An empirical study on Twitter's use and crisis retweeting dynamics amid Covid-19

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Abstract

This study conducts an analysis on topics of the most diffused tweets and retweeting dynamics of crisis information amid Covid-19 to provide insights into how Twitter is used by the public and how crisis information is diffused on Twitter amid this pandemic. Results show that Twitter is first and foremost used as a news seeking and sharing platform with more than 70% of the most diffused tweets being related to news and comments on crisis updates. As for the retweeting dynamics, our results show an almost immediate response from Twitter users, with some first retweets occurring as quickly as within 2 s and the vast majority (90%) of them done within 10 min. Nearly 86% of the retweeting processes could have 75% of their retweets finished within 24 h, indicating a 1-day information value of tweets. Distribution of retweeting behaviors could be modeled by Power law, Weibull, and Log normal in this study, but still there are 20% original tweets whose retweeting distributions left unexplained. Results of retweeting community analysis show that following retweeters contribute to nearly 50% of the retweets. In addition, the retweeting contribution of verified Twitter users is significantly ($P < 0.05$) different from that of unverified users. A similar significant ($P < 0.05$) difference is also found in their rates of verified retweeters, and it has been shown that verified Twitter users enjoy seven times as high value as that of unverified users. In other words, users with the same verification status are more likely to get together to diffuse crisis information.

Keywords Covid-19 · Twitter use · Crisis communication · Retweeting dynamics

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1 Introduction

The beginning of 2020 has witnessed the outbreak of Covid-19, which has become a devastating threat to global public health. People of the whole world are suffering and struggling to tackle the immediate threat. According to the daily report of the World Health Organization (WHO), by the time of this study, there are over 8 million confirmed cases and 450 thousand deaths caused by the virus around the world (World Health Organization 2020). What is more worry-some is that the confirmed cases still maintain a rapid increasing momentum. Within the battle with the pandemic, effective public communication plays an important role in reducing the spread of the virus (Thelwall and Thelwall 2020b), which necessitates a complete understanding of people's reactions to this crisis, regarding their attitudes, consensus, and information diffusion behaviors. Besides, the analysis may facilitate the understanding of the virus's epidemiology, which in turn benefits the containment of the pandemic (Lipsitch et al. 2020). Viewing this, in this study we resort to social media for crisis information, where people often share their opinions, stories, and eye-witness news during crisis events (Thelwall and Thelwall 2020b; Wang and Zhuang 2017; Lachlan et al. 2016). Twitter, one of the most widely used microblog services around the world, is an important source of breaking news (Hamidian and Diab 2019) and an important platform for disseminating new public health information (Liang et al. 2019). Dates back to the H1N1 pandemic, social media severed only as a secondary channel for crisis information following the traditional mass media (Vijaykumar et al. 2015). When used as a secondary information source, social media was able to attract researchers to examine the potential use of Twitter, a popular social media application, as an effective real-time information and sentiment tracking tool (Cynthia et al. 2010). Their results show that official messages (e.g., those from the WHO) could effectively manipulate people's knowledge towards the H1N1 pandemic, and Twitter users are active in sharing and providing news regarding the virus (Cynthia et al. 2010). Besides news, Twitter users are also proven active in spreading their situations and emotional responses during disasters (Thelwall and Thelwall 2020b; Lachlan et al. 2016). Information from these tweets could be exploited by officials and experts to understand the situation on the ground and respond accordingly (Thelwall and Thelwall 2020b). Despite the previous efforts investigating the online communication patterns of pandemic crises, for the most recent Covid-19 crisis, insights into people's attitudes, reactions, and diffusion behaviors are still needed for better response work. Viewing this, we are motivated to investigate: (1) how people react to the Covid-19 pandemic; (2) how Twitter is used by the public; and (3) the dynamics of retweeting behaviors amid the pandemic. Results of this study signify themselves by enriching knowledge on social media crisis communication and by providing response officials and experts with valuable insights into crisis information management.

The study is organized as follows: Sect. 2 summarizes the existing research on Twitter use for crisis communication and dynamics of retweeting behaviors; Sect. 3 introduces methods and data used in this study; Sect. 4 presents our analysis results; Sect. 5 discusses the results and potential insights; and Sect. 6 concludes.

