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Research Article

Using a Heuristic-Systematic Model to assess the Twitter user profile's impact on disaster tweet credibility

Jaebong Son[a,*], Jintae Lee[b], Onook Oh[c], Hyung Koo Lee[d], Jiyoung Woo[e]

[a] College of Business, California State University, Chico, 400 West 1st Street, Chico, CA 95929, United States
[b] Leeds School of Business, University of Colorado, Boulder, 995 Regent Dr., Boulder, CO 80309-0419, United States
[c] Business School, University of Colorado, Denver, 1475 Lawrence St, Denver, CO 80202, United States
[d] Department of Information Technologies, HEC Montréal, 3000 Côte-Sainte-Catherine Road, Montréal, QC, H3T 2A7, Canada
[e] SCH Media Labs, Soonchunhyang University, 22, Soonchunhyang-ro, Eumnae-ri, Sinchang-myeon, Asan-si, Chungcheongnam-do, Republic of Korea

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ABSTRACT

Journalists, emergency responders, and the general public use Twitter during disasters as an effective means to disseminate emergency information. However, there is a growing concern about the credibility of disaster tweets. This concern negatively influences Twitter users' decisions about whether to retweet information, which can delay the dissemination of accurate—and sometimes essential—communications during a crisis. Although verifying information credibility is often a time-consuming task requiring considerable cognitive effort, researchers have yet to explore how people manage this task while using Twitter during disaster situations.

To address this, we adopt the Heuristic-Systematic Model of information processing to understand how Twitter users make retweet decisions by categorizing tweet content as systematically processed information and a Twitter user's profile as heuristically processed information. We then empirically examine tweet content and Twitter user profiles, as well as how they interact to verify the credibility of tweets collected during two disaster events: the 2011 Queensland floods, and the 2013 Colorado floods. Our empirical results suggest that using a Twitter profile as source-credibility information makes it easier for Twitter users to assess the credibility of disaster tweets. Our study also reveals that the Twitter user profile is a reliable source of credibility information and enhances our understanding of timely communication on Twitter during disasters.

1. Introduction

Rapid dissemination of warnings and alerts to the public increases public safety by enhancing people's awareness of their surroundings and allowing them to take protective actions before life-threatening events unfold (Mileti & Sorensen, 1990). Social media has thus joined mainstream media in being an integral part of disaster communications (Bean et al., 2016; Oh, Agrawal, & Rao, 2013). Indeed, Twitter has emerged as a particularly useful means for both emergency responders and online volunteers to quickly spread disaster information to large audiences (Zhang, Fan, Yao, Hu, & Mostafavi, 2019). In part because of its length limitations[1], Twitter enables its users, or *twitterers*, to virtually exchange first-hand experiences everywhere in real-time through their communication devices, including old-style cellular phones (Castillo, Mendoza, & Poblete, 2013; Vieweg, Hughes, Starbird, & Palen, 2010). As such, Twitter enabled the era of messages for disaster communication.

Despite Twitter's communication capability, researchers have raised concerns about the credibility of information conveyed in disaster tweets (Bean et al., 2016; Oh et al., 2013). Unlike mainstream media, social media often lacks *gatekeeping*—that is, an expert to verify information and choose the appropriate topics, news, and stories to broadcast and disseminate (Bruns, 2003; Metzger, 2007). In fact, in traditional media, gatekeeping has long played a central role in establishing fact-based, objective reporting as a means to prevent anything and everything from being published or broadcast (McQuail, 2010). While professional gatekeepers—including journalists, editors, and nonprofit organizations—continue to vet and maintain information on traditional media, social media depends on its nonprofessional online users for information control (Westerman, Spence, & Van Der Heide, 2014). Hence, information disseminated through social media should receive careful examination and validation (Metzger, 2007; Sutton,

* Corresponding author.
E-mail addresses: json@csuchico.edu (J. Son), jintae@colorado.edu (J. Lee), onook.oh@ucdenver.edu (O. Oh), hyung-koo.lee@hec.ca (H.K. Lee), jywoo@sch.ac.kr (J. Woo).

[1] Twitter increased the maximum length of tweets from 140 characters to 280 characters in some languages in November 2017.

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Palen, & Shklovski, 2008) rather than be taken at face value.

Twitter is no exception to such an imperative, as its information dissemination rests on twitterers' tweet and retweet impulses rather than formal gatekeeping (*e.g.*, Hermida, 2010; Kapoor et al., 2018; Westerman et al., 2014). As such, information generated and passed on in Twitter is more likely to be suspect than information disseminated in mainstream media (Westerman et al., 2014). The credibility concern becomes an even more serious matter in nonroutine, urgent situations (Vieweg et al., 2010). Indeed, several studies have indicated that disaster information conveyed in tweets is often equivocal and thus less credible than information conveyed through mainstream media (*e.g.*, Bean et al., 2016; Castillo et al., 2013; Westerman et al., 2014).

Twitter researchers generally assess *information credibility* by scrutinizing the *content credibility* of tweets. For example, Castillo et al. (2013) showed that tweets containing unverified content (*e.g.*, rumors) negatively affected how often those tweets were retweeted during disasters. Further, a study conducted by Ito, Song, Toda, Koike, and Oyama (2015)) discovered that topics or themes conveyed in disaster tweets significantly influenced recipient perception of the tweets' content credibility. A tweet's content components, such as embedded URLs, hashtags, and words (*e.g.*, message length), were also investigated as proxies for estimating its information credibility (O'Donovan, Kang, Meyer, Hollerer, & Adalii, 2012). In addition to content credibility, information recipients examine *source credibility—e.g.*, the credibility of the twitterer (Metzger, Flanagin, Eyal, Lemus, & McCann, 2003). The literature on communication and social media has shown that *information source* supplements content credibility. For example, Hu and Shyam Sundar (2010) reported that the credibility of online health information was affected by its publication source (*e.g.*, web sites, blogs, or personal home pages). Furthermore, Sundar (2008) devised a model that evaluates source credibility based on the information source's characteristics, including interactivity and navigability. Based on these studies, we view *information credibility* as a combination of content credibility and source credibility. However, only a single study in the literature on Twitter use for disaster communication has focused on source credibility. That study, by Thomson et al. (2012), found that participants deemed tweets about the Fukushima nuclear accident that were posted by traditional media, public institutions, experts, and local individuals more credible than tweets lacking such credentials. While the Thomson study focused on source credibility, it was limited to a subjective assessment of *who* posted a tweet, and neglected other information about twitterers that reflect source credibility. The literature thus offers scant guidance on how twitterers, as information sources, actually influence the credibility of information conveyed in their tweets.

Given Twitter's weak gatekeeping (Westerman et al., 2014), content credibility alone is often insufficient for people trying to decide whether to retweet information—particularly when they face the added pressure of an urgent situation. In such cases, assessing source credibility can help twitterers quickly decide whether to repost received tweets. A twitterer's basic profile information, number of followers, posted tweets (*i.e.*, status), and likes (or favorites) can reflect the degree of credibility. This profile information does not require high-level cognitive effort to understand, but rather evokes a simple heuristic such as: *the more followers twitterers have, the higher the popularity they enjoy, and the more credible the information their tweets convey*. These measures can characterize each twitterer as an author of his or her tweets (*e.g.*, Suh, Hong, Pirolli, & Chi, 2010; Westerman et al., 2014).

The literature on disaster communication emphasizes the importance of *heuristically processed information* for emergency communication because it can minimize information-processing efforts (Liu, Liu, & Li, 2012; Metzger, Flanagin, & Medders, 2010). Examining the twitterer profile as a basis for inferring source credibility should enhance our understanding of how twitterers deal with information credibility issues during times of disaster. We therefore address the following research question:

RQ. How does the twitterer profile, as a basis for inferring source credibility, help twitterers to quickly evaluate the information credibility of tweets in order to decide whether to retweet during disaster situations?

To address this research question, we draw on the Heuristic-Systematic Model of Information-Processing (HSM) (Chaiken & Maheswaran, 1994). The HSM theory explains the differences between heuristic and systematic information processing, as well as why people systematically examine a message while heuristically processing its superficial cues (*i.e.*, message length, popularity, and author expertise) (Chaiken, 1980; Chaiken & Maheswaran, 1994). By differentiating between a *tweet's content* as systematically processed information and a *twitterer's profile* as heuristically processed information, HSM offers an appropriate theoretical framework to investigate twitterer profiles in association with tweet content.

Our study contributes to the literature by providing empirical evidence that a twitterer's profile information can be used as informational cues that reflect a tweet's source credibility. Furthermore, we empirically demonstrate the interplay between source credibility and content credibility, and how they influence retweeting during disasters. Based on our study's empirical findings, we provide practical recommendations to public health agencies, emergency responders, and online volunteers on how to manage disaster tweet content and their profile information to encourage rapid dissemination of disaster information through Twitter.

In the following sections, we review the literature on Twitter, disaster communication, and information credibility in social media. We then elucidate the HSM, which undergirds the research model and our study's hypotheses. Following that, we describe our methodology, data, and the results of our hypothesis testing. We then conclude with discussions of our findings and the implications for future research.

2. Theoretical foundation and research model

2.1. Disaster communication on Twitter and information credibility

Twitter fulfills several important roles for disaster communication. First, it offers a means to share time-sensitive, first-hand disaster information with the effected public. Sutton et al. (2008) reported that during the 2007 California wildfires, situational information broadcast by mainstream media was nonlocal, inaccurate, and slowly updated. As a result, the effected California residents turned to social media—especially Twitter—to create, seek, and share locally relevant and up-to-the-minute information, including details about road closures, evacuation/shelter instructions, and fire-line shifts (Hughes & Palen, 2009). Second, Twitter offers a reliable means of communication. When the 2011 Tohoku tsunami in Japan destroyed all communication and power infrastructure facilities, Twitter proved to be a viable tool for keeping the effected public aware of continually moving threats (Acar & Muraki, 2011). Third, Twitter's improvised follower–followee networks helped twitterers to quickly disseminate disaster-related information on a large scale. During the 2013 Boston Marathon bombings, twitterers improvised collaboration networks across a wide audience to exchange warnings and alerts for potential threats, guidance to minimize damage, and aid for bombing recovery (Sutton, Spiro, Fitzhugh et al., 2014).

Finally, by reposting original tweets, retweeting harnesses the collective intelligence of loosely connected twitterers to validate tweet information and share that information with other twitterers (Hutto, Yardi, & Gilbert, 2013; Zubiaga, Spina, Martinez, & Fresno, 2015). During emergency or disaster situations, retweeting becomes an even more salient action to spread credible, locally relevant information as widely and quickly as possible (Metzger et al., 2010; Zhang & Watts, 2008). As nonprofessional gatekeepers, or *public editors*, twitterers participate in fact-checking a received tweet's information credibility to collectively decide which information should be emphasized, further discussed, and released to others (Heverin & Zach, 2012; Metzger et al., 2010; Westerman et al., 2014). Hence, retweeting disaster tweets is viewed as implying that twitterers agree with what those tweets convey and with their general credibility. Because disaster events shift rapidly, retweeting shortly after a tweet is posted can better reflect effective disaster communication (*e.g.*, Son, Lee, Jin, & Lee, 2019; Wilensky, 2014). Therefore, leveraging a sufficiently short time interval between tweets and retweets (*i.e.*, *quick retweeting*) allows us to empirically examine the information credibility of disaster tweets.

2.2. Information credibility of disaster tweets

Although Twitter has several advantages over mainstream media for disaster communication, it is subject to information credibility concerns that arise from weak gatekeeping (Bean et al., 2016; Schmierbach & Oeldorf-Hirsch, 2012; Westerman et al., 2014). In the mainstream media environment, where information production costs are expensive and distribution channels are scarce, central authorities—editorial desks and other gatekeepers—play a key role in verifying and confirming information relevancy and credibility prior to publication and dissemination (Bruns, 2003; Westerman et al., 2014). In contrast, social media's environment differs greatly from mainstream media in that (1) "space is anything but scarce" (Bruns, 2003, p. 33); (2) diverse information formats (*e.g.*, text, picture, and audio/video) can be created at little or no cost (Bruns, 2003; Dwivedi, Kapoor, & Chen, 2015); and (3) amateur "citizen journalists" are actually just ordinary people who produce and consume information (Hermida, 2010; Schmierbach & Oeldorf-Hirsch, 2012). When determining which events to report, which stories to cover, and how to effectively present information, most citizen journalists lack expertise compared to mainstream media's central authorities. Such amateurism may raise serious concerns about communication in urgent situations, in which reliable, fact-based information must be instantly verified and widely disseminated as quickly as possible (Stein, 2004).

Verifying information credibility is a complex and multifaceted task that requires a comprehensive evaluation of the extent to which a given medium, message content, and content source are credible or trustworthy (Flanagin & Metzger, 2000). Accordingly, volunteer twitterers who intend to quickly relay disaster information to others should be tasked with assessing the information credibility of received tweets either by content credibility, source credibility, or both. In fact, however, when and how twitterers evaluate disaster tweets' information credibility is still largely unexplored. Some studies have argued that evaluating content credibility is a time-consuming task as it entails high-level cognitive effort (Hu & Shyam Sundar, 2010; Sundar, 2008), while other studies have found that source credibility provides a mental shortcut for further assessing information credibility (Lang, 2000; Stein, 2004). For instance, Eastin (2001) empirically demonstrated that authors' expertise enhanced the perceived credibility of their information. Similarly, Metzger et al. (2010) found that amid imminent threats, online information seekers actively engaged in processing source-related information to assess the credibility of received information as a means to cope with time pressure. These studies illuminate source information as both (a) *credibility markers* that can supplement content credibility (Sundar, 2008, p. 74), and (b) *informational cues* that are heuristically processed through existing knowledge (Todorov, Chaiken, & Henderson, 2002). In fact, research has highlighted source information as a quick decision-making facilitator for information credibility in urgent situations where people lack the time to explore and process information (Hu & Shyam Sundar, 2010; Liu et al., 2012). Hence, we distinguish *content credibility* and *source credibility* as the two compartments of information credibility.

2.3. Twitterer profile as a basis for inferring source credibility

As Table 1 shows, on Twitter, *source information* consists of quantitative information in the twitterer's profile, while *content information* consists of a tweet's qualitative elements, including words, hashtags, and URLs (Son, Lee, Jin et al., 2019; Suh et al., 2010).[2]

Unlike tweet content, which people can interpret directly, a twitterer's profile opens up possibilities for different interpretations that can be influenced by Twitter's socially interactive environment. In daily conversation on Twitter, for instance, a person's number of followers indicates his or her popularity, prestige, and/or influence (Hutto et al., 2013; Kwak, Lee, Park, & Moon, 2010). The literature on politics generally recognizes a twitterer's number of followers as indicative of his or her role as an opinion leader (Park, 2013), while social media marketing uses the number of followers to estimate user awareness and engagement (Alalwan, Rana, Dwivedi, & Algharabat, 2017; Hoffman & Fodor, 2010). We can explicate such differences using the concept of *technological affordances*.

As objects in the world, technological affordances are the action possibilities available to an actor in a particular environment (Gibson, 2014). In other words, an *affordance* is an action potential that influences an actor's goal-oriented activities. Individuals can recognize this potential in different ways in the various contexts they belong to (Hutchby, 2001; Pozzi, Pigni, & Vitari, 2014). Hutchby explained affordances as "functional and relational aspects which frame, while not determining, the possibilities for agentic action in relation to an object" (2001, p. 444). For example, a rock may afford animals the ability to take shelter from a storm, while a keyboard as an input device allows computer users to type characters and numbers. Similarly, a computer mouse affords users various actions, such as clicking buttons, scrolling documents or web pages, and dragging digital objects on computer screens. An affordance is thus an action potential that influences goal-oriented actions, but individuals can perceive this potential differently depending on their capability level (Pozzi et al., 2014) or context (Hutchby, 2001). As a dynamic action potential, we also apply the concept of affordances to the relationship between a technology and its users because a technology artifact's meanings and usages are socially shaped and reshaped as users interact with their particular goals (Hutchby, 2001; Majchrzak, Markus, & Wareham, 2016). That is, instead of understanding technology as immutable and permanent, we can see it as dynamic and mutable *via* the technological affordances that unfold a range of opportunities for investigating how IT artifacts are associated with social phenomena (Pozzi et al., 2014).

