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RESEARCH ARTICLE

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# Understanding the Uncertainty of Disaster Tweets and Its Effect on Retweeting: The Perspectives of Uncertainty Reduction Theory and Information Entropy

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[Corrections added on 15 April 2020, after first online publication: The section "4.3 Statistical analysis" has been updated.]

**Abstract**

The rapid and wide dissemination of up-to-date, localized information is a central issue during disasters. Being attributed to the original 140-character length, Twitter provides its users with quick-posting and easy-forwarding features that facilitate the timely dissemination of warnings and alerts. However, a concern arises with respect to the terseness of tweets that restricts the amount of information conveyed in a tweet and thus increases a tweet's uncertainty. We tackle such concerns by proposing entropy as a measure for a tweet's uncertainty. Based on the perspectives of Uncertainty Reduction Theory (URT), we theorize that the more uncertain information of a disaster tweet, the higher the entropy, which will lead to a lower retweet count. By leveraging the statistical and predictive analyses, we provide evidence supporting that entropy validly and reliably assesses the uncertainty of a tweet. This study contributes to improving our understanding of information propagation on Twitter during disasters. Academically, we offer a new variable of entropy to measure a tweet's uncertainty, an important factor influencing disaster tweets' retweeting. Entropy plays a critical role to better comprehend URLs and emoticons as a means to convey information. Practically, this research suggests a set of guidelines for effectively crafting disaster messages on Twitter.

## 1 | INTRODUCTION

Disasters are inherently associated with lack of information due to the nature of dynamic, nonroutine events (Sellnow & Seeger, 2013). The affected public is motivated to seek disaster-related information to be aware of their surroundings (Boyle et al., 2004). While mainstream media play key roles in providing disaster information, it often lacks specific and timely information for people in the affected areas (Oh, Agrawal, & Rao, 2013). Social media, on the other hand, is known to convey localized and timely first-hand observations to inhabitants (Lachlan, Spence, Lin, & Del Greco, 2014). In particular, Twitter has received great attention from emergency practitioners, online volunteers, and academic scholars because of its communication characteristics: (i) improvised follower–followee[1] networks (Sutton et al., 2015) and (ii) short-length messages (or tweets) (Ma, Sun, & Cong, 2013). These characteristics allow Twitter users (or twitterers) to quickly post their tweets; instantly receive others' tweets; and easily repost (or retweet) received tweets (Suh, Lichan, Pirolli, & Chi, 2010).

Quick posting and easy reposting make Twitter one of the most effective mediums for disaster communication (Bean et al., 2016). For example, the original 140-alphanumeric character limit was beneficial for quickly updating situational

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information as events emerge (Fraustino, Liu, & Jin, 2012). In the 2008 Mumbai terror attacks, laypersons, not journalists or government agencies, broke the news on Twitter within minutes of the attacks' beginning, generating around 16 tweets per second of eyewitness accounts (Busari, 2008). A one-word tweet showcases the power of Twitter: in April 2008, a US journalism graduate student was detained in Egypt while photographing an antigovernment rally. On the way to the police station, he tweeted using his cellular phone: "Arrested." Shortly after, his school sent a lawyer to Egypt, and he was released from jail (Murthy, 2011). Although Twitter has become an important communication venue, its limited message length causes concerns. Bruns and Stieglitz (2012) reported that during the 2011 Queensland floods, tweets conveyed less specific information about the disastrous events. An excerpt from the Bean et al. (2016) interview study on tweet-length disaster messages supports such concerns: "To me, it just doesn't seem complete. It seems like just enough to terrify you, but not to really help you do anything" (p. 6). The literature on disaster communication defines two requirements for disaster messages: (i) clear and accurate communication (Bergeron & Friedman, 2015) and (ii) sufficient information (Mileti & Sorensen, 1990). Viewed in this light, a tweet's limited length is a double-edged sword—a facilitator to quickly post and repost tweets, but a restrictor to convey the amount of information per tweet. Interestingly, however, most Twitter studies on disaster communication have neglected how the length of tweets affects twitterers' information-seeking and sharing behaviors during disasters.

