Retweet count matters: Social influences on sharing of disaster-related tweets

Abstract
Communication during disasters increasingly relies on social media technologies. For example, many people used Twitter to share information in the aftermath of the 2011 Great East Japan Earthquake. The current paper concerns how a forwarding count, or the number of others who have already shared a message, might influence people’s likelihood of forwarding disaster-related tweets. The results of a human-subjects experiment demonstrated that, when forwarding counts increased, the likelihood of sharing increased for tweets by persons but decreased for tweets by media. These social influences disappeared when forwarding counts were over 1,000 people. The results from a questionnaire further showed that how people perceived the tweets could not explain the social influences observed in the experiment well, but could predict the likelihood of sharing. These findings extend the understanding of how people share disaster-related information using social media technologies, which is essential for improving social media for disaster management.
Introduction

Social media technologies, such as Twitter and Facebook, have become part of people’s everyday lives. Using these technologies, people not only acquire new information but also generate content and influence trends. Given the growing use and participatory nature of social media, better understanding of how people behave in such an environment is essential.

The work reported here aims at better understanding how people make decision about whether or not to share, or forward, disaster-related messages in a Twitter-like environment. The motivation is that communication during disasters increasingly relies on social media technologies. For example, Twitter played an important role in sharing information and coordinating responses during the disasters caused by the Great East Japan Earthquake in March, 2011 (Ogiue 2011; Tachiiri 2011). In Twitter, users post brief messages of 140 characters or less. These messages called tweets are immediately broadcast to the users’ followers. Twitter users can also re-tweet others’ tweets through a click of a button, allowing them to pass information instantly to their followers and contribute to the far-reaching spread of information. The sharing decision studied in the current work is akin to the re-tweeting decision.

Although Twitter and other social media technologies allow people to obtain useful information in real time and make sense of the situation (Doan et al. 2012; Cataldi et al. 2010; Jansen et al. 2009; Demirbas et al. 2010; Sankaranarayana et al. 2009; Sasaki et al. 2010; Sriram et al. 2010, Sutton et al. 2008), these technologies also facilitate the spread of inaccurate information. In fact, in the aftermath of the Great East Japan Earthquake, Twitter was filled with false tweets about radiation, supplies, and other disaster-related issues, which caused psychological stress to citizens and interfered with the disaster response coordination (Inose 2011). The Japanese government posted messages online that alerted people to unverified information on social media. Similarly, the Federal Emergency Management Agency (FEMA) created rumor control web sites for the 2012 Hurricane Sandy and the 2013 Oklahoma Tornado, which listed false social media messages together with facts (FEMA 2012; 2013). However, these rumor control techniques may not prevent some individuals to keep spreading false information (Tanaka et al. 2013). Disasters will happen in the future. People will share information with others using social media technologies, and far-reaching spread of misinformation during disasters will have significant impact on society. Better understanding of how people pass information in social media will be helpful for increasing the proportion of useful information in social media during responses to disasters. The practical implications of the current work will help better prepare citizens and officials for disaster management using social media.
In particular, the work presented here addresses two research questions. The first question is:

*How does social influence play a role in people’s decision to share a disaster-related message in a social media environment?*

Social information, such as information about how many people have liked or shared a message, is part of social media technologies. In Twitter, an example of social information is the number of re-tweets, or the number of people who re-tweeted the message. Re-tweeting is a kind of sharing, in which an original tweet is broadcast to the re-tweeter’s followers through a simple clicking of a re-tweet button. Past studies show that social information influences judgment and decision-making (e.g., Salganik, Dodds, & Watts 2006). However, it is unclear whether or not this social influence extends to sharing of disaster-related messages in social media. Thus, the main topic of the current paper is whether or not and what kinds of social influences take place on sharing of disaster-related tweets. In addition, the present paper focuses on understanding why social influences take place, in particular, if people’s perceptions of disaster-related messages can explain the observed social influences on these messages. The data on perceptions of messages are also useful for predicting observed sharing decisions, which leads to the second research question:

*How does people’s perception of a disaster-related message relate to their decision to share it in a social media environment?*

Rumor psychologists have identified some perceptions such as anxiety and importance that affect rumor transmission in face-to-face environments (e.g., Rosnow 1991). One goal of the current work is to test if these findings extend to sharing of disaster-related tweets.

Through a human-subjects experiment and a questionnaire using actual tweets related to the Great East Japan Earthquake, the work reported here makes theoretical contributions by extending theories of social influence and rumor psychology to sharing of disaster-related messages in social media. By doing so, the current work also adds to research on revealing the relationship between the structure of online social networks and the spread of information and behaviors (e.g., Aral et al. 2009; Aral & Walker 2011, 2012; Cha et al. 2010; Fang et al. 2013; Huberman et al. 2009; Kwak et al. 2010; Leskovec et al. 2007). Moreover, it complements research on predicting the spread of information based on its content (e.g., Asur & Huberman 2010; Bandari et al. 2012; Ha & Ahn 2011).

**Theoretical Background**

Relevant to the current paper’s topic of how people share disaster-related messages, people spread rumors during responses to disasters (e.g., Prasad 1935, 1950; Sinha 1952). A rumor is
unverified information in times of uncertainty that is relevant and seems useful to understand the situation and manage risk (Allport & Postman 1947; DiFonzo & Bordia 2007; Rosnow 1991; Shibutani 1966). Similarly, the messages related to the Great East Japan Earthquake used in the current work, including messages discussing tsunamis and nuclear disasters, appeared in uncertain times and were unverified and relevant.

Most prior work on rumor psychology examined rumormongering in face-to-face environments. One difference between face-to-face and social media environments is that social information, or the collective opinion of others, is often available to the users in social media environments. For example, Twitter provides re-tweet counts. In face-to-face environments, information about how many others have shared a message is not readily available.

The work presented here extends ideas from research on rumor psychology and social influence to better understand how people use social information for their sharing decisions. Table 1 shows the overlap between the topics of some closely related work and those of the current work, where a ✗ indicates that a given line of research covers a particular topic.

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<th>Table 1. The Overlap between the Topics of Relevant and Current Research</th>
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<td><strong>Research</strong></td>
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<td>Collective opinion online (e.g., Salganik et al. 2006; blinded 2009)</td>
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<td>Social networks online (e.g., Aral &amp; Walker 2011; Huberman et al. 2009)</td>
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<td>Information transmission (e.g., Berger &amp; Milkman 2012; Ha &amp; Ahn 2011)</td>
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<td>Rumor transmission (e.g., DiFonzo &amp; Bordia 2007; Rosnow 1991)</td>
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**Social Influence**

People are social beings. They often rely on other’s behavior to shape their own. By observing and imitating others, people can entertain solutions that they would not have even considered otherwise (Bandura, 1965). Previous studies in face-to-face environments have suggested that people have a strong motivation to compare their opinions with others (Festinger 1954). People often adopt the decisions of others (e.g., Cialdini & Goldstein 2004; Deutsch & Gerard 1995; Gureckis & Goldstone 2006) due to their desire to make correct responses under uncertainty (Sherif 1935) or their desire to be liked by others (Asch 1951; 1955; 1956). During responses to disasters, people are uncertain about the current situation and future outcome. In such an environment, people will try to reduce the uncertainty by relying on others to obtain accurate information (cf. Deutsch & Gerard 1995; DiFonzo & Bordia 2000).

More recent work has shown that knowing other’s decisions also influences people’s decisions in online environments. In an online market experiment, whereas good pieces of music were always popular (i.e., downloaded by many people) and poor ones were always unpopular, the popularities of the pieces in between varied depending on whether or not people knew the number of downloads the pieces had (Salganik, Dodds, & Watts 2006). In another set of online experiments, subjects liked the same information more when associated with many supporters than a few supporters (blinded 2009). The subjects even switched their preferences when the assumed numbers of previous supporters were flipped (blinded 2009; Salganik & Watts 2008). Social information, such as the number of existing supporters and average ratings, can influence liking and rating in online environments (blinded 2010; 2012). This influence of social information on behavior is the definition of social influence in the current paper.