Viewed in this light, we must understand Twitter within the context of the social relations that dynamically unfold among twitterers. As mutable IT artifact, Twitter comprises a set of affordances that allow various interactions among twitterers who may have different communication goals. Accordingly, behavioral consequences—such as retweeting—must be interpreted based on how Twitter's functions and features interface with twitterers as they pursue their specific goals. During times of disaster, the twitterer profile therefore becomes important information for tweet recipients to achieve their communication goals—that is, quick and wide dissemination of relevant and trustworthy information to the at-risk public (*e.g.*, Babrow, Hines, & Kasch, 2000; Mileti & Sorensen, 1990). This rapid dissemination of disaster information is crucial for emergency responders and online volunteers, who hope to save lives and minimize harmful consequences during and after a hazard (Sutton, Gibson, Spiro et al., 2015). Volunteer twitterers have a similar goal as they try to share warnings and alerts with others before the information becomes outdated amid unfolding and often life-threating events.

However, content credibility could be a factor that prevents

[2] Two sample tweets are (1) *Flood cuts #Capricorn #Highway near Emerald Courier Mail: #RISING floodwaters in central Queensland have clo #Australia:* http://bit.ly/fKrAaa and (2) *Watch closely.;-) @JohnGGalt: Chinook helicopter rescuing flood victims from Poudre Canyon, Colorado. #COFlood* http://t.co/uZr3e4IK8P

Table 1
Two Twitter Information Types.

	Features	Characteristics	Information Processing Modes
Tweet	Words, hashtags, URLs	Qualitative information	Systematic
Twitterer	Followers, followees, status, likes, join date	Quantitative information	Heuristic

twitterers from quickly relaying received tweets (*e.g.*, Bean et al., 2015; Son, Lee, Larsen, & Woo, 2019). To address this issue, twitterers need supplementary information that is easily processed and implies credibility beyond the content alone. One such information source is twitterer profiles, which suit this purpose for several reasons. First, twitterer profiles can be easily found on Twitter by simply clicking a link on a received tweet. Second, studies provide a solid foundation for using such a profile as an informational cue to assess credibility (Bean et al., 2016; Westerman et al., 2014). Finally, given the quantitative nature of twitterer profiles, the meaning of their components—such as followers and likes—can be effortlessly understood based on cognitive heuristics and a learned knowledge structure (Liu et al., 2012).

Given that (1) Twitter is a mutable IT artifact, (2) the credibility of tweet content is an ongoing concern, and (3) emergency responders and online volunteers use Twitter with the goal of facilitating rapid, accurate communication, we now recast twitterer profile information as cues to the source credibility of tweets.

2.4. Heuristic-Systematic Model of information processing (HSM)

During disasters, an overwhelming volume of tweets are posted and shared on Twitter (Purohit et al., 2013)—and not all are created equal in terms of information credibility (*e.g.*, Bean et al., 2016; Westerman et al., 2014). In terms of volume alone, it is unlikely that twitterers scrutinize the information credibility of all received original tweets before deciding whether to retweet them (*e.g.*, Wilensky, 2014; Zeng, Starbird, & Spiro, 2016). Twitterers should balance processing time and the information being processed in order to disseminate disaster information in a timely way (Fisher & Kingma, 2001). The HSM's premise is that "People rarely process information in perfect conditions. There are both environmental and cognitive constraints on information-processing" (Todorov et al., 2002, p. 196). The model therefore fits the communication context that twitterers encounter during disasters.

The HSM assumes that people's motivations (*i.e.*, environmental constraints) and cognitive resources (*i.e.*, cognitive constrains) trigger them to process information in qualitatively disparate ways—specifically, *systematic* and *heuristic* modes of processing information—in order to validate their judgment about information they receive (Chaiken, 1980). People in a *systematic mode* comprehensively analyze a message's information and then form a judgment about it. By comparison, heuristic information-processing involves processing a few superficial cues that elicit simple decision rules such as: "experts can be trusted," "consensus implies correctness" (Todorov et al., 2002, p. 197), and "long messages are valid messages" (Chaiken & Maheswaran, 1994, p. 460). Consequently, compared to systematic mode, in *heuristic mode,* people tend to rely on mental shortcuts that require less cognitive effort to form judgments (Chaiken & Maheswaran, 1994). It is highly likely that, in disaster situations (an environment constraint) where time pressures can be intense (a cognitive constraint), people would engage in different information-processing styles in order to effectively evaluate disaster information and quickly communicate it to others.

Of even greater significance to our study, the HSM provides three modes of interaction between heuristic and systematic information processing: (1) the additive hypothesis, (2) the attenuation hypothesis, and (3) the bias hypothesis (Todorov et al., 2002). The *additive hypothesis* assumes that heuristic and systematic information-processing modes imply consistent judgmental implications on a message's conclusion. The *attenuation hypothesis* presumes that the systematic approach's judgment can attenuate or overwrite that of heuristic information processing when implications from both information processing are in opposition to one another. Finally, the *bias hypothesis* proposes that judgments formed through heuristic information processing can influence judgments derived from systematic information processing. For example, an ambiguous message can be evaluated differently by recipients who have different perceptions about the credibility of the message's source.

In our study, we leveraged the bias hypothesis to examine content credibility, source credibility, and their interplay, viewing the twitterer profile (source credibility) as a supplement to the tweet content (content credibility) for quick retweeting during disasters. When people have limited time to process information, heuristic information processing prevails as it reduces the cognitive workload needed to reach conclusions (Chaiken & Maheswaran, 1994; Ferran & Watts, 2008). Fig. 1 shows our HSM-based research model.

Chaiken and Maheswaran (1994) pointed out that, to examine how the two different processing modes interact, it is best to use an equivocal or ambiguous message. Their primary reason was that when a message is fully understood, the two processing modes are either mutually exclusive, or systematic processing would suppress the manifestation of heuristic processing. In other words, we can empirically observe twitterers' heuristic information processing as a complement to systematic information processing only when tweets need further assessment (*e.g.*, the information is ambiguous or lacks credibility).

We now discuss the hypotheses we developed to examine twitterer motivation for processing additional information, as well as the twitterer profile's role in disaster communication on Twitter.

3. Hypothesis development

3.1. Content ambiguity

The content of disaster messages plays a key role in public perception and response, which directly affect the at-risk populations' judicious and well-timed protective actions (Bean et al., 2015). Literature on disaster communication has expressed concerns about whether tweet-length messages are enough to convey in-depth disaster information (*e.g.*, Bean et al., 2015; Sutton, Gibson, Spiro et al., 2015). Mileti and Sorensen's (1990) posited guidelines for effective disaster messages: (1) describe a hazard's specific characteristics, including its

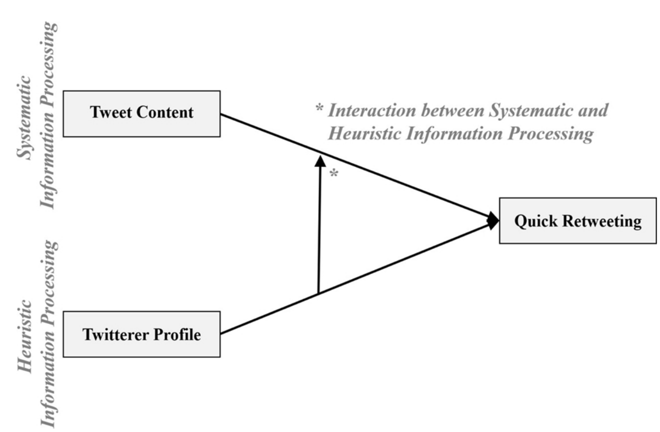


Fig. 1. Research Model.

location and time; (2) clearly state actionable information; and (3) include the verifiable source of the information. Not surprisingly, in seeking communications that met these guidelines, most studies on disaster communication relied on relatively long message lengths—*e.g.*, up to 1380 characters (Sutton, Gibson, Spiro et al., 2015). For disaster messages, the more sufficient and detailed the information they convey, the better able the effected public is to develop an accurate understanding of situations (Bean et al., 2016; Perry, Lindell, & Greene, 1982).

Bean et al. (2016) conducted an interview study on how the public perceived tweet-length (140 character) disaster messages and found that the disaster information conveyed was ambiguous and confusing. Similarly, Son, Lee, Larsen et al. (2019) measured the extent of each disaster tweet's content uncertainty—hereafter, its *ambiguity*—using the information theory of entropy and demonstrated the negative effect of that ambiguity on retweet count. Reviews of social media have pointed out that tweet ambiguity motivates volunteer twitterers to seek additional information to elucidate the content (Fraustino, Liu, & Jin, 2012) and verify its trustworthiness (Kuligowski & Doermann, 2018). For instance, Oh et al. (2013) affirmed that when encountering suspicious or doubtful disaster tweets, twitterers tend to pose questions rather than retweet. Indeed, compared to other social media channels with less-restrictive message lengths (Sutton, Spiro, Fitzhugh et al., 2014), Twitter content ambiguity is much more prevalent. As a result, *quick retweeting*—which is essential in disaster situations—is impeded.

Clearly, a tweet's character limits can hinder the ability of twitterers to convey extensive details about disaster events; as a result, individual tweets may be viewed as either ambiguous, less believable, or both (Bean et al., 2016; Son, Lee, Larsen et al., 2019). Our first hypothesis thus addresses the relationship between content ambiguity and quick retweeting.

Hypothesis 1 (H1). During times of disaster, content ambiguity of the original tweets negatively affects quick retweeting.

According to a recent National Institute of Standards and Technology (NIST) study, content credibility is a potential limitation of tweet-length disaster messages (Kuligowski & Doermann, 2018). The study found that when encountering a disaster tweet's content ambiguity, twitterers sought additional information to better understand its content, evaluate its information credibility, or both. In seeking additional information to better understand a tweet's content, twitterers typically consult a tweet's embedded URL (if available) in order to find rich, in-depth details (Son, Lee, Jin et al., 2019; Son, Lee, Larsen et al., 2019). Alternatively—or in addition—people can turn to the tweet author's profile to evaluate the credibility of the tweet's source and thus better understand the content credibility. A twitterer's profile becomes *social proof* of the extent to which a twitterer is believable (Cialdini, Wosinska, Barrett, Butner, & Gornik-Durose, 1999, p. 1243). Metzger states, "A common strategy employed by Internet information seekers is to minimize cognitive effort and mitigate time pressures through the use of heuristics" (2010, p. 426). Therefore, a heuristically processed twitterer profile can become a significant piece of information for twitterers to gauge the source credibility of received tweets in a timely fashion. Given the above discussion, we employed a disaster tweet's content ambiguity as a proxy for its content credibility: as a disaster tweet's content ambiguity increases, its content credibility decreases.

3.2. Reputation heuristic

People generally favor prior reputation (or recognized names) (Metzger et al., 2010). This tendency is true for Internet users as well. Sundar (2008) reported that online information from reputable sources was considered more credible than that from lesser-known sources. Metzger and Flanagin (2013) also viewed a person's online reputation as a credibility cue.

A similar credibility cue on Twitter is that of a twitterer's number of followers. A person acquires followers mainly by posting original tweets as a means of sharing information or conversing with other twitterers (Klotz, Ross, Clark, & Martell, 2014). For example, once twitterer A *follows* twitterer B, twitterer A automatically receives all of twitterer B's tweets. Hence, twitterer B can be considered twitterer A's information source (*e.g.*, Tang & Chen, 2020; Zubiaga et al., 2015). As such, one's number of followers can indicate the extent to which he or she, as an information source, is *popular* (Hutto et al., 2013; Kwak et al., 2010), *reputable* (Liu et al., 2012), and *influential* (Christakou & Klimis, 2013). Further, Westerman et al. (2014) claimed that as a person's number of followers increases, his or her gatekeeping strengthens. That is, twitterers with a high number of followers are much more likely to check information veracity and determine which information is important enough to release into their communities. In so doing, twitterers keep their current social positions reputable and influential to their followers. Given this, we expect that a twitterer's number of followers, as a reputation credibility cue, positively affects his or her disaster tweets' quick retweeting when such tweets lack content credibility.

Hypothesis 2a (H2a). During times of disaster, a twitterer's number of followers weakens the effect of his or her original tweets' content credibility on quick retweeting.

3.3. Social presence heuristic

Computer-mediated communication (CMC) affects the way people communicate (Walther, 1996). While instant messaging services, emails, and websites allow people to overcome limitations imposed by time and space, a lack of shared social norms can lead to uninhibited behaviors, such as spreading disinformation (Kim, 2003). Research on the relationship between CMC and information trustworthiness has shown that a person's trustworthy CMC presence increases the person's information credibility (Bente, Rüggenberg, Krämer, & Eschenburg, 2008; Skalski & Tamborini, 2007). Sundar regarded CMC presence as "the user is communicating with a social entity rather than an inanimate object" (2008, p. 84) and viewed a CMC user's social presence as having an influence on the belivability of his or her information. Similarly, Flaherty, Pearce, and Rubin (1998) found that social presence—which they defined as *a feeling of being together*—contributes to online users perceiving CMC as interpersonal communication. Thus, most CMC—including Twitter—aims to create systems that are akin to face-to-face communication by offering rich interactions among users (Rice & Love, 1987); the more user interactions a system provides, the more it fosters a sense of togetherness. This togetherness (social presence) plays an important role in making CMC more attractive, interpersonal, and effective as a functional alternative to traditional face-to-face communication (Niinimäki, Piri, Lassenius, & Paasivaara, 2012).

On Twitter, a twitterer's total number of posted tweets, or *status*, implies social presence in that the more a twitterer posts, the more often others receive his or her tweets, and the stronger the sense of togetherness they feel with the twitterer (Kehrwald, 2008). Another cue for social presence is the age of a Twitter account, or its *affiliation length*, which is easily visible to other users through the join date in the profile. Sundar (2008) referred to the length of affiliation as *loyalty*. Thus, the age of a Twitter account is also likely to strengthen the sense of togetherness that other twitterers experience with a particular twitterer. We therefore conjecture that, as social presence credibility cues, a twitterer's total number of tweets and length of affiliation positively impact that person's crediblity as an information source.

Hypothesis 2b (H2b). During times of disaster, a twitterer's total number of posted tweets weakens the effect of his or her original tweets' content credibility on quick retweeting.

Hypothesis 2c (H2c). During times of disaster, a twitterer's affiliation length weakens the effect of his or her original tweets' content credibility on quick retweeting.

3.4. Recency heuristic

Recency indicates the time-sensitive value of information, which is a virtue of Twitter (Sutton, Spiro, Johnson et al., 2014). Such recency is extremely important in communicating during disasters, when information about unexpected, life-threatening events quickly becomes obsolete and inaccurate (Wilensky, 2014). The literature on disaster and communication emphasizes information recency as an influential factor in the degree of information credibility. Sundar (2008) noted that cues about the timeliness of information could positively affect its credibility; similiarly, Metzger (2007) pointed out that, given the highly volatile nature of online information, information timeliness closely relates to information credibility. Further, an empirical study by Westerman et al. (2014) demonstrated that update frequency positively influenced a person's credibility as an information source. In fact, Twitter maintains a similar notion of recency by allowing tweets to be searched and accessed from individual twitterers' pages for 21 days (Marwick & Boyd, 2011). To account for twitterers' information recency, we aggregated each twitterer's posted tweets about the current disaster events, which we deem *recent tweets,* to examine the statement: *The more recent tweets a twitterer posts, the more exposure he or she has to other twitterers.* Greater exposure may in turn positively affect his or her role as an information source. Although this credibility cue seems to be similar to that of social presence—such as status—the recency credibility cue differs in that it reflects the timeliness of information that individual twitterers provide. To examine the recency credibility cue in association with tweets' content credibility, we offer the following hypothesis:

Hypothesis 2d (H2d). During times of disaster, a twitterer's number of recent tweets weakens the effect of his or her original tweets' content credibility on quick retweeting.