This study fills in this gap by utilizing the Berger and Calabrese (1974) Uncertainty Reduction Theory (URT) and Shannon and Weaver's (1964) information entropy, as the limited amount of information is associated with uncertainty (e.g., Bean et al., 2016; Sutton et al., 2014). In detail, using the theoretical framework of URT we investigate uncertainty and its relationship with information-seeking and sharing behaviors. We then evaluate individual tweets by entropy, a state measure of the continuum between certainty and uncertainty—the less information, the higher the uncertainty (Shannon & Weaver, 1964; van Stralen, 2015). Since entropy determines the degree of a tweet's uncertainty by the probability distribution of its conveying topics, we extract a tweet's topics and each topic's proportion using a Latent Dirichlet Allocation topic model that describes a topic as a set of words and word distribution (Blei, Ng, & Jordan, 2003). Thus, we pose the following research questions:

**RQ 1.** *How do we evaluate entropy as a measure for the uncertainty of disaster tweets?*

**RQ 2.** *How does the information uncertainty of disaster tweets measured by entropy contribute to enhancing our understanding of retweeting as a means to disseminate disaster information?*

This study makes two contributions. First, based on the foothold of URT, this research reveals a hidden truth of tweets' length as a factor to cause uncertainty and proposes entropy to measure a tweet's uncertainty. Second, for emergency officials and online citizens who purposely create and relay disaster information, we offer strategies to avoid or minimize uncertainty when crafting tweets to timely and widely propagate that information. This study is organized as follows. We review the literature on Twitter for disaster communication followed by URT. We then develop a set of hypotheses to verify entropy as a measure of a tweet's uncertainty. After that, we share our approach to model topics in tweets and the results of statistical and predictive analyses. We conclude by discussing the findings, limitations, and implications for future research.

## 2 | LITERATURE REVIEW AND THEORETICAL BASES

### 2.1 | Disaster communication on Twitter

The first tweet by cocreator Jack Dorsey in 2006 (Siese, 2016), "just setting up my twttr," signaled a new era of communication brevity. Since then, Twitter has been used by emergency responders, online citizens, and the affected public to exchange alerts and warnings (Heverin & Zach, 2012). Terse and compact, tweets are broadcast over virtually all communication platforms including the web, smart devices, and cell phones—enabling time-sensitive, first-hand information to be quickly posted and widely shared (Sutton et al., 2015). These practical advantages of Twitter have attracted interest from national agencies, such as the U.S. Federal Emergency Management Agency (FEMA), and from academia. FEMA allows emergency officials to utilize 90-character limited Wireless Emergency Alerts (WEAs) to warn the public about critical situations, including imminent threats and weather emergencies (Bean et al., 2016). Higher education institutions in the United States are legally required to instantaneously notify the campus community about dangerous situations through alerting systems such as cellular messaging services (Sattler, Larpenteur, & Shipley, 2011).

