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AN EXPLORATION OF SOCIAL MEDIA IN EXTREME EVENTS: RUMOR THEORY AND TWITTER DURING THE HAITI EARTHQUAKE 2010

Completed Research Paper

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Abstract

Due to its rapid speed of information spread, wide user bases, and extreme mobility, Twitter is drawing attention as a potential emergency reporting tool under extreme events. However, at the same time, Twitter is sometimes despised as a citizen based non-professional social medium for propagating misinformation, rumors, and, in extreme case, propaganda. This study explores the working dynamics of the rumor mill by analyzing Twitter data of the Haiti Earthquake in 2010. For this analysis, two key variables of anxiety and informational uncertainty are derived from rumor theory, and their interactive dynamics are measured by both quantitative and qualitative methods. Our research finds that information with credible sources contribute to suppress the level of anxiety in Twitter community, which leads to rumor control and high information quality.

Keywords: Twitter, Social Media, Rumor Theory, Haiti Earthquake, Non-Parametric ANOVA, Semantic Network Analysis

Introduction

When it comes to breaking news, Twitter has seemed to replace the legacy mainstream media. In 2008, before the Sichuan earthquake, which killed nearly 70,000 Chinese people, a tremor was tweeted by a local resident to the outside world. It was three minutes ahead of U.S. Geological Survey (Gabarain 2008; Li et al. 2010). Recently, in January 2010, pictures of Haiti earthquake were first covered by Twitter and Facebook, which were later broadcast by CNN (Rosario 2010). Twitter reporting is so fast and real that, by the time mainstream media air those extreme events, they already become a trend word on Twitter search (Twitter As News-wire 2008).

The strength of Twitter lies not just on the speed of information spread. From the perspective of social media, another advantage is that, in a short period of time, Twitter users collectively cover major facets of disasters from multiple angles. Tweet texts linked to TwitPic (photshare site for Twitter) or Facebook video increase its reality. For instance, during the first day of Haiti earthquake, a Twitter user in Haiti tweeted that "lots of rumors about which buildings were toppled..The Castel Haiti behind the Oloffson is a pile of rubble..it was 8 stories high..," "we're back on line..went to St Gerard Church..people are trapped in the school..others are dead in the rubble." [1]A short moment later, pictures of disaster stricken Haiti followed. As Twitter spreads multi-faceted eyewitness stories so rapidly, mainstream media companies follow Twitter to cite those tweets or pictures as their news sources (O'Connor 2009).

Despite many advantages, however, warnings have been raised about the information quality of Twitter. During the Haiti earthquake, rumors circulated that UPS will "ship any package under 50 pounds to Haiti" or "several airlines would take medical personnel to Haiti free of charge to help with earthquake relief" (Leberecht 2010). These turned out to be hearsay rather than eyewitness accounts, and subsequently refuted by UPS and airline companies as false information. For this reason, Twitter is sometimes despised as a social media for propagating misinformation, rumors, and, in extreme case, propaganda (Leberecht 2010). This criticism is somewhat acknowledged by Biz Stone, a co-founder of Twitter, when he said that "credibility is key" for social media (O'Connor 2009).

The main thesis of this paper is largely to investigate social media in the extreme event scenario. The paper applies rumor theory to tweets posted during the Haiti Earthquake of 2010. This paper is organized as follows. The next section describes the theoretical framework by synthesizing two types of literatures: extreme events and rumor theory. Subsequently, data analysis of Twitter collected during the Haiti earthquake follows. Based on the result of quantitative data analysis, we subsequently carry out a semantic network analysis to further explore the tweet data. Practical implication of rumor theory in the context of social media and extreme events follows in conclusion.

Background Literature

This section synthesizes two main literatures to analyze Twitter data of Haiti earthquake. First, extreme event literatures are introduced to identify the environmental characteristics of natural disasters. Second, by applying rumor theory from psychology and sociology domains, we identify key variables which influence information quality in Twitter during extreme events.

Characteristics of Extreme Events: Uncertainties

Large scale natural disasters are usually characterized by "high consequence, low probability, ambiguity, and decision making pressure" (Runyan 2006). These characteristics cause abnormal pattern of communication and collaboration which is very distinct from that of normal business operations which presume some degree of stability, predictability, and common operating procedure. As the causes of natural disasters are uncontrollable and its future state is unpredictable, it easily renders infeasible the standard response and planning procedures. As the Haiti earthquake of January 12th in 2010 has shown, catastrophic events can quickly incapacitate national response capabilities and communication infrastructure, and hamper standard procedures of communication and collaboration. Therefore, it is essential for successful emergency response to anticipate the improvised assistance, ad-hoc communication endeavors, and adaptive collaboration among multiple agents such as firemen, police, volunteers, and governments with whom they have never collaborated before. In the mashed up Web 2.0 era, web users need to be included to the list of multiple agents that can rapidly improvise social collaboration and solve problems by exchanging situational information and creative ideas as a response to natural disaster.

[1] http://twitter.com/ramhaiti (from tweets of January 12th, 2010; accessed April 15th, 2010).