Would the same type of social influence take place when people make decision about information sharing in a Twitter-like environment? The answer to this question is unclear. In contrast to the work reviewed previously (e.g., blinded 2009; blinded 2010), which has suggested that people would adopt social information in social media contexts, other studies have concluded that people might share information that others have not shared (Berger & Heath 2007; Snyder & Fromkin 1980; Tian, Bearden, & Hunter 2001). Some people might want to be unique and try to differentiate their behavior from others’. In this case, people will go against social information. Although these two conjectures make opposing predictions, they agree on the idea that social information will influence people’s decision about whether or not to share messages in social media environments. By contrast, the third possibility is that people
ignore social information and their sharing decision is solely based on the content of the message (Haidt 2001; Hilton 1995). In this case, there will be no social influence.

One contribution of the present work is the extension of past work in social influence to people’s information sharing behavior in a social media environment. Researchers who focus on the social dimensions of the spread of information and behaviors tend to examine the effects of aspects related to social network structures, such as the number of followers and the position in the social network, on spread (e.g., Aral & Walker 2012; Cha et al. 2010; Huberman et al. 2009; Kwak et al. 2010; Xin et al. 2012). Other researchers examining information spread focuses on factors such as valence and credibility (e.g., Berger & Milkman 2012; Castillo et al. 2011; Fragale & Heath 2004; Ha & Ahn 2011; Heath 1996; Oh et al. 2010; Rene et al. 2012). These past studies on information spread tended to focus on the data mining methodology (see Raafat et al. 2009 for a review), although newer studies have started to use field experiments (e.g., Aral et al. 2009; Aral & Walker 2011, 2012). In contrast, rumor psychologists have conducted experiments with humans to understand rumormongering, but they have not focused on how social information might affect the spread of rumors. Instead they have studied the effects of psychological factors, such as anxiety and importance, on rumor transmission (e.g., Anthony 1973; DiFonzo & Bordia 2000; Rosnow 1991), which is the focus of the next review.

Perception

In rumor research, Allport & Postman (1947) developed a basic law of rumor based on their analysis the spread of rumors after WWII. They proposed that rumor transmission was a function of the importance of the rumor to the person multiplied by the ambiguity of the evidence pertaining to the rumor. Later, Anthony (1973) introduced anxiety as another key element in rumormongering. In school settings, anxious students were more likely to report that they heard a rumor (Anthony 1973) and that they passed on a rumor (Jaeger et al. 1980). Moreover, how anxious people felt after reading a rumor predicted how likely they were to share the rumor (Rosnow et al. 1988). Jaeger et al. (1980) and Rosnow et al. (1988) also showed that people were more likely to share a rumor when they believed the rumor to be more accurate or true (see also DiFonzo & Bordia 2007; blinded 2013; Rosnow 2001).

Rosnow (1991) combined these findings and extended the basic law of rumor by Allport and Postman (1947). He proposed four factors behind rumor transmission: uncertainty of the situation, relevance of the rumor to the person, anxiety associated with the rumor, and trust in the rumor based on its perceived accuracy. Of these four factors, uncertainty and relevance are
akin to ambiguity and importance in the basic law, and anxiety and trust are new additions that are absent in the basic law.

In addition to the four factors identified by Rosnow (1991), the perceived familiarity and informativeness of messages can also predict rumor transmission under some conditions (DiFonzo & Bordia 2007). For example, increasing the familiarity of a message can increase its perceived truth (Hawkins & Hoch 1992; Hawkins et al. 2001), and, as mentioned before, people are more likely to spread rumors that they believe to be truer (DiFonzo & Bordia 2007; blinded 2013; Rosnow 2001). People are also more likely to share a message that they believe to be informative, because they want to help others by passing on useful information (DiFonzo & Bordia 2007).

A few recent studies have tested these proposals mostly developed through rumor studies in face-to-face environments, such as universities, organizations, and communities, in social media environments (Oh et al. 2010; Spiro et al. 2012; Tanaka et al. 2012). For example, Spiro et al. (2012) analyzed tweets about the Deepwater Horizon oil spill in 2010 and concluded that perceived importance was a key element of rumormongering based on their observation that an event with high media coverage was more likely to be re-tweeted. Tanaka et al. (2012) directly asked Japanese subjects how important, accurate, anxiety provoking, and familiar they thought a series of rumor tweets related to the Great East Japan Earthquake as well as their intent to share the tweets. They found that familiar tweets were perceived as more accurate, as in the past work (e.g., Hawkins & Hoch 1992). However, inconsistent with the past findings from rumor research, Tanaka et al. (2012) found that only the perceived importance of a tweet had significant positive relation to Japanese people's intent to share the tweet. The current work aims at gaining deeper understanding of the extent to which perceptions that past studies have identified to be related to rumor transmission also apply to information sharing on social media.

Another perceptual factor, which has not been extensively researched in relation to information sharing, is fluency, or the ease of processing information. The feelings-as-information theory (see Schwarz and Clore 2007 for a review) proposes that fluency can influence various judgments, including people's perceptions of truthfulness (Begg et al. 1992), effortlessness (Song & Schwarz 2008), risk (Song & Schwarz 2009), intelligence (Oppenheimer 2006), and liking (Reber et al. 2004). For example, in the Song and Schwarz (2008) studies, subjects thought that the instructions for exercise routine and Japanese roll recipe written in an easy-to-read font type would require less effort to follow than the same instructions written in a hard-to-read font type. Similarly, people may like the same message better and find it more believable in
an easy-to-understand form than in a hard-to-understand form. Fluency might affect people’s perception of messages in social media and their intention to share these messages.

Of the factors reviewed in this section, the ones that relate to the perceptions of disaster-related messages are importance, anxiety, accuracy, familiarity, informativeness, and fluency. Uncertainty is more about the situation than about individual messages. The current studies focus on examining the relationship between these six perceptions associated with a disaster-related message and the decision to share it on social media. By doing so, the results from the present work will contribute to better understanding how perception relates to sharing of disaster-related messages in social media.

**Source**

Messages on social media come from various sources. One concern is whether or not people’s perceptions of a disaster-related message and their decision to share it would differ depending on whether it comes from a person or media. The interest here is not the effect of knowing the source on sharing decision, but whether or not there are differences in the way media and persons express messages that people are sensitive to. The current work will provide an answer to this question by examining whether people differ in their responses to messages by persons and those by media without knowing the sources of the messages.

Past studies on rumors suggest that people are more likely to pass along rumors by credible sources (Knapp 1944). When a credible source communicates a rumor, the believability of the rumor can increase (Blake et al. 1974; Porter 1984), which in turn can increase the sharing of the rumor (DiFonzo & Bordia 2007; blinded 2013; Rosnow 2001). On the other hand, Oh et al. (2010), who analyzed the source credibility of tweets related to the Haiti Earthquake, concluded that having a credible source could play an important role in reducing the anxiety level of Twitter users, which could in turn control the spread of false rumors. However, these studies do not address how differences in writing style between media and individuals might influence people’s perception and sharing decision. The results from the work reported here will reveal if people process messages by persons differently from those by media without knowing information about the source. The results will also reveal whether or not messages by media and those by persons result in different ways in which social information affects sharing behavior.
Hypotheses

Based on the review of the relevant research, we hypothesize that social influence will play a role in individuals’ decision about whether or not to share a disaster-related message in social media environments (H1). In particular, one hypothesis is that people adopt social information in social media contexts (cf. blinded 2009; Salganik & Watts 2008):

_H1a: Positive Social Influence_ – in deciding their likelihood of sharing a disaster-related message in a social media environment, people will follow the information about the number of others who have already shared the message.