Researchers have endeavored to better understand Twitter's communication conventions—hashtags, URLs, and words to carry information (Son, Lee, Jin, & Lee, 2019); emoticons to express emotional states (e.g., Lo, 2008); and mention (e.g., @) to directly converse with other twitterers (Suh et al., 2010). Hashtags represent an annotation convention communicating the topical information of tweets or the common interests of a community, such as #boulderflood and #coloradostrong (Zubiaga, Spina, Martinez, & Fresno, 2015). Oh, Eom, and Rao (2015) found by investigating tweets about the 2011 Egypt revolution that online volunteers used hashtags to share information centering around a particular topic. The Burnap et al. (2014) study on a terrorist attack revealed that the presence of a hashtag increased the retweet count. As a means to overcome a tweet's length restriction, URLs allow twitterers to embed external online links in their tweets for additional media, such as news articles, blogs, pictures, and videos. Hughes and Palen (2009) identified that roughly 50% of the tweets about a hurricane event contained URLs, 10% higher than other tweets about general events. However, the effects of URLs on disaster tweets' retweeting are inconsistent. Sutton et al. (2015) observed that the inclusion of a URL negatively affected disaster tweets' retweets, while the Pervin, Takeda, and Toriumi (2014) study pointed out both the positive and negative effects of URLs on retweeting in the different phases of disasters. Words are the most basic element to express the meaning of a tweet, and therefore researchers leverage words in a tweet to understand its meanings or topics (Zubiaga et al., 2015). For example, by manually categorizing tweets into 11 topics, Sutton et al. (2015) and Sutton et al. (2014) found that disaster tweets containing "hazard impact" were more retweeted than those expressing "thanks." Unlike the above communication conventions, emoticons are pictorial representations that replicate facial expressions, such as happy, sad, or pleased (Rezabek & Cochenour, 1998). Emoticons can help twitterers interpret the subtle nuances in meaning and tone that textual elements alone do not express (e.g., Lo, 2008; Park, Barash, Fink, & Cha, 2013). According to Stieglitz and Dang-Xuan (2013), a Twitter study on political communication, emotionally charged tweets were retweeted more frequently than neutral ones. Along with these symbols, mention (or the user designation) is the last convention of communication. A tweet acknowledging a twitterer with the @ symbol forms a conversation by directing that twitterer or replying to his/her earlier tweet (Zubiaga et al., 2015). The following two actual tweets present how these conventions are used together.

> Watch closely.;-) @JohnGGalt: Chinook helicopter rescuing flood victims from Poudre Canyon, Colorado. #COFlood http://t.co/uZr3e4IK8P
> It's like a tsunami. Poor, poor Queensland: (http://youtu.be/kYUpkPTcqPY (via @Chas Licc) #qldfloods

Although text-based, terse messages have been gaining momentum for disaster communication, most disaster studies have focused on the Common Alerting Protocol, which allows up to 1,380 characters per message (Sutton et al., 2015). As a result, little evidence has been accumulated to elucidate how the limited content of a terse disaster message influences recipients' information-seeking and sharing behaviors. Among others, uncertainty is of great concern due to the terseness of communication—"[T]erse communication can generate uncertainty, thereby promoting WEA and tweet recipients to mill for additional and confirming information" (Bean et al., 2016, p. 10). In the next section, we introduce the theoretical foundation of URT as a basis to understand uncertainty during disasters.

## 2.2 | Uncertainty reduction theory

The concept of uncertainty adheres to that of information, as information removes doubt, restricts suspicion, and decreases variance (Nauta, 1972). Hence, information is maximized when uncertainty is reduced, while more uncertainty suggests less information (Artandi, 1973). In this regard, uncertainty is perceived as a motivating factor to seek information (Driskill & Goldstein, 1986). URT states that uncertainty exists in a situation where a number of alternatives are allowed, whereas uncertainty is reduced as the number of alternatives decreases (Berger & Calabrese, 1974). Berger and Calabrese originally developed URT to explain the interpersonal communication process of two strangers upon meeting. This theory posits that people are uncomfortable with uncertainty, and thus they are motivated to reduce uncertainty about their own and others' behaviors through communication or interaction. URT's underlying principles indicate that information gained at each interaction reduces uncertainty, resulting in positive outcomes of attraction, liking, and/or reduced stress. In extending URT, Neuliep and Grohskopf (2000) added the additional axiom of communication satisfaction as an effective response to the achievement of communication goals, an imperative proposition to relate uncertainty to a specific communication outcome variable.