2 Literature review

The advent of social media makes everyone with a smartphone an on-site journalist, providing almost immediate updates about an event. Nowadays, it has been normal that breaking news appears first on social media before making it through traditional mass

media outlets (Hamidian and Diab 2019; Oh et al. 2013). Twitter, in recent decades, has become an important channel for breaking news and situational updates either in normal or crisis times (Gil de Zúñiga et al. 2012; Hamidian and Diab 2019; Vieweg et al. 2010), and a huge number of online community members take social media as their first choice for information (Asghar et al. 2018). Its advantages over traditional mass media are amplified during crisis times, especially when the demand for situation awareness could not be met by official reports. Therefore, massive efforts have been made to investigate people's use of social media during crisis events. It has been shown that people depend heavily on Twitter to show their concerns and panics (Glowacki et al. 2016), to say thanks and to update their situation awareness during crisis times (Shaw et al. 2013). Along with this popular use of social media, a new type of collective action is formed online. To bring insights into the forming process, research from Vaast et al. (2017) investigates how multiple types of Twitter users enact their roles in the collective action with their own distinguished posting patterns during the crisis of Gulf Mexico Oil Spill. Despite the fact that each type of user could contribute to the forming of collective action, their power regarding information diffusion varies significantly. As indicated in the case study of the 2012 Hurricane Sandy from Wang and Zhuang (2017), messages of news agents and official governments are better engaged than those from an average Twitter user. Similar efforts have also been found in other studies on natural disasters (Kaigo 2012; Wilensky 2014), public health crises (Paul and Dredze 2011; Jordan et al. 2019), and commercial crises (Stieglitz and Krüger 2011).

Except for the use of social media during disasters, diffusion dynamics of crisis information on this platform is another focus of researchers. Such research questions have been examined, as how crisis messages of official agents are diffused to the public (Eriksson and Olsson 2012), what the potential distributions of tweets cascading sizes are (Zhou et al. 2010), how temporal features of crisis information (Stefanidis et al. 2017; Zhou et al. 2010), retweeting ratio of social media users (Bild et al. 2015), and other retweeting dynamics (Suh et al. 2010; Metaxas et al. 2015) look like on Twitter during crisis times. For instance, messages from disaster-impacting areas are more likely to be retweeted than those from non-impacting areas (Starbird and Palen 2010) and tweets from official accounts usually enjoy a higher level of engagement in terms of retweeting (Wang and Zhuang 2017). As for the most recent pandemic, researchers show their interest as well. Research from Thelwall and Thelwall (2020b) analyzes the content of highly diffused tweets to discover people's attitudes and consensus toward the virus. Their study supports a positive role that tweets from average users have played in diffusing beneficial news by sharing tweets regarding social distancing, thanks to doctors and work staff, etc. They also discover a different using pattern of female and male Twitter users during the pandemic via a content analysis on popular tweets related to Covid-19 (Thelwall and Thelwall 2020a). Specifically, female Twitter users are more likely than their male counterparts to tweet messages regarding scientific guidance (e.g., social distancing) to avoid potential virus infection. Another similar work from Kouzy et al. (2020) focuses on the spreading of misinformation among different types of Twitter users. Their results show that unverified accounts are more likely to spread misinformation than verified accounts. These studies provide valuable insights into the use of Twitter during this most recent pandemic; however, their work is far from enough to get a complete understanding of social media use and diffusion dynamics for this unprecedented and lasting Covid-19 pandemic. Moreover, only hundreds of or even fewer tweets are analyzed in these studies, which may cause biased conclusions. In light of this, our study collected about 1 million original tweets related to the pandemic within a 3-month

period and conducted both thematic and retweeting dynamic analyses of these crisis tweets. Results of this study could bring more valuable insights into social media use amid the pandemic and provide potential managerial suggestions for crisis management.

3 Method

3.1 Data collection

Twitter standard search API and Twitter Advanced Search service are used in this study to collect English tweets related to Covid-19 and posted from Feb 01 to Apr 30, 2020, amid which the apex and most updated development of the pandemic are covered as of this study. Keywords, hashtags, and their different combinations used for this collection include #Covid19, #Covid-19, #coronavirus, coronavirus, etc. As a result, we collected 983,990 original tweets, posted by 324,735 unique users. Figure 1 illustrates the number of original tweets, involved users, and average posting frequency of Twitter users each day during the collection period, indicating a much more massive attention on the pandemic in March, when the virus gained the highest momentum by the time of this study by starting to infect people on a global scale.