During the natural disasters, Twitter has shown the potential of improvising collaboration in a previously unthought-of way. Since the birth of Twitter, many web users have adopted Twitter as a tool for reporting their eyewitness accounts and relief activities during the natural disasters and relief operations (Mills et al. 2009). Distinct from the previous activities of Twitter, however, one unique feature of the Haiti earthquake in January 2010 was the dynamic collaboration of networked citizens. As soon as a magnitude 7.0 earthquake hit the capital city of Haiti, Port-au-Prince, the first pictures of the devastated scenes were first covered by Twitter and Facebook, which were later shown to the world by CNN. Following that, thousands of more pictures quickly spread through TwitPics and Twitter along with well wishes (Parr 2010). In addition, Twitter users shared the situational information of disaster stricken Haiti, tweeted the information on how to adopt orphaned children, and spread the way to send emergency supplies or aid money to Haiti. We believe there are important factors which condition the quality of the communication mode. In this paper we study what factors enable cooperative discourse under extreme events. Two key variables (anxiety and informational ambiguity) of rumor theory are introduced in the next section.

Rumor Theory: Anxiety and Uncertain Information

Rumor is a form of collective behavior surrounding information and psychology. It is a collective transaction in which many people offer, evaluate, interpret information, and from which they predict something. However, rumor sets in motion "in situations of relative collective ignorance and ambiguity about an event" (Aguirre et al. 2001). When ignorance and ambiguity are removed, rumor disappears. This section lays a foundation for using rumor theory to evaluate Twitter as a social reporting tool in the context of extreme events.

Rumor research originated from a study on abnormal communication under extreme events. After investigating characteristics of rumors which were prevalent during the World War II, Allport and Postman (1947) postulated rumor mongering condition as a multiplicative function of "importance" and informational "ambiguity" ($Rumor \approx importance \times ambiguity$) (p. 33). This formula emphasizes the multiplicative, not additive, relationship between importance and ambiguity. It implies that if either importance or ambiguity factor has zero value, then rumor never occurs. For a rumor to occur and travel, the rumor content must be important for rumor recipient, and information about the rumor must be shrouded with some degree of ambiguity.

Anthony (1973) argues that the importance factor in this rumor formula is difficult to measure. So, she subsumes the importance factor under the "anxiety" concept such that it is quantifiable by a psychometric tool such as the "Taylor Manifest Anxiety Scale." Her reasoning for this change is that, although a rumor recipient may not feel *anxious* about an *un*-important rumor, if s/he feels *anxious* about the rumor, then it is a signal that the rumor is *important* for her/him. In her new formulation, the level of *anxiety* is the proxy that measures the *importance* factor. The greater the anxiety, the more the content of rumor is important for the rumor recipient. Anthony's experimental test shows that the rumors travel faster in high anxiety groups than low anxiety ones. Simply put, Anthony's (1973) rumor formulation implies that the rumor is a multiplicative function of anxiety and informational ambiguity. In this formulation, the rumor is conceptualized as a verbal outlet to release emotional pressure (anxiety or concern) by rationalizing ambiguous information.

Rosnow and Fine (1976) maintain that "disasters and other crises are characterized by high importance, high ambiguity, low critical sensibility, and many rumors" (p. 52). It is similar to the argument of Allport and Postman (1947) that "In wartime, …, the conditions for rumor are optimal" (p. 34). Their statements imply that extreme conditions such as natural disaster and war cause high anxiety and high informational ambiguity, which lead to optimal condition of rumor mongering. Therefore, during the extreme event, unless proper information is provided to citizens in a timely manner, it is likely to stimulate anxiety of citizens to craft rumors. For instance, an examination of tweets on Mumbai terrorist attack in November 2008 shows that the lack of credential and timely information regarding activities of national security forces stimulated collective anxiety among minds of Indians, who in turn propagated groundless rumors filled with anger and distrust in national leadership through Twitter (Oh et al. 2010).

Rumor research in the sociology domain cites and shares key variables of rumoring in the psychology discipline: anxiety and informational ambiguity. Shibutani (1966) uses informational ambiguity and anxiety as key variables for rumoring. According to him, natural disasters accompany the stress of "collective ambiguity and anxiety" at the community level. These stressful conditions stimulate information seeking behavior, be it through mass media or peers, to release their stress. If they fail in obtaining the necessary information through governmental channels or mass media, then they improvise imaginary stories with plausible reasoning, and it begins to circulate as "unofficial news" among community to close the crack of collective ambiguity and anxiety (Aguirre et al. 2001). This

sociological approach basically views rumor as "collective process that arises when adequate information is unavailable, from formal or legitimate sources, to interpret a problematic situation or event" (Dahlhamer et al. 1994). Sociological rumor research stresses that the timely provision of assured information from trustful sources can reduce rumor spread by lifting informational uncertainties and its attendant anxieties from minds of citizens.

Recalling Anthony's rumor function ($rumor \approx anxiety \times informational\ ambiguity$), the sociological view of rumor shares fundamentally the same logic of rumor research in psychology. Rumor researches of both domains agree that those extreme events, such as earthquakes (Dahlhamer 1994; Festinger 1962), floods (Danzig et al. 1958), war (Allport et al. 1945; Allport et al. 1947), and terrorism (Oh et al. 2010), provide the optimal conditions of rumor mongering in that they create high level of anxiety and uncertain information. At the same time, these rumor theories provide insights that, during the extreme events, collective anxiety can be reduced and rumor spread can be controlled through the supply of correct and timely information with credible sources.