3.5. Endorsement heuristic

"People are inclined to perceive information and sources as credible if others do so also" (Metzger et al., 2010, p. 427). As Metzger et al. (2010) note, individuals tend to consider something correct or truthful when others believe it is correct or truthful. Chaiken and Eagly labeled this phenomenon a *liking-agreement heuristic*: "people agree with people they like" or "people I like usually have correct opinions on issues" (1989, p. 4). Likewise, Sundar (2008) introduced the concept of a *bandwagon heuristic*, defined as either the endorsement of a group or the reputation of a source as possibly influencing a twitterer's source credibility.

Twitter provides a *liking* function so twitterers can express their appreciation for, agreement with, or acknowledgment of tweets they receive (Warzel, 2014). Liked tweets, or *likes*, are summed up for each twitterer and indicate his or her endorsement by other twitterers. Thus, a twitterer's credibility as an information source is positively correlated with the extent to which his or her tweets have been liked or favorited. We assume that, as an endorsement credibility cue, a twitterer's number of likes positively influences his or her source credibility and thus affects his or her diaster tweets' quick retweeting. Our last hypothesis states a positive relationship between number of likes and quick retweeting:

Hypothesis 2e (H2e). During times of disaster, a twitterer's number of likes weakens the effect of his or her original tweets' content credibility on quick retweeting.

Table 2
Keywords and Hashtags.

Date	Keywords	Hashtags
2013 Colorado floods		
September 11	boulderflood, cowx, nwsboulder	
September 12	coflood, cofloods, coflodding, cuboulder flood	#boulder, #cccf
September 15	boulderfloods	
September 19	flood gas, flood infrastructure	#cofloodrelief
September 20		#coloradostrong
2011 Queensland floods		
January 1–27	queensland, qldfloods, qldflood	#qldfloods, #thebigwet

4. Research methodology

4.1. Data collection

4.1.1. 2013 Colorado floods

In 2013, 15–20 inches of rain poured into northern Colorado. Immediately following the Federal Emergency Management Agency's initial warnings, altruistic online citizens intending to relay urgent information to others began to produce, share, and disseminate diverse flood-related information on Twitter. During the floods, the University of Colorado Boulder Department of Computer Science's Empowering the Public with Information in Crisis, or *Project EPIC*, collected flood-related tweets and their retweets in near real-time by systematically identifying keywords, hashtags, and twitterers (Dashti, Palen, Heris, Anderson, & Anderson, 2014) (see Table 2).

From September 12–25, there were 102,426 original tweets and 122,276 retweets posted by 75,460 twitterers: 39,037 twitterers posted at least one original tweet; 44,593 twitterers retweeted at least one original tweet; and only 9170 twitterers were engaged in both tweeting and retweeting. Table 3 shows this activity in more detail.

4.1.2. 2011 Queensland floods

In early 2011, a series of floods hit central and southern Australia. Flood emergencies were declared for half of the Queensland territory, which is similar in size to France and Germany combined (Bruns, Burgess, Crawford, & Shaw, 2012). From the beginning of this disaster, social media became an important means of communication. Twitter was particularly used both by public and private online citizens to

Table 3
Descriptive Twitter Statistics of Two Flood Events.

	2013 Colorado (September 12–25)	2011 Queensland (January 8–21)
Tweets		
Original	102,426	109,456
Retweets	122,276	120,082
Twitterers		
Total	74,460	52,781
Number of postings:		
at least one original tweet	39,037 (52.42 %)	31,288 (59.27 %)
only original tweets	29,867 (40.11 %)	21,332 (40.41 %)
at least one retweet	44,593 (59.88 %)	31,499 (59.67 %)
only retweets	35,423 (47.57 %)	21,493 (40.72 %)
both original tweets and retweets	9170 (12.31 %)	9956 (18.81 %)
Twitterers whose original tweets were retweeted	10,042 (25.72 %)	9422 (30 %)
Original tweets and retweets per twitterer	2.99	3.66
Average affiliation length (months)	32.58	16.9

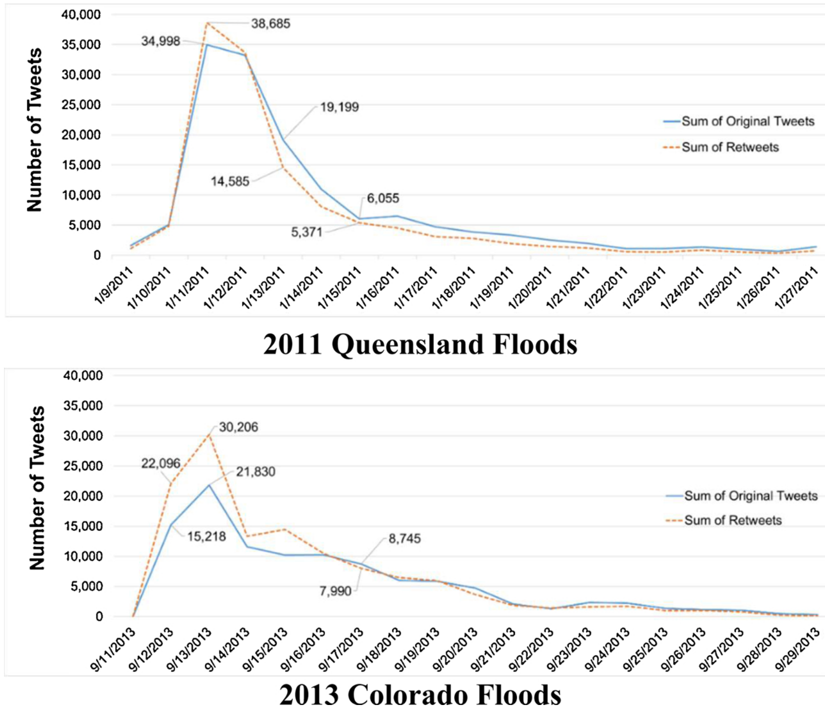


Fig. 2. Trends of Tweets and Retweets in Two Flooding Events.

rapidly disseminate and amplify first-hand footage of emergency situations to others (Bruns et al., 2012). GNIP, a Twitter subsidiary, provided us with data about the Queensland floods. Following Project EPIC's data collection processes, the GNIP data scientists identified keywords, hashtags, and twitterers to retrieve tweets and their related information. Table 3 shows statistics about the tweets and twitterers: 52,781 twitterers produced 109,456 original tweets and 120,082 retweets; 59.27 % posted original tweets and 59.67 % relayed at least one original tweet; and 18.81 % participated in both posting and reposting at least one original tweet.

Fig. 2 shows the overall trends of tweets and retweets in both the Queensland and Colorado flood incidents.

4.2. Variables

Using the Twitter datasets of the 2011 Queensland and the 2013 Colorado floods, we operationalized our study's dependent and independent variables. An outcome of twitterers' evaluation of received tweets is a retweet in *a timely manner*—that is, a short enough period to prevent disaster information from becoming obsolete (Wilensky, 2014). By performing a series of statistical analyses, we empirically determined as explained in Appendix A that the first 10 min after the original tweets' posting best represents the retweetability of the original tweets. We therefore coded a positive response as 1 when a tweet is first retweeted within 10 min of being posted, and coded 0 for a negative response if a tweet is not retweeted within 10 min of being posted.

For *heuristically processed information*, the independent variables are the number of followers, status (total number of past tweets), recent tweets, likes, and length of affiliation. We took the number of followers, status, and likes directly from the datasets, as Twitter records twitterers' profile information whenever twitterers post tweets and retweet other tweets. We measured affiliation length as the difference of years between individual twitterers' join dates and the dates of the flood incidents. The number of recent tweets is the number of a twitterer's tweets regarding the current floods. For *systematically processed information* the independent variable is a disaster tweet's content ambiguity as a proxy for content credibility. We now offer more details about how we determined this content ambiguity for individual disaster tweets.

4.2.1. Content ambiguity of tweets

Bean et al.'s study (2016) on the public perception of 140-character limited disaster messages reported that the majority of participants were confused by and suspicious of these tweet-length messages, stating that such alerts and warnings were "very short," "so limited," and "too uninformative" (p. 7). On the other hand, the study also found a positive perception of tweet-length disaster messages, with some noting that: *"… it's very short, to the point, and succinct, and good … "* and *"I would take it seriously"* (Bean et al., 2016, p. 7). Study participants also cited such length-limited disaster messages as helpful for obtaining a quick awareness of their environments. Given these conflicting findings, making claims that all disaster tweets are equivocal, confusing, and thus less believable seems unwarranted; clearly, some tweets convey succinct and precise disaster-related information.

To address these contradicting perceptions on terse disaster tweets, our study analyzed the implications of the number of topics in a single tweet. This consideration is justified by the fact that, as twitterers craft a 140-character tweet on multiple topics, the tweet's amount of information per topic unavoidably decreases (Son, Lee, Larsen et al., 2019). That is, once n characters are allocated to one topic of a single tweet, 140–n characters remain for its other topics. In this multiple-topic scenario, recipients could be confused as to which topic the tweet aims to focus on. Nothing in the fact of subtracting relevant information per topic in a multitopic tweet indicates that including multiple topics in a single tweet would be beneficial. *ceteris paribus*, single tweets carrying multiple disaster topics will bear less detailed and potentially deficient information than tweets with fewer disaster topics, and thus the truthfulness and persuasiveness of the former in conveying information would be in doubt (Bean et al., 2016; Son, Lee, Larsen et al., 2019). Therefore, we used the number of topics in individual tweets to estimate the content ambiguity of tweets, which we in turn used as circumstantial evidence to infer the extent of disaster tweets' content credibility.

4.2.2. Between-group estimate

Based on the HSM and the length-limited tweets, we speculated

Table 4
Orthogonal Contrasts to Examine Three Groups of Tweets.

Variable	Topic Count		
	One	Two	Three or More
OneVSTwoMore	2	–1	–1
TwoVSMore	0	1	–1

disaster tweets' content ambiguity, measured by topic number, as a condition to observe the manifestation of source credibility. From this speculation, we categorized disaster tweets into three groups: tweets with one topic; tweets with two topics; and tweets with three or more topics. As Table 4 shows, we represent these three groups of tweets using two orthogonal contrast codes: *OneVSTwoMore* compares the first group with the other two groups; and *TwoVSMore* compares the second and third groups. As a coding scheme to numerically indicate categorical variables, orthogonal contrasts whose sum of cross products is zero facilitate an interpretation of interaction terms between the categorical and continuous variables by removing comparisons with reference groups (Judd, McClelland, & Ryan, 2011).[3]

As we discussed above, it is highly probable that one-topic tweets convey unambiguous content; as such, upon receiving them, twitterers would be less likely to seek further information to decide whether or not to retweet. This reasoning corresponds to the findings of Bean et al. (2016)—*e.g.*, that tweet-length disaster message are *succinct and to the point*. Given this, we concluded that the first group (single-topic tweets) is inappropriate to examine the HSM's bias hypothesis between heuristic information processing (using the twitterer profile) and systematic information processing (using tweet content alone). However, twitterers who include more topics (*i.e.*, more ambiguous information) would increase the motivation for tweet recipients to seek additional information. We therefore use the second and the third groups, *TwoVsMore*, and their interactions with twitterer profiles to evaluate our research hypotheses.

4.2.3. Topic modeling and optimal number of topics

To identify topics in disaster tweets, we used two computational linguistics techniques: (1) *TweetNLP* extracts an individual tweet's words, URLs, hashtags, and so on using a part-of-speech (POS) analysis (Owoputi et al., 2013); (2) MAchine Learning for LanguagE Toolkit (MALLET) performs Latent Dirichlet allocation (LDA)-based topic modeling (Wang, McCallum, & Wei, 2007). The LDA topic analysis defines a topic by word distributions in documents. Hence, by varying distributions of words per topic, multiple topics can be represented in a single document (Blei, Ng, & Jordan, 2003).

To obtain more reliable and interpretable topics in the 140-length limited tweets, we extracted multiple-word phrases based on each word's POS tag (*e.g.*, *heavy rain*, *road damage photos*, and *state emergency operation center*) and used them as inputs for the LDA topic modeling (*e.g.*, Wang et al., 2007). Table 5 shows the top five multiple-word phrases per dataset. We excluded stop words—such as *the*, *a*, *is*, and *are*—as they convey little topical information (Debortoli, Müller, Junglas, & vom Brocke, 2016). We included hashtags as inputs for the topic modeling, as they are used to convey summary information about a tweet's topics (Son, Lee, Larsen et al., 2019). However, we excluded embedded URLs as they typically comprise random characters and numbers that do not convey topical information (*e.g.*, http://t.co/ntqdy1o7rw).

As a clustering analysis, topic modeling groups similar documents based on topic similarity. An important input parameter for clustering

[3] The sum of the cross products of Table 4's contrasts is equal to zero: $2 \times 0 + (-1 \times 1) + (-1 \times -1) = 0$. By these contrasts, we can orthogonally compare the three groups of tweets.

Table 5
Top 5 Multiple-word Phrases.

Rank	2011 Queensland Floods	2013 Colorado Floods
1	flood relief appeal	colorado flood
2	flood victims	flood victim
3	flood appeal	colorado relief
4	anna bligh	boulder creek
5	brisbane river	higher ground

analysis is the optimal number of clusters (or groups) (Blei et al., 2003). To identify this parameter, we must identify the optimal number of topics to group tweets by topic. Hence, we use the measure of *perplexity,* which aims to assess each topic model's generalizability—that is, the lower a topic model's perplexity, the higher its generalizability (Blei et al., 2003). To find a topic model with the highest generalizability (lowest perplexity) per dataset, we performed three procedures: (1) We generated 199 topic models by a number of topics ranging from 2 to 200. (2) We calculated each model's perplexity value. (3) We applied cumulative sum analysis to the 199 topic models' perplexity values to find one topic model whose perplexity value significantly lowered and eventually became stable (*e.g.*, Ellaway, 1978), signifying that additional topics did not substantially improve further topic models' generalizability. As a result, we found a preferred topic model for each disaster: for the 2011 Queensland floods, the topic model had 72 topics; and for the 2013 Colorado floods, the topic model had 57 topics. Appendix B shows the relationship between 199 topic models and their perplexity values.

According to the results of LDA, Tweet A shown below conveys one topic that is described by *higher ground*, *immediately*, *water*, *coming*, *move*. Tweet B expresses two topics about (1) *move*, *higher ground*, *rain* and (2) *loved*, *pray*, *mercy*. Lastly, Tweet C holds three topics about (1) *higher ground*, (2) *stay*, *safe*, *people*, and (3) *boulder creek*.[4]

Tweet A: SEEK HIGHER GROUND IMMEDIATELY: WALL of water coming down Boulder Canyon. Move away from Boulder Creek! #BoulderFlood

Tweet B: Move to higher ground. Hold your loved ones close & pray this rain shows mercy, cleanly washing away this town. #coflood #GoodnightNightvale

Tweet C: Boulder creek running at 5000 cubic feet per second. Stay safe people get to higher ground. #boulderflood

Based on the two Twitter datasets and the computational linguistics techniques, we produced our study's dependent and independent variables. Table 6 shows these variables and their descriptive statistics.