An alternative account is that people share information that others have not shared in an attempt to differentiate themselves from others (Berger & Heath 2007; Snyder & Fromkin 1980; Tian et al. 2001):

_H1b: Negative Social Influence_ – in deciding their likelihood of sharing a disaster-related message in a social media environment, people will go against the information about the number of others who have already shared the message.

Another plausible outcome is that people ignore social information and their sharing decision is solely based on the content of the message (Haidt 2001; Hilton 1995). In this case, there will be no social influence. _H1a_ and _H1b_ relate to our first research question: _How does social influence play a role in people’s decision to share a disaster-related message in a social media environment?_ These two hypotheses are pit against each other using subjects’ responses from an experiment.

The second research question was: _How does people’s perception of a disaster-related message relate to their decision to share it in a social media environment?_ The review of past work on rumor theories (Allport & postman 1947; DiFonzo & Bordia 2000; Rosnow 1991) and the feelings-as-information theory (Schwarz & Clore 2007) has suggested the following hypothesis:

_H2: Perception_ – perceived importance, accuracy, anxiety, familiarity, informativeness and fluency associated with a message will relate positively to people’s likelihood of sharing the message in a social media environment.

Table 9 summarizes our research questions and hypotheses. The main purpose of the work presented here was to test the three hypotheses. Study 1 is about testing _H1a: Positive Social Influence_ and _H1b: Negative Social Influence_ through a human-subject experiment using actual tweets related to the Great East Japan Earthquake. Study 2 is a questionnaire using the same tweets as Study 1, and concerns _H2: Perception_ as well as whether or not people’s perceptions
of the tweets can explain the results observed in Study 1. The current work will also reveal whether or not the pattern of social influence and the likelihood of sharing observed in Study 1 differ between messages by media and those by individuals. Figure 1 visualizes the main interests of the current paper.

![Figure 1](image-url)

**Figure 1.** The main interests of the current paper are how social information (H1a and H1b) might influence (single-headed arrow) and perception (H2) might relate to (double-headed arrow) people’s likelihood of sharing disaster-related messages on social media. See text for descriptions of H1a, H1b, and H2. The present paper also focuses on whether or not people’s perceptions of disaster-related messages can explain the observed social influences on these messages and the likelihood of sharing as well as whether or not the pattern of social influence and the likelihood of sharing differ between messages by media and those by individuals.

**Study 1: An Experiment in Social Influences on Information Sharing**

Study 1 addressed how knowing sharing decisions of others might affect people’s sharing behavior in social media during responses to disasters. In Twitter, for example, re-tweet counts indicate the aggregate sharing decisions. How does such social information influence people’s sharing of disaster-related tweets? Do people adopt social information, in accord with H1a:
Positive Social Influence, or do they go against social information, consistent with H1b: Negative Social Influence?

In particular, Study 1 focused on sharing of English tweets related to the Great East Japan Earthquake as an example. Past work has reported a strong correlation between English and Japanese tweets discussing events related to this earthquake (Doan et al. 2012). Study 1 took place in April, 2012, 13 months after the earthquake hit Japan. All subjects were residents of the USA when they participated in Study 1. The disasters that followed the earthquake were unexpectedly severe and involved worldwide concerns such as nuclear plant failures and resulting radiation leaks. Consequently, one year after the earthquake, people in the USA were still posting messages related to the earthquake on Twitter, and the event was still fresh in people’s minds, especially those of residents in Japan. Examining the sharing behavior of people in the USA is important because messages on social media can have worldwide influence. In fact, one message re-tweeted from London resulted in saving the lives of children isolated at a school during the disasters in Japan (Inose 2011).

Subjects in Study 1 read 200 tweets, 100 by media and 100 by persons, related to the Great East Japan Earthquake and rated their likelihood of sharing the tweets in one of four conditions. In the control condition, re-tweet counts were absent for all 200 tweets. In the other three experimental conditions, all 200 tweets were presented with social information. The re-tweet counts of 200 tweets were relatively low in the low condition, medium in the medium condition, and high in the high condition. According to H1a: Positive Social Influence, the likelihood of sharing the same tweet will become higher as the associated re-tweet count increases. In sharp contrast, H1b: Negative Social Influence predicts the opposite pattern; the likelihood of sharing the same tweet will become lower as the associated re-tweet count increases. If there is no social influence, then there will be no difference in the likelihood of sharing between the four conditions. The results from Study 1 will also reveal whether or not tweets by media and those by individuals result in different patterns of social influence.

Method

Subjects

Subjects in Study 1 were 144 workers of Amazon’s Mechanical Turk (https://www.mturk.com). Of those, 93 were females, 46 were males, and 5 did not report their sex. Their average age was 28. Subjects were all residents of the USA. A few research groups have shown that researchers can collect high-quality data from Mechanical Turk (e.g., Buhrmester et al. 2011;
Crump et al. 2013; Mason & Suri 2011; Mason & Watts 2009; Paolacci et al. 2010). The procedure in the current work followed their recommendations. The recruitment of subjects ended when each tweet resulted in the pre-specified number of responses. This procedure, detailed in Procedure, determined the total number of subjects in Study 1.

**Materials**

The stimuli were 200 English tweets related to the Great East Japan Earthquake, collected from Twitter on March 5th, 2012. The first step was to identify media and persons who communicated information about the disasters using Twitter. A screening of tweets related to the earthquake revealed two major news agencies in Japan, Tokyo Times and Mainichi Daily, and three persons that regularly tweeted in English about the disasters caused by the earthquake. The second step was to collect all of their tweets uploaded after March 11th, 2011. The next step was to identify relevant tweets by searching the following five keywords: earthquake, tsunami, nuclear, Fukushima, and radiation. The last step was to randomly sample 100 tweets from media and 100 from individuals that were unique and were not re-tweets.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Example</th>
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<td>Control</td>
<td>&quot;In 20-30km range from FUKUSHIMA 1, Edano repeats: stay indoors, close windows&quot;</td>
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| Low       | "In 20-30km range from FUKUSHIMA 1, Edano repeats: stay indoors, close windows"  
Shared by 7 people |
| Medium    | "In 20-30km range from FUKUSHIMA 1, Edano repeats: stay indoors, close windows"  
Shared by 550 people |
| High      | "In 20-30km range from FUKUSHIMA 1, Edano repeats: stay indoors, close windows"  
Shared by 52341 people |

**Design**

The manipulated variable was the social information provided to the subjects and the measured variable was their likelihood of sharing the 200 tweets. Whether the tweets came from media or individuals was a characteristic of tweets. There were four conditions: control, low, medium, and
high. Each condition contained the same 200 tweets, 100 from media and 100 from individuals. In the control condition, social information was absent. In the other three conditions, each tweet was presented with social information that indicated the number of people who already shared the tweet. The social information was a random number between 0 and 9 in the low condition, 10 and 999 in the medium condition, and 1000 and 99999 in the high condition. Table 2 shows an example of a tweet in each condition. Each subject participated in one of only four conditions. The assignment of a subject to a condition was random.

Background: This study about people's responses to disaster-related information on social media, such as Twitter and Facebook, is particularly important given the 2011 Tohoku earthquake, which hit Japan on March 11th. This earthquake triggered tsunamis, which caused massive destruction of infrastructure. The tsunami caused a nuclear accident in Fukushima, which affected hundreds of thousands of residents. If you respond to valuable, you will help prepare for future disasters.

Instructions: Imagine that you read the following information on social media, such as Twitter and Facebook. Please answer the question below.

"Fukushima caused world's worst sea pollution slow.us/vJKMh"
Shared by 3238 people

Question: How likely would you be to share this information on social media, such as Facebook and Twitter?

1 2 3 4 5 6 7
not at all ○ ○ ○ ○ ○ ○ ○ extremely

***If you want to know more about the above statement, please email us (intuitive.analytic@gmail.com)***

If this is your first HIT from this batch, please complete the following:

I am a □ years old □ male □ female, born in the city of _________.
How often do you use Twitter? Never □□□□□□□□ Everyday

Thank you for your participation!

