Inf Syst Front (2015) 17:997–1005
DOI 10.1007/s10796-015-9568-z

Message diffusion through social network service: The case of rumor and non-rumor related tweets during Boston bombing 2013

Jaeung Lee[1] · **Manish Agrawal**[2] · **H. R. Rao**[1]

Published online: 12 June 2015

Abstract Social Network Services (SNS) such as Twitter play a significant role in reporting media, particularly during the extreme events. We examined the impact of tweet features on the diffusion of two types of messages during 2013 Boston marathon tragedy—rumor related and non-rumor related (both in the context of the Boston tragedy). Negative binomial analysis revealed that tweet features such as reaction time, number of followers, and usage of hashtag have an impact on tweet message diffusion during the tragedy. The number of followers showed a positive relationship with message diffusion. However, the relationship between tweet reaction time and message diffusion was negative. Finally, tweet messages that did not include hashtags diffused more than messages that contained hashtags. This paper contributes by adapting the innovation diffusion model to explore tweet message diffusion in Twitter space during extreme events.

Keywords Extreme event · Social network services · Diffusion of messages · Rumor and non-rumor

✉ Jaeung Lee
jaeungle@buffalo.edu

Manish Agrawal
magrawal@usf.edu

H. R. Rao
mgmtrao@buffalo.edu

1 Department of Management Science and Systems, School of Management, State University of New York at Buffalo, Buffalo, NY, USA

2 Department of Information Systems Decision Sciences, Muma College of Business, University of South Florida, Tampa, FL, USA

1 Introduction

Ever since Social Network Services (SNS) have emerged, the way people share news has changed drastically. People have begun to share information about a wide range of issues, from personal to political, and particularly news about special events. In the past, before SNS, information sources were limited to mass broadcasting systems or newspapers. However, nowadays, the selection of information sources has become much broader than in the past. People can certainly receive information from mass media as before, but they can also obtain information via SNS, from messages posted by people or organizations from everywhere in the world.

SNS have become significantly important as reporting tools, especially during extreme events. Prior studies have explored the impact of SNS, especially Twitter, on the public in the context of emergency events. Examples include Hurricane Katrina in 2005 (Chen et al. 2010), the 2007 Virginia Tech Shootings (Ada et al. 2010), the 2008 China Sichuan Earthquake (Li and Rao 2010), and the 2011 Japan Fukushima nuclear disaster (Li et al. 2014). In addition, Oh et al. (2013) have studied information processing through the SNS during three social crises, the Mumbai Terror attacks in 2008, Toyota Recall in 2010 and the Seattle Shooting incident in 2012. Given the wide adoption of SNS as information sources during extreme events, investigating features of SNS during extreme events is valuable for researchers to understand information diffusion.

The widespread use of SNS during unexpected situations has made the integrity and utility of messages disseminated over SNS such as Twitter an important issue during such situations. In such a context it is relevant to understand rumor related messages in contrast to non-rumor related messages. For example, during the recent extreme event of the Boston Bombings in 2013, although there were many useful messages (non-rumor related) such as informational messages that provided alerts, or valuable information about the real time situation to the public, there were also a lot of rumor related messages that caused widespread disruptions and agony. In order to correct the harm from broadly diffused rumors, users and emergency response agencies had to post anti-rumor messages. One example of such a message was about a fire in a nearby library. The messages read, "BREAKING - Boston police reporting a third explosion this time at the JFK Library." In order to mitigate this rumor message, people used messages like "Authorities say fire at JFK Library has not been linked #BostonMarathon explosions http://t.co/xBjDVDpZ9J". In addition to rumor related messages, there were many non-rumor related messages relating to informational or emotional tweets such as "With live updates… Dozens Seriously Injured In Explosions at the Boston Marathon Finish Line http://t.co/tIHOqwo0HH" or "POTUS: The American people will say a prayer for the people of Boston tonight".

In case of diffused rumor messages, whenever people believed the information they received through the SNS to be correct information, they then retweeted the messages to other people. This diffusion of rumor messages continued and required significant effort to dispel and correct. Through non-rumor related messages, people could receive useful information or emotional restoration. Examples of such messages include official updates by police or prayer messages. In addition, such messages may have had a positive impact on the public to mitigate their perceived situational risk.

In this study, we focus on the features of SNS messages that affected message diffusion during the Boston Bombing incident of 2013. Drawing from the theory of innovation diffusion, we identify several features of tweets as important to diffusion; a) reaction time of tweet, b) type of message, c) number of followers, and d) hashtag usage of tweet. By understanding how these features influence message diffusion, emergency agencies and the public can find appropriate mechanisms to mitigate chaos and provide helpful information more efficiently during future extreme events. This can help emergency response authorities such as government agencies, law enforcement, firefighting agencies and hospitals, which have begun to use SNS to keep people informed, to greatly expand the positive effects of SNS.