The principles of URT apply to disaster communication, as the public needs to be aware of constantly changing disastrous events (Sellnow & Seeger, 2013; Sturges, 1994). Procopio and Procopio (2007) researched the use of Internet communication and reported that Internet users behaved more actively to reduce uncertainty as they experienced higher degrees of perceived damage. In a similar vein, the Lachlan, Westerman, and Spence (2010) investigation on telepresence (i.e., spatial presence) found that an increase in telepresence use while broadcasting disaster news stories motivated audiences to seek disaster-related information. More recently, Rainear, Entropy = ↑ # ☺ ↓ https, RT

Lachlan, and Fishlock (2019) studied a new technology tool—a robot with a 10-inch screen—as a platform to disseminate warning messages to people living in hard-to-reach regions. Their observation indicated that the robot's unfamiliarity distracted participants from correctly interpreting the content of warning messages (i.e., time, location, severity), inducing an unnecessary amount of message uncertainty. URT has been widely used to evaluate communication media and to understand people's information-seeking behavior during times of disaster.

To use URT as a theoretical lens to examine Twitter, we need to align Twitter's communication practices with URT's central tenets. First, communication (or interaction) on Twitter is generally accomplished by posting and reposting tweets; hence, tweets are a source of information. Second, individual tweets are evaluated by the notion of URT's uncertainty—the more likely a tweet is to be interpreted in different ways, its uncertainty increases. Last, communication satisfaction is manifested in retweeting, the reposting of an original tweet. Retransmission of a tweet is a clear marker that the tweet holds certain value (Sutton et al., 2015). As a tweet holds useful, imperative, or valuable information to others, its retweet count increases (Starbird & Palen, 2010). In the following section we discuss the meaning and implication of entropy for disaster tweets.

## 2.3 | Information entropy and its implication for tweets

Information is encoded in a message comprising an agreed set of signals (e.g., phonemes, words, letters); accordingly, a message's information must be extracted by decoding (or interpreting) its signaling components (Mai, 2016). Shannon and Weaver (1964) provided the intriguing definition of information during communication, "a measure of one's freedom of choice when one selects a message" (p. 9)—the greater the information in a message, the lower uncertainty (or randomness) in interpreting the message's meaning (Brissaud, 2005; Burgin, 2003). Shannon and Weaver (1964) viewed that when noise is present, some information in a message can be lost or distorted, increasing a message's uncertainty. To quantify such noise, he devised *entropy*, consisting of two components that shape the meaning of a message: $p_i$ is the proportion of the $i$th topic out of $n$ topics of message $m$.

$$Entropy_m = -\sum_{i=1}^{n} p_i \ \mathrm{In}\ p_i$$

According to the entropy equation, a message conveying only one topic does not allow its recipients any freedom to interpret its meaning. Hence, its entropy is 0 (i.e., no noise). When a message has two topics with different proportions of 90% (or 0.9) and 10% (or 0.1), respectively, the message's recipients will interpret its meaning by choosing a topic with 90% proportion as primary, while possibly considering 10% proportion topic as noise. So, this message's entropy is 0.325. When two topics with the same proportion appear in a message, the message's recipients will have much higher freedom to interpret its meaning by choosing either topic, thereby resulting in its entropy of 0.693. In this sense, the higher entropy, the more uncertain the information. Moreover, with length-constrained tweets, entropy becomes more meaningful as a measure for uncertainty: a twitterer who expresses more topics in a single tweet will inevitably use fewer characters to convey each topic's meaning, possibly restricting the amount of information per topic. For example, once $n$ characters are used to describe one topic, other topics must be explained by 140–$n$ characters. Insufficiently explained topics are harder to interpret (Rangrej, Kulkarni, & Tendulkar, 2011).

Not all Twitter communications conventions convey information equally. Words and hashtags convey directly interpretable information, while the information in URLs is unavailable before visiting linked resources (e.g., http://t.co/f5TN63OOLK) (Son et al., 2019); emoticons indicate emotional states rather than situational information. Words and hashtags are conventions that can be directly decoded (or interpreted), while URLs and emoticons are supplementary information after interpretation occurs. Based on URT and the above-mentioned characteristics of Twitter's conventions, we investigate whether entropy validly measures a disaster tweet's uncertainty.