Figure 2. Subjects’ main task in Study 1 was to rate the likelihood that they would share a given message in social media such as Twitter and Facebook.
Procedure

Subjects completed the experiment online through Amazon’s Mechanical Turk. Figure 2 shows an example web page that subjects saw in the high condition. At the top of the page, there was background information that described the disasters associated with the Great East Japan Earthquake. Then the instructions stated to imagine reading a given message on social media and rate the likelihood of sharing the given message on social media. Subjects indicated their responses by clicking the appropriate value on a scale of 1 to 7, where 1 indicated not at all likely to share and 7 indicated extremely likely to share. Subjects were unaware of the source of the given message. After submitting their response, subjects decided whether they would like to rate the next tweet or not. The presentation order of tweets was random, and each subject could rate anywhere between 1 and 200 tweets from a single condition. A subject could rate the same tweet only once. Data collection ended when each tweet had ten ratings. Subjects received one cent for each tweet they rated. Thus they earned anywhere between one cent and two dollars. The amount of compensation was based on the past findings that increasing pay can speed up the completion time but does not affect the quality of responses (Mason & Watts 2009).

Results

The analyses included all responses from all subjects. Figure 3 shows the overall pattern of the results. On average, subjects’ likelihood of sharing disaster-related information was 3.47.

The main interest in Study 1 was to examine the effect of social information on likelihood of sharing. As the associated re-tweet count increases, the same tweet should result in higher likelihood of sharing according to \textit{H1a: Positive Social Influence}, lower likelihood of sharing according to \textit{H1b: Negative Social Influence}, and the same likelihood of sharing if there is no social influence. Another interest was whether this effect of social information differs between tweets posted by media and those posted by individuals. A visual inspection of Figure 3 reveals that the occurrence of positive or negative social influence depends on whether the messages come from media or individuals, and that there may be no social influence when the associated re-tweet count is very high. The results presented next expand on these observations.

Social Influences on Likelihood of Sharing

A 2 (source: media, individuals) by 4 (social information: control, low, medium, high) analysis of variance (ANOVA), with likelihood of sharing as a dependent measure, revealed no significant main effect of source, $F(1, 198) = 0.051$, $p = .821$. Subjects’ likelihood of sharing messages
from media (3.45) and that from individuals (3.48) did not differ significantly. There was no significant main effect of social information either, $F(3, 594) = 2.162, p = .091$. Subjects' likelihood of sharing messages did not differ significantly in the control (3.44), low (3.38), medium (3.55) and high (3.49) conditions. As suggested by Figure 3, the interaction between source and social information was significant, $F(3, 594) = 29.73, p < .001$. The pattern of social influence for messages by media was different from that for messages by individuals.

![Figure 3](attachment:image.png)

**Figure 3.** Social information influenced subjects’ likelihood of sharing messages differently depending on whether the messages were from media or from individuals. For messages by media, the control and high conditions resulted in higher likelihood of sharing than the low and medium conditions, and this pattern reversed for messages by individuals. Error bars indicate 95% confidence intervals. The light blue band shows the 95% confidence interval for the messages by media in the control condition, and the light pink band shows the 95% confidence interval for the messages by individuals in the control condition.

Further analyses of the source by social information interaction indicated that the effect of social information within messages by media and that within messages by individuals were both...
significant. A one-way ANOVA for messages by media, with social information as independent variable and likelihood of sharing as a dependent measure, was significant, $F(3, 297) = 13.62$, $p < .001$, rejecting the null hypothesis that likelihood of sharing was statistically the same in all four conditions. Error bars in Figure 3 indicate the 95% confidence intervals. Based on the overlaps of the 95% confidence intervals, for messages by media, the control (3.69) and high (3.68) conditions resulted in higher likelihood of sharing than the low (3.20) and medium (3.24) conditions. A one-way ANOVA for messages by individuals was also significant, $F(3, 297) = 18.47$, $p < .001$. However, in sharp contrast to messages by media, messages by individuals resulted in higher likelihood of sharing in the low (3.55) and medium (3.87) conditions than the control (3.19) and high (3.25) conditions.

The light blue band in Figure 3 shows the 95% confidence interval for the messages by media in the control condition. For the likelihood of sharing messages by media, the control and low conditions differed significantly, as confirmed by a planned comparison, $t(99) = 4.92$, $p < .001$, and the control and medium conditions also differed significantly, $t(99) = 4.89$, $p < .001$. These results indicate that negative social influence takes place for messages by media. However, there was no significant difference between the low and medium conditions, $t(99) = 0.32$, $p = .750$, as well as between the control and high condition, $t(99) = 0.12$, $p = .907$, indicating that the effect of social information was not linear.

Similarly, the light pink band in Figure 3 shows the 95% confidence interval for the messages by individuals in the control condition. For the likelihood of sharing messages by individuals, there was a significant difference between the control and low conditions, $t(99) = 3.70$, $p < .001$, between the control and medium conditions, $t(99) = 6.70$, $p < .001$, and between the low and medium conditions, $t(99) = 2.96$, $p = .004$, suggesting the presence of positive social influence. The control and high conditions, however, did not differ significantly, $t(99) = 1.21$, $p = .231$, indicating that the positive social influence on sharing messages by individuals disappeared in the high condition.

In sum, social information influenced subjects’ likelihood of sharing messages differently depending on whether the messages were from media or from individuals. Social information increased subjects’ likelihood of sharing messages by individuals, consistent with $H1$: Positive Social Influence, and it decreased their likelihood of sharing messages by media, consistent with $H2$: Negative Social Influence, but up to a certain point. When social information indicated that an extremely large number of people already shared a message, it no longer influenced the likelihood of sharing.
Further Analysis of Social Influences on Likelihood of Sharing

The previous analyses of social influence focused on the effect of the magnitude of social information on likelihood of sharing. In other words, a message had three social influence measures, one when it was in the low condition, one when it was in the medium condition, and one when it was in the high condition. A complementary analysis would be to develop a single measure of social influence for each of the 200 messages.

A simple way to calculate a social influence score of a message, $i$, was to take the mean of its three social influence scores:

$$\frac{1}{3} \sum_{j=1}^{3} (S_{ij} - S_{control})$$

where $j$ was one of the three social information conditions and $S$ was likelihood of sharing. $S_{ij} - S_{control}$ was a social influence score in one condition, measured by subtracting the likelihood of sharing in the control condition from the likelihood of sharing $i$ in the $j^{th}$ condition. Taking the mean of the three social influence scores was reasonable because the three social influence scores were generally in agreement. In this scheme, a positive value indicates that social information tends to increases the likelihood of sharing. A negative value indicates the opposite: social information tends to decreases the likelihood of sharing. A value close to zero means that social influence plays little role in most cases. Figure 4 shows the social influence score for each of the 200 messages, grouped by whether the message came from media or from individuals.

Figure 4 reveals that social influence scores for messages by media (-0.32) tends to be negative, $t(99) = -3.88$, $p < .001$, and the reverse is the case for messages by individuals (0.39), $t(99) = 4.86$, $p < .001$. The social influence scores of messages by individuals were on average much higher than the social influence scores of messages by media, $t(99) = 6.16$, $p < .001$. The count data revealed the same pattern of results. Whereas only 34 of 100 messages by media resulted in positive social influence scores, $\chi^2(1, N = 100) = 10.24$, $p = .001$, as many as 70 of 100 messages by individuals resulted in positive social influence scores, $\chi^2(1, N = 100) = 16.00$, $p < .001$. The distribution of positive and negative social influence scores was significantly different between messages by media and messages by individuals, $\chi^2(1, N = 200) = 24.53$, $p < .001$. These results reinforce the conclusions from the previous analysis that messages by media tend to result in negative social influence and messages by individuals tend to result in positive social influence.
Figure 4: Each bar indicates the social influence score of a tweet message. There are more social influence scores on the negative than positive side for tweets by media, and the reverse is the case for tweets by individuals.