The results of this study are expected to be beneficial to emergency response authorities, especially during extreme events. By understanding the diffusion of tweets, this research can contribute to dampen the growth of rumors and perhaps help propagate useful messages.

The rest of this paper is organized as follows: first, we discuss the background and prior work on SNS, focusing on the relationship between characteristics of tweets and retweeting practices. Next, we develop the research hypotheses. Then we introduce the data sets used in this research and describe the analysis and results. Finally, we conclude with a discussion of the potential implications of our findings.

2 Research background and literature review

2.1 Boston bombing

According to the official report of the Department of Homeland Security (DHS 2014), at 2:49 PM on April 15, 2013, "two pressure cooker bombs placed near the finish line of the Boston Marathon detonated within seconds of each other, killing three and injuring more than two hundred people. After an extensive search for the unidentified suspects, law enforcement officials encountered Tamerlan and Dzhokhar Tsarnaev in Watertown, Massachusetts. Tamerlan Tsarnaev was shot during the encounter and was pronounced dead shortly thereafter. Dzhokhar Tsarnaev, who fled the scene, was apprehended the following day and remains in federal custody." The suspect was captured at 8:50 PM on April 19th. When the explosions occurred near the finish line on April 15th, around 5700 runners were still in the race. The bombs exploded about 13 s and 210 yards apart. (Piddock 2014). Within 1 min, the event had been announced on SNS.

During this period (April 15–19), many tweet messages about the bombings were propagated through Twitter and it created significant benefits but also considerable confusion among the public. For instance, informational and emotional messages provided useful information or emotional restoration. On the other hand, unverified messages, i.e., rumors, generated social chaos because many people believed that the information they received was worthy of dispersal. They therefore retweeted the messages to other people. This circulation of unverified messages continued and required significant effort in the form of rumor mitigating messages to correct the wrong information.

2.2 Diffusion theory

Diffusion theory is a sociological theory that was introduced by Rogers (1962). Diffusion is described as "the process by which an innovation is communicated through certain channels over time among the members of a social system." According to diffusion theory, four major components influence the diffusion of a new idea: innovation, time, communication channels, and social system.

This diffusion of innovation theory has been widely adopted in a variety of research domains such as sociology, psychology, and anthropology. In the information systems research domain, this theory has been applied to understand the adoption of technological innovation (Hovav et al. 2001). In the context of SNS, and especially the Twitter domain, Yang et al. (2012) studied the idea of retweeting behavior. They expressed that "Retweeting relationship is akin to the practice of forwarding interesting blogs posts and links via email, and can be understood as an adoption of innovation and diffusion of information." Thus, by adapting diffusion theory to tweet diffusion, we argue that retweeting messages that are related to social issues, is analogous to the diffusion of an innovative idea. Moreover, Johnson (2001) mentioned that although uncertainty is an innate characteristic of innovation (and probably cannot be avoided), it can be controlled by people who are aware of the sources of uncertainty and their possible manifestations. Along similar lines, in the context of social crisis, since rumor related messages (rumors and rumor mitigation) are mechanisms for dispelling uncertainty about the situation, these can be considered to be analogous to innovations. In addition, informational or emotional non-rumor related messages can also be regarded as innovative information, since these messages are also created in response to the incident, and contain novel information.

Therefore, in this paper, based on the four major elements of diffusion of innovations, we investigate the information diffusion (in terms of retweets) during extreme events. Particularly, for the people of Boston, the Boston bombing was a new type of extreme event. Most people in Boston may never have experienced terrorist attacks earlier and that would have been instrumental in creating greater chaos. In addition, this event acted as a catalyst for resurfacing concerns about terrorism in post 9/11 America. We applied diffusion theory as follows: re-tweets were studied to understand diffusion, while Tweet reaction time was considered as time, Twitter was considered to be a communication channel and the public affected by message diffusion was considered as the social system.

Time is an important factor in the context of diffusion of innovation. In our context, these innovations take the form of rumor related messages or non-rumor related informational and emotional messages. In addition to diffusion theory, prior research has indicated that the time factor has an impact on message diffusion in the SNS environment (Cha et al. 2009. Ye and Wu (2010) confirmed that messages that are replied to quickly are diffused more. This means that if the delay between the event time and the first tweet time (the reaction time) is short, the probability of tweet diffusion is higher than for messages that have long delays between event time and first tweet time. Therefore, we suggest that for message diffusion regarding the Boston bombing, the reaction time of tweets (time between event time and first tweet time) may have a negative relationship with tweet message diffusion. That is, during the specific extreme event, messages with longer reaction times may propagate less than messages with shorter reaction times. Thus, we propose hypothesis 1 as follows:

Hypothesis 1 There is a negative relationship between reaction time of tweets (time between event time and first tweet time) and amount of tweet message diffusion during extreme events.