Rumor theory gives us a framework to evaluate the utility of Twitter as a social reporting tool during the Haiti earthquake. This paper started with an attempt to understand two issues: (1) the conditions in which Twitter be used as a reliable social reporting and social collaboration tool, and (2) the conditions under which Twitter can degenerate into a tool of collective rumor mongering. Rumor theory can give some hints to answer these questions. During the Haiti earthquake, many tweets, which were linked to reliable sources such as pictures, mainstream media, and organizations (such as Red Cross), contributed to reduce informational ambiguities and anxiety among networked citizens. According to rumor theory, during the large scale natural disasters, information quality (ambiguous or not), reliability of informational source, and level of anxiety among citizens are highly correlated. Following the logic of rumor theory, we posit that reduced anxiety and enhanced informational certainty in Twitter cyberspace can suppress rumors, and that is the necessary, although not sufficient, condition for emergence of problem solving discourse. Using two key variables of rumor theory, anxiety and informational uncertainty, the next section analyzes Twitter data on Haiti earthquake.

Methods

To collect data, we used #haitiearthquake as a search keyword at http://search.twitter.com[2]. We collected 10 days of primary Twitter data starting from the first day of Haiti earthquake, which ranged from January 12th, 2010 to January 21st, 2010. As we planned to carry out a content analysis through manual coding, our goal was to retrieve a comprehensive but manageable size of English language tweets that can best represent Haiti earthquake. For this reason, first, we excluded #Haiti from our search keyword list. The main reason was that it not only returned too large an amount of data (more than 3,000 tweets per day), but included lots of non-English tweets such as Creole and French. In addition, lots of tweets returned by the "#Haiti" keyword included posts which are not topically relevant to the Haiti earthquake. After trying several searches with various hash-keywords, we found that many users posted incident reports by attaching multiple hash-keywords such as #HaitiEarthquake, #HaitiQuake, or #HaitiHelp within their messages. As these three hash-keywords seemed to be the most frequently used and topically relevant ones made in English language, we selected #HaitiEarthquake as our search keyword. The initial sample size of English language was 962, and the data that we used in this paper includes content and time stamp of each tweet.

Data Description

Tweetting was most active on the first and second days after the Haiti earthquake. From the third day, number of tweet posts rapidly decreased. The first day, right after the earthquake hit Haiti, 15.5% (149/962) of total tweets were posted. Note that the first tweet of the first day was posted at 5:30pm US Eastern Time, 15.5% is a large amount of traffic for a single day. On the second, third, and fourth day, 34.9% (336/962), 15.0% (144/962), and 10.7% (103/962) of total tweets were posted respectively (See figure 2 in page 7 for details). Since then, the number

[2] Hashtag(#) is a user convention to include search context or metadata to each tweet. For example, users who intend to respond to specific event or topic include hash-tagged keyword (e.g., #haitiearthquake) at any place of their message so that other users can easily find the specific hash-tagged topic. During the Haiti earthquake, many users tweeted using such hash tags as #Haiti, #HelpHaiti, #Haitiquake etc.

of tweet posts rapidly declined. This posting pattern is consistent with Shibutani's (1966) finding that information providing and information seeking behaviors are most active right after the occurrence of a disaster.

Coding Scheme

To identify the content types of tweet posts, we used the Rumor Interaction Analysis Systems (RIAS) as our coding scheme, which was originally developed by Bordia (1996), Bordia and Rosnow (1998), and modified by Bordia and DiFonzo (2004). The updated RIAS includes 14 categories of communication modes: prudent, apprehensive, authenticating, interrogatory, providing information, belief, disbelief, sensemaking, directive, sarcastic, wish, personal involvement, digressive, and uncodable. From these 14 categories, we dropped 7 categories of digressive, personal involvement, wish, sarcastic, apprehensive, providing information, and sense making. The decision for dropping those 7 categories was made based on a survey of sample data. According to our survey, statements that belong to those 7 dropped categories were very rare. It may be due to the 140 character based Twitter interface with which it is impossible to do digressional or sense-making talk.

It is important to mention that, as a proxy of the anxiety variable, *apprehensive statements* are replaced by *emotional statements* in our coding scheme. Bordia (1996) and Bordia and DiFonzo (2004) originally defined the *apprehensive statements* to represent the anxiety variable as: "those [statements] that express *rumor related fear*, dread, anxiety or apprehension. Apprehensive statements would include statements that express a 'threatened' feeling" (Bordia 1996, p. 89). However, this definition is too narrow to describe the anxiety variable in that it implies only negative aspects of emotional feeling. In fact, Allport and Postman (1947) describe the anxiety variable by using such terms as "emotional tension,", "emotional pressure," or "emotional urge" (p. 36-37). They contend that the emotional tension not only includes negative feelings such as hate which creates "macabre and threatening tales," but positive feelings such as "hope and desire" that "underlie pipe-dream rumors" (p. 36). The underlying proposition that supports this emotional tension is that "our minds protest against chaos" (p. 37), hence, human beings desire to extract meaning out of uncertain information or situation to release their emotional tensions, be it positive or negative. Therefore, following Allport and Postman's (1947) original contention regarding the anxiety variable, we expand the *apprehensive statements* in RIAS to *emotional statements* to include both positive and negative emotional dimensions. Our final coding scheme is presented in Table 1.