To understand the diffusion dynamics of crisis information, we have to analyze tweets with reasonable sizes of retweet counts. Statistically, a sample with at least 75–100 data points is required for reliable distribution fitting results. However, during our retweets collection, a wired bug on Twitter has been found that removes retweets randomly (Lieu 2019). To ensure enough data points are collected for distribution modeling, we have to increase the lower threshold value of retwet count and decide to only analyze original tweets whose retweet counts are over 100 and at least 95% of their retweets are collected. With these two filters, a total of 3013 original tweets along with 916,568 pieces of their retweets are used for the retweeting dynamic analysis.

Fig. 1 No. of collected original tweets, involved users, and user posting frequency each day from February 01 to April 30, 2020

3.2 Content analysis

Content analysis (CA) has been used widely to derive quantitative information from open-ended qualitative data by analyzing frequency of ideas or of opinions (Berg et al. 2004; Neuendorf 2002; Patton 1990). To grab an insight into the themes of the most popular topics on social media amid the pandemic, we use the techniques of CA to categorize tweet topics. The method performs well in pattern discovery thanks to its reliable coding scheme, which requires a completely independent data coding by at least two coders (Berg et al. 2004). In this study, we define popular tweets as those with over 10,000 retweets and get 1215 qualified tweets in total. The two coders were first trained by a sample of 138 popular tweets to make a subjective judgment on the information type or the motivation of a tweet. Specifically, the tweets were marked with one or more tags, and then grouped and classified repeatedly to generate several consistent tags or descriptions to reflect the main purpose(s) or idea(s) of each tweet. For instance, a tweet with both comments and a link to a piece of news could be tagged with both news sharing and comments. To decide which tag is more appropriate, the two coders have to base their decisions on whether the user tends to share important news and attach a few words describing the news content or to express their opinions on the news and cite the news source by attaching it to their tweets. Cohen's Kappa is used to measure the inter-coder reliability of our coding. The value came to 0.63 after the pilot test and was improved to a much more satisfactory level of 0.83 after thorough discussions of the two coders. The two coders then coded the remaining 1077 popular tweets separately and finally came to an agreement on disputed information types.

3.3 Statistical analysis

Descriptive statistics are used to summarize measures like tweets frequency, retweeting efficiency, retweeter structures, etc. Histograms, bar graphs and box plots are generated to illustrate the features of analyzed measures. The Pearson test has been used to investigate the potential relationships between different measures, such as the one between first retweeting efficiency and the time needed to finish the whole retweeting process. ANOVA is conducted in our study to identify potential factors that cause different performances of the measures mentioned above, such as the difference in verified retweeters rates between verified and unverified Twitter users.

4 Results

4.1 Topology of popular tweets

The thematic topology of popular tweets amid the pandemic is abstracted into six different types, including comments & opinions, news, own story, appeal, wish & support, and others. Three sub-themes are identified and classified into the themes of comments & opinions, and news respectively in this study, as shown in Table 1, which summarizes the topology and defines each theme and sub-theme. Definitely, there is absolutely no clear boundary between each type as some tweets may fit more than one theme. The two coders solve the

Table 1 Topology structure and definitions of most retweeted tweets

Themes	Sub-themes	Count	Definitions
Comments and opinions	Joke	21	Joking the virus or virus-related events
	Politics	188	Talking about politics, such as governmental crisis response
	Opinions	356	Personal opinions on pandemic-related news or events
News	Gossip news	27	Grass-root news such as neighborhood life under pandemic
	Tips	49	Antivirus tips or suggestions from doctors and professionals
	Official news	233	updated news about the pandemic, such as global death tolls
Own story		131	User's own experience or stories related to the pandemic, such as infection of a relative
Appeal		105	Making a plea for doing or stop doing things, such as stop spreading rumors
Wish and support		65	Expressing support, best wishes or appreciation to doctors, workers, etc.
Others		40	Topics belong to none above-mentioned groups
Total		1215	

problem by discussing the potential proper themes and picking the best-fit one as the final result.