Differences between Messages by Media and Messages by Individuals

Given that sharing of messages by media and sharing of messages by individuals result in different patterns of social influence, it would be fruitful to conduct further analysis to gain insights on why this might be the case. As Figure 3 shows, without social information in the control condition, messages by media resulted in higher likelihood of sharing than those by
individuals, $t(198) = 3.54$, $p < .001$. This pattern reversed in the low and medium conditions; messages by individuals resulted in higher likelihood of sharing than those by media in the low condition, $t(198) = 2.43$, $p = .016$, as well as in the medium condition, $t(198) = 4.60$, $p < .001$. As in the control condition, messages by media resulted in higher likelihood of sharing than messages by individuals in the high condition, $t(198) = 2.68$, $p = .008$.

In Study 1, subjects did not receive information about the source of the message but treated messages from media and those from individuals differently. There might be something different about these tweets that people are sensitive to. Table 3 shows the results from comparing the characteristics of the messages by media and those by individuals in Study 1.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Media</th>
<th>Individuals</th>
<th>Statistical results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Word count</td>
<td>$M = 11.65$</td>
<td>$M = 16.68$</td>
<td>$t(198) = -7.79$</td>
</tr>
<tr>
<td>Link</td>
<td>95 of 100</td>
<td>31 of 100</td>
<td>$\chi^2(1, N = 100) = 85.14$</td>
</tr>
<tr>
<td>Data</td>
<td>3 of 100</td>
<td>36 of 100</td>
<td>$\chi^2(1, N = 100) = 32.62$</td>
</tr>
<tr>
<td># tag</td>
<td>1 of 100</td>
<td>18 of 100</td>
<td>$\chi^2(1, N = 100) = 14.89$</td>
</tr>
<tr>
<td>@ sign</td>
<td>1 of 100</td>
<td>12 of 100</td>
<td>$\chi^2(1, N = 100) = 8.23$</td>
</tr>
</tbody>
</table>

Messages by media contained significantly fewer words and significantly more hyperlinks than those by individuals. A hyperlink takes the reader to the source of information contained in a tweet, which can provides further details that cannot be expressed in the tweet due to the 140-character limit. By contrast, messages by individuals included more data, defined as numeric values, such as distance from the disaster center, magnitude and frequency of earthquakes, and time of events, than messages by media. Moreover, messages by individuals contained more # tags and @ signs than those by media. A # tag indicates that the message is about a certain topic, and an @ sign means that the message will grab attention of a user whose username comes after it.

The messages by media and those by individuals also differed in the distribution of the frequencies of the five keywords used to sample the tweets: earthquake, tsunami, radiation, Fukushima, and nuclear, $\chi^2(4, N = 230) = 30.78$, $p < .001$. Table 4 shows the results from the keyword analysis.
Table 4. Frequency of Keyword in Messages by Media and Those by Individuals

<table>
<thead>
<tr>
<th>Keyword</th>
<th>Media</th>
<th>Individuals</th>
<th>Statistical results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nuclear</td>
<td>49</td>
<td>13</td>
<td>$\chi^2(1, N = 62) = 20.90$ $p &lt; .001$</td>
</tr>
<tr>
<td>Fukushima</td>
<td>28</td>
<td>45</td>
<td>$\chi^2(1, N = 73) = 3.96$ $p = .047$</td>
</tr>
<tr>
<td>Tsunami</td>
<td>11</td>
<td>24</td>
<td>$\chi^2(1, N = 35) = 4.83$ $p = .028$</td>
</tr>
<tr>
<td>Radiation</td>
<td>12</td>
<td>17</td>
<td>$\chi^2(1, N = 29) = 0.86$ $p = .353$</td>
</tr>
<tr>
<td>Earthquake</td>
<td>17</td>
<td>14</td>
<td>$\chi^2(1, N = 31) = 0.29$ $p = .590$</td>
</tr>
</tbody>
</table>

The five keywords collectively appeared 117 times in the messages by media and 113 times in the messages by individuals. The keyword “nuclear” appeared more frequently in messages by media than messages by individuals. On the other hand, the keywords “tsunami” and “Fukushima” appeared more often in messages by individuals than messages by media. Although messages by media and those by individuals in Study 1 focused on different topics, this difference did not relate directly to likelihood of sharing. For example, the keyword “nuclear” appeared in media messages much more often than in individual messages.

Although characteristics such as having hyperlinks and discussing nuclear-related issues could distinguish messages by media from those by individuals, these characteristics were not the only reasons why people’s sharing likelihood differed between messages by media and those by individuals. For example, without social information, the difference in the mean likelihood of sharing between nuclear-relevant messages (3.50) and nuclear-irrelevant messages (3.28) did not reach significance, $t(198) = 1.37$, $p = .172$. Likewise, without social information, the difference in the mean likelihood of sharing between messages with hyperlinks (3.53) and those without hyperlinks (3.29) did not reach significance, $t(198) = 1.61$, $p = .109$.

**Discussion**

In Study 1, social information positively affected the likelihood of sharing messages by individuals; knowing that others already shared a message increased one’s likelihood of sharing. Consistent with $H1a$: *Positive Social Influence*, people go along with the opinion of others (e.g., blinded 2009; Salganik & Watts 2008). However, there was a saturation point; knowing that *many* others shared a message did not increase the likelihood of sharing messages by
individuals. Perhaps in this case people ignore social information and base their sharing decision on the content of the message (Haidt 2001; Hilton 1995).

By contrast, social information negatively affected the intention to share messages by media; knowing that others already shared a message decreased one’s likelihood of sharing. This result is consistent with H1b: Negative Social Influence, and suggests that people may try to differentiate themselves from others and share only information that others have not shared previously (e.g., Berger & Heath 2007; Tian et al. 2001). There was a saturation point for messages by media as well; knowing that many others already shared a message did not affect subjects’ likelihood of sharing.

The different patterns of social influence observed in Study 1 are likely due to the differences in the characteristics of messages by these two sources. Subjects in Study 1 were not aware of whether the messages came from media or from individuals. The messages by media in Study 1 contained fewer words and more hyperlinks than the messages by individuals. In developing an algorithm to predict credibility of tweets related to the 2010 Earthquake in Chile, Castillo et al. (2011) have found that messages without hyperlinks are more likely to be perceived as false. People might be sensitive to the presence of hyperlinks, and, as a result, messages from media resulted in higher likelihood of sharing than those by individuals without social information.

Taken together, the results from Study 1 suggest a three-part answer to one of the research questions posted earlier: How does social influence play a role in people’s decision to share a disaster-related message in a social media environment? (1) Positive social influence tends to take place on sharing of disaster-related messages from individuals, and (2) negative social influence tends to take place on sharing of disaster-related messages from media, but (3) regardless of whether messages come from media or individuals, social influence disappears when people see that many others have previously shared the messages.

**Study 2: A Questionnaire on Perceptions of Disaster-Related Tweets**

Study 2 focused on examining the extent to which people’s perceptions of disaster-related messages could successfully predict the direction and degree of its social influence found in Study 1. It also involved examining the relationship between perceptions of a message and the source of the message as Study 1’s results revealed that messages by media and those by individuals differed in some characteristics including the pattern of social influence. People’s perceptions may be able to distinguish messages by media from those by individuals and explain why social influence was negative for the former and positive for the latter in Study 1.
The data on perceptions collected in Study 2 were also useful for testing rumor theories in a social media context. Study 2 also addressed the second research question: how does people’s perception of a disaster-related message relates to their decision to share it in a social media environment? Specifically, do people’s perceptions of importance, accuracy, anxiety, familiarity, informativeness, and fluency associated with a disaster-related message relate to their likelihood of sharing the message, as proposed by *H2: Perception*? According to the rumor theories reviewed before, the perceptions of importance, accuracy, anxiety, familiarity, and informativeness related to rumor transmission (Allport & postman 1947; Anthony 1973; DiFonzo & Bordia 2007; Rosnow 2001). It is unclear whether or not rumor theories developed in face-to-face environments apply to a social media environment. The feelings-as-information theory proposes that the perception of fluency, or ease of processing, influences various judgments (e.g., Schwarz & Clore 2007) such as the judgments of truthfulness (Begg et al. 1992), risk (Song & Schwarz 2009), and liking (Reber et al. 2004). The perception of fluency might also affect information sharing behavior.