Note that 'emotional statements' and 'authenticating statements' are our main interests for exploring the validity of rumor theory described in the previous section. Following rumor theory, we argued that anxiety and ambiguous information are key drivers of rumor mongering during the extreme events. In our coding scheme (Table 1), 'emotional statements' correspond to the anxiety variable of rumor formula, and authenticating statements correspond to tweets containing reliable sources such as links to pictures, mainstream media, or well-known organization (e.g., Red Cross). Therefore, the authenticating statements indicate *un*-ambiguous information which can reduce anxiety level. Exploring the relationship between anxiety and *un*-ambiguous information is the main purpose of data analysis, which will be detailed in the results section.

Table 1. Coding Category and its Definition

Category	Definition
Emotional Statements	Emotionally charged expression that includes both positive and negative feelings.
	Ex) "My soul is deeply sad"
Authenticating Statements	" Those that express the person's attempt to add credence to what he or she is saying. Thus, citing news media as source, references to self as an expert on something" (Bordia 1996, p.90)
	Ex) "CNN reporting a further 2 aftershocks in Haiti mag 5.9 and 5.5"
Interrogatory statements	"Questions seeking information. This category does not include sarcastic remarks or persuation attempts" (Bordia 1996, p.90).
	Ex) "Which relief agencies donate aid to re: **#haitiearthquake**? Red Cross?"
Prudent disclaimer statement	"Cautionary statements usually used to qualify what follows as being 'hearsay'. They can be thought of as guarded attempts at avoiding responsibility for what is being said" (Bordia 1996, p. 89)
	Ex) "I have no idea if it's true or not"
Disbelief statements	"Those that indicate that the person does not believe in the rumor" (Bordia 196, p.91)

	Ex) “That’s far-fetched…”
Belief statements	“Those which indicate that the person believes in the rumor ”
	“yes it is indeed....#haitiearthquake”
Work statements	Statements that “suggest a course of action.” (Bordia and DiFonzo, 2004, p.42).
	Ex) “Please RT to help the victims of today's earthquake.”
Not Codable	Statements that are not codable.

Unitizing

To use RIAS, Bordia et al. (1999; 2004) suggests dissecting a paragraph, sentence, or narrative into a unit of “one complete thought.” This process is needed to avoid some texts belong to more than one category. They say that “a complete thought provides enough information so that it can be interpreted by others and can stimulate a reaction in them” (Bordia et al. 1999). Our Twitter data sample, which has maximum 140 character strings, was already unitized. So no unitizing process was required.

Inter-Coder Reliability

For coding of Twitter data, we hired two masters’ students majoring in management information systems. Before coding, the two students were trained to understand the context of Haiti earthquake and definition of each coding category. The coding was made in two rounds. The first round was a pilot coding with a randomly chosen data sample of 100 points. The pilot coding produced a Kappa value of .974, which is extremely high. Confirming reliable pilot coding, the coders conducted a second coding with full data. The coding produced a Kappa value of .958, which is higher than acceptable level of reliability (.70). One author moderated the discussion with the students to re-code the disagreed data.

Quantitative Analysis: Non-Parametric ANOVA and Post-Hoc Tests

As shown in Figure 1, the most dominant communication modes during the Haiti earthquake are ‘authenticating’ (52.9%, 508/960), ‘emotional’ (12.3%, 118/960), and ‘work’ (23.6%, 227/960) statements. The implication is that, during the Haiti earthquake, dominant tweets were about expression of sorrow or compassion, credible situation update through links to pictures, mainstream media or Red Cross, and action statements which, for example, encouraged donation of aid money and relief supplies. To see how emotional statements (representing ‘anxiety’ factor in rumor theory) and authenticating statements (representing level of informational ambiguity in rumor theory) changed over time, we partitioned the whole data into four equal sample sizes (240 sample size for each) in chronological order, in which each dataset represents first to fourth stages.

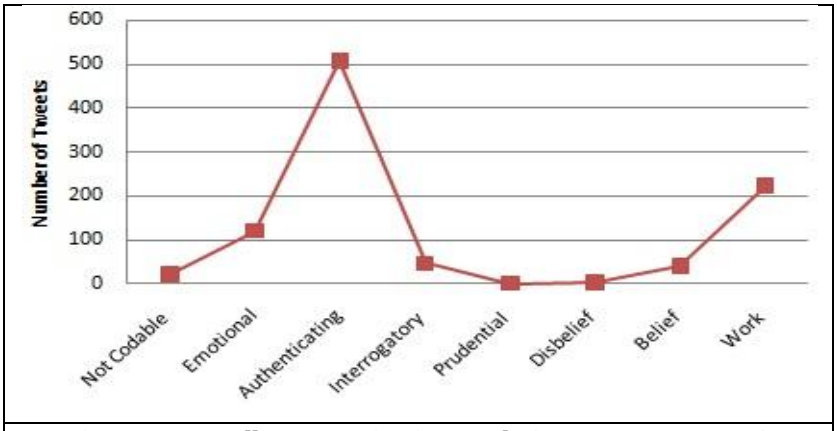


Figure 1. Overall Communication Mode (1/12/2010-1/21/2010)

To decide on the four-stage model, we ran multiple Friedman's non-parametric test for repeated measures with different candidate models of three-stage, four-stage, and five-stage.[3] The reason for choosing Friedman's non-parametric test was that our data was categorical. Friedman's test results for the three stage model results in: $\chi^2(2) = 1.22, p = 0.541)$. This means that the three equally divided datasets do not show any systematic differences in the communication mode. Therefore, the three-stage model is not adequate. Friedman's test result for the five stage model results in: $\chi^2(4) = 5.15, p = 0.272$. This means that the five equally divided datasets do not have any systematic differences in the communication mode. Therefore, five-stage model is not proper either. However, Friedman's test result for the four stage model shows: $\chi^2(3) = 9.919, p < 0.01$. This signifies that four equally divided datasets show significant differences in the communication mode over time. Therefore, the four-stage model is best for further analysis.