4.3. Analysis method

Given the dependent variable's binary nature, we used logistic regression to examine the hypotheses. We used tweet content features—URLs, words, and hashtags—as control variables, so that we could examine the tweets' content ambiguity while accounting for an individual tweet's total length. We also controlled for a twitterer's number of followees, since that number is the opposite heuristic from that of followers. We further controlled whether individual tweets mentioned other twitterers (*Mentions*). Spiro, Dubois, and Butts (2012) found that including mentions delayed retweet speed, which in turn negatively influenced a tweet's retweet likelihood. Similarly, Suh et al. (2010) pointed out a negative effect of mentions on retweeting, though that effect was marginal. We controlled for the following profile-related features: (1) the length of profile summary (*Profile_Length*); (2) whether a profile image was included (*Profile_Image_YN*); and (3) whether a

[4] Tweet A: https://twitter.com/CUBoulder/statuses/378210912693264385, Tweet B: https://twitter.com/IncrediSquish/statuses/379036515742916608, and Tweet C: https://twitter.com/1DancingCrane/statuses/378369601215545345.

Table 6
Variable Description.

Variables	Explanation	Datasets: 2011 Queensland Mean; Std.; Range	Datasets: 2013 Colorado Mean; Std.; Range
Dependent			
Retweet_YN_10 m$_i$	Whether or not tweet *i* is retweeted within the first 10 min after it is posted: 1 for *retweeted* and 0 for *not retweeted*		
Systematic Information—*Tweet Content*			
OneVSTwoMore	A contrast code for group comparison between tweets with only one topic and those with two or more topics		
TwoVSMore	A contrast code for group comparison between tweets with two topics and those with three or more topics		
Heuristic Information—*Twitterer Profile*			
Ln(Followers$_{i,t}$)	The log-transformed number of followers of tweet *i*'s author between join date and the posting date of tweet *i*	5.465; 0.8; 0 − 15.1	6.11; 2.31; 0 − 16.4
Ln(Status$_{i,t}$)	The log-transformed number of tweets of tweet *i*'s author between join date and the posting date of tweet *i*	7.443; 1.98; 0 − 12.7	8.14; 2.23; 0 − 14.0
Affiliation_Length$_{i,t}$	The age of the Twitter account in year after each twitterer's account creation at time *t* of tweet *i's* posting	1.931; 0.85; 0 − 5	2.730; 1.70; 0 − 7
Ln(Recent_Tweets$_{i,t}$)	The log-transformed number of recent tweets about current events of the twitterer of tweet *i* between the start date of an incident and the posting date of tweet *i*	2.68; 1.59; 0.69 − 6.6	2.26; 1.57; 0.69 − 6.3
Ln(Likes$_{i,t}$)	The log-transformed number of liked tweets of tweet *i*'s author between join date and the posting date of tweet *i*	1.783; 1.95; 0 − 9.32	3.3; 2.6; 0 − 13.6
Control			
Words$_i$	The total number of words in tweet *i*	9.54; 3.99; 0 − 24	8.61; 3.84; 0 − 24
Hashtags$_i$	The total number of hashtags in tweet *i*	1.26; 0.89; 0 − 13	1.27; 1.21; 0 − 15
URLs$_i$	The number of URLs in tweet *i*	0.462; 0.55; 0 − 5	0.667; 0.54; 0 − 4
Ln(Followees$_{i,t}$)	The log-transformed number of followees of tweet *i*'s author between join date and the posting date of tweet *i*	5.37; 1.61; 0 ~ 12.1	5.83; 1.95; 0 − 12.7
Profile_Length$_i$	The character length of profile summary of tweet *i*'s author	84.99; 54.5; 0 − 190	95.84; 54.87; 0 − 186
Profile_Image_YN$_i$	Whether tweet *i*'s author has a profile image—1 for *with an image* and –1 for *without an image*		
Account_Types$_i$	Whether tweet *i*'s author is a journalist, emergency services representative, or none—1 for *journalist or emergency service representative* and –1 for *none*		
Mention_YN$_i$	Whether tweet *i* contains other twitterers' name—1 for *yes* and –1 for *no*		

twitterer was a journalist or an emergency service representative (*Account_Type*). To determine the latter, we performed a keyword search in the profile summary (*e.g.*, CNN, ABC, FOX, FEMA, etc.). Appendix C shows the full list of keywords we used to identify twitterers' account type. Finally, while content ambiguity is related to content credibility, ambiguity could also motivate recipients to seek contextual information through embedded URLs. Therefore, we controlled for this case by including an interaction term between *TwoVSMore* and *URLs* (*e.g.*, *TwoVSMore* × *URLs*) so that content ambiguity better implied content credibility.

We log-transformed the number of followers, status, likes, and recent tweets for two reasons. First, log transformation stabilizes data variability and thus could enhance statistical inference (Judd et al., 2011; Mosteller & Tukey, 1977). Second, log transformation can make skewed data conform to normality for a better model fit (Meaney, Fang, Rubæk, Demidenko, & Paulsen, 2007). Including the explanatory and control variables all together let us conduct the variance inflation factor (VIF) analysis to assess multicollinearity. The VIF results were: max of 3.53 and mean of 1.54 for the Queensland floods; and max of 3.54 and mean of 1.62 for the Colorado floods. Because none of the VIF values exceed the acceptable VIF value of 5 (Belsley, Kuh, & Welsch, 2005), multicollinearity was not a concern for our study. To correct the heteroscedasticity of variance, we performed logistic regression with robust standard errors (White, 1980). Appendix D shows the correlation matrix of these variables, and Fig. 3 shows our study's empirical model.

5. Results

Table 7 summarizes the empirical model's regression results. In H1, we examined the relationship between content ambiguity (measured by the number of topics) and quick retweeting by postulating that a disaster tweet's content ambiguity decreases its content credibility. We found strong evidence supporting H1 in both disaster cases—the number of topics in a tweet negatively affected its quick retweeting, while all other model variables held constant (Queensland: Wald $\text{Chi}^2_{2,\ 109,450}$ = 2,021.99***; Colorado: Wald $\text{Chi}^2_{2,\ 102,423}$ = 1,336.4***).

Within the first 10 min after posting, the odds ratio of retweeting for tweets with one topic was 3.350 times higher than that for tweets with

$$
\begin{aligned}
Retweet\_YN\_10m_i = {} & \beta_0 + \underbrace{\beta_1 OneVSTwoMore_i + \beta_2 TwoVSMore_i}_{Systematic\ Information-Tweet\ Content} \\
& + \underbrace{\beta_3 Ln(Followers_{i,t}) + \beta_4 Ln(Status_{i,t}) + \beta_5 Affilication\_Length_{i,t} + \beta_6 Ln(Recent\_Tweets_{i,t}) + \beta_7 Ln(Likes_{i,t})}_{Heuristic\ Information-Twitterer\ Profile} \\
& + \underbrace{\beta_8 TwoVSMore_i \times Ln(Followers_{i,t}) + \beta_9 TwoVSMore_i \times Ln(Status_{i,t})}_{Bias\ Hypothesis-Interplay} \\
& + \underbrace{\beta_{10} TwoVSMore_i \times Affilication\_Length_{i,t} + \beta_{11} TwoVSMore_i \times Ln(Recent\_Tweets_{i,t}) + \beta_{12} TwoVSMore_i \times Ln(Likes_{i,t})}_{Bias\ Hypothesis-Interplay\ cont'd} \\
& + \underbrace{\beta_{13} TwoVSMore_i \times URLs_i + \underbrace{\beta_{14} Words_i + \beta_{15} Hashatgs_i + \beta_{16} URLs_i}_{Tweet\ Length} + \beta_{17} Mention_{YN_i} + \beta_{18} Ln(Followees_{i,t})}_{Control\ Variables} \\
& + \underbrace{\beta_{19} Profile\_Image\_YN_i + \beta_{20} Profile\_Summary\_Length_i + \beta_{21} Account\_Types_i}_{Control\ Variables\ cont'd} \\
& + \varepsilon_i
\end{aligned}
$$

Fig. 3. Empirical Model.

Table 7
Statistical Results.

Variables		Cases 2011 Queensland	2013 Colorado	Hypothesis Testing
Heuristically Processed Information—*Twitterer Profile*				
		Wald Chi^2(5) = 4,176.12***	*Wald Chi*^{2}(5) = 9,210.4***	
Ln(Followers$_{i,t}$)		0.506*** (0.00907)	0.568*** (0.00757)	(N/A)
Ln(Status$_{i,t}$)		–0.188*** (0.00777)	–0.383*** (0.00709)	
Affiliation_Length$_{i,t}$		0.0784*** (0.0126)	0.0543*** (0.00689)	
Ln(Recent_Tweets$_{i,t}$)		0.122*** (0.00669)	0.282*** (0.00645)	
Ln(Likes$_{i,t}$)		0.0264*** (0.00562)	0.123*** (0.00454)	
Systematically Processed Information—*Tweet Content*				**H1**
		Wald Chi^2(2) = 2,021.99***	*Wald Chi*^{2}(2) = 1,336.4***	
OneVSTwoMore$_i$		0.403*** (0.00982)	0.421*** (0.0262)	Supported
TwoVSMore$_i$		0.517*** (0.0287)	0.678*** (0.0420)	Supported
Dual Processing (or Bias)—*Twitterer Profile* × *Tweet Content*				**H2a ~ H2e**
		Wald Chi^2(5) = 39.27***	*Wald Chi*^{2}(5) = 61.1***	
TwoVSMore$_i$ × Ln(Followers$_{i,t}$)		–0.0490*** (0.0148)	–0.0780*** (0.0148)	H2a: Supported
TwoVSMore$_i$ × Ln(Status$_{i,t}$)		0.0578*** (0.0139)	0.0860*** (0.0149)	H2b: Rejected
TwoVSMorei × Affiliation_Length$_{i,t}$		–0.0729*** (0.0221)	–0.0291* (0.0137)	H2c: Supported
TwoVSMore$_i$ × Ln(Recent_Tweets$_{i,t}$)		–0.0367** (0.0118)	–0.0253* (0.0126)	H2d: Supported
TwoVSMore$_i$ × Ln(Likes$_{i,t}$)		–0.0114 (0.00954)	–0.0322*** (0.00885)	H2e: Partially Supported
Control				
		Wald Chi^2(9) = 2,278.47***	*Wald Chi*^{2}(9) = 1,331.6***	
TwoVSMore$_i$ × URLs$_i$		0.0814* (0.0335)	0.140*** (0.0383)	(N/A)
Words$_i$		0.0395*** (0.00240)	0.0520*** (0.00260)	
Hashtags$_i$		0.272*** (0.00943)	0.181*** (0.00745)	
URLs$_i$		–0.0219 (0.0193)	–0.213*** (0.0200)	
Mention_YN$_i$		–0.239*** (0.00981)	–0.0612*** (0.00954)	
Ln(Followees$_{i,t}$)		–0.0649*** (0.00659)	–0.0652*** (0.00716)	
Profile_Image_YN$_i$		–0.399*** (0.0214)	0.367*** (0.0656)	
Profile_Length$_i$		–0.00118*** (0.000184)	–0.0000745 (0.000195)	
Account_Types$_i$		0.0805*** (0.0209)	0.159*** (0.0188)	
Constant		–1.859*** (0.0360)	–2.649*** (0.0741)	
Model Summary				
Correct Prediction (%)		85.05 %	82.98 %	(N/A)
Predicted Probability	Sensitivity	11.49 %	30.99 %	
	Specificity	98.88 %	95.96 %	
Likelihood Ratio (21)		11,469.745***	22,177.886***	
McFadden's Pseudo R^2		0.12	0.216	
n		109,453	102,426	

†All predictors are mean centered in the regressions.
††Unstandardized regression coefficients are shown (*p < 0.05; **p < 0.01; ***p < 0.001).

multiple topics in the Queensland dataset (34.88 % *vs*. 10.41 %, Queensland: $\beta_{OneVSTwoMore}$ = 0.403***).[5] We found a similar result in the Colorado dataset; the odds ratio of retweeting for tweets with only one topic was 3.536 times higher than that for multiple topic tweets (16.41 % *vs*. 4.64 %, Colorado: $\beta_{OneVSTwoMore}$ = 0.421***). We also confirmed that multiple topics significantly affected a tweet's probability of quick retweeting. In the Queensland dataset, the odds ratio of quick retweeting for tweets with two topics was 2.812 times higher than that for tweets with more than two topics (17.46 % *vs*. 6.21 %, $\beta_{TwoVSMore}$ = 0.517***).[6] 2). In the Colorado dataset, when tweets included two topics, their odds ratio of quick retweeting was 3.880 times higher than that for tweets with more than two topics (9.14 % *vs*. 2.35 %, $\beta_{TwoVSMore}$ = 0.678***). Therefore, we empirically demonstrated that as a disaster tweet's content credibility decreases, the probability of its quick retweeting decreases as well.

In Hypotheses 2 (H2a–H2e), we conjectured that, as a source-credibility cue, the twitterer profile can mitigate the negative effect of a tweet's content credibility on quick retweeting. All continuous variables were centered from their means to alleviate multicollinearity (Aiken, West, & Reno, 1991) and offer easier interpretations (Judd et al., 2011). Overall, we found interesting empirical evidence supporting our moderation hypotheses in both flood incidents (Queensland: Wald $\text{Chi}^2_{5,\ 109{,}455}$ = 39.27***; Colorado: Wald $\text{Chi}^2_{5,\ 102{,}428}$ = 61.1***). Of the five moderation hypotheses, we found four statistically significant, including one that was partially supported.

In H2a, we expected a person's number of followers to be a cue for reputation credibility, and both datasets strongly supported this hypothesis. The relationship between content credibility and quick retweeting was significantly moderated by the number of followers. In the Queensland dataset, for example, a 10 % increase in the number of followers resulted in a 4.94 % increase in the probability of quick retweeting ($\beta_{Ln(Followers)}$ = 0.506***), becoming stronger for tweets with more than two topics than those with two topics (5.42 % *vs*. 4.45 %; $\beta_{TwoVSMore \times Ln(Followers)}$ = –0.049***).[7] As a result, the difference in the probability of quick retweeting between tweets with more than two topics and those with two topics was reduced by 0.938 % per a 10 % increase in the number of followers.[8] In the Colorado floods, a 10 % increase in a twitterer's number of followers resulted in a 5.56 % increase in the probability of his or her tweets' being quickly retweeted ($\beta_{Ln(Followers)}$ = 0.568***); this increase was conditional upon a tweet's content credibility, with a 6.35 % increase for tweets with more than two topics and a 4.78 % increase for tweets with two topics

[5] $e^{-1.859+0.403\times2} = 0.3488$ (34.88 %); $e^{-1.859+0.403\times-1} = 0.1041$ (10.41 %); $e^{0.403\times3} = 3.350$

[6] $e^{-1.859+0.403\times-1+0.517\times1} = 0.1746$ (17.46 %); $e^{-1.859+0.403\times-1+0.517\times-1} = 0.0621$ (6.21 %); $e^{0.517\times2} = 2.812$

[7] $e^{(0.506)\times\log(1.1)} = 1.0494$ (4.94 %); $e^{(0.506-0.049\times-1)\times\log(1.1)} = 1.0543$ (5.43 %); $e^{(0.506-0.049\times1)\times\log(1.1)} = 1.0445$ (4.45 %)

[8] $e^{(0.049\times2)\times\log(1.1)} = 1.00938$ (0.938 %)