Subjects in Study 2 rated the same 200 tweets used in Study 1 on six factors: importance, accuracy, anxiety, fluency, familiarity, and informativeness. Whether or not these six perceptions of a message obtained in Study 2 can successfully predict (1) the direction and degree of its social influence and (2) its likelihood of sharing obtained in Study 1 are the two main interests of Study 2.

**Method**

**Subjects**

Subjects in Study 2 were 43 workers of Mechanical Turk who lived in the USA. There were 21 females and 22 males. Their average age was 36.

**Materials**

The stimuli in Study 2 were the same 200 tweets as those in Study 1.

**Design**

Study 2 was a questionnaire. For each of 200 tweets, there were six main questions. Each question corresponded to one of six perceptual factors: familiarity, accuracy, informativeness, importance, fluency, and anxiety. Figure 5 displays the main questions subjects saw.
Please read this tweet:

"Fukushima caused world's worst sea pollution
slow.us/vJKMh"

Please answer the following questions:

1. Overall, how familiar (recognizable, well-known) is this tweet to you?

   1  2  3  4  5  6  7
   not at all familiar  ○ ○ ○ ○ ○ ○ extremely familiar

2. Overall, how accurate or true (as opposed to distorted or false) do you think this tweet is?

   1  2  3  4  5  6  7
   not at all accurate   ○ ○ ○ ○ ○ ○ extremely accurate

3. Overall, how informative (useful, educational) is this tweet to you?

   1  2  3  4  5  6  7
   not at all informative ○ ○ ○ ○ ○ ○ extremely informative

4. Overall, how important (significant, consequential) is this tweet to you?

   1  2  3  4  5  6  7
   not at all important   ○ ○ ○ ○ ○ ○ extremely important

5. Overall, how easy (as opposed to hard) is it for you to understand this tweet?

   1  2  3  4  5  6  7
   not at all easy   ○ ○ ○ ○ ○ ○ extremely easy

6. Overall, how anxious (worried, concerned) does this tweet make you?

   1  2  3  4  5  6  7
   not at all anxious   ○ ○ ○ ○ ○ ○ highly anxious

Figure 5. Subjects in Study 2 rated their perceptions of a given message on familiarity, accuracy, informativeness, importance, fluency, and anxiety.

Procedure

Subjects completed the questionnaire online through Mechanical Turk. Subjects read a given tweet and indicated their responses for each question by clicking the appropriate value on a
scale of 1 to 7, where 1 indicated not at all and 7 indicated extremely. As in Study 1, subjects saw one tweet at a time and rated anywhere between 1 and 200 tweets for one cent per tweet. The sequential presentation of the tweets was in a random order and ended when each tweet had ten ratings.

Results

The analyses included all responses from all subjects in Study 2. Figure 6 summarizes the overall pattern of the results from Study 2. On average, subjects perceived the messages to be relatively low on anxiety (media: 2.70, individuals: 2.82), familiarity (media: 2.68, individuals: 2.76), and importance (media: 3.16, individuals: 3.06). Subjects rated the messages relatively high on fluency (media: 5.43, individuals: 5.29) and accuracy (media: 4.62, individuals: 4.83). The perception of informativeness was around the middle of the scale (media: 4.12, individuals: 4.06).

Figure 6. Subjects perceived the messages to be relatively low on anxiety, familiarity, and importance, but relatively high on fluency and accuracy. Error bars indicate 95% confidence intervals.
Comparing responses on tweets by media and those by individuals, there was a significant difference in perceived accuracy, $t(198) = -2.56, p < .001$, but not in the perception of anxiety, $t(198) = -1.14, p = .254$, familiarity, $t(198) = -1.04, p = .300$, fluency, $t(198) = 1.38, p = .168$, importance, $t(198) = 1.17, p = .244$, and informativeness, $t(198) = -1.19, p = .236$.

Table 5 shows correlation coefficients among the six perceptions, the sharing likelihood observed in Study 1’s control condition, and social influence scores measured in Study 1. The six perceptions all had significant positive correlations with the likelihood of sharing, consistent with $H2$: Perception. The relationship between perceptions and the likelihood of sharing was the same as the one in Table 5 for both messages by media and those by individuals. Thus, source did not change the relationship between perceptions and the likelihood of sharing.

The six perceptions could not explain the varying social influences observed in Study 1 well. There was a weak but significant positive correlation ($r = .14$) between perceived accuracy and
social influence; as perceived accuracy increases, the social influence score tends to also increase. None of the other perceptions had significant correlations with social influence.

The significant negative correlation between sharing likelihood in the control condition of Study 1 and the social influence score makes sense because the social influence score is based on subtracting the likelihood of sharing in the control condition from the likelihood of sharing in the social information conditions. When the likelihood of sharing a message is very low in the control condition, it is likely that its sharing likelihood is higher in the other conditions.

Table 5 also reveals multicollinearity for the six perceptions. They are highly correlated. Nevertheless, reports of regression analyses with six perceptions as predictors follow. Although the presence of correlated predictors reduces the validity of interpreting the estimate for each predictor, it does not reduce the predictive power of a regression model as a whole.

**Relationship between Perception and Likelihood of Sharing**

*H2: Perception* proposed that perceived importance, accuracy, anxiety, familiarity, informativeness, and fluency should positively relate to sharing likelihood. Table 6 shows the results of fitting a linear regression model to the likelihood of sharing obtained in the control condition of Study 1, with the six perceptions obtained in Study 2 as predictors. The regression model was significant, $F(6, 193) = 14.30, p < .001$, with adjusted $R^2$ of .29, indicating that the six perceptions were all related to the likelihood of sharing, consistent with *H2: Perception*. Only anxiety and fluency shows significant estimates in Table 6 because of the multicollinearity of the six perceptions as mentioned previously.

**Table 6. Linear Regression Analysis on Information Sharing**

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Standard Error</th>
<th>Statistical significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.46</td>
<td>0.62</td>
<td>$t = 0.73, p = .464$</td>
</tr>
<tr>
<td>Accuracy</td>
<td>-0.23</td>
<td>0.15</td>
<td>$t = -1.49, p = .139$</td>
</tr>
<tr>
<td>Anxiety</td>
<td>0.52</td>
<td>0.11</td>
<td>$t = 4.74, p = .000$</td>
</tr>
<tr>
<td>Familiarity</td>
<td>0.01</td>
<td>0.14</td>
<td>$t = 0.05, p = .958$</td>
</tr>
<tr>
<td>Fluency</td>
<td>0.38</td>
<td>0.11</td>
<td>$t = 3.34, p = .001$</td>
</tr>
<tr>
<td>Importance</td>
<td>0.10</td>
<td>0.15</td>
<td>$t = 0.67, p = .502$</td>
</tr>
<tr>
<td>Informativeness</td>
<td>0.06</td>
<td>0.15</td>
<td>$t = 0.39, p = .692$</td>
</tr>
</tbody>
</table>
Relationship between Perception and Social Influence

A linear regression model that predicted the social influence scores developed in Study 1, with the six perceptions measured in Study 2 as predictors, was not significant, $F(6, 193) = 1.58$, $p = .159$, with adjusted $R^2$ of .02, indicating that the six perceptions bundled together accounted for only 2% of the variance and did not predict the social influence scores. As Table 7 shows, the relationship between perceived accuracy and social influence was marginal in this model.