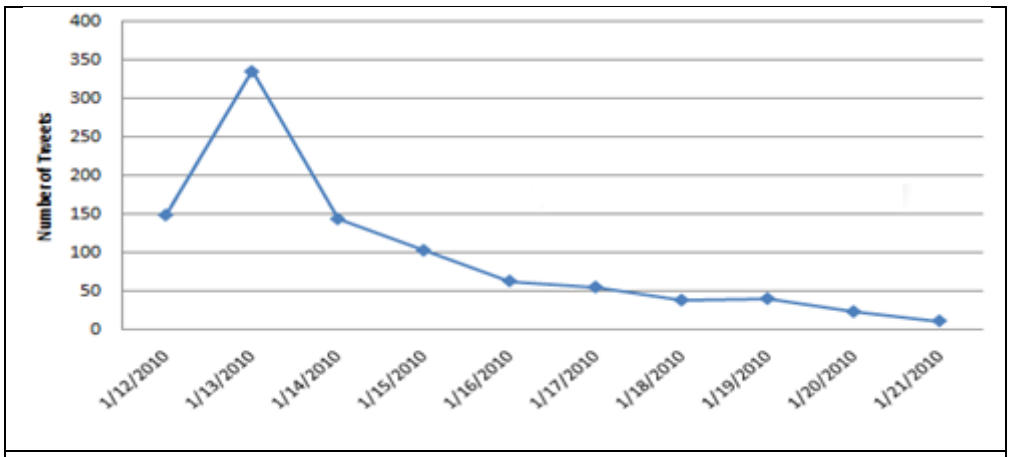


Figure 2. Number of Tweets Posted Each Day

Comparison of Figure 2 and Table 2 reveals the implication of the four-stage model. 50% of total tweets were very rapidly posted during the first and second stages (total 27 hours and 20 minutes), and the remaining 50% of tweets were made over a long periods of third and fourth stage (total 182 hours and 27 minutes). That is, as soon as earthquake hit Haiti, information providing and information seeking behaviors were most active in the first 27 hours, and the same activities declined sharply thereafter.

Table 2. Timeline of Four Different Stage

	Time Range	Time Duration	Number of Tweets
First Stage	1/12/2010 5:30 PM to 1/13/2010 11:00 AM	17hr 30min	240
Second Stage	1/13/2010 1:30 PM to 1/13/2010 11:20 PM	9hr 50 mins	240
Third Stage	1/13/2010 11:32 PM to 1/15/2010 1:30 PM	35hr 58mins	240
Fourth Stage	1/15/2010 6:30 PM to 1/21/2010 8:59 PM	146hr 29mins	240

After confirming that four stage model is best for our analysis, we ran Wilcox signed rank test, a nonparametric equivalent to the contrast test in ANOVA (Field 2005, p. 563; Siegel et al. 1988). In other words, after confirming that the four stage model is adequate for further analysis, we attempted to find if there was any significant difference in the communication mode by contrasting mean differences between each stage.

[3] In principle, the theory for Friedman's non-parametric ANOVA is equivalent to ANOVA. This method measures group differences based on ranked data. To use ANOVA, the data has to meet the requirements of normal distribution, homogeneous variance, and continuous or interval data (Field 2005, p. 557). However, our Haiti Twitter data is a categorical data. Therefore, as an alternative to ANOVA, we used the Friedman's non-parametric ANOVA.

Table 3. Wilcox Signed Rank Test			
	Stage2 - Stage1	**Stage3 - Stage2**	**Stage4 - Stage3**
Z	-3.408	-1.933	-.358
Asymp. Sig. (2-tailed)	0.001 ***	0.053*	0.720

Table 3 shows that significant mean differences exists between stage one and stage two at $p<0.01$, and marginal differences between stage two and stage three at $p<0.1$. However, no significant mean difference pattern exists between stage three and stage four. This means that communication patterns were significantly changing between stage one and stage two, and marginally changing between stage two and stage three. Figure 3 illustrates changes of communication modes from stage one to stage four.