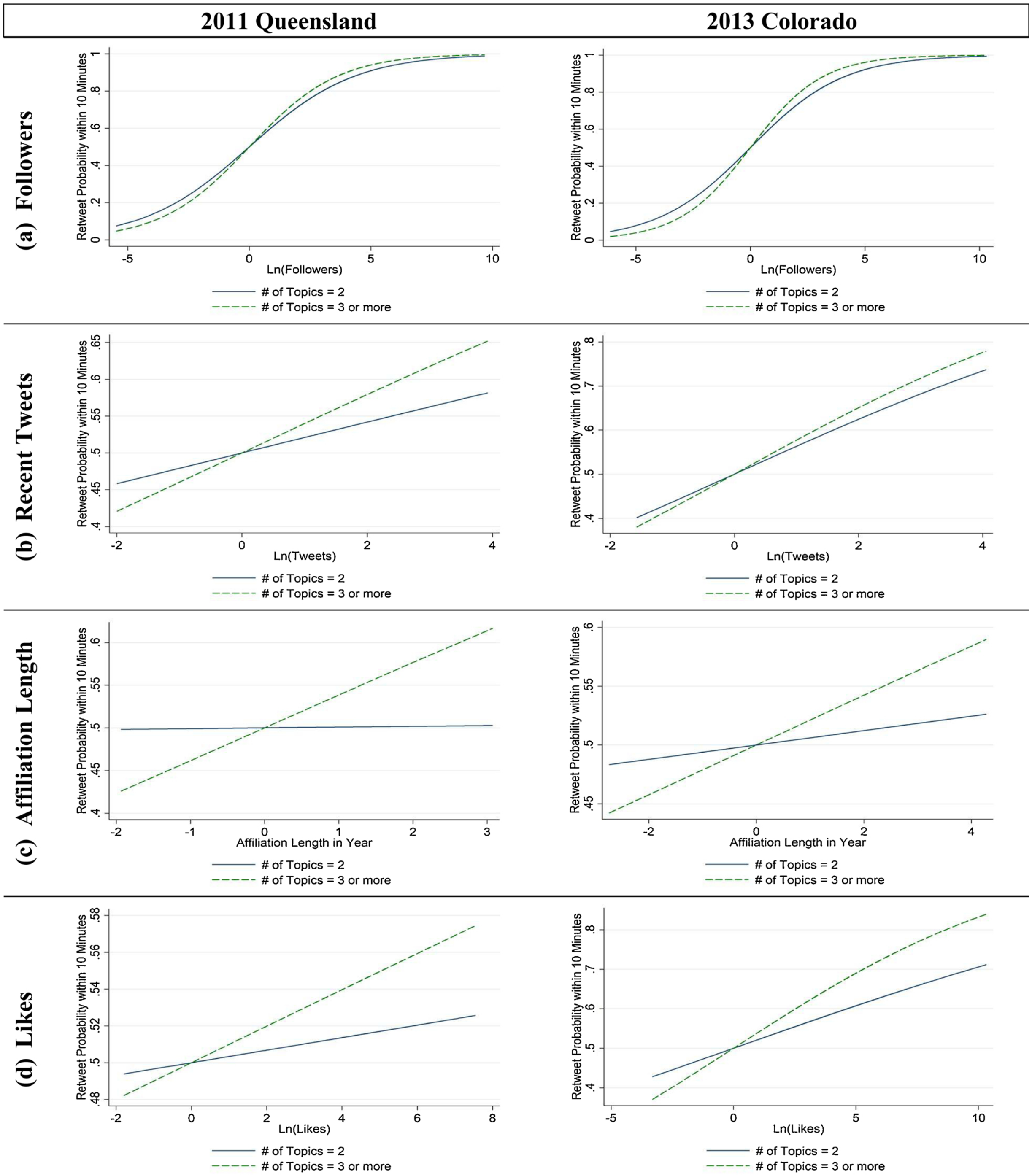


Fig. 4. Interaction Plots.

($\beta_{TwoVSMore \times Ln(Followers)}$ = –0.078***). Consequently, the difference in the quick retweeting probability rendered by a tweet's content credibility was reduced by 1.498 % for every 10 % increase in a person's number of followers. Therefore, we conclude that H2a is supported.

In H2b and H2c, we viewed a twitterer's total number of tweets and affiliation length as social-presence cues. We found that in both flood incidents, the total number of tweets had a significant moderating affect, but its direction was opposite to what we hypothesized. Therefore, H2b is not supported. However, a person's affiliation length had significant moderating effect on a tweet's content credibility. In the Queensland dataset, an additional year of Twitter affiliation increased the likelihood of a person's tweets being quickly retweeted by 8.15 % on average ($\beta_{Affiliation\_Length}$ = 0.0784***); this increase depended on content credibility, with an increase of 16.33 % for tweets with more than two topics and 0.55 % for tweets with two topics ($\beta_{TwoVSMore \times Affiliation\_Length}$ = –0.0729***).[9] Thus, the difference in the probability of quick retweeting based on a tweet's content credibility was decreased by 15.69 % on average in the Queensland dataset. In the Colorado dataset, a 5.58 % increase in the probability of quick retweeting per additional year ($\beta_{Affiliation\_Length}$ = 0.0543***) became stronger for tweets with more than two topics than for tweets with two topics (8.69 % *vs.* 2.55 %; $\beta_{TwoVSMore \times Affiliation\_Length}$ = –0.0291*),

[9] $e^{(0.0784)} = 1.0815$ (8.15 %); $e^{(0.0784-0.0729\times -1)} = 1.1633$ (16.33 %); $e^{(0.0784-0.0729\times 1)} = 1.0055$ (0.55 %)

Table 8
Robustness Check.

Variables	Retweet_YN					
	2011 Queensland Floods			2013 Colorado Floods		
	5 m Coefficient (Robust Err.)	10 m Coefficient (Robust Err.)	15 m Coefficient (Robust Err.)	5 m Coefficient (Robust Err.)	10 m Coefficient (Robust Err.)	15 m Coefficient (Robust Err.)
Heuristically Processable Information—*Twitterer Profile*						
Ln(Followers$_{i,t}$)	0.500*** (0.00959)	0.506*** (0.00907)	0.516*** (0.00892)	0.562*** (0.00781)	0.568*** (0.00757)	0.583*** (0.00757)
Ln(Status$_{i,t}$)	−0.179*** (0.00821)	−0.188*** (0.00777)	−0.195*** (0.00763)	−0.370*** (0.00750)	−0.383*** (0.00709)	−0.390*** (0.00695)
Affiliation_Length$_{i,t}$	0.0780*** (0.0135)	0.0784*** (0.0126)	0.0842*** (0.0123)	0.0408*** (0.00738)	0.0543*** (0.00689)	0.0554*** (0.00673)
Ln(Recent_Tweets$_{i,t}$)	0.128*** (0.00717)	0.122*** (0.00669)	0.120*** (0.00653)	0.281*** (0.00674)	0.282*** (0.00645)	0.279*** (0.00635)
Ln(Likes$_{i,t}$)	0.0231*** (0.00604)	0.0264*** (0.00562)	0.0260*** (0.00549)	0.114*** (0.00484)	0.123*** (0.00454)	0.126*** (0.00443)
Systematically Processable Information—*Tweet Content*						
OneVSTwoMore$_i$	0.404*** (0.0216)	0.403*** (0.0196)	0.404*** (0.0190)	0.413*** (0.0289)	0.421*** (0.0262)	0.420*** (0.0253)
TwoVSMore$_i$	0.521*** (0.0319)	0.517*** (0.0287)	0.527*** (0.0278)	0.697*** (0.0466)	0.678*** (0.0420)	0.674*** (0.0403)
Dual Processing (or Bias)—*Twitterer Profile × Tweet Content*						
TwoVSMore$_i$ × Ln(Followers$_{i,t}$)	−0.0432** (0.0159)	−0.0490*** (0.0148)	−0.0456** (0.0143)	−0.0780*** (0.0148)	−0.0731*** (0.0148)	−0.0762*** (0.0145)
TwoVSMore$_i$ × Ln(Status$_{i,t}$)	0.0464** (0.0150)	0.0578*** (0.0139)	0.0555*** (0.0135)	0.0860*** (0.0149)	0.0890*** (0.0149)	0.0928*** (0.0145)
TwoVSMore$_i$ × Affiliation_Length$_{i,t}$	−0.0768** (0.0242)	−0.0729*** (0.0221)	−0.0781*** (0.0213)	−0.0291* (0.0137)	−0.0302* (0.0137)	−0.0329* (0.0132)
TwoVSMore$_i$ × Ln(Recent Tweets$_{i,t}$)	−0.0346** (0.0129)	−0.0367** (0.0118)	−0.0399*** (0.0115)	−0.0253* (0.0126)	−0.0283* (0.0126)	−0.0231 (0.0122)
TwoVSMore$_i$ × Ln(Likes$_{i,t}$)	−0.00814 (0.0104)	−0.0114 (0.00954)	−0.0135 (0.00925)	−0.0322*** (0.00885)	−0.0363*** (0.00876)	−0.0374*** (0.00858)
Control Variables						
TwoVSMore$_i$ × URLs$_i$	0.0467 (0.0369)	0.0814* (0.0335)	0.0827* (0.0323)	0.147*** (0.0420)	0.140*** (0.0383)	0.129*** (0.0370)
Words$_i$	0.0364*** (0.00256)	0.0395*** (0.00240)	0.0418*** (0.00234)	0.0511*** (0.00278)	0.0520*** (0.00260)	0.0520*** (0.00254)
Hashtags$_i$	0.277*** (0.00995)	0.272*** (0.00943)	0.275*** (0.00931)	0.162*** (0.00789)	0.181*** (0.00745)	0.195*** (0.00730)
URLs$_i$	−0.0663** (0.0208)	−0.0219 (0.0193)	−0.00215 (0.0188)	−0.285*** (0.0215)	−0.213*** (0.0200)	−0.184*** (0.0195)
Mention_YN$_i$	−0.249*** (0.0106)	−0.239*** (0.00981)	−0.239*** (0.00954)	−0.0719*** (0.0102)	−0.0612*** (0.00954)	−0.0545*** (0.00931)
Ln(Followees$_{i,t}$)	−0.0676*** (0.00692)	−0.0649*** (0.00659)	−0.0651*** (0.00649)	−0.0681*** (0.00752)	−0.0652*** (0.00716)	−0.0708*** (0.00707)
Profile_Image_YN$_i$	−0.386*** (0.0230)	−0.399*** (0.0214)	−0.416*** (0.0208)	0.412*** (0.0753)	0.367*** (0.0656)	0.354*** (0.0624)
Profile_Length$_i$	−0.00123*** (0.000198)	−0.00118*** (0.000184)	−0.00108*** (0.000179)	−0.000184 (0.000210)	−0.0000745 (0.000195)	−0.0000184 (0.000190)
Account_Types$_i$	0.0777*** (0.0218)	0.0805*** (0.0209)	0.0800*** (0.0205)	0.149*** (0.0195)	0.159*** (0.0188)	0.148*** (0.0187)
Constant	−2.121*** (0.0387)	−1.859*** (0.0360)	−1.760*** (0.0351)	−2.988*** (0.0842)	−2.649*** (0.0741)	−2.525*** (0.0707)
Model Summary						
Percent Predicted Correctly	87.42 %	85.05 %	84.04 %	85.57 %	82.98 %	82.03 %
Predicted Probability Sensitivity	11.49 %	10.81 %	13.16 %	30.99 %	30.99 %	34.23 %
Specificity	98.88 %	98.97 %	98.60 %	95.96 %	95.97 %	95.23 %
Log Likelihood (21)	10,171.5***	11,469.7***	12,248.0***	19,110.6***	22,177.9***	23,646.4***
McFadden's Pseudo R^2	0.119	0.12	0.123	0.210	0.216	0.221
n	109,456			102,426		

decreasing the difference in the probability of quick retweeting between tweets with more than two topics and those with two topics by 5.99 %. As these results show, H2c is supported.

Our results also provided strong support for H2d, which assumes that a person's number of recent tweets (*i.e.*, the recency–credibility cue) moderates the relationship between his or her tweets' content credibility and the probability of quick retweeting. In the Queensland dataset, a 10 % increase in the number of recent tweets resulted in a 1.169 % increase in the probability of quick retweeting ($\beta_{\mathrm{Ln(Recent\_Tweets)}} = 0.122^{***}$), which turned out to be stronger for tweets with more than two topics than for those with two topics (1.524 % *vs.* 0.81 %; $\beta_{\mathrm{TwoVSMore \times Ln(Recent\_Tweets)}} = -0.0367^{**}$).[10] Every 10 % increase in the number of recent tweets decreased the difference in the probability of quick retweeting by 0.7 %.[11] In the Colorado dataset, for a 10 % increase in the number of recent tweets, we observed a 2.72 % increase in the quick retweeting probability; this was higher for tweets with more than two topics than for tweets with two topics (2.97 % *vs.* 2.47 %; $\beta_{\mathrm{TwoVSMore \times Ln(Recent\_Tweets)}} = -0.0253^{*}$), reducing the difference in the quick retweeting probability resulting from tweet content credibility by 0.48 %.

Finally, we found partial support for H2e. Although we detected no significant moderation effect due to the number of likes (*i.e.*, the endorsement-credibility cue) in the Queensland dataset, the Colorado dataset showed a significant moderation effect on the relationship between tweet content credibility and retweet likelihood within 10 min of posting. Specifically, a 10 % increase in the number of likes corresponded to a 1.179 % increase in the probability of quick retweeting, and this effect was stronger for tweets with more than two topics than for tweets with two topics (1.49 % *vs.* 0.869 %; $\beta_{\mathrm{TwoVSMore \times Ln(Likes)}} = -0.0322^{***}$)[12], decreasing the gap in the quick retweeting probability of tweets with different content-credibility levels by 0.62 %. To provide a better understanding of the twitterer profile as a source-credibility cue, we graphed interaction plots between the profile components and tweet content credibility (see Fig. 4).

[10] $e^{(0.122)\times\log(1.1)} = 1.01169$ (1.169 %); $e^{(0.122-0.0367\times-1)\times\log(1.1)} = 1.0152$ (1.52 %); $e^{(0.122-0.0367\times1)\times\log(1.1)} = 1.0081$ (0.81 %)

[11] $e^{(0.0367\times2)\times\log(1.1)} = 1.0070$ (0.7 %)

[12] $e^{(0.123)\times\log(1.1)} = 1.01179$ (1.179 %); $e^{(0.123-0.0322\times1)\times\log(1.1)} = 1.00869$ (0.869 %); $e^{(0.123-0.0322\times-1)\times\log(1.1)} = 1.0149$ (1.49 %)

6. Discussion

In this study, we examined how the twitterer profile, as a source-credibility cue, influenced the quickness of retweeting during the two natural disasters. We used retweet likelihood as a function of tweet credibility, and twitterer credibility as an information source. To better reflect communication practices in disasters, we leveraged the first 10 min (rather than hours, days, or weeks) after the original tweets' posting as a relevant time index to evaluate disaster tweets' retweet likelihood. Drawing on HSM, we investigated how the twitterer profile, as a source-credibility cue, interplays with the content credibility of tweets.

Our study offers strong evidence for the role of the twitterer profile in tweet propagation during times of disaster. Several insights emerge from the empirical results. First, the twitterer profile is not just about numbers. Rather, it offers heuristically interpretable cues as to how believable twitterers are as a tweet information source. The profile's components offer different credibility cues—ranging from reputation (*i.e.*, followers) to social presence (*i.e.*, affiliation length) to recency (*i.e.*, recent tweets) and endorsements (*i.e.*, likes). Each of these components makes a unique contribution to how quickly a tweet is retweeted.

That said, however, the impact of the total number of past tweets was actually the opposite of what we expected. It turned out that a person's presence in terms of total past tweets does not necessarily indicate his or her source credibility for disaster communication. This is a thought-provoking result; a person's presence on a CMC such as Twitter is traditionally viewed as an important factor that indicates source credibility (Bente et al., 2008; Skalski & Tamborini, 2007). To help ensure their safety during a disaster, however, twitterers need up-to-the-minute information that precisely describes dynamically changing, threatening events because disaster information easily becomes irrelevant or outdated (Wilensky, 2014; Zeng et al., 2016). Given this, we conjecture that a twitterer's social presence—suggested by his or her total tweets—may not be considered to be a source-credibility cue because past tweets are irrelevant to the current disaster events.

Moreover, because it is heuristically interpretable, the twitterer profile plays a critical role for people who need to quickly assess a tweet's source credibility. As such, the twitterer profile contributes conditionally to rapid dissemination of disaster information. As our study shows, during disasters, the twitterer profile is used as a source-credibility cue. Of course, we do not mean to imply that the profile does not serve this function during non-disaster times; it very well may. Because Twitter communication functions in a unique way during disasters, however, it is necessary to specify the context under which we are making our claims, without implying any generalizability beyond the specified context.