As discussed earlier, we are interested in the differences in information diffusion patterns between different types of rumor related and non-rumor related messages. According to Hansen et al. (2011), depending on the context, such as news or non-news, the degree of tweet message diffusion differs based on negativity and positivity of emotions, with negative contents diffusing more than positive contents. Romero et al. (2011) also reported that there is a diffusion difference among various topics such as sports, politics, or celebrity messages. Moreover, Doerr et al. (2012) pointed out that rumor messages spread much more quickly over social networks than over other networks. This was also observed during the Boston marathon incident, where rumors diffused very quickly via Twitter. To suppress these rumors, a lot of rumor mitigating messages were also propagated. Starbird et al. (2014) compared the diffusion of three rumors during the Boston bombing incident. They found different propagation patterns for each rumor. To investigate the diffusion difference between rumor-related and non-rumor related messages, we developed Hypothesis 2 as follows:

Hypothesis 2 Rumor related messages diffuse more than non-rumor related messages during extreme events.

On the Twitter SNS channel, followers are people who receive tweet messages from other users they are following. For instance, if one person receives a tweet message from the Boston Police Department by following that organization's account, that person is a follower of the Boston Police Department's Twitter account. In addition, Twitter users can choose other users to follow for obtaining their updates. Once a tweet is posted by a user, this tweet message is immediately propagated to followers and is displayed on each follower's tweet window as a single chronological list (Suh et al. 2010). Thus in Twitter, the term "Follower" is a person who subscribes to other users' Twitter accounts and the term "Following" can be described as an account that the user subscribes to.

After the emergence of SNS, many studies have already shown the importance of large number of followers in the diffusion of tweet messages. Zhou et al. (2010) confirmed that followers and following structure played a significant role in propagating tweet messages. Suh et al. (2010) also mentioned that the number of followers has a positive impact on retweeting. In addition, Zaman et al. (2010) and Harvey et al. (2011) also pointed out the importance of the number of followers for estimating future retweets. However, the role of followers in tweet diffusion has not been tested in the context of terrorist attacks to the best of our knowledge. Thus, the following hypothesis is developed based on prior research.

Hypothesis 3 Amount of information diffusion is positively associated with number of followers during extreme events.

A hashtag is a feature of SNS that is expressed by the hash (#) symbol. Many SNS users have adopted this symbol through the use of Twitter, Facebook, Google+or Instagram. According to the official help center of the Twitter service, this function is defined accordingly: "The # symbol, called a hashtag, is used to mark keywords or topics in a Tweet. It was created originally by Twitter users as a way to categorize messages." The major purpose of this feature is to categorize tweets by using hashtags in Twitter and this helps users search for information more easily. In addition, by clicking on a hashtag, users can see all other tweets that have the same hashtag. Usually in case of popular topics such as celebrities, famous brands, or trending topics, specific hashtags become very popular (Twitter 2013). Therefore, during the Boston bombing incident, #boston, #bostonmarathon, and #bostonbombing were commonly used hashtags and became very well known as trending topics.

Following other researchers, we suggest that hashtags have an impact on message diffusion. Suh et al. (2010) have studied the factors affecting the probability of retweets. They found that usage of hashtags improved the probability of retweet behavior. Petrovic et al. (2011) investigated the question "What kinds of factors contribute most in predicting retweets?" Their results showed that usage of hashtags is positively related to the probability of retweets. Therefore, hypothesis 4 is stated as follows.

Hypothesis 4 The degree of message diffusion is positively associated with the usage of hashtags in tweet messages during extreme events.

To summarize, our conceptual model "impact of twitter message features on degree of message diffusion" is represented as Fig. 1.

3 Method

3.1 Data collection

Almost 4 h after the incident happened by Mon, 15 April 2013 22:28 [GMT], we began collecting data from Twitter using a custom tool developed for Twitter Data collection. This tool uses the Twitter Streaming Application Program Interface (API) which enables live Twitter information capture. A search was conducted using three keywords (including hashtags) boston, bostonmarathon and bostonbombing. Data from the 4 h window that we missed earlier, from "Mon, 15 Apr 2013 18:50 [GMT]" to "Mon, 15 Apr 2013 21:50 [GMT]" was captured later from a third party service called Topsy, which stores all historical Tweets and indexes them for search. Using this service, we performed a keywords based search where we used the same three keywords for uniformity in the data collection. We collected four fields that were relevant to the research which are Tweet ID, Tweet Time, User Name and Content. Tweet ID is the unique number that Twitter generates sequentially for each tweet. The Tweet Time is the time in GMT when the user sent the tweet. User Name is the profile name of the user who tweeted the message and finally content is the actual Tweet message.