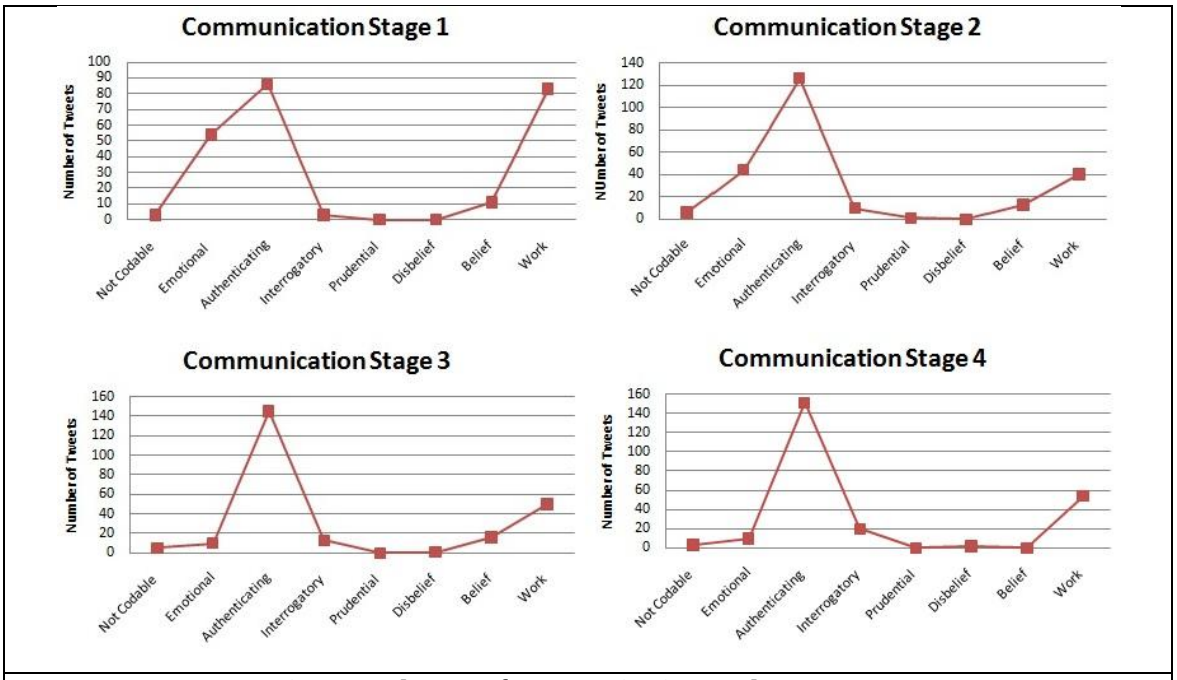


Figure 3. Changes of Communication Mode Over Stage

Figure 3 shows that changes of communication modes were mainly occurring in 'emotional statements,' 'authentication statements,' and 'work statements.' Especially, figure 3 shows that, as communication mode progresses from stage one to stage four, 'emotional statements' (representing anxiety in rumor theory) are declining dramatically. Note that, according to rumor theory, anxiety is one important variable which causes rumor mongering, and it can be controlled through *un*-ambiguous information ('authenticating statement' in this case).

Figure 3 represents that, as time progresses from stage one to stage four, main change of communication modes occurs in emotional statements (anxiety in rumor theory), authenticating statements (*un*-ambiguous information in rumor theory), and work statements. However, we still don't know (1) how they change, (2) if those changes are statistically significant, and (3) if there exists any interaction pattern between emotional statements (anxiety), authenticating statements (*un*-ambiguous information), and work statements. To answer these three questions, the same information for those three communication modes is differently visualized as Figure 4.

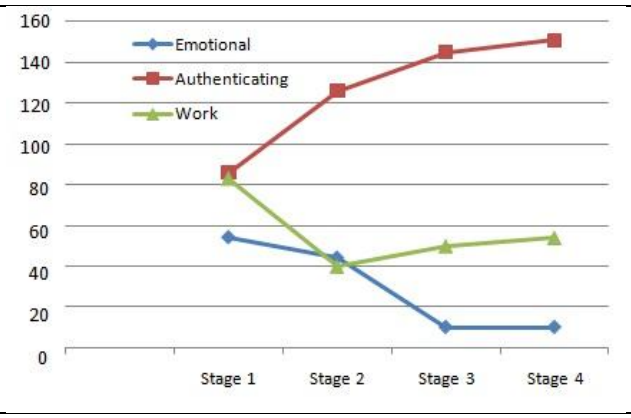


Figure 4. Changing Pattern of Emotional, Authenticating, and Work Statements Over Time

Figure 4 shows how emotional statements (anxiety in rumor theory), authenticating statements (*un*-ambiguous information in rumor theory), and work statements are changing as time progress from stage one to stage four. It also shows a pattern of interaction effects between emotional statements and authenticating statements. It means that, as number of authenticating statements increase, the number of emotional statements decrease over time.

To test if changes in communication modes represented in figure 4 are statistically significant and if reliable information contributes to suppress the level of anxiety, McNemar test is carried out. McNemar test is used to measure mean difference between two groups when data type is dichotomous (Field 2005, p. 538). The test results are presented in Table 4. The test result shows that number of authentication statements significantly increase as times goes from stage one to stage two. In contrast, work statements significantly decrease as time progress from stage one to stage two, and then its stays almost constant from stage two onward. In contrast, emotional statements significantly decrease as time passes from stage two to stage three. It is notable that, while the number of authenticating statements significantly increase between stage 1 and stage 2 at $p<.01$, the number of emotional statements significantly decrease between stage 2 and stage 3 at $p<.01$. This time lag effect between authenticating statements and emotional statements indicates that sufficient amount of authenticating information is required to suppress rumor in the community.