Finally, to strengthen the generalizability of our findings, we examined the retweetability of disaster tweets within the first 5 min (5 m) and the first 15 min (10 m) after posting. Table 8 summarizes the empirical results of the additional time intervals. We found only one inconsistency in the Colorado dataset, when we considered the first 15 min as quick retweeting ($\beta_{\mathrm{TwoVSMore} \times \mathrm{Ln(Recent\_Tweets)}} = 0.0231$).

6.1. Theoretical contributions

Our work provides several contributions to research on disaster communication and Twitter. First, we extend the literature by taking into account the credibility of Twitter information during disasters. To date, prior research has focused on how tweet content and features (*e.g.*, URLs, hashtags, etc.) influence information propagation *via* retweeting during disasters. For instance, studies by Sutton, Gibson, Phillips et al. (2015) and Zeng et al. (2016) found that content-related features (*i.e.*, situational information) and styles (*i.e.*, imperative sentences using all caps for emphasis) had a significant influence on retweeting. While these studies improve our understanding of disaster communication using Twitter, they fail to consider a critical aspect of tweets: their *information credibility*. In our study, we used extant literature findings to conceptualize a tweet's information credibility as consisting of both its content credibility and its source credibility; we then investigated how they could impact the rapid dissemination of disaster information through retweeting.

Our study's second contribution is in our accounting for tweet length limitations and finding that the disaster information conveyed in tweets can confuse recipients. This finding is aligned with that of studies by Bean et al. (2016) and Sutton, Spiro, Johnson et al. (2014), which found that the length limitation of tweets has both positive and negative effects. On the positive side, tweets allow easy-and-quick communication through virtually all devices. On the negative, length limits may result in twitterers conveying ambiguous, confusing content, which thus renders the tweet less credible. In finding strong evidence that content credibility negatively affects retweet likelihood, our study adds an additional content feature to the Twitter literature: *content credibility*, which is influenced by the number of topics a tweet covers.

In addition, our study contributes to the literature by examining the interplay of the different credibility cues that Twitter provides. Leveraging the HSM bias hypothesis, we demonstrate that when a tweet's content is deemed less credible, the author's profile information can offer supplementary cues to aid the decision to retweet. These informational cues, which reflect the tweet's source credibility, include the number of followers, recent tweets, likes, and the twitterer's affiliation length. While studies on Twitter suggest that these factors could individually influence information propagation by retweeting, our study extends this literature by empirically demonstrating how source credibility can mitigate the negative influence of content credibility on retweeting.

6.2. Implications for practice

Our study also has implications for the at-risk public, emergency responders, and online volunteers. First, to achieve rapid dissemination of disaster information, we suggest that public health and emergency agencies focus each tweet on a single topic. Unlike blog services and Facebook, Twitter and Wireless Emergency Alert (WEA) restrict message length to 140 characters (up to 280 for some languages) and 90 characters, respectively. Given these restrictions, multiple topics in a single message can blur a tweet's central argument and weaken the tweet's credibility, thereby confusing recipients' ability to understand the intention of a message.

Second, our findings suggest that to effectively disseminate disaster information, public health agencies and emergency responders must continuously manage their Twitter profiles. Having a long-term Twitter presence, recent postings of disaster-related tweets, and many followers and likes can enhance the credibility of those posting a tweet. However, simply having posted many tweets in the past does not necessarily improve a twitterer's source credibility. Rather, our findings suggest that public health agencies and emergency responders need recent tweets pertaining to the current, ongoing disaster event to facilitate rapid dissemination of additional disaster information.

For twitterers who receive questionable information in emergency situations, rather than simply ignore that information, our findings suggest that they use the twitterer's author profile as an information source to estimate that author's trustworthiness; they can then better decide whether or not to share the message. Finally, we recommend that Twitter itself consider adding further profile information to help users better assess—and twitterers more thoroughly present—source credibility. For example, Twitter could display twitterers' recent tweeting activities about an ongoing event, so that tweet recipients can make informed decisions under time pressure. The company could also further investigate new profile components to be used as source-credibility cues in disaster tweets to help people instantly judge a received tweet's source credibility.

6.3. Limitations and future research directions

The limitations of this study open future research possibilities. First, our study results are based on Twitter datasets about floods; although this restricts its generalizability, our datasets held a large sample of disaster tweets. Future studies can explore these empirical findings in different disaster contexts, such as wildfires, earthquakes, and tornadoes in order to verify the consistency of our findings independent of disaster type. For instance, retweeting patterns may vary according to dissimilar aspects of events (Kim, 2014; Sutton, Gibson, Spiro et al., 2015), implying that there might be other factors that influence how twitterers assess tweet content and source credibility. Second, we indirectly estimated tweet content credibility by relying on the LDA algorithm and the findings of previous research on disaster communication and social media; this research showed that disaster information conveyed by length-limited tweets can be perceived as ambiguous—and thus less convincing—than messages without length restrictions (Bean et al., 2016; Westerman et al., 2014). Future research can leverage human subjects to directly observe and evaluate the extent of disaster tweets' content credibility. Third, our research model can be extended by including additional factors that are already identified as influencing retweeting. For example, Sutton, Gibson, Spiro et al. (2015) investigated tweets' thematic content—including "Hazard Impact," "Thank You/Appreciation," and "Emotion/Judgment/Evaluative"—and its effect on retweeting. Further, previous research on Twitter and disaster communication examined whether tweets convey rumors as a function of retweeting (Oh et al., 2013; Zeng et al., 2016). These characteristics are not reflected in our research model and can conceivably influence twitterers' retweeting decisions during disasters. Finally, following the events we examined, Twitter extended the length of tweets to 280 characters for some languages. Future studies may investigate how such a change impacts twitterer perceptions of disaster tweet credibility.

7. Conclusions

As an effective means of disaster communication, Twitter has gained considerable attention in the literature. Drawing on HSM as the theoretical lens, this study is the first to view Twitter's information as both systematically processed information (tweets) and heuristically processed information (twitterers); it also investigates the different roles of qualitatively disparate information in association with retweeting. Notably, by aligning people's purposes for using Twitter for disaster communication, we interpreted twitterer profile information as source-credibility cues separate from a tweet's content elements of words, URLs, and hashtags. Our key findings suggest that examining twitterer profile elements for source-credibility cues significantly influences retweeting during disasters. Our endeavor partly explains how twitterers quickly decide whether to retweet less-credible disaster tweets.

Our work here illuminates how disaster information is quickly shared and disseminated on Twitter despite content-credibility concerns. Further, given the growing awareness of credibility issues with online information—especially in the disaster communication context—our study offers an important test case for using the HSM as a means to explore other crucial issues related to disaster communication in online media.

CRediT authorship contribution statement

Jaebong Son: Conceptualization, Supervision, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing, Data curation, Visualization. **Jintae Lee:** Conceptualization. **Onook Oh:** Conceptualization. **Hyung Koo Lee:** Conceptualization, Writing - review & editing, Visualization. **Jiyoung Woo:** Data curation.

Appendix A

To closely examine a tweet's retweetability within the first 60 min, we conducted statistical analyses on tweet retweet frequency within the first 24 h after posting. From the analyses, we found that a first retweet occurring within 10 min after posting best represented tweets' retweetability compared to first retweets in other time periods. We therefore use this 10-minute period to measure retweet likelihood. We now explain the statistical approaches we devised to reach this finding.

We identified an individual tweet's first retweet and calculated the time difference between this tweet and its first retweet. For instance, if a tweet is retweeted 15 min after its posting, this tweet's elapsed time is 15. However, if another tweet's first retweet is made after the first 60 min since its posting, we give an elapsed time of 61, as we are interested only in a one-hour period. Table A1 explains the control and exploratory variables.

From a negative binomial analysis (see Table A2), we found that, in both cases, the relationship between a tweet's first retweet and its retweet frequency within 24 h was not linear, but rather curvilinear (Queensland: Wald $Chi^2 = 7{,}816.82$, df = 3, $p < 0.000$; Colorado: Wald $Chi^2 = 12{,}571.53$, df = 3, $p < 0.000$) (see Fig. A1). That is, there was a steep decrease in the relationship between the first retweet made within

Table A1
Description of Variables.

Variables	Explanation	Cases					
		2011 Queensland			2013 Colorado		
		Mean	S.D.	Range	Mean	S.D.	Range
Dependent Variable							
$Retweets\_24h_i$	The total number of retweets of tweet *i* within the 24 h after posting						
Explanatory Variables							
- Point Estimate							
$Retweet\_Minute_i$	The time interval in minutes between tweet *i* and its first retweet. If tweet *i*'s first retweet is not made within 60 min, its *Retweet_Minute* is coded 61.	49.4	22.8	0 – 61	47.3	24.1	0 – 61
$Retweet\_Minute_i^2$	A code for testing non-linearity of *Retweet_Minute* – Quadratic relationship						
$Retweet\_Minute_i^3$	A code for testing non-linearity of *Retweet_Minute* – Cubic relationship						
- Between Group Estimate							
50 mVSOthers	(Not a meaningful contrast code)						
20mVS(50 m, 30 m, 40 m, 10 m)	(Not a meaningful contrast code)						
50 mVS(30 m, 40 m, 10 m)	(Not a meaningful contrast code)						
30 mVS(40 m, 10 m)	(Not a meaningful contrast code)						
10 mVS40 m	A contrast code to compare the retweet frequency between a group of tweets whose first retweet is made within the first 10 min after posting and a group of tweets whose first retweet is made between the 30 and 39 min after posting.						

Table A2
Statistical Results between Entropy and Topic Quantity.

Variables	Cases			
	2011 Queensland		2013 Colorado	
	Coefficient (Robust Error)	Significance Level	Coefficient (Robust Error)	Significance Level
Explanatory	*Wald Chi*^{2} = 7816.82***, df = 3		*Wald Chi*^{2} = 12571.53***, df = 3	
$Retweet\_Minute_i$	−0.158*** (0.00920)	0.000	−0.168*** (0.00523)	0.000
$Retweet\_Minute_i^2$	0.00758*** (0.000388)	0.000	0.00784*** (0.000288)	0.000
$Retweet\_Minute_i^3$	−0.000100*** (0.00000416)	0.000	−0.000101*** (0.00000354)	0.000
Control	*Wald Chi*^{2} = 882.74***, df = 8		*Wald Chi*^{2} = 3142.94***, df = 8	
$Mention\_YN_i$	−0.0793*** (0.0180)	0.000	−0.0481*** (0.0124)	0.000
$Words_i$	0.0400*** (0.00412)	0.000	0.0230*** (0.00289)	0.000
$URLs_i$	0.124*** (0.0301)	0.000	0.170*** (0.0222)	0.000
$Hashtags_i$	0.00185 (0.0238)	0.938	0.0569*** (0.00845)	0.000
$Ln(Followers_{i,t})$	0.311*** (0.0135)	0.000	0.351*** (0.00747)	0.000
$Ln(Followees_{i,t})$	0.0323 (0.0168)	0.000	0.0494*** (0.00530)	0.000
$Ln(Likes_{i,t})$	−0.0935*** (0.0108)	0.055	−0.0576*** (0.00751)	0.000
$Ln(Status_{i,t})$	−0.130*** (0.0173)	0.000	−0.228*** (0.00829)	0.000
Constant	1.029*** (0.100)	0.000	1.117*** (0.0567)	0.000
Model Summary				
Wald χ^2	12506.52***		24184.33***	
McFadden's R^2	0.339		0.363	
n	109,456		102,426	

†All predictors are mean centered in the regressions.
††Unstandardized regression coefficients are shown (*p < 0.05; **p < 0.01; ***p < 0.001).

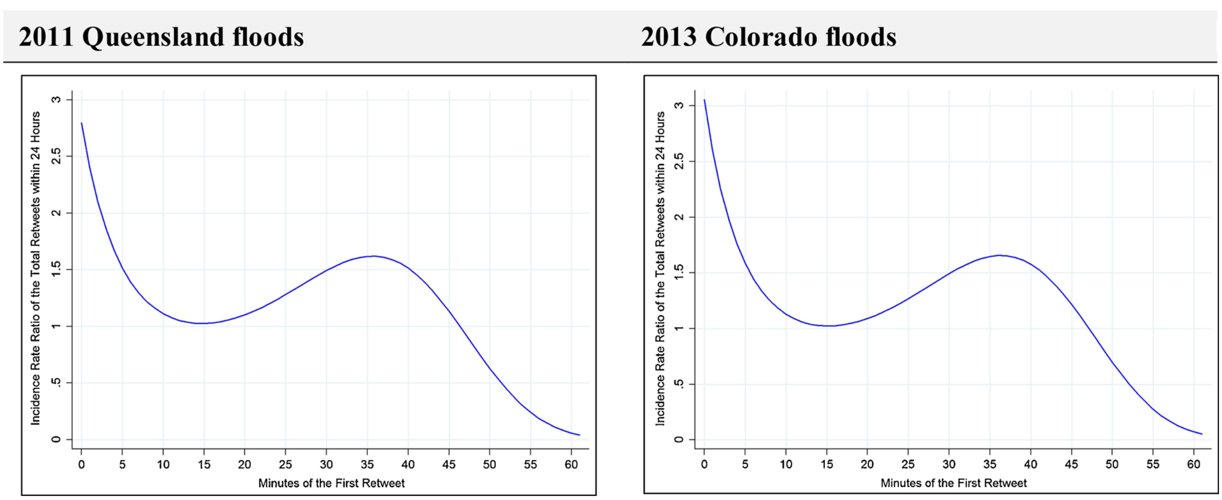


Fig. A1. Polynomial Relationships.

Table A3
Contrast Codes for Group Comparison.

Variables	Intervals					
	50_59m	10_19m	40_49m	20_29m	30_39m	0_9m
50 mVSOthers	1	−1/5	−1/5	−1/5	−1/5	−1/5
20mVS(50 m, 30 m, 40 m, 10 m)	0	1	−1/4	−1/4	−1/4	−1/4
50 mVS(30 m, 40 m, 10 m)	0	0	1	−1/3	−1/3	−1/3
30 mVS(40 m, 10 m)	0	0	0	1	−1/2	−1/2
10 mVS40 m	0	0	0	0	1	−1

Table A4
Statistical Results between Entropy and the number of Topics.

Variables	Cases			
	2011 Queensland		2013 Colorado	
	Coefficient (Robust Error[1])	Sig. Level	Coefficient (Robust Error[1])	Sig. Level
Explanatory	*Wald* $Chi^2 = 8236.6^{***}$, df = 5		*Wald* $Chi^2 = 10{,}013^{***}$, df = 5	
50 mVSOthers	−9.314*** (0.909)	0.000	−10.01*** (0.557)	0.000
20mVS(50 m, 30 m, 40 m, 10 m)	0.567*** (0.122)	0.000	0.322*** (0.0764)	0.000
50 mVS(30 m, 40 m, 10 m)	−1.212*** (0.265)	0.000	−1.118*** (0.158)	0.000
30 mVS(40 m, 10 m)	−0.166* (0.0681)	0.015	−0.280* (0.109)	0.010
10 mVS40 m	−1.077*** (0.0963)	0.000	−0.717*** (0.137)	0.000
Control	*Wald* $Chi^2 = 1138.5^{***}$, df = 8		*Wald* $Chi^2 = 3552.9^{***}$, df = 8	
$Mention\_YN_i$	−0·103*** (0.0179)	0.000	−0.0502*** (0.0129)	0.000
$Words_i$	0.0446*** (0.00407)	0.000	0.0272*** (0.00305)	0.000
$URLs_i$	0.128*** (0.0298)	0.000	0.148*** (0.0241)	0.000
$Hashtags_i$	0.0415 (0.0226)	0.067	0.0855*** (0.00893)	0.000
$Ln(Followers_{i,t})$	0.360*** (0.0134)	0.000	0.411*** (0.00783)	0.000
$Ln(Followees_{i,t})$	0.0344 (0.0177)	0.000	0.0600*** (0.00576)	0.000
$Ln(Likes_{i,t})$	−0.0982*** (0.0105)	0.052	−0.0622*** (0.00742)	0.000
$Ln(Status_{i,t})$	−0.143*** (0.0170)	0.000	−0.258*** (0.00806)	0.000
Constant	−2.787*** (0.104)	0.000	−2.594*** (0.0644)	0.000
Model Summary				
Wald χ^2	13923.93***		24092.02***	
McFadden's R^2	0.261		0.297	
n	109,456		102,426	

[†]All predictors are mean centered in the regressions.
[††]Unstandardized regression coefficients are shown (*p < 0.05; **p < 0.01; ***p < 0.001).