In general, Twitter is first and foremost used as a tool for sharing news and opinions amid the pandemic, with the two groups of comments & opinions, and news combined ranking first in frequency. It is used less frequently as a channel for emotional support, with the wish & support type taking only 5%, as shown in Fig. 2. The findings are consistent with those from previous studies claiming that Twitter is used more as a news seeking and sharing tool compared with Facebook (Eriksson and Olsson 2016).

4.1.1 Comments and opinions

Among the popular tweets, those belonging to the theme of comments & opinions are the most frequently identified and further divided into three sub-themes. As summarized in Table 2, tweets are classified into personal opinions when they show a user's comments and opinions on pandemic-related news (e.g., "I can't believe this is so hard for people to grasp: yes, the current death toll for covid19 is roughly = to seasonal flu season..."). The type of politics concerns comments on governments or politicians, such as on their pandemic response work. Joking is also discovered in our study. People are willing to share funny stories and to joke in the hope of making life easier and lighting up the spirits amid city lockdowns. Among all three sub-themes within the type of comments & opinions, personal opinions ranks first by taking 29.30% among all popular tweets, politics second by taking about 15%, followed by joking taking 1.73%, as shown in Fig. 2.

4.1.2 News

News is among the most diffused messages on Twitter amid the pandemic in our study. Among the three types of news, the one from official news outlets is still in Twitter users'

Fig. 2 Percentages of different themes within the tweet topology

favor, taking almost 20% of all popular tweets and 75% of the news-themed tweets, as shown in Fig. 2. Besides forwarding and commenting on official news, users also post gossip news filmed by their phones to record life under the pandemic. For instance, a user forwards a piece of on-scene news about the O'Hare airport under the pandemic, the post reads "This is the scene at O'Hare airport. The traveler who took the photo said it's a 6-h wait for bags then..." Besides, Twitter users are enthusiastic in sharing antivirus tips to their online communities to enhance people's awareness of virus prevention. Among the tips, some of them come from personal Twitter accounts of doctors, who utilize Twitter as a channel to spread their antivirus suggestions. These suggestions, along with official tips from the WHO and the CDC, could prepare the public for the pandemic and facilitate sense building in antivirus measures.

4.1.3 Own story

Despite the huge volume of official reports on the pandemic, everyone has their own versions of life and experiences under this crisis. Grass-root stories about the pandemic are also attractive to Twitter users, taking almost 10% of the popular tweets. For instance, a user shows his anxieties after knowing both his parents tested positive for the virus, the post reads as "Both my parents tested positive for COVID-19. My biggest nightmare. Doakan my parents." Some users share interesting stories of their family members under lockdowns. For example, a young lady shares a funny story during her father's quarantine time at home, "day 6 of quarantine: my dad gave a talk to the cats about covid-19..." These stories project the life of average people into public, and unlike those official reports, they provide a more real and practical aspect of life under this unprecedented crisis. After all, official news probably never reports a story that tells how a father during quarantine time gives a talk to cats on Covid-19. But this story could draw massive attention on social media.

4.1.4 Wish and support

One of the most distinguished characteristics of humanity is to be optimistic when hard days hit. Though the whole world is devastated by the Covid-19 pandemic, people never forget to show best wishes and desires for normal life. They present best wishes, prayers, and support for their friends and families, doctors, experts, and other front-line workers fighting against the virus. For instance, a user shows his gratitude to doctors with a post saying "Not all heroes wear capes. We pay tribute to doctors who put their lives at risk to help the country fight the Covid-19 crisis..." However, what comes is not always good news. Death from Covid-19 makes people suffer from losing loved ones. They may turn to Twitter to express their love and grieve. For instance, "RIP ..., 36. An NHS nurse for 16 years, loving wife & mother of 3 young children. Killed by #Coronavirus that she contracted ... An absolute heroine." The sheer number of retweets of these messages echo the same wishes and hope from other users who show their support via retweeting. This type of use turns Twitter into a tune for emotional support.