Table 4. Mean Difference of Each Statements Over Time ***=p<0.01

	Stage 1-Stage 2			**Stage 2- Stage 3**			**Stage 3-Stage4**		
	N	χ^2	**Sig**	**N**	χ^2	**Sig**	**N**	χ^2	**Sig**
Authenticating	240	13.556	.000***	240	2.592	.107	240	.132	.716
Emotional Statements	240	1.635	.201	240	15.373	.000***	240	N/A	.832
Work Statements	240	18.391	.000***	240	0.681	.409	240	.115	.734

Although an interaction and time lag effect between emotional statements and authentication statements can be explicated through rumor theory, it is not clear if the relationship between emotional, authenticating, and work statements can be seen as a three-way interaction effect. What we can infer from rumor theory is that, in a condition where both anxiety and informational ambiguity are at high level, work statements cannot arise. In that setting, only rumors will flourish, and work statements which encourage helping others will rarely occur. But, we leave the possibility of three way interaction effects between emotional, authenticating, and work statements as a future research agenda.

Qualitative Analysis: Word Relations for the Haiti Earthquake Tweets

The previous section analyzed changing patterns of communication mode in a quantitative manner using non-parametric statistic methods. To further explore the inter-relation among different words and statement categories,

we analyze the same data using a qualitative text analysis method. To extract meaning that may be hidden in each statement category or between categories, we employ semantic network analysis.

Semantic network analysis originated from theories of meaning. Krippendorff (2004) maintains that "associations of concepts in someone's mind manifest themselves in co-occuring words" (p. 290). In semantic network analysis, identifying which word co-occurs with which word how frequently is important to extract its deeper meaning. Semantic network analysis investigates meaning not through a word, but through word relation. Therefore, semantic network analysis takes a pair of words as unit of analysis (Carley 1997a). For semantic network analysis of Twitter data, we use Automap software to visualize the semantic map (Carley 1997a, 1997b; Diesner, Frantz, & Carley, 2005).

Measure: Word Frequency, Co-occurrences, and Eigenvector Centrality

Using Automap software, we computed three measures: word frequencies, co-occurrences among words, and the relative centrality of words (available on request) within a semantic network. Prior to the computations, we first processed data cleaning by removing numbers, punctuations, and meaningless words (e.g., 'am,' 'the,' 'was' etc) and by unifying different forms of same words (e.g., pray, prays, praying and prayer were unified into a pray). After completing data cleaning, a total of 1069 words remained for further analysis.

With the co-occurrences of all pairs of words, we constructed a word-by-word matrix which embodied a semantic network. The matrix data allowed us to compute a network property of each word, called eigenvector centrality (available on request). Simply put, eigenvector centrality weighs the relational (or co-occurrence) strengths by considering the prominence of the co-occurred words. If a word is connected with a high frequent word, the word will be positioned more central in a network compared to a word which is connected with a less frequent word. Eigenvector centrality is an appropriate indicator to examine which concepts are important to understand social information processing of tweets, because a word connected to a more popular keyword is more likely to be used (and searched) and more likely to contribute to build a discourse pattern surrounding a specific issue. Let's suppose that the words 'donation' and 'children' appeared at an equal frequency. Despite the same frequency, the eigenvector centrality between the two can be different depending on with which word that they co-occur. Stated differently, the eigenvector centrality of 'donation' would be higher than 'children' if 'donation' co-occurs with a very popular hash tag (e.g. #HaitiEarthquake) while 'children' co-occurs with a hash tag of less popularity (e.g. #Adoption). In this example, cognitive processing may highlight the issue of 'donation' more importantly than 'children', not because 'donation' appeared more frequently but because 'donation' is associated with a more prominent hash tag than 'children'

Result of Semantic Network Analysis

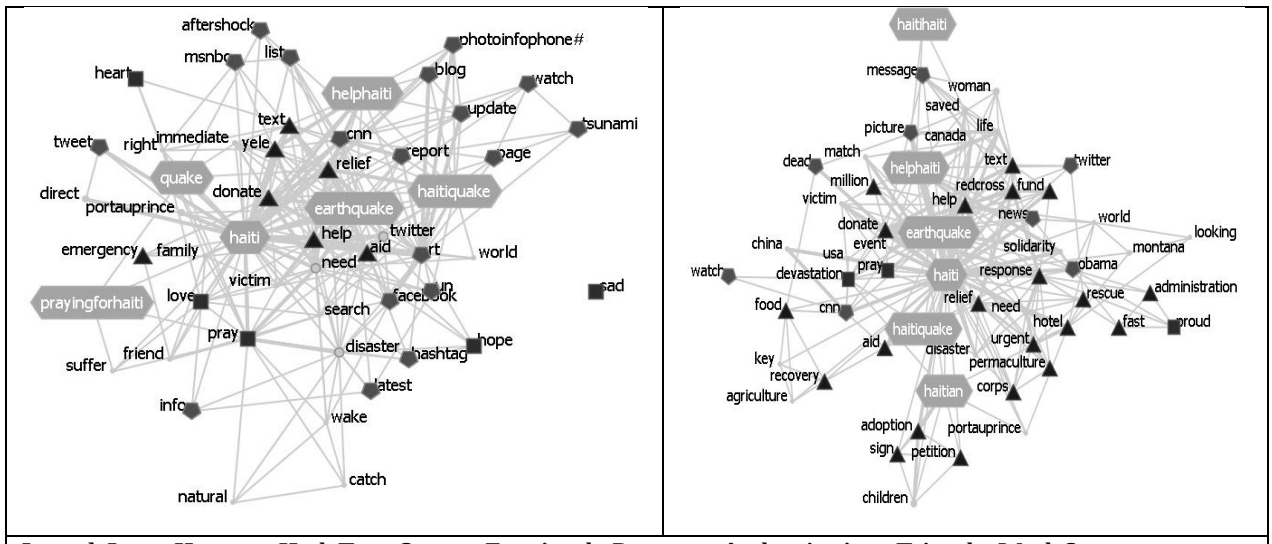
We ran semantic network analysis with the four equally divided data sets identified earlier to explore the changing patterns of communication mode from stage one to stage four. From 240 data samples of each stage, 50 most frequent words and their relations were further analyzed. As expected, such words as "Haiti," "Earthquake," and "HelpHaiti" are seen to be constructing the overall theme of our dataset across four all stages. Hash tagged words are represented as a large hexagon in figure 5.