For analysis purposes, we needed to search the data for certain keywords. We performed this search using the MySQL database. After importing the text files containing the tweets collected into the database, we identified the two different types of messages - rumor-related and non-rumor related messages.

There are some common definitions of rumor. "A specific proposition for belief, passed along from person to person, usually by word of mouth, without secure standards of evidence being present" (Allport and Postman 1947). "A currently circulating story or report of uncertain or doubtful truth." (oxforddictionaries.com 2015), and "Information or story that is passed from person to person but has not been proven to be true." (Merriam-Webster.com 2015). Based on these definitions, we defined rumors as "unverified idea which diffuses through SNS" and applied this definition for our data collection process. For this study, the truth or non-truth of the message content was not relevant. For our data, we considered the web article (Kulakowski 2013) which identified the best-known Boston bombing related rumors. The article identified 13 rumors. Out of these thirteen rumors, six rumors—(a) girl dying before boyfriend proposed, (b) Denise Richard's son killed, (c) tax day motive, (d) donations for retweets (e) Sandy Hook principal alive, and (f) false flag - were not directly related to

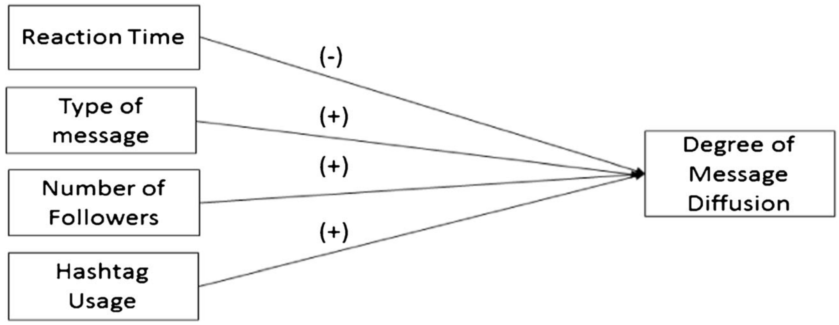

Fig. 1 Conceptual model

the incident and were judged to be unlikely to cause panic or anxiety among users and hence were not considered. Therefore, 7 rumors that were associated with the Boston bombings - JFK Library, Man on the roof, Saudi suspect, Cell phone, Death toll, American Airlines, and Facebook page - were identified for this study. Table 1 shows samples of rumor related messages which contain one or more of the seven rumors and associated rumor - mitigation tweets.

To select non-rumor related messages that did not mention any of the selected 7 topics, we started with the tweets that remained after the tweets associated with the rumors were pulled out. Among these, we manually extracted messages which contained non-rumor related information or emotional messages but mentioned the Boston bombing tragedy. Table 2 shows samples of non-rumor related messages.

Using the extracted tweets, we collected comprehensive information on each tweet such as first tweet posting time, number of retweets, initial source of the tweet, top two influencers of each initial source, and the number of followers for these influencers using the Topsy Pro third party twitter service.

3.2 Independent variables

In this study, we explored the relationships between four independent variables (Reaction time, Type of message, Number of followers, Hashtag usage) and one dependent variable (Number of retweets). In this section, we provide the detailed procedure we followed to obtain information about all variables using the example of a sample tweet as follows:

Table 1 Sample of rumor related message (Rumor and anti rumor)

Topic	Rumor	Sample	Anti-rumor	Sample
JFK Library	3rd explosion occurred in JFK library	Boston police say 3rd explosion at JFK Library; no injuries reported	It is not an explosion. It was a fire	Authorities say fire at JFK Library has not been linked #BostonMarathon explosions
Man on the roof	There was a strange man on the roof	People saying the man on the roof was the same roof the pressure cooker lid was on	Man on the roof is not related to bombing	The best picture for "man on the roof" shows a guy asleep in a chair, woke up cause of the bomb and then went to pee
Saudi Arabia suspect	Suspect is Saudi Arabian person	New York Post reporting authorities ID a Saudi national as a suspect in Boston Marathon bombings	It is not true. It is unverified information	Boston PD says NYPost report on "Saudi national" in custody is not true.
Cell phone shut down	Because of the incident, cell phone service will be shut down	Cellphone service shut down in #Boston to prevent remote detonations of explosives	It is not true.	UPDATE: cellphone service not turned off in Boston
Number of death toll	The death toll is at a dozen	Multiple reports coming in that death toll at Boston Marathon may be closer to a dozen	The information about the number of death toll was wrong	Latest Boston Marathon toll via AP: 2 dead, 57 injured, 8 critical as of 5:31 pm ET
American Airlines	Because of the bombing, American Airlines flights are canceled	What is going on world? bostonMarathon bombing, #Oklahoma on lockdown and now #americanairlines grounded all flights until 5 pm.	It was because of computer related problems	American Airlines flights across the country grounded because of computer problems
Fake Facebook page	The Facebook page about Boston bombing created before the bombing	Facebook page about the boston explosions before the boston explosions happened	It was a fake Facebook account and it has been deleted.	Two days ago, a page was created on Facebook for the Boston Marathon incidents. This page is now removed