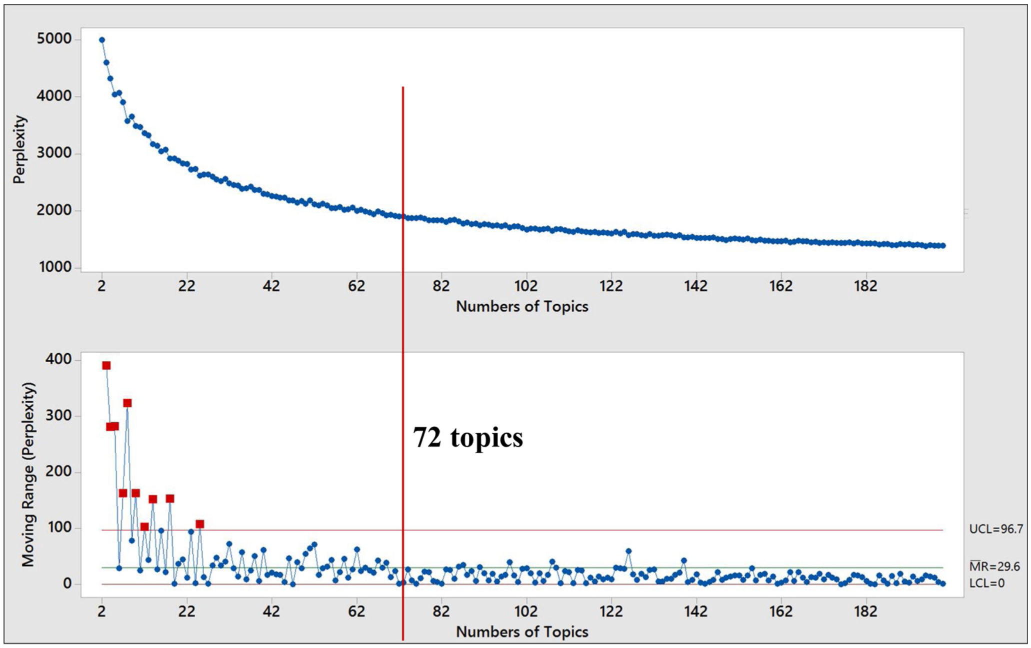
10 min (0 − 9 min) and the total retweet frequency. The steep decrease then plateaued (10 − 19 min), followed by a gradual increase in retweet frequency (20 − 40 min) before drastically decreasing (40 − 59 min). Based upon this observation, 10-minute intervals seem to reflect this nonlinear pattern well; as such, the interval could be a potential time unit to measure the likelihood of tweet retweets. Using a 10-minute interval, we created the following six intervals: 0_9 m (that is, an interval of 0 and 9 min), 10_19 m, 20_29 m, 30_39 m, 40_49 m, and 50_59 m. Because we considered only the first retweet, each tweet belonged to only one time period.

Using the above six intervals, our subsequent analysis aimed to identify the time interval that best represents tweet retweetability in terms of the total retweet frequency within the first 24 h. We therefore performed another negative binomial regression to estimate between-group differences. To effectively compare our multilevel categories, we ordered these six intervals by their relationship strength with the total retweet frequency and then devised completely orthogonal contrasts (Judd et al., 2011). We thus ordered the intervals from low to high incidence rate ratio (IRR) as follows: 50_59 m, 10_19 m, 40_49 m, 20_29 m, 30_39 m, and 0_9 m (see Table A3). This simplified our statistical analysis of between-group differences. That is, if we successfully demonstrate that the first retweet made within the first 10 min (0_9 m) has a stronger relationship with total retweet frequency than the first retweet made between 30 and 39 min (30_39 m), we can claim that the first retweet made within the first 10 min best describes tweet retweetability.

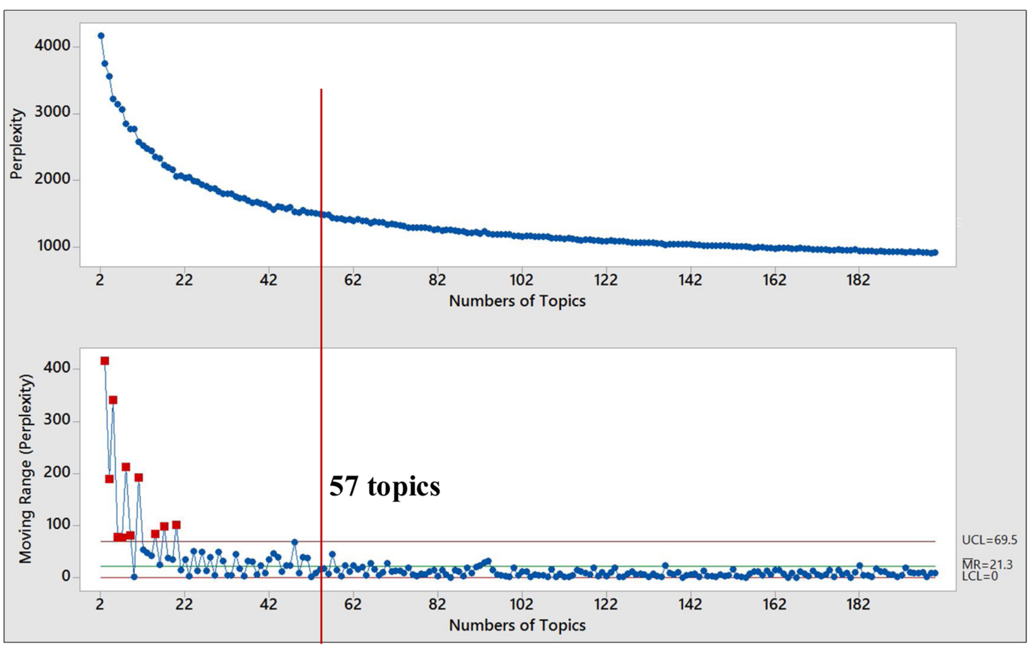
Our statistical results revealed that tweets that were retweeted within the first 10 min (0_9 m) after posting were retweeted significantly more than tweets that were first retweeted between the 30 and 39 min interval (30_39 m) (Queensland: $\beta_{10mVS40m} = -1.077$, df = 1, $p < 0.000$; Colorado: $\beta_{10mVS40m} = -0.717$, df = 1, $p < 0.000$) (see Table A4). As a result, we used this empirically identified time interval to establish the relationship between tweets and retweets for testing our hypotheses.

Appendix B

See Fig. B1.



< 2011 Queensland floods >



< 2013 Colorado floods >

Fig. B1. Perplexity Scores and Their Moving Ranges for the Two Twitter Datasets.

Appendix C

See Table C1.

Table C1
Keywords to Identify Twitterer Account Type.

Journalism	Emergency Service Representative
abc	emergency management officer
cbs	federal emergency
bbc	fema
cnn	emergency office
tbs	disaster management
fox	
usa today	
broadcast	
network tv	
boulder daily	
daily camera	
news websites	
newsroom	
public radio	
local radio	
local tv	
4kq 693am	
news producer	
tv reporter	
radio reporter	
news radio	
news network	
news updates	
news reporter	

Appendix D

See Tables D1 and D2.

Table D1
Correlation Matrix of the Research Model – Queensland.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	1															
2	0.141***	1														
3	−0.037***	−0.527***	1													
4	0.0196***	−0.118***	−0.033***	1												
5	0.0919***	−0.0097**	0.00600*	−0.173***	1											
6	0.0168***	0.130***	−0.028***	−0.316***	−0.068***	1										
7	−0.063***	0.105***	−0.032***	−0.097***	0.0339***	0.0599***	1									
8	−0.032***	−0.023***	0.00492	−0.011***	0.0749***	−0.044***	0.0348***	1								
9	0.0221***	−0.025***	0.0109***	0.0205***	0.108***	−0.026***	0.0820***	0.269***	1							
10	0.0825***	0.0233***	−0.0064*	0.0257***	−0.026***	0.0562***	−0.068***	0.0259***	0.0477***	1						
11	0.228***	0.0604***	−0.021***	−0.0078*	0.0665***	0.0557***	0.0556***	0.165***	0.320***	0.168***	1					
12	0.107***	0.0261***	−0.011***	−0.024***	0.0855***	−0.047***	0.148***	0.204***	0.314***	−0.020***	0.680***	1				
13	0.112***	0.0507***	−0.013***	−0.021***	0.0491***	0.0243***	0.0980***	0.129***	0.266***	0.0974***	0.742***	0.488***	1			
14	0.0790***	0.000956	−0.00134	−0.016***	0.0265***	−0.015***	0.0232***	0.105***	0.0375***	0.0244***	0.389***	0.323***	0.383***	1		
15	0.122***	0.0364***	−0.018***	−0.041***	0.230***	−0.00117	0.115***	0.0629***	0.199***	0.148***	0.317***	0.157***	0.379***	0.0674***	1	
16	0.0451***	0.0177***	0.000693	−0.045***	0.0914***	−0.029***	0.146***	0.101***	0.196***	−0.073***	0.329***	0.362***	0.442***	0.281***	0.174***	1

Table D2
Correlation Matrix of the Research Model – *Colorado*.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	1															
2	0.123***	1														
3	−0.061***	−0.696***	1													
4	0.0655***	−0.02***	−0.067***	1												
5	0.136***	−0.055***	0.0343***	−0.207***	1											
6	−0.056***	0.114***	−0.051***	−0.240***	−0.106***	1										
7	0.0555***	0.0532***	−0.024***	−0.0079*	0.0822***	−0.028***	1									
8	0.0749***	−0.00518	−0.00062	0.0369***	0.0475***	0.0340***	0.0623***	1								
9	0.139***	0.0189***	−0.025***	0.0640***	0.106***	0.0312***	0.146***	0.253***	1							
10	0.104***	0.0259***	−0.02***	0.0103***	0.00502	0.0157***	0.0471***	0.0328***	0.112***	1						
11	0.332***	0.0897***	−0.062***	0.0846***	0.0517***	0.0818***	0.140***	0.308***	0.416***	0.164***	1					
12	0.207***	0.0351***	−0.029***	0.0439***	0.0900***	0.0226***	0.185***	0.330***	0.430***	0.0672***	0.737***	1				
13	0.101***	0.124***	−0.079***	0.0948***	−0.096***	0.155***	0.0517***	0.212***	0.262***	0.111***	0.670***	0.498***	1			
14	0.181***	−0.016***	0.00506	0.0319***	0.0778***	−0.021***	0.119***	0.178***	0.222***	0.0590***	0.516***	0.444***	0.345***	1		
15	0.294***	0.0317***	−0.025***	0.0729***	0.211***	−0.024***	0.103***	0.0883***	0.234***	0.159***	0.368***	0.243***	0.279***	0.199***	1	
16	0.134***	−0.032***	0.0220***	−0.011***	0.144***	−0.141***	0.187***	0.181***	0.216***	−0.00374	0.361***	0.476***	0.347***	0.275***	0.0839***	1

Number	Variables
1	Retweet_YN_10 m
2	OneVSTwoMore
3	TwoVSMore
4	Words
5	Hashtags
6	URLs
7	Mention_YN
8	Profile_Image_YN
9	Profile_Length
10	Account_Types
11	Ln(Followers)
12	Ln(Followees)
13	Ln(Status)
14	Affilication_Length
15	Ln(Tweets)
16	Ln(Likes)

*p < 0.05.
**p < 0.01.
***p < 0.001.

References

Acar, A., & Muraki, Y. (2011). Twitter for crisis communication: Lessons learned from Japan's tsunami disaster. *International Journal of Web Based Communities, 7*, 392–402.

Aiken, L. S., West, S. G., & Reno, R. R. (1991). *Multiple regression: Testing and interpreting interactions.* Sage Publications.

Alalwan, A. A., Rana, N. P., Dwivedi, Y. K., & Algharabat, R. (2017). Social media in marketing: A review and analysis of the existing literature. *Telematics and Informatics, 34*, 1177–1190.

Babrow, A. S., Hines, S. C., & Kasch, C. R. (2000). *Managing uncertainty in illness explanation: An application of problematic integration theory. Explaining illness: Research, theory, and strategies*41–67.

Bean, H., Liu, B. F., Madden, S., Sutton, J., Wood, M. M., & Mileti, D. S. (2016). Disaster warnings in your pocket: How audiences interpret mobile alerts for an unfamiliar hazard. *Journal of Contingencies and Crisis Management, 24*, 136–147.

Bean, H., Sutton, J., Liu, B. F., Madden, S., Wood, M. M., & Mileti, D. S. (2015). The study of mobile public warning messages: A research review and agenda. *The Review of Communication, 15*, 60–80.

Belsley, D. A., Kuh, E., & Welsch, R. E. (2005). *Regression diagnostics: Identifying influential data and sources of Collinearity.* New York: John Wiley & Sons.

Bente, G., Rüggenberg, S., Krämer, N. C., & Eschenburg, F. (2008). Avatar-mediated networking: Increasing social presence and interpersonal trust in net-based collaborations. *Human Communication Research, 34*, 287–318.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research, 3*, 993–1022.

Bruns, A. (2003). Gatewatching, not gatekeeping: Collaborative online news. *Media International Australia Incorporating Culture and Policy, 107*, 31–44.

Bruns, A., Burgess, J. E., Crawford, K., & Shaw, F. (2012). *#qldfloods and@ QPSMedia: Crisis communication on Twitter in the 2011 south east Queensland floods.* ARC Centre of Excellence for Creative Industries and Innovation1–57. https://eprints.qut.edu.au/48241/.

Castillo, C., Mendoza, M., & Poblete, B. (2013). Predicting information credibility in time-sensitive social media. *Internet Research, 23*, 560–588.

Chaiken, S. (1980). Heuristic versus systematic information processing and the use of source versus message cues in persuasion. *Journal of Personality and Social Psychology, 39*, 752.

Chaiken, S., & Eagly, A. H. (1989). Heuristic and systematic information processing within and. In J. S. Uleman, & J. A. Barg (Eds.). *Unintended thought.* The Guilford Press.

Chaiken, S., & Maheswaran, D. (1994). Heuristic processing can bias systematic processing: Effects of source credibility, argument ambiguity, and task importance on attitude judgment. *Journal of Personality and Social Psychology, 66*, 460.

Christakou, E. R., & Klimis, G.-M. (2013). *Blogs and social media: The new word of mouth and its impact on the reputation of banks and on their profitability. Handbook of social media management.* Springer715–735.

Cialdini, R. B., Wosinska, W., Barrett, D. W., Butner, J., & Gornik-Durose, M. (1999). Compliance with a request in two cultures: The differential influence of social proof and commitment/consistency on collectivists and individualists. *Personality & Social Psychology Bulletin, 25*, 1242–1253.

Dashti, S., Palen, L., Heris, M. P., Anderson, K. M., & Anderson, S. (2014). Supporting disaster reconnaissance with social media data: A design-oriented case study of the 2013 Colorado floods. *11th International Systems of Crisis Response and Management* (pp. 18–21).