# 3 | HYPOTHESIS DEVELOPMENT

The public at risk becomes "information hungry" as disaster events impend (Mileti & Sorensen, 1990, pp. 3–8). They immediately begin seeking disaster-relevant information from television, terrestrial radio, newspapers, social media, and so on. Twitter is capable of disseminating up-to-the-minute information in a near-real-time fashion (Lachlan et al., 2014), although the terseness of tweets limits the amount of information conveyed (Sutton et al., 2014). One negative consequence is the uncertainty of a tweet, which hinders recipients from properly comprehending its intended meaning (Bean et al., 2016). Human beings desire adequate information for proper understanding, while resisting lack of understanding (Allport & Postman, 1947; Todorov, Chaiken, & Henderson, 2002). Therefore, the collection of confirming information to improve their "incomplete" understanding (Weick, 1985, p. 51) is an essential cognitive process.

When encountering uncertain information, twitterers further engage in a series of processes to search for information, and work with others to exchange confirming and verifying information (Oh et al., 2015; Sutton et al., 2014). Twitterers who do not improve their understanding may deter or abandon retweeting. Regarding entropy as a measure for a tweet's uncertainty, we state that when a tweet's entropy is higher, its disaster information is considered less sufficient, clear, and accurate, lowering its retweet frequency. Consequently, we hypothesize the following relationship between entropy and the retweet count.

**Hypothesis 1 (H1).** *As a disaster tweet's entropy increases, its retweet count decreases.*

Embedding URLs into disaster tweets is a key practice to disseminate rich, in-depth information, because online resources can supplement tweets with more pertinent information (Hughes & Palen, 2009). An experiment conducted by Dong et al. (2010) demonstrated that twitterers shared and read more news articles linked by URLs. Additionally, a large-scale data analysis by Suh et al. (2010) revealed the positive relationship between URLs and the retweet count. By analyzing tweets on German political events, Stieglitz and Dang-Xuan (2013) discovered that URLs increased the quantity of retweet counts. A study on rumors during disasters also described URLs' positive relationships with retweeting (Tanaka, Sakamoto, & Honda, 2014). Certainly, URLs enable twitterers to share supplementary information over and above tweets' words and hashtags, making their disaster tweets more informative. Thus, we formulate the following hypothesis:

**Hypothesis 2a (H2a).** *URLs embedded in a disaster tweet increase its retweet count*.

A study by the National Institute of Standards and Technology (NIST) reported that uncertain statements and terminology conveyed in tweet-length disaster messages provoke the recipients to seek extra information to promote their understanding (Kuligowski & Doermann, 2018). Under such a situation, URLs can be an effective means to alleviate or address disaster tweets' information uncertainty for the following two reasons. First, it is a common practice that twitterers embed URLs in their tweets to share detailed information for disaster communication (Hughes & Palen, 2009). It is therefore likely that twitterers perceive the benefits of URL embedding, likely as a result of past experience in posting and reading tweets with and without URLs. Second, unlike tweets' textual content, rich information can be furnished by URLs and range from pictures and maps, to multimedia content such as video and audio clips (Kostkova, Szomszor, & St Louis, 2014; Ma et al., 2013). In consequence, with the addition of URLs, disaster tweets' information uncertainty can be compensated, eventually leading to retweeting—because an increase in information decreases uncertainty (Daft & Lengel, 1986). From this perspective, we postulate the conditional relationship between URLs and uncertainty as follows:

**Hypothesis 2b (H2b).** *URLs weaken the negative relationship between a disaster tweet's entropy and its retweet count.*

Persuasion influences people's attitude and motivation, and the process of persuasion becomes more effective when emotional cues are provided (Fogg, 2002). One such example is Stieglitz et al.'s study on Twitter in political communication (2013). They found a tendency that emotionally charged tweets are retweeted more freqently and quickly than neutral ones. Computer-Mediated Communication (CMC) users express feelings and sentiments such as happy, sad, or pleased by emoticons (Rezabek & Cochenour, 1998). As nonverbal, typographical symbols, emoticons can supplement, reiterate, or clarify the meaning of texts (Westman & Freund, 2010). Rezabek and Cochenour emphasized the use of nonverbal cues for effective communication by stating, "Effective communication is not simply a matter of analyzing individual word denotations and connotations, it is a blend of many factors. Words, grammar and structure, context and experience, nonverbal signals, and other cues all contribute meaning in a message" (1998, p. 202).