Table 2 Sample of non-rumor related message (Informational and emotional message)

	Informational message	Emotional message
Sample tweet	WATCH: Boston officials give update on Boston Marathon bombings bit.ly/HwvNyV #BostonMarathon	POTUS: The American people will say a prayer for the people of Boston tonight

Sample tweet message:

"*Third explosion at JFK library....absolutely awful. #bostonmarathon*"

1) Search for this specific tweet message using topsy pro
2) Capture first posting time, initial source, and number of retweets.
3) Using initial source information, identify top two influencers of initial source and information about their number of followers.
4) Calculate the reaction time between event time and first posting time (event time was 4/15/2013/18:49 and first posting time of this tweet message was 4/15/2013/21:02) → 133 min
5) Calculate the number of followers by adding top two influencers' number of followers (1st : 651,965+ 2nd :1210=653,175)
6) Check the hashtag usage (#bostonmarathon was used in this tweet message)
7) Because this message contains rumor related content, the type of message is classified as rumor related

Based on the above procedure, we gathered relevant information for all five variables. Thus, we had three continuous variables called reaction time, number of followers and number of retweets, and two dichotomous variables called hashtag usage and message type. Finally, we had 256 tweet records and those were retweeted an average of 214.76 times. Therefore, we considered 549,789 tweet and retweet messages. Specifically, the number of rumor related tweets was 120 (46.9 %) that were retweeted an average of 300.82 and the number of non rumor related tweets was 136 (53.1 %) which retweeted an average of 138.83. In addition, the number of tweets containing hashtags was 138 (53.9 %), which were retweeted an average of 109.74; and the number of tweets that did not include hashtags was 118 (46.1 %) and these were retweeted 337.58. Therefore, we considered approximately 36,098 rumor related tweets, 18,880 non-rumor related tweets, 15,144 tweets that contained hashtags, and 39,834 tweets that did not have hashtags. Table 3 shows descriptive statistics and correlation analysis results for these tweets. According to the Pearson correlation analysis results, there were two statistically significant negative correlations. The first was

Table 3 Descriptive statistics and correlation analysis results

	N	*Mean*	*S.D*	*1*	*2*	*3*	*4*	*5*
1	256	214.76	845.625	1	–	–	–	–
2	256	6.061	1.603	−.159**	1	–	–	–
3	256	0.47	0.500	.096	−.435**	1	–	–
4	256	8.791	2.230	.348**	−.140*	.004	1	–
5	256	0.54	0.499	−.135*	.057	.021	−.138*	1

[1] Number of Retweet

[2] Log Reaction Time

[3] Message Type

[4] Log Number of followers

[5] Hashtag usage

** Correlation is significant at the 0.01 level (1-tailed)

* Correlation is significant at 0.05 level (1-tailed)

between reaction time and the number of retweets (r=−.159, p<.01); and the second was the relationship between hashtag usage and the number of retweets (r=−.139, p<.05). There was also one statistically significant positive correlation which was the relationship between the number of followers and the message being dispersed/diffused (r=.348, p<.01). However, these correlations between independent variables and dependent variable are all less than 0.6 (Taylor 1990).

3.3 Analysis method

In order to examine the impact of tweet features on tweet message diffusion in the context of the 2013 Boston Marathon bombing incident, we ran negative binomial regression models. When the dependent variable is a count variable, as in our case of the number of retweets, Ordinary Least Square (OLS) regression cannot estimate the appropriate statistics because of the violation of normality in residuals. Poisson regression and Negative binomial regression are possible methods to deal with count dependent variables. The major assumption of the Poisson regression model is that the variance is equal to the mean. To test this assumption, the residual deviation must be approximately equal to the degrees of freedom (Kwon et al. 2012).

However, the data we analyzed in this study violated this assumption. Our data was over-dispersed; the ratio of residual deviance (106458.520) to degrees of freedom (251) was (424.138). As an alternative to over-dispersed Poisson model, the negative binomial model has been suggested by other researchers (Osgood 2000; Paternoster and Brame 1997). Therefore, we conducted negative binomial regression as recommended.

The dependent variable we used in this analysis was the number of retweets and the independent variables were Reaction time, Message type, Number of Followers, and Hashtag Usage. We coded message type and hashtag usage as nominal variables. Therefore, if the tweet message contained a hashtag, it was coded as 1, if not, it was coded as 0. In the case of the message type, we coded it as 1 if messages were rumor related, and 0 if the messages were non-rumor related. The remaining variables—Reaction time, Number of Followers, and Number of retweets were all continuous variables. We used the minute time scale to code reaction time as it was judged to be the most appropriate measurement unit. In addition, the number of followers and number of retweets were coded as integer numbers.