<table>
<thead>
<tr>
<th>Table 7. Linear Regression Analysis of Social Influence Scores</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>(Intercept)</td>
</tr>
<tr>
<td>Accuracy</td>
</tr>
<tr>
<td>Anxiety</td>
</tr>
<tr>
<td>Familiarity</td>
</tr>
<tr>
<td>Fluency</td>
</tr>
<tr>
<td>Importance</td>
</tr>
<tr>
<td>Informativeness</td>
</tr>
</tbody>
</table>

Earlier analysis has shown a significant bias toward positive social influence for messages from individuals and a significant bias toward negative social influence for messages from media. Then, whether messages are from media or individuals might be a good predictor of whether the messages result in positive or negative social influence. In fact, a linear regression model with source (media = 0, individuals = 1) as a sole predictor was able to predict the social influence scores, $F(1, 198) = 37.98$, $p < .001$, with adjusted $R^2$ of .16. The estimate for source in this model was 0.70, $t(198) = 6.16$, $p < .001$. Source was a much better predictor of social influence scores than the six perceptions.

Relationship between Perception and Source

Although not a main interest, Table 8 shows the result of fitting a logistic regression model to source (media = 0, individuals = 1), with six perceptions as predictors. The model correctly classified 68% of messages by media and also 68% of messages by individuals. This model was a significant improvement over the null model with just the intercept based on the difference between the model deviance and null deviance, $\chi^2(6) = 26.28$, $p < .001$, where the degrees of
freedom was the difference in the number of estimated parameters between the two models. As highlighted in Table 8, perceived accuracy, fluency, and importance were strong predictors of whether a message was from media or an individual. Messages by individuals were associated with being more accurate, less fluent, and less important than those by media.

### Table 8. Logistic Regression Analysis on Source

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Standard Error</th>
<th>Statistical significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>-0.40</td>
<td>1.51</td>
<td>$z = -0.27$ $p = .791$</td>
</tr>
<tr>
<td>Accuracy</td>
<td>0.97</td>
<td>0.38</td>
<td>$z = 2.54$ $p = .011$</td>
</tr>
<tr>
<td>Anxiety</td>
<td>0.44</td>
<td>0.27</td>
<td>$z = 1.64$ $p = .101$</td>
</tr>
<tr>
<td>Familiarity</td>
<td>0.24</td>
<td>0.34</td>
<td>$z = 0.69$ $p = .489$</td>
</tr>
<tr>
<td>Fluency</td>
<td>-0.88</td>
<td>0.29</td>
<td>$z = -3.01$ $p = .003$</td>
</tr>
<tr>
<td>Importance</td>
<td>-1.10</td>
<td>0.40</td>
<td>$z = -2.74$ $p = .006$</td>
</tr>
<tr>
<td>Informativeness</td>
<td>0.50</td>
<td>0.37</td>
<td>$z = 1.36$ $p = .175$</td>
</tr>
</tbody>
</table>

**Discussion**

The two main focuses of Study 2 were to examine the relationships between people’s perceptions of a message and (1) the direction and degree of social influence for the message observed in Study 1 and (2) the likelihood of sharing the message obtained in Study 1. Subjects in Study 2 rated the same 200 disaster-related tweets used in Study 1 on six factors: importance, accuracy, anxiety, familiarity, informativeness, and fluency.

The results of Study 2 indicated that the six perceptions did not predict the extent of social influence well but was able to predict the likelihood of sharing well. Correlational analysis revealed that the six perceptions all had significant positive correlations with the likelihood of sharing, supporting $H2$: Perception. A linear regression model, with the six perceptual factors in $H2$: Perception as predictors, was able to fit the likelihood of sharing obtained in Study 1.

Because in Study 1 messages from media resulted in positive social influence and those from individuals resulted in negative social influence, study 2 also concerned the relationship between the perceptions of a message and source, whether the message is from media or an individual. The results of Study 2 indicated that people perceived messages by media as less accurate, more fluent, and more important than messages by individuals. This was reasonable
because Study 1’s results showed that messages by individuals contained a lot of data, such as magnitude of earthquake, which could increase the perceived accuracy and reduce the perceived fluency of these messages relative to messages by media. The topic of nuclear disaster appeared more often in messages by media than those by individuals, which could increase the perceived importance of messages by individuals. Although the six perceptions could not predict social influence, perceived accuracy, fluency, and importance were related to source, and source was a significant predictor of social influence.

The take home message of Study 2 is that the six perceptions do not predict the direction and degree of social influence well but do predict the likelihood of sharing. The latter addresses the second research question: How does people’s perception of a disaster-related message relate to their decision to share it in a social media environment? The answer to this question is that perceived accuracy, anxiety, familiarity, importance, informativeness, and fluency of disaster-related tweets positively relate to people’s decision to share these tweets.

**General Discussion**

The results from an experiment and a questionnaire using actual tweets related to the Great East Japan Earthquake suggested that exposing people to collective sharing decision, such as re-tweet counts, could influence their sharing of disaster-related tweets, and that people’s perceptions of disaster-related tweets could relate to their sharing of these tweets. The two studies reported here extended past research on social influence and rumor psychology, and the findings could provide useful information for improving the use of social media during disaster management. The remainder of this section consists of an overview of the results, discussion of theoretical and practical implications, and finally consideration of limitations and future directions.

**Overview of Results**

Table 9 summarizes the two research questions addressed in the two studies reported here, the three hypotheses tested, and the main results.

Study 1 concerned research question 1: how social influence plays a role in the sharing of disaster-related messages on social media. Consistent with *H1a: Positive Social Influence*, when people rated their likelihood of sharing a disaster-related message by individuals, they followed social information, defined as information about how many others have already shared the message. By contrast, when the message was by media, people’s likelihood of sharing the
message went against the social information, in accord with $H1b$: Negative Social Influence. Furthermore, when the social information indicated that over 1,000 people already shared the disaster-related message, social influence disappeared regardless of the source of the message. An additional finding was that, without social information and without knowing the source, people were more likely to share messages by media than those by individuals.

Table 9. A Summary of Research Questions, Hypotheses, and Results.

<table>
<thead>
<tr>
<th>Research question 1</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>How does social influence play a role in people’s decision to share a disaster-related message in a social media environment?</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Hypotheses 1</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$H1a$: Positive Social Influence – in deciding their likelihood of sharing a disaster-related message in a social media environment, people will follow the information about the number of others who have already shared the message.</td>
<td></td>
</tr>
<tr>
<td>Supported for messages by individuals</td>
<td></td>
</tr>
</tbody>
</table>

| $H1b$: Negative Social Influence – in deciding their likelihood of sharing a disaster-related message in a social media environment, people will go against the information about the number of others who have already shared the message. |
| Supported for messages by media |

<table>
<thead>
<tr>
<th>Research question 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>How does people’s perception of a disaster-related message relate to their decision to share it in a social media environment?</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Hypothesis 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$H2$: Perception – perceived importance, accuracy, anxiety, familiarity, informativeness and fluency associated with a message will relate positively to people’s likelihood of sharing the message in a social media environment.</td>
<td></td>
</tr>
<tr>
<td>Supported for both messages by individuals and media</td>
<td></td>
</tr>
</tbody>
</table>

Study 2 focused on examining whether or not people’s perceptions could predict the social influence and the likelihood of sharing obtained in Study 1. In particular, past research suggested six perceptions that could be interesting to examine in a social media context: importance, accuracy, anxiety, familiarity, informativeness, and fluency. The six perceptions
could not predict the direction and degree of social influence. However, perceived accuracy, fluency, and importance were strong predictors of whether the message came from media or a person, and the source of the message was a significant predictor of social influence. Study 2 addressed research question 2: how people’s perception of a disaster-related message relates to their decision to share it on social media. Consistent with H2: Perception, all of the six perceptions had significant positive correlations with the likelihood of sharing. Thus, perceived accuracy, anxiety, familiarity, importance, informativeness, and fluency of disaster-related tweets positively relate to people’s decision to share these tweets.