4.1.5 Appeal

By allowing average people to create and publish content themselves, web 2.0 has dramatically changed the ecosystem of traditional mass media, where every piece of news has to undergo thorough scrutiny before publication (Lazer et al. 2018). As a result, Twitter has

made it possible that the voice of an average user is heard by the public. Analysis of the popular tweets confirms this web 2.0 communication pattern by discovering people's use of Twitter to broadcast their needs and petitions amid this pandemic. For instance, a user pleaded for prayers for her sister by posting a tweet saying “My sister has #Covid_19. She's 7 months pregnant. Will you pray for her? ” Other appeals concern widely spread rumors or fake news on Twitter. For instance, some users appealed to their followers to stop rumor spreading, e.g., “As a certified tax professional, the stimulus bill is NOT A LOAN... Please stop spreading false information.” Other appeals include cooling panics (e.g., “My fellow citizens, THERE IS ABSOLUTELY NO NEED TO PANIC. Essential commodities...”), soliciting more retweets (e.g., “Hey, @amazon, is there any way a lowly Urgent Care doc who's on his last N95 and wondering ... Any retweets to gain attention would be great! ”), etc.

4.1.6 Others

The theme of others includes tweets whose information belongs to none of the above mentioned types. Such tweets are coded into the theme of others as “Bill Gates did this TED Talk 4 years ago #COVID2019...”

4.2 Dynamics of crisis retweeting

4.2.1 Efficiency

Empirical distributions of retweets are highly right skewed with the skewness index taking an average of 5.12, suggesting a much earlier and quicker condensed retweeting behaviors. In this study, we use: (1) first efficiency to measure how quickly the very beginning first retweet occurs, and (2) complete efficiency to measure how quickly the whole retweeting process is done. For the first efficiency, results indicate almost an immediate retweeting response from Twitter users with 51% of the first retweets occurring within 1 min, over 60% of which occurring within only 30 s. Given 10 min, more than 90% of the first retweets would occur, as shown in Fig. 3. While, on the other hand, some original tweets have undergone a much longer period of time (e.g., over 20 h) until they see their first retweets. One potential reason for this late first response is that the original tweet is probably posted at a very late night, when followers or friends are inactive. The late response could also originate from the incompleteness of retweets collection (though at least 95% of them are collected) in this study, causing the missing of the very beginning retweets.

Fig. 3 Frequency and running total of time (h) until 75% of the retweets are done

As for the complete efficiency, we only have the time stamp of the last retweet by the time of our data collection, which is done 1 week after the original tweets, when the majority of retweets should be finished (Wang and Zhuang 2017). Therefore, despite the fact that our data may not reflect the real length of a complete retweeting process, still they could equip us with an outright understanding of this process. As the retweet time is highly skewed and long-tailed, the efficiency of the whole retweeting process is highly biased and sensitive to the time of the last retweeting behavior. For instance, a retweeting process may have 90% of its retweets done within 2 h, but the complete efficiency of this process turns out to be 100 h if the last retweet is done several days later. Therefore, in this study, we measure the complete efficiency of retweets when 75% of the process is done. As shown in Fig. 3, over 60% of the complete efficiency is less than 12 h, and 86% is within 24 h. As for the whole retweeting process, results show that on average, it could last about 313.28 h, with 50% of them done within 175.69 h.

While some original tweets have to wait for a long time before their first retweets come, their messages still get diffused at least 100 times. In other words, whether the process gets started or not may outweigh how quickly the process gets started. Our Pearson test results also deny a potential relationship ($r = -0.02$, $P > 0.5$) between the efficiency of first retweets and the count of retweets. Moreover, we test the relationship between the first retweet efficiency and the difference between the time of first retweet and that when 75% of the retweeting behaviors are done. As a result, the Pearson correlation index value takes only 0.02 ($P > 0.05$), indicating a nonsignificant relationship between the first retweeting efficiency and the complete retweeting efficiency. As long as the first retweeters initialize the retweeting process, either quickly or not, the process is done with a significantly equivalent speed.

4.2.2 Distribution

To model the complete retweeting process, we investigate the potential distributions of retweeting behaviors. We first conduct a skewness-kurtosis analysis to select proper candidate distributions of this process. As shown in the Cullen and Frey graphs in Fig. 4, three candidate distributions are selected, including Log normal, Beta, and Weibull. Since Power law has been widely used for online behaviors modeling (Lu et al. 2014; Bild et al. 2015), we also make it as a distribution candidate.