In addition, since the original tweet also needed to be counted, we added 1 to all values for the number of retweets. To minimize violations of the normality assumption, we took logarithms on reaction time and number of followers. Finally, we prepared 256 tweets that had a total of 549,789 retweet messages which included all required information on each variable.

The omnibus test showed a good fit for models, with the likelihood ratio X^2 (4)=142.067, p<0.001. Moreover, the ratio of residual variance to degrees of freedom for this model was 1.280 (320.001 / 250). Because this value was closer to 1, this model fit was found to be appropriate for interpreting the findings of this study. To execute the statistical analysis, we used SPSS 20.0 software.

4 Results

We analyzed the effects from the overall model. The model equation for parameter estimates is as follows: Message Diffusion is measured as

$$Log(Retweets) = \alpha + \beta 1\, Reaction\, time + \beta 2\, Message\, Type(Rumor/Non\, Rumor) \\ + \beta 3\, Number\, of\, Followers + \beta 4\, Hashtag\, Usage$$

The parameter estimates are shown in Table 4.

Table 4 shows the analysis results of our research model. Hypothesis 1 suggested that there is a negative relationship between reaction time of the tweet (Time between event time and first tweet time) and amount of tweet message diffusion during the extreme event. The results revealed that there is a statistically significant negative relationship between tweet reaction time and the number of retweets during the Boston Bombing incident (Wald X^2(1)=15.331, p<.001) as proposed in our hypothesis 1. A one-point increase in the log of reaction time reduced the number of retweets by approximately 23.6 %, β=−.270, Exp(β)=.764, p<.001. We believe this empirical result reflects the ability of popular messages to resolve extreme event related information quickly. These messages are disseminated quickly by all interested people and reach their target audience quickly. On the other hand, less popular messages only capture the interests of a few users who may hesitate to propagate the tweet.

Hypothesis 2 suggested that rumor related messages diffuse more than non-rumor related messages during extreme events. This was not statistically supported. (Wald X^2(1)=0.114, p>.0.05), indicating that there was no statistically significant relationship between message type and number of retweets during the incident. This meant that both rumors and non-rumors about the extreme event diffused to the same extent.

Hypothesis 3 suggested that the degree of rumor information diffusion is positively associated with the numbers of followers. This was statistically significant (positive relationship) in the expected direction, β=.359, Exp(β)= 1.432, Wald X^2(1)=64.165, p<.01. This result suggested that a one-point increase in the log of number of followers increased the number of retweets by around 43.2 %. This is intuitive since tweet messages posted by users who have many followers are likely to be viewed by a large number of users and this was true for the 2013 Boston bombing incident as well.

Hypothesis 4 suggested that the usage of hashtags in tweet messages is positively associated with the degree of message diffusion. This was statistically significant in an unexpected way (β=.561, Exp(β)=1.753, Wald X^2(1)=9.271, p<.01). The results revealed that when there was no hashtag in the tweet message, the number of retweets was 75.3 % more than for messages with hashtags. Interestingly, this result is in opposition to hypotheses propounded by prior research.

The predictor variables in a regression model can be endogenous for several reasons such as, omitted variable biases, measurement errors, or simultaneity / reverse causation. By using the Hausman test (Hausman 1978) an instrumental variable estimation can be performed to investigate whether there are some missed variable biases in the regression model (Jabr & Zheng 2014). According to the Hausman test, under null

Table 4 Negative binomial regression analysis result (N=256)

Parameter	Coefficient (β)	Standard Errors (SE)	Wald (df)	Sig.	Exp(β)	95 % Confidence interval
(Intercept) ***	2.837	0.6496	19.076 (1)	0.000	17.070	4.778~60.982
Reaction time ***	−0.270	0.0689	15.331 (1)	0.000	0.764	0.667~0.874
Message type (0)	0.069	0.2047	.114 (1)	0.736	1.072	0.717~1.601
Followers ***	0.359	0.0448	64.165 (1)	0.000	1.432	1.312~1.564
Hashtag usage (0) **	0.561	0.1843	9.271 (1)	0.002	1.753	1.221~2.516

*p<.05, **p<.01, ***p<.001

hypothesis, the specified endogenous regressors can be considered as exogenous.

Oh et al. (2013) studied message type (Rumor) as a potential endogenous variable. URL usage and the Log number of characters in each message may likely affect message type. We tested this assumption by running reduced form regression (with message type as dependent variable, and URL usage and log number of characters as independent variables). We tested whether the residual from the regression correlates to the number of retweets. The results indicated that residuals are not significant, Wald $X^2(1) = 0.441$ and $p > .05$, confirming that message type is exogenous and does not suffer from omitted variable bias.