Figure 5 represents the word connection patterns, which form the Twitter discourse surrounding #Haitiearthquake[4]. First, figure 5 shows that emotional statements appear during the first stage. For example, "pray" appeared 25 times in stage 1, 13 times in stage 2, 9 times in stage 3 and completely disappeared in stage 4. Also note that the influential hash tagged word "PrayingForHaiti" in stage 1 completely disappears from stage 2. This pattern is consistent with our statistical findings, which were represented in figure 3 and figure 4. In stage 1, emotional statements are hinted by such words as 'hope,' 'heart,' and 'sad'.

Even though stage 1 and stage 2 show many emotional statements, the network analysis result shows that the positions of those emotional words are marginal rather than central. For instance, in stage 1, although 'pray' (emotional statement) and 'rt' have a same frequency of 25, eigenvector centrality value of prayer is only 0.128 which is much less than that of 'rt (0.467)'. The case is similar in stage 2. Although frequency of 'prayer (13)' is

[4] Due to the page limit, only the first and last stage network maps are presented in Figure 5.

similar to 'relief (15)' (work statement), and 'life (12),' the eigenvector centrality value (0.117) is much lower than that of 'relief (0.228)' and 'life (0.295). This means that emotional statements are connected to less influential words (low eigenvector centrality words), thus, their position is only marginal in the complete semantic network map. Instead, what emerged as central are the authentication statements. Some words belonging to authentication statement category include "blog," "CNN," "picture," "list," "info," "report," and "update" etc. These words represent reliable sources of information to authenticate the veracity of tweets. Therefore, consistent with our statistical findings of the previous section, these words contribute to reduce the level of informational ambiguity in tweet posts. Interestingly, while authenticating statements construct their own cluster during stage 1 and stage 2, they not only more strongly connected to but also evenly distributed towards work statements in stage 4.



Legend: **Large Hexagon: Hash Tag; Square: Emotional; Pentagon: Authenticating; Triangle: Work Statements**

Figure 5. Semantic Network Map of Haiti Twitter (Left Map – Stage 1, Right Map – Stage 4)

Another interesting finding, which was not clearly visible in the previous statistical finding (see figure 4), is the relative importance of work statements throughout all four stages. Exemplary words include "donate," "help," "relief," "adoption," "aid," "yele,[5]" "redcross," "bush-foundation" and "text" (texting was the main channel for mobile donation). Especially, a work statement, "donate," shows the highest frequency (49) and highest eigenvector centrality (0.624) next to central theme words of "Haiti" and "Earthquake". This meaning of work statements could not have been captured by quantitative statistic methods, as it did not take into account word relations. However, qualitative semantic network analysis has helped find the central role of work statement by considering word relations.

Conclusion

Rumors are a collective behavior surrounding information and based on the psychology of humans. Rumors involve an activity of creating, exchanging, and evaluating information at the collective level (Shibutani 1966). This paper analyzed Twitter data of Haiti earthquake 2010 through the lens of rumor theory. Results of both quantitative and qualitative analysis validate that 'anxiety' and 'informational ambiguity' are key variables to understand abnormal communication patterns under extreme events. Our finding confirms that reliable information with credible sources can contribute to reduce anxiety, suppressing groundless rumor.

[5] Yele is a shortname for Yele Haiti Foundation. During the Haiti earthquake, Yele played central role in raising relief fund to restore Haiti.

Summarizing human behavior studies of extreme events, collective problems are associated with difficulties in reaching common sense-making in uncertain situations (Hudson 1954; Quarntelli 1986). These problems tend to arouse levels of anxiety in disaster stricken communities. In this context, our study sheds light on a mechanism to control level of anxiety through certain information with reliable sources, particularly at the early stages of post-disaster. Our study suggests that the high levels of anxiety can be controlled at the early stage through feeds of credible and accurate information by means of links to websites of the emergency response center or authenticating governmental organizations, RSS, streaming videos, photo, text message, or Retweet etc. This finding is important for emergency response strategy in the so called Web 2.0 era when many people are interconnected with social media. This suggestion is in line with Shibutani's thesis that under extreme events, citizens show urgent information seeking and exchanging behavior (Aguiree et al. 2001). If reliable information is not provided in this short period of urgent time, then it is likely to stimulate citizen's anxiety such that rumor propagates to fill the gap of informational uncertainties. Therefore, speedy provision of credible information is important to turn citizens' anxiety to positive energy of helping relief activity. From our findings, as a practical implication of rumor theory in online communities under the extreme event scenario, we argue that it is important to (1) monitor social media to assess the level of social tension, and (2) feed in certain information at the early stage of post-disasters as a emergency response strategy in the Web 2.0 era.

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