The modeling results are summarized in Fig. 5, among the four candidate distributions, Beta distribution the least fits the retweeting process; the other three distributions fit nearly on par with each other, i.e., the retweeting process is not dominated by any particular distribution. There are about 20% of the retweeting processes whose distributions could not be explained by any of the four candidate distributions. About 47% of the processes are modeled properly by at least two distributions. In view of this, more samples and in-depth analysis are in need to provide additional insights into the distribution of retweeting behaviors.

4.2.3 Community

To become viral, a tweet message needs numerous retweets from other users, with whom a retweeting community is automatically formed. Within the communities, a retweeter is not necessarily a follower of the original tweet user as Twitter provides a search service (<https://twitter.com/explore>) that enables its users to discover trending topics by tweets retrieval and to forward a tweet without following its user. Therefore,

Fig. 4 Cullen and Frey graphs (with 1000 times of bootstrap) for occurring time of retweets of 16 original tweets. X-axis is the square of skewness and Y-axis is the kurtosis

Fig. 5 Distribution test results for retweet behaviors

retweeters could be classified into followers and non-followers. In this section, we compare retweeting behaviors of these two types of retweeters in terms of frequency and speed. We also test the impact of user authentication status on retweeter structures of retweeting communities.

On average, the following retweeters contribute 52% of retweets of an original tweet, with at least half of the original tweets having that number higher than 56.9%, as summarized in Table 2. Since followers have subscribed to updates of their followees, they are better informed than non-followers. To figure out more insights, we compared the retweeting efficiency of following and non-following retweeters. Results from ANOVA ($df = 1, N_f = 2,933, N_{nf} = 3,011, P = 0.01$) suggest a significant slower, 4 h on average, retweeting response from non-following retweeters than that from following retweeters. Retweeting time of the following retweeters is much more right skewed than that of non-following retweeters, with half of the following retweeters finishing retweeting within about 9 h, while that time is nearly 14 h for non-following retweeters, as summarized in Table 2.

We analyze how features of original tweet users impact the retweeter structures of retweeting communities. Figure 6 illustrates the quantiles of verified retweeters rate and following retweeters rate for both verified and unverified Twitter users, suggesting a higher value of the verified Twitter users for both measures. Statistic summary and ANOVA results are summarized in Table 3; the verified Twitter users see an average of 2.7% of verified retweeters out of the retweeting community, while that number takes only 0.4% for their unverified counterparts. The difference is supported significantly with the P values being 0 from the results of ANOVA.

Following retweeter rates of both verified and unverified users differ significantly ($p < 0.05$) from each other, suggested by the results of ANOVA in Table 4. The verified Twitter users see an average of 60.1% of following retweeters out of the whole retweeting members, the value of unverified users, though being slightly lower, still takes nearly 50%. Moreover, the percentages are consistent within both retweeting communities as the variance of following retweeters rates is nearly 0 (0.07 and 0.08) for both verified and unverified users.

Table 2 Statistic summary of following retweeters (following RT) rate, verified retweeters (verified RT) rate, and average retweeting time of following retweeters and non-following retweeters for the most diffused original tweets

Measures	Following RT rate	Verified RT rate	Following RT time (h)	Non-following RT time (h)
Mean	0.52	0.01	20.82	24.09
Median	0.57	0.00	9.35	13.75
Mode	0.00	0.00	1.00	1.00
Kurtosis	− 1.12	106.59	624.43	114.55
Skewness	− 0.32	8.49	19.43	7.80
Minimum	0.00	0.00	0.02	0.08
Maximum	0.99	0.70	2004.79	892.54
Count	3013	3004	2933	3011

Fig. 6 Box plots of verified retweeters rate and following retweeters rate with different verification statuses

5 Discussions

5.1 Twitter use during a crisis

With news sharing and commenting topics taking the vast majority of widely diffused tweets in our analysis, our study confirms the previous finding that Twitter is first and foremost used as a news sharing and commenting platform (Eriksson and Olsson 2016). Our study proves a good resonating of popular topics on Twitter with their counterparts within real society. For instance, triggered by the statement of disinfectant treating of Covid-19 from the U.S. President Donald Trump, Twitter responds quickly with massive widely diffused tweets warning the dangers of using disinfectant against the virus. In this light, in addition to providing instant news, Twitter could also serve as a platform for useful suggestions. Besides, it is also shown in our study that Twitter is used as a platform for sharing users' own experience of the pandemic. Compared with official news reports, these grass-root stories mirror closer the life of an average person and may deserve more attention of crisis managers when investigating people's needs during a crisis.