5 Discussion

In this paper, we examined the impacts of factors drawn from the innovation diffusion literature on the diffusion of tweet messages during the 2013 Boston bombing incident. The paper has two main contributions.

The first contribution concerns the adaptation of the innovation diffusion model to the diffusion of information, specifically to the diffusion of tweet messages. Drawing an analogy between innovations and novel information released in the aftermath of an extreme event, we applied diffusion theory to develop our hypotheses

On the time dimension, our results were intriguing because they suggested that tweet messages that have longer reaction times diffused less than tweet messages with shorter reaction times. This indicates that the popularity of tweet messages is decided in a short period from incident time (reaction time). Therefore, we can understand that prompt reaction regarding the incident may improve the probability of message diffusion. Our other result, about hashtags usage, was also very intriguing. Prior literature has suggested that hashtags had a positive impact on message diffusion. However, our result indicated that tweet messages that did not include a hashtag were diffused more widely than tweets with hashtags. We interpreted this as a result from context differences. In positive contexts such as marketing or advertising, the impact of hashtag usage on message diffusion may be positive. However, in the case of negative contexts like terrorist incidents or disasters, hashtag usage may have negative impacts. This requires further investigation in future research.

We also used a more comprehensive measure of followers using the metric of the top two influencers of each specific tweet. We believe this provided more relevant results than only considering the followers of the original tweeter. Influencers are users who follow the user who posted a specific tweet.

There are limitations to this study. First, we have only considered one extreme event. This may limit the generalizability of the results.

Second, we only focused on the Twitter channel as an SNS. Even though Twitter is the most commonly used SNS to propagate messages, there are other popular social media channels such as Facebook, Google + or Instagram. Message diffusion during extreme event should be observed on these channels too. In future research, message diffusion needs to be investigated in the entire spectrum of social media channels. This will improve our understanding of this phenomenon.

Acknowledgments This research is funded by National Science Foundation under grants 1353119 and 1353195. The usual disclaimer applies. We would like to thank Anu Mary Eapen, Basma Abdul Rehman, Sabharish Sainath, Megan Saldanha, and Swati Upadhya for their research support.

References

Ada, S., Rao, H. R., & Sharman, R. (2010). *Online Social Networking Site (SNS) Use at the Campus Emergencies.* Paper presented at the ICIS.

Allport, G. W., & Postman, L. (1947). The psychology of rumor. New York: Holt, Rinehart, & Wilson.

Cha, M., Mislove, A., & Gummadi, K. P. (2009). *A measurement-driven analysis of information propagation in the flickr social network.* Paper presented at the Proceedings of the 18th international conference on World wide web.

Chen, R., Rao, H. R., Sharman, R., Upadhyaya, S. J., & Kim, J. (2010). An empirical examination of it-enabled emergency response: the cases of hurricane Katrina and hurricane Rita. *Communications of the Association for Information Systems, 26*(8), 141–156.

DHS. (2014). Unclassified summary of information handling and sharing prior to the April 15, 2013 Boston Marathon Bombings.

Doerr, B., Fouz, M., & Friedrich, T. (2012). Why rumors spread so quickly in social networks. *Communications of the ACM, 55*(6), 70–75.

Hansen, L. K., Arvidsson, A., Nielsen, F. Å., Colleoni, E., & Etter, M. (2011). Good friends, bad news-affect and virality in twitter *Future information technology* (pp. 34–43): Berlin Heidelberg: Springer.

Harvey, C. G., Stewart, D. B., & Ewing, M. T. (2011). Forward or delete: What drives peer-to-peer message propagation across social networks? *Journal of Consumer Behaviour, 10*(6), 365–372.

Hausman, J. (1978). Specification tests in econometrics. *Econometrica, 46*(6), 1251–1271.

Hovav, A., Patnayakuni, R., & Schuff, D. (2001). *Internet technology diffusion: Adoption of IPV6.* Paper presented at the ECIS.

Jabr, W., & Zheng, E. (2014). Know yourself and know your enemy: An analysis of firm recommendations and consumer reviews in a competitive environment. *Mis Quarterly, 38*(3), 635–654.

Johnson, D. (2001). What is innovation and entrepreneurship? Lessons for larger organisations. *Industrial and Commercial Training, 33*(4), 135–140.

Kulakowski, K. (2013, April 20). Debunking rumors surrounding boston bombing, *Infinity News Network*. Retrieved from http://infinitynewsnetwork.com/2013/04/20/debunking-rumors-surrounding-boston-bombing/.