Debortoli, S., Müller, O., Junglas, I., & vom Brocke, J. (2016). Text mining for information systems researchers: An annotated topic modeling tutorial. *Communications of the Association for Information Systems, 39*, 7.

Dwivedi, Y. K., Kapoor, K. K., & Chen, H. (2015). Social media marketing and advertising. *The Marketing Review, 15*, 289–309.

Eastin, M. S. (2001). Credibility assessments of online health information: The effects of source expertise and knowledge of content. *Journal of Computer-Mediated Communication, 6*.

Ellaway, P. (1978). Cumulative sum technique and its application to the analysis of peristimulus time histograms. *Electroencephalography and Clinical Neurophysiology, 45*, 302–304.

Ferran, C., & Watts, S. (2008). Videoconferencing in the field: A heuristic processing model. *Management Science, 54*, 1565–1578.

Fisher, C. W., & Kingma, B. R. (2001). Criticality of data quality as exemplified in two disasters. *Information & Management, 39*, 109–116.

Flaherty, L. M., Pearce, K. J., & Rubin, R. B. (1998). Internet and face-to-face communication: Not functional alternatives. *Communication Quarterly, 46*, 250–268.

Flanagin, A. J., & Metzger, M. J. (2000). Perceptions of Internet information credibility. *Journalism & Mass Communication Quarterly, 77*, 515–540.

Fraustino, J. D., Liu, B., & Jin, Y. (2012). *Social media use during disasters: A review of the knowledge base and gaps. Human factors/behavioral sciences division.* Science and Technology Directorate1–39.

Gibson, J. J. (2014). *The ecological approach to visual perception: Classic edition.* Psychology Press, Taylor & Francis Group.

Hermida, A. (2010). Twittering the news: The emergence of ambient journalism. *Journalism Practice, 4*, 297–308.

Heverin, T., & Zach, L. (2012). Use of microblogging for collective sense-making during violent crises: A study of three campus shootings. *Journal of the American Society for Information Science and Technology, 63*, 34–47.

Hoffman, D. L., & Fodor, M. (2010). Can you measure the ROI of your social media marketing? *MIT Sloan Management Review, 52*, 41.

Hu, Y., & Shyam Sundar, S. (2010). Effects of online health sources on credibility and behavioral intentions. *Communication Research, 37*, 105–132.

Hughes, A. L., & Palen, L. (2009). Twitter adoption and use in mass convergence and emergency events. *International Journal of Emergency Management, 6*, 248–260.

Hutchby, I. (2001). Technologies, texts and affordances. *Sociology, 35*, 441–456.

Hutto, C. J., Yardi, S., & Gilbert, E. (2013). A longitudinal study of follow predictors on twitter. *Conference on Human Factors in Computing Systems* (pp. 821–830).

Ito, J., Song, J., Toda, H., Koike, Y., & Oyama, S. (2015). Assessment of tweet credibility with LDA features. *International Conference on World Wide Web* (pp. 953–958).

Judd, C. M., McClelland, G. H., & Ryan, C. S. (2011). *Data analysis: A model comparison approach.* Routledge.

Kapoor, K. K., Tamilmani, K., Rana, N. P., Patil, P., Dwivedi, Y. K., & Nerur, S. (2018). Advances in social media research: Past, present and future. *Information Systems Frontiers, 20*, 531–558.

Kehrwald, B. (2008). Understanding social presence in text-based online learning environments. *Distance Education, 29*, 89–106.

Kim, J. (2003). Interpersonal interaction in computer mediated communication (CMC): Exploratory qualitative research based on critical review of existing theories. *Annual Meeting of the International Communication Association* (pp. 1–26).

Kim, T. (2014). Observation on copying and pasting behavior during the Tohoku earthquake: Retweet pattern changes. *International Journal of Information Management, 34*, 546–555.

Klotz, C., Ross, A., Clark, E., & Martell, C. (2014). *Tweet!–and I can tell how many followers you have. Recent advances in information and communication technology*. Springer245–253.

Kuligowski, E. D., & Doermann, J. (2018). *A review of public response to short message alerts under imminent threat.* National Institute of Standards and Technology, U.S. Department of Commerce1–39.

Kwak, H., Lee, C., Park, H., & Moon, S. (2010). What is Twitter, a social network or a news media? *International Conference on World Wide Web* (pp. 591–600).

Lang, A. (2000). The limited capacity model of mediated message processing. *The Journal of Communication, 50*, 46–70.

Liu, Z., Liu, L., & Li, H. (2012). Determinants of information retweeting in microblogging. *Internet Research, 22*, 443–466.

Majchrzak, A., Markus, M. L., & Wareham, J. (2016). Designing for digital transformation: Lessons for information systems research from the study of ICT and societal challenges. *MIS Quarterly, 40*, 267–277.

Marwick, A., & Boyd, D. (2011). To see and be seen: Celebrity practice on Twitter. *Convergence, 17*, 139–158.

McQuail, D. (2010). *McQuail's mass communication theory.* Sage Publications.

Meaney, P. M., Fang, Q., Rubæk, T., Demidenko, E., & Paulsen, K. D. (2007). Log transformation benefits parameter estimation in microwave tomographic imaging. *Medical Physics, 34*, 2014–2023.

Metzger, M. J. (2007). Making sense of credibility on the Web: Models for evaluating online information and recommendations for future research. *Journal of the American Society for Information Science and Technology, 58*, 2078–2091.

Metzger, M. J., & Flanagin, A. J. (2013). Credibility and trust of information in online environments: The use of cognitive heuristics. *Journal of Pragmatics, 59*, 210–220.

Metzger, M. J., Flanagin, A. J., Eyal, K., Lemus, D. R., & McCann, R. M. (2003). Credibility for the 21st century: Integrating perspectives on source, message, and media credibility in the contemporary media environment. *Annals of the International Communication Association, 27*, 293–335.

Metzger, M. J., Flanagin, A. J., & Medders, R. B. (2010). Social and heuristic approaches to credibility evaluation online. *The Journal of Communication, 60*, 413–439.

Mileti, D. S., & Sorensen, J. H. (1990). *Communication of emergency public warnings: A social science perspective and state-of-the-art assessment.* TN (USA): Oak Ridge National Lab.

Mosteller, F., & Tukey, J. W. (1977). *Data analysis and regression: A second course in statistics.* Addison-Wesley Publications.

Niinimäki, T., Piri, A., Lassenius, C., & Paasivaara, M. (2012). Reflecting the choice and usage of communication tools in global software development projects with media synchronicity theory. *Journal of Software Evolution and Process, 24*, 677–692.

O'Donovan, J., Kang, B., Meyer, G., Hollerer, T., & Adalii, S. (2012). Credibility in context: An analysis of feature distributions in twitter. *IEEE International Confernece on Social Computing* (pp. 293–301).

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*, 407–426.

Owoputi, O., O'Connor, B., Dyer, C., Gimpel, K., Schneider, N., & Smith, N. A. (2013). Improved part-of-speech tagging for online conversational text with word clusters. *North American Chapter of the Association for Computational Linguistics* (pp. 380–390).

Park, C. S. (2013). Does Twitter motivate involvement in politics? tweeting, opinion leadership, and political engagement. *Computers in Human Behavior, 29*, 1641–1648.

Perry, R. W., Lindell, M. K., & Greene, M. R. (1982). Crisis communications: Ethnic differentials in interpreting and acting on disaster warnings. *Social Behavior and Personality an International Journal, 10*, 97–104.

Pozzi, G., Pigni, F., & Vitari, C. (2014). Affordance theory in the IS discipline: A review and synthesis of the literature. *Americas Conference on Information Systems*.

Purohit, H., Hampton, A., Shalin, V. L., Sheth, A. P., Flach, J., & Bhatt, S. (2013). What kind of #conversation is Twitter? Mining #psycholinguistic cues for emergency coordination. *Computers in Human Behavior, 29*, 2438–2447.

Rice, R. E., & Love, G. (1987). Electronic emotion socioemotional content in a computer-mediated communication network. *Communication Research, 14*, 85–108.

Schmierbach, M., & Oeldorf-Hirsch, A. (2012). A little bird told me, so I didn't believe it: Twitter, credibility, and issue perceptions. *Communication Quarterly, 60*, 317–337.

Skalski, P., & Tamborini, R. (2007). The role of social presence in interactive agent-based persuasion. *Media Psychology, 10*, 385–413.

Son, J., Lee, H. K., Jin, S., & Lee, J. (2019). Content features of tweets for effective communication during disasters: A media synchronicity theory perspective. *International Journal of Information Management, 45*, 56–68.
Son, J., Lee, J., Larsen, K. R., & Woo, J. (2019). Understanding the uncertainty of disaster tweets and its effect on retweeting: The perspectives of uncertainty reduction theory and information entropy. *Journal of the Association for Information Science and Technology,* 1–17.
Spiro, E. S., Dubois, C. L., & Butts, C. T. (2012). Waiting for a retweet: Modeling waiting times in information propagation. *NIPS Workshop of Social Networks* (pp. 1–8). Vol. 12.
Stein, M. (2004). The critical period of disasters: Insights from sense-making and psychoanalytic theory. *Human Relations, 57*, 1243–1261.
Suh, B., Hong, L., Pirolli, P., & Chi, E. H. (2010). Want to be retweeted? Large scale analytics on factors impacting retweet in twitter network. *IEEE International Conference on Social Computing* (pp. 177–184).
Sundar, S. S. (2008). *The MAIN model: A heuristic approach to understanding technology effects on credibility. Digital media, youth, and credibility* 73100.
Sutton, J., Palen, L., & Shklovski, I. (2008). Backchannels on the front lines: Emergent uses of social media in the 2007 southern California wildfires. *International Conference on Information Systems for Crisis Response and Management* (pp. 624–632).
Sutton, J., Gibson, B. C., Phillips, N. E., Spiro, E. S., League, C., Johnson, B., et al. (2015). A cross-hazard analysis of terse message retransmission on Twitter. *Proceedings of the National Academy of Sciences, 112*, 14793–14798.
Sutton, J., Gibson, B. C., Spiro, E. S., League, C., Fitzhugh, S. M., & Butts, C. T. (2015). What it takes to get passed on: Message content, style, and structure as predictors of retransmission in the Boston Marathon bombing response. *PloS One, 10*, 1–20.
Sutton, J., Spiro, E. S., Fitzhugh, S., Johnson, B., Gibson, B., & Butts, C. T. (2014). Terse message amplification in the Boston bombing response. *International Conference on Information Systems for Crisis Response and Management* (pp. 612–621).
Sutton, J., Spiro, E. S., Johnson, B., Fitzhugh, S., Gibson, B. C., & Butts, C. T. (2014). Warning tweets: Serial transmission of messages during the warning phase of a disaster event. *Information, Communication and Society, 17*, 765–787.
Tang, Z., & Chen, L. (2020). An empirical study of brand microblog users' unfollowing motivations: The perspective of push-pull-mooring model. *International Journal of Information Management, 52*, 1–11 102066.
Thomson, R., Ito, N., Suda, H., Lin, F., Liu, Y., Hayasaka, R., et al. (2012). Trusting tweets: The Fukushima disaster and information source credibility on twitter. *International ISCRAM Conference* (pp. 1–10).
Todorov, A., Chaiken, S., & Henderson, M. D. (2002). *The heuristic-systematic model of social information processing. The persuasion handbook: Developments in theory and practice*. Sage Publications195–211.
Vieweg, S., Hughes, A. L., Starbird, K., & Palen, L. (2010). Microblogging during two natural hazards events: What twitter may contribute to situational awareness. *Conference on Human Factors in Computing Systems* (pp. 1079–1088). ACM.
Walther, J. B. (1996). Computer-mediated communication: Impersonal, interpersonal, and hyperpersonal interaction. *Communication Research, 23*, 3–43.
Wang, X., McCallum, A., & Wei, X. (2007). Topical n-grams: Phrase and topic discovery, with an application to information retrieval. *IEEE International Conference on Data Mining* (pp. 697–702).
Warzel, C. (2014). *Why We favorite tweets. According to science, Vol. 2016*. Tech: BuzzFeedNews.
Westerman, D., Spence, P. R., & Van Der Heide, B. (2014). Social media as information source: Recency of updates and credibility of information. *Journal of Computer-Mediated Communication, 19*, 171–183.
White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica,* 817–838.
Wilensky, H. (2014). Twitter as a navigator for stranded commuters during the Great East Japan earthquake. *International Conference on Information Systems for Crisis Response and Management* (pp. 695–704).
Zeng, L., Starbird, K., & Spiro, E. S. (2016). *Rumors at the speed of light? Modeling the rate of rumor transmission during crisis. Hawaii international conference on system sciences*. HI, USA: IEEE1969–1978.
Zhang, W., & Watts, S. (2008). Capitalizing on content: Information adoption in two online communities. *Journal of the Association for Information Systems, 9*, 73.
Zhang, C., Fan, C., Yao, W., Hu, X., & Mostafavi, A. (2019). Social media for intelligent public information and warning in disasters: An interdisciplinary review. *International Journal of Information Management, 49*, 190–207.
Zubiaga, A., Spina, D., Martinez, R., & Fresno, V. (2015). Real-time classification of Twitter trends. *Journal of the Association for Information Science and Technology, 66*, 462–473.

Jaebong Son is an assistant professor of management information systems in the College of Business at California State University, Chico. He holds an M.S. degree in Management Information Systems from the University of Arizona, and a Ph.D. degree in Information Management from the University of Colorado Boulder. His research interests include the organizational and societal impact of information communication technology, social media, user-generated content, and knowledge extraction and representation using computational techniques, such as Natural Language Processing and Social Network Analysis. His research has appeared in the *Journal of the Association for Information Science and Technology*, the *International Journal of Information Management*, the *Journal of Nanoparticle Research*, and the major conferences in information systems, such as the *International Conference on Information Systems*, the *Americas Conference on Information Systems*, and the *Hawaii International Conference on System Sciences*.

Jintae Lee is an associate professor of information analytics in the Leeds School of Business, Univ. of Colorado at Boulder. His research interest is in knowledge management and text mining. His past research has focused on process knowledge as captured in the form of process model and ontology. This effort led to successful results such as the Process Interchange Format, which has been incorporated into the National Institute of Standards and Technology Process Specification Language. He has published in *MIS Quarterly*, *Management Science*, *CACM*, among others. He has received grants from NSF, NIST, and NIH.

Onook Oh is an Assistant Professor of Information Systems at the University of Colorado at Denver. He has studied rumor theory to investigate the information management issue during community crises such as natural disasters, terrorist attacks and gun-shooting incidents. Since 2017, as a principle investigator of NSF funded research project, he has been exploring the issue of organizational transformation in response to the introduction of wearable devices (*e.g.*, body worn camera and AI devices) into policing organizations. He is currently developing a next generation theory for information and organization research that can take into account the environmental and climate change issues. His research has been published in *MIS Quarterly*, *Information Systems Research* and many other journals.

Hyung Koo Lee is an assistant professor in the Department of Information Technologies at HEC Montréal. He holds an M.S. degree in Management Information Systems from the University of Arizona, and a Ph.D. degree in Computer Information Systems from Georgia State University. His research focuses on IT project management issues including IT project escalation, error reporting within IT projects, and IT project personnel management. His research has appeared in *the Journal of Management Information Systems, Information Systems Journal, and the International Journal of Information Management, as well as in the International Conference on Information Systems, the Academy of Management Proceedings,* and other conferences.

Jiyoung Woo is an assistant professor in the department of Big Data Engineering at Soonchunhyang University. She received her B.S., M.S., and Ph.D. degrees in industrial engineering from KAIST. She was a research professor at the Graduate School of Information Security, Korea University. From 2008 to 2010, she was a visiting scholar at the Artificial Intelligence (AI) Lab of the Eller College of Business, the University of Arizona. Her research interests include business intelligence and security informatics. She has published in *Technological forecasting and Social Change, IEEE Transactions on Information Forensics and Security*, *ACM SIGCOMM Computer Communication Review*, among others.