Since the advent of web 2.0, the voice of an average person is able to make a hard hit via social media applications. The evidence is found when we code the most diffused tweets in our data set, indicating people's appeal to spread their messages and therefore to make their voice heard. For some reason, emotional involved tweets showing wish and support take a much smaller percentage (about 5%) among the popular tweets in this study. This is probably due to the social media-prone features of Twitter, where users are more likely to seek updates there, instead of social networking or making intimate communications (Eriksson and Olsson 2016).

Rumors, fake news, and misinformation are always an accompaniment of crisis events and are prevalent on Twitter as well. In this study, besides rumors, we also find widely diffused rumor debunking tweets combating country lockdown rumors, virus-related rumors, and other fake news. Though Twitter users are notorious for their poor rumor judgment (Rubin 2017), our study shows that they are also passionate about retweeting rumor debunking tweets. For instance, a rumor debunking tweet, saying "So I'm hearing many myths about #COVID-19 ... Coronavirus will go away in Summer months. Wrong...", had been retweeted nearly 100,000 times by the time of our data collection.

5.2 Retweeting behaviors

To become viral, a tweet message depends heavily on the retweeting passion from other users. Twitter is a good place to make this happen. Our results indicate an almost immediate response from Twitter users after the posting of an original tweet, with some retweets made

Table 3 ANOVA results for verified retweeters rates of verified and unverified Twitter users

Groups		Count	Sum	Average	Median	Variance
<i>Statistic summary</i>						
Verified-RT-verified		1215	32.24	0.027	0.01	0.00
Verified-RT-unverified		1746	6.82	0.004	0.00	0.00
Source of variation	SS	df	MS	p	P value	F crit
<i>ANOVA results</i>						
Between groups	0.37	1	0.37	278.78	0.00	3.85
Within groups	3.90	2959	0.00			
Total	4.26	2960				

Table 4 ANOVA results for following retweeters rates of verified and unverified Twitter users

Groups		Count	Sum	Average	Median	Variance	
<i>Statistic summary</i>							
Following-RT-verified		1218	731.50	0.60	0.67	0.07	
Following-RT-unverified		1752	839.23	0.48	0.50	0.08	
Source of variation	SS		<i>df</i>	MS	<i>F</i>	<i>P</i> value	<i>F</i> crit
<i>ANOVA results</i>							
Between groups	10.62		1	10.62	134.68	0.00	3.85
Within groups	234.03		2968	0.08			
Total	244.65		2969				

within only 2 s. It takes only about 10 min on average for at least 90% of the original tweets to have their first retweets done. The rapid response from its users enables Twitter to broadcast crisis event updates quickly and widely. However, interest in a tweet message is short-lived at the same time, with most of (86%) the retweeting processes having 75% of their retweets done within 24 h, indicating a 1-day information value of tweet messages. In summary, Twitter users respond quickly, but shortly in terms of retweeting. The result is a double-edged sword for crisis managers. On the one hand, the results validate the fact that crisis messages from managers could reach the public members widely within a short period of time, which would help them build the situation awareness of the public members quickly. On the other hand, rumors, fake news and misinformation could also be diffused with similar efficiency and coverage, challenging their already harsh-demanding work on rumor control and therefore justifying an early rumor detection and containment effort during crisis times.

As for the mathematical patterns of retweeting behaviors, we fail to find the best model to characterize the retweeting process perfectly, a similar situation found in the modeling of Twitter users' posting behaviors (Bild et al. 2015). Power law, Weibull, and Log normal could fit about 80% of the retweeting processes, leaving the other 20% unexplained. Future research is directed to dig out more insights into the potential mathematical distributions of this process.