Kwon, K. H., Oh, O., Agrawal, M., & Rao, H. R. (2012). Audience gatekeeping in the twitter service: an investigation of tweets about the 2009 gaza conflict. *AIS Transactions on Human-Computer Interaction, 4*(4), 212–229.

Li, J., & Rao, H. (2010). Twitter as a rapid response news service: an exploration in the context of the 2008 China earthquake. *The Electronic Journal of Information Systems in Developing Countries, 42*(4), 1–22.

Li, J., Vishwanath, A., & Rao, H. R. (2014). Retweeting the Fukushima nuclear radiation disaster. *Communications of the ACM, 57*(1), 78–85.

Merriam-Webster.com. (2015). Rumor. Retrieved January 27, 2015, from http://www.merriam-webster.com/dictionary/rumor.

Oh, O., Agrawal, M., & Rao, H. R. (2013). Community intelligence and social media services: a rumor theoretic analysis of tweets during social crises. *MIS Quarterly, 37*(2), 407–426.

Osgood, D. W. (2000). Poisson-based regression analysis of aggregate crime rates. *Journal of Quantitative Criminology, 16*(1), 21–43.

oxforddictionaries.com. (2015). Rumor. Retrieved January 27, 2015, from http://www.oxforddictionaries.com/us/definition/american_english/rumor?searchDictCode=all.

Paternoster, R., & Brame, R. (1997). Multiple routes to delinquency? A test of developmental and general theories of crime. *Criminology, 35*(1), 49–84.

Petrovic, S., Osborne, M., & Lavrenko, V. (2011). *RT to Win! Predicting message propagation in twitter.* Paper presented at the ICWSM.

Piddock, C. (2014). Anatomy of a terrorist attack:The boston marathon bombing. *Homeland security surverillance, detection, prevention & protection,* 24–33.

Rogers, E. (1962). *Diffusion of innovations* (1st ed.). New York: Free Press.

Romero, D. M., Meeder, B., & Kleinberg, J. (2011). *Differences in the mechanics of information diffusion across topics: idioms, political hashtags, and complex contagion on twitter.* Paper presented at the Proceedings of the 20th international conference on World wide web.

Starbird, K., Maddock, J., Orand, M., & Mason, R. M. (2014). Rumors, false flags, and digital vigilantes: misinformation on twitter after the 2013 Boston Marathon bombing. iConference.

Suh, B., Hong, L., Pirolli, P., & Chi, E. H. (2010). *Want to be retweeted? large scale analytics on factors impacting retweet in twitter network.* Paper presented at the Social computing (socialcom), 2010 ieee second international conference on.

Taylor, R. (1990). Interpretation of the correlation coefficient: a basic review. *Journal of Diagnostic Medical Sonography, 6*(1), 35–39.

Twitter. (2013). Using hashtags on Twitter. Retrieved January 28, 2015, from https://support.twitter.com/.

Yang, L., Sun, T., Zhang, M., & Mei, Q. (2012). *We know what@ you# tag: does the dual role affect hashtag adoption?* Paper presented at the Proceedings of the 21st international conference on World Wide Web.

Ye, S., & Wu, S. F. (2010). *Measuring message propagation and social influence on Twitter. com*: Springer.

Zaman, T. R., Herbrich, R., Van Gael, J., & Stern, D. (2010). *Predicting information spreading in twitter.* Paper presented at the Workshop on computational social science and the wisdom of crowds, nips.

Zhou, Z., Bandari, R., Kong, J., Qian, H., & Roychowdhury, V. (2010). *Information resonance on twitter: watching iran.* Paper presented at the Proceedings of the First Workshop on Social Media Analytics.

Jaeung Lee is a Ph.d candidate in the department of Management Science and Systems at the State University of New York at Buffalo. His primary areas of research interests include Information security, Emergency response management system and requirement management. His publications include the Proceedings such as AMCIS 2015, SKM 2014, WMSC 2011, and IRM 2011.

Manish Agrawal is an associate professor in the department of Information Systems and Decision Sciences of the College of Business Administration at the University of South Florida, Tampa, Florida. His current research interests include information security, software quality, and the use of IT during extreme events. His articleshave appeared or are to appear in journals including Management Science, Journal of Management Information Systems, MIS Quarterly, INFORMS Journal on Computing, and IEEE Transactions on SoftwareEngineering. His research received the Design Science Award from the INFORMS Information Systems Society. He completed his Ph.D. at SUNY Buffalo.

H. R. Rao is a Distinguished Service Professor in the department of Management Science and Systems at SUNY Buffalo, with a courtesy appointment with Computer Science and Engineering as adjunct professor. His interests are in the areas of management information systems, e-business, emergency response management systems, and information assurance. He received a Fulbright fellowship in 2004. His research is supported by the National Science Foundation and the Department of Defense. He completed his Ph.D. at Purdue University.