similarly, home language was significantly higher during and after the event than before the flooding started, X^2 (2, n = 210,303) = 342.524, $p < .001$. The percentage of language referencing the home was only 4.3% before the event, but 12.1% and 9.3% during and after the event, respectively.

5. DISCUSSION

Communication is part of managing the stress that accompanies the experience of an extreme weather event. This study analyzed the trajectory of expressions of resilience over time in tweets before, during, and after a major regional flooding event in Colorado in 2013. Findings show that Twitter discussions of the weather in Colorado and the flooding event engaged in higher emotional language -- both positive and negative -- after the event started, with positive language enduring after the event. Evidence also shows that issues with our work life and home life are impacted, with language around these categories increasing once the event starts and work language continuing after the event. Finally, the data show that once our emotions are triggered and our lives are impacted, people turn to their social support network with language around social issues high during and after the event.

Before we address the findings further, it's important to address limitations of the study. First, this study analyzed data on one platform over a limited time period for one weather event. Continuing this analysis over a longer period of time and across media platforms would help inform how the findings from this study generalize to other contexts. Still, analysis of data from Twitter affords a unique perspective on how individuals not associated with traditional media channels discuss major events. Furthermore, the data collected for this study included several dates before the flooding actually started. This allowed a baseline understanding of what kinds of language are used in the context of weather before things turn extreme. Second, the use of a dictionary-based computer-aided content analysis precludes the researcher from more advanced analysis of texts. In other words, identifying latent content, or more complex categories for which meaning is more subjective, was given up in favor of manifest content, or that which is more easily identifiable based on simple groupings of terms. Such an approach loses some of the nuances and complexities of human communication, but it gains the ability to more easily analyze large amounts of data available in such sources as social media.

The language people express during crises provides important insights into how they develop resilience and cope with such events. Recent perspectives on resilience consider communication to be a central component of it, and the data presented here supports this perspective. Two activities that are an important part of communicative resilience were displayed in the tweets during the Colorado floods: the foregrounding of positive emotions while downplaying negative emotions and the reliance on one's social network (Buzzanell 2010). Once the floods started, people expressed heightened emotions around life events, with positive emotions enduring. Additionally, social language (e.g., family, friends, neighbors) increased significantly once the floods started.

These findings have important implications for understanding how organizations can reach individuals during such events. The language organizations or other official sources involved in communication around crisis events such as extreme weather events use matters for how people perceive them and engage with the information they provide. If they reach them at the right times about the most salient topics in the moment, they are more likely to have successful communication. For instance, a hopeful frame may not be as effective prior to the turning point when individuals start expressing more positive than negative emotions. Or, engaging individuals in information seeking may be most effective if it is connected to their ideas around social support networks immediately after the start of the event, when those concerns are highest. In short, there are clear practical applications of this research for when and how we communicate with individuals in communities impacted by extreme weather.

Future research should continue to examine other aspects of communicative resilience during the flood events via social media analysis. How are people engaging in information seeking and sharing during events, and to what sources are they turning? Which organizations or trusted actors are they relying on for these information events? How are they developing efficacy aaround information gathering after such events? Such aspects can inform a deeper understanding of the communicative nature of resilience and how people cope with extreme weather events. They can also shape how we communicate with individuals affected by crises such as extreme weather events.

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