5.3 Retweeting communities

A retweeting community is formed when a message starts to cascade. Within each community, patterns may differ with the features of original users, relationships between the end users of a retweeting edge, and other potential factors. Results of this study show that followers contribute to an average of 50% of all retweets. For verified users, followers contribute to about 60%, which is significantly higher than that of unverified users. We find a similar difference regarding the percentages of verified retweeters within the communities of verified and unverified users respectively. In summary, verification status of original tweet users impacts the user structures of their retweeting communities. In light of this, for official tweets to reach as many users as possible, which is a challenging problem for official information officers (Jin et al. 2019), increasing the retweets from strangers serves as the breaking-through point. To this end, message promotion (e.g., advertising) may become necessary when diffusion efficiency and scale are demanding for important crisis messages.

As for retweeting edges, we find affinity of relationships exerts a significant influence on information diffusion efficiency. A following edge diffuses information more quickly than a non-following edge does. The potential reasons are twofold. To begin with, non-following retweeters are probably followers of the original user's followers, i.e., second-tier followers. There is time latency when a second-tier follower reads the message after the retweeting of a first-tier follower. Secondly, tweets of a Twitter user will be pushed into "Homelines" of their followers, and therefore, their followers are better informed than non-followers, a quicker response from following retweeters makes sense.

6 Conclusions

In our study, we show that Twitter is mostly used as a platform for information seeking and sharing, which is consistent with the previous study from Eriksson and Olsson (2016). This study recognizes people's different use of Twitter service amid this crisis by conducting a content analysis on the most widely diffused tweets. These tweets are coded into six different themes, including comments & opinions (46.5%), news (25.43%), own story (10.78%), appeal (8.64%), wish & support (5.35%), and others (3.29%). News and news comments combined take the overwhelming majority (70%) proportion of all widely diffused tweets. Besides the official news, we find that gossip and grass-root news are able to get a huge momentum on Twitter as well. On the one hand, their wide spread on Twitter reflects people's interest in early unofficial news during a crisis; on the other hand, the availability of early gossip news also makes Twitter advantaged over other platforms by providing first-hand news from all sources, which in turn motivates more people to join.

As for the retweeting dynamics, we find that Twitter users respond almost immediately and most of their interest in Twitter messages persists short. It may take only 2 s for an original tweet to get retweeted, and nearly 90% of them start to cascade within 10 min. As for the retweeting process, the vast majority (86%) of original tweets have 75% of their retweets done within 24 h. In other words, information values of tweet messages vanish rapidly on Twitter, and few of them could survive a day longer. The finding is consistent with the situation of traditional mass media news, where yesterday's news matters little compared to today's breaking ones. For crisis managers, chances that their tweets start to cascade after 10 min diminish dramatically. In this case, an effort

becomes necessary to trigger the process, e.g., asking for retweeting help from friends. As over 60% of the tweets would stop diffusing within 12 h, to maintain the diffusion, managers may keep injecting important messages (e.g., social distancing) regularly into the platform to keep the information alive and affront of the public attention.

Retweeting communities are impacted significantly by the verification status of original tweet users and by the relationship between the end users of a retweeting edge. To be specific, retweeting communities initialized by verified users enjoy a higher percentage of following retweeters and verified retweeters, respectively, than their unverified counterparts do. Besides, the percentage (2.7%) of verified retweeters within the retweeting communities from verified users is almost as seven times high as that (0.4%) from unverified communities. Just as the old saying goes, “birds of the same feather get together”. Twitter users of the same verification status are more likely to establish retweeting relationships. We also find that, a Twitter user, be it verified or unverified, has an average of nearly 50% of retweeters are their followers as well, i.e., half of the retweets are from followers and friends. Moreover, they retweet much more quickly than non-followers do with their retweeting medians being 9.35 and 13.75 h, respectively. The almost equivalent proportions of retweets from strangers and followers/friends should solicit more attention of crisis managers on the retweeting power of loose connections. Instead of simply increasing the size of followers/friends to get more retweets, managers may get better off to increase the exposure of their messages to strangers either by advertising or by increasing the diffusion power of their followers.

In terms of limitations, this study models retweeting distributions of tweets with at least 100 retweets, which may cause a biased conclusion. Further research is directed to take a much more complete and comprehensive analysis on this regard. Besides, more details about how following and non-following retweeters differ in their retweeting speed deserve more future efforts as well.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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