**Theoretical Implications**

One conclusion based on the current results is that people integrate collective sharing decision into their decision about whether or not to share a message in social media, and that this social influence is not uniform. Negative social influence can take place for tweets by media, in which knowing collective sharing decision decreases the likelihood of sharing. In contrast, Positive social influence can take place for tweets by individuals, in which knowing collective sharing decision increases the likelihood of sharing. No social influence takes place when the collective decision indicates that a large number of people have already shared the message. These results demonstrate that whether or not and what kinds of social influences take place on sharing of disaster-related messages in social media depend on contexts. One implication then is that there is a need to integrate varying theories related to social influence and information sharing to describe and predict people's information sharing behavior in social media.

Unifying diverse theories of social influence and information transmission involves identifying under which context particular theories apply. For example, the current work has focused on identifying when people adopt collective opinion and when they go against it. The results suggest that perceived accuracy of a message may predict whether people follow or go against collective opinion when they decide whether or not to share the message. When a person perceives a tweet as accurate, seeing that others have shared it increases her willingness to share it. This is consistent with the positive social influence observed for messages by individuals, which tend to result in higher perceived accuracy. In contrast, when she believes that the tweet is inaccurate, learning that others have shared it further decreases her willingness to share it. This is in accord with the negative social influence found for messages by media, which tend to result in lower perceived accuracy. This account, for example, can become a proposition testable through further observations.
Another conclusion of the current work is that the basic law of rumor transmission and its extension apply to sharing of disaster-related messages in a social media environment. Perceived accuracy, importance, anxiety, familiarity, informativeness, and fluency all relate positively to the likelihood of sharing. This finding implies an additional extension to the basic law of rumor: perceived fluency, or ease of processing, may play a role in rumormongering.

![Diagram of sharing of disaster-related messages in social media](image)

**Figure 7.** The results of the two studies reported here imply a model of sharing of disaster-related messages in social media that unifies different accounts of social influence and rumor transmission. Single-headed arrows indicate influences and double-headed arrows indicate relationships. The dotted arrow indicates a significant but weak effect.

Taken together, the current findings suggest a model of sharing of disaster-related messages in social media that integrates theories of social influence and rumor psychology. Figure 7 displays the model. The results of the current work not only demonstrate that different types of social influences can take place, but also reveal which type of social influence will take place under which conditions.

**Practical Implications**

The results of the work presented here may be useful for the development of recommendations for the design and use of social media technologies during disaster response management. One of the challenges of using social media during disaster response is that, although useful
information exists in social media, this information is extremely hard to find because rumors spread widely during disasters (e.g., Inose 2011). The results from the current work suggest that exposing people to collective opinion like re-tweet count may facilitate the spread of unverified information, especially when the information contains details and seems accurate like the tweets by individuals in the work reported here. In contrast, collective opinion may be able to curb the spread of rumor tweets that contain hyperlinks like the tweets by media in the current work. To deal with the spread of unverified information during responses to disasters, one potentially effective solution may be to have re-tweet counts available for tweets by media but not for tweets by individuals.

On the flip side, government agencies and media need to spread warnings and official messages during disasters. With respect to re-tweet counts, the current work did not involve messages by government. However, a previous analysis of forwarding behavior has indicated that tweets by government may spread in a fashion similar to those by media (blinded 2013). If this is the case, then re-tweet counts should not be associated with tweets by government given the negative social influence for messages by media. The current results further suggest that people will share warning messages more when they perceive the messages as accurate, easy to understand, important, informative, familiar, and anxiety provoking. Although it is not easy to control all of these perceptions, some may be easier. For example, citing a credible source may increase perceived accuracy, and writing simply will contribute to the ease of processing.

The take home message here is that designers and users of social media as well as government officials should be aware that collective opinion could have significant influences on the spread of information in social media during disasters. Ideally, users of social media will remind themselves that misinformation abounds during disasters and that they need to turn on their analytic thinking mode and refrain from making quick decisions based on collective opinion. However, changing people’s behavior during stress is not easy (e.g., Ecker et al. 2010; Lewandowsky et al. 2012; Tanaka et al. 2013). Then, designers of social media should take advantage of people’s reliance on collective opinion and snap decision. Designers may consider an option of a disaster mode, in which certain collective opinion like re-tweet counts can be easily turned on and off during disasters depending on the message. More work is needed to identify which collective information is useful and which is not during responses to disasters (blinded 2013).
Limitations

One limitation of the work reported here is the use of residents in the USA only. All the subjects were far from the disaster center. Examining information-sharing behavior of people who are far from disaster center is important because messages from these people can actually save lives (cf. Inose 2011). However, the current results may or may not generalize to the behavior of people in the disaster center. Persons in a disaster center may perceive and react to information differently from those who are far from the disaster center (cf. blinded 2013). In addition to the distance to the disaster center, cultural differences may play a role in shaping behavior. There are a few studies that have examined the information sharing behavior of Japanese residents (e.g., Tanaka et al. 2012; 2013), but they have focused on aspects other than social influence. Systematic studies of distance and cultural effects on sharing of disaster-related tweets will be useful to gain overall understanding.

A second limitation is the artificial nature of the experiment reported in the current paper. Although the experiment like the one presented in the current paper can allow researchers to isolate main variables of interest by controlling for extraneous variables, it results in a task that lacks the complexity of the real world environments. Nevertheless, laboratory experiments can provide useful information and complement field experiments, in which the task is natural but it is harder to pinpoint the relationship between variables.

For example, the collective opinion was artificial, devised by the experimenters. It is possible that some combinations of tweet and re-tweet count were strange such as an extremely uninteresting tweet associated with a large re-tweet count. Nevertheless, the present results suggest that social influence takes place even when the collective opinion is invented. Furthermore, the subjects’ response in the experiment was the likelihood of sharing rather than the binary decision about whether or not to share a given tweet. Although the likelihood of sharing provides information about the strength of people’s response, people decide to either share or not share in the real environment. Ongoing research is examining social influences on binary sharing decision using collective opinion based on real collective sharing decisions.

Another artificial aspect of the current work was that some features of the real social media were missing. One such feature was the structure of the social network. In Twitter, for example, users follow other users, and this structure can no doubt play a role in sharing behavior (Aral & Walker 2011) but its role may be modest (Watts & Dodds 2007). For example, having many followers does not always translate to generating many re-tweets (Cha et al. 2010). The results from the current work coupled with the results from research examining the effect of social
network structures on sharing behavior may be able to advance understanding of spread of information in social media.

Source of information was also a feature available in Twitter but missing in the experiment. The current results demonstrated that people were sensitive to differences between messages by media and those by individuals without being explicitly told about the source of the messages. It would be useful to conduct an experiment that examines whether or not citing a credible source could change people’s perceptions of and decisions to share a message in social media.

A third limitation is that the current studies do not address whether or not exposing people to information about the count of people who have forwarded a message changes their perceptions of the message. This was because the subjects in the experiment presented in the current paper did not report on their perceptions of the messages they saw because doing so might have influenced their likelihood of sharing the messages. In other words, the third limitation was due to an attempt to isolate the effect of social information on sharing in the experiment. However, investigating whether or not exposing people to forwarding counts affect their perceptions can provide insights into the psychology behind the influences of forwarding counts on sharing behaviors.

**Conclusions**

Although social media technologies are essential for communication during disasters, they can cause problems. For example, Twitter helped information sharing and response coordination during the aftermath of the 2011 Great East Japan Earthquake, but it also facilitated the spreading of false tweets even though there were often other tweets that criticized the false tweets. Thus one challenge in using social media during disaster response is that the information that can help save lives is buried under a sea of other information and misinformation. Studies like the one reported here, which advance understanding of factors that influence people’s sharing of information on social media, can be fruitful for the development of techniques to prevent the spread of false information on social media and make it easier to find relevant information during disaster response. This way, continued work in this area will contribute to our society and our future by making social media more effective for disaster management.
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