Although emoticons are generally considered a means of facilitating effective communication, we challenge the traditional view by arguing that emoticons are not effective for disaster communication. That is, during disasters the affected public needs up-to-the-minute, situational updates of their surroundings (Bean et al., 2016). However, information by emoticons is limited to emotional states such as anxiety, frustration, and/or surprise (Picard & Picard, 1997), rarely helping them improve their situational awareness. Viewed in this light, the role of emoticons is significantly different from that of URLs: URLs provide detailed, additional information on top of words and hashtags, while emoticons deliver little situational information. What emoticons convey during disasters may not improve twitterers' situaitonal understanding, reducing their intention to retweet. The following hypothesis states the relationship between emoticons and the retweet count:

**Hypothesis 3a (H3a)** *Emoticons in a disaster tweet decrease its retweet count.*

By applying the same logic established in H2b, we examine how emoticons interact with entropy. Unlike URLs, emoticons are nonverbal cues carrying emotional messages (Lo, 2008) that barely improve twitterers' understanding of uncertain information. In fact, we expect that emoticons' valueless information does not reduce uncertainty nor add confusion to existing uncertainty. Consequently, entropy should not be affected by emotions either positively or negatively—(i) emoticons do *not* significantly strengthen the relationship between entropy and the retweet count *and* (ii) emoticons do *not* significantly weaken the above-mentioned relationship. If entropy turns out to correlate with emoticons, its validity as a measure for uncertainty will not be guranteed. It is noteworthy that these two conditions cannot be statistically proved (i.e., proving the null hypotheses; Johnson, 1999). Therefore, we restate these conditions by the following testable hypotheses.[2]

**Hypothesis 3b-1 (H3b-1).** *Emoticons strengthen the negative relationship between a disaster tweet's entropy and its retweet count.*

**Hypothesis 3b-2 (H3b-2).** *Emoticons weaken the negative relationship between a disaster tweet's entropy and its retweet count.*

## 4 | DATA AND ANALYSIS METHODS

### 4.1 | Two Twitter data sets

#### 4.1.1 | 2011 Queensland floods

A series of floods hit much of the central and southern parts of Australia, including Queensland. Twitter played an important communication role as twitterers voluntarily created, disseminated, and relayed disaster information (Bruns & Stieglitz, 2012). In all, 79,213 tweets and 63,590 retweets posted between January 8 and 14 were collected by Gnip, a Twitter subsidiary.[3]

#### 4.1.2 | 2013 Colorado floods

Up to 15 inches of rain poured into Colorado, affecting more than 11,000 residents. Immediately following the warnings by government agencies, people in affected areas started producing, sharing, and disseminating flood-related information on Twitter. We obtained 77,898 tweets and 95,549 retweets posted between September 12 and 18 from Project EPIC.[4] We used both tweet data sets for the hypothesis testing.

### 4.2 | Topic modeling

To discover topics in tweets, we utilized the Latent Dirichlet Allocation (LDA)-based topic modeling technique that is implemented in the MAchine Learning for LanguagE Toolkit (*MALLET*), a Java-based machine learning library (McCallum, 2002). The LDA represents a document as a mixture of topics by defining a topic as a group of words and word distribution (Blei et al., 2003). As a result, the outcomes of LDA are the number of topics per document and each topic's proportion; both are used to estimate a document's uncertainty (entropy). The whole framework of topic modeling is shown in Figure 1.

Before applying the LDA technique to discover topics in tweets, we compensated for the short length of tweets by adding multiple-word noun phrases (e.g., "flood victims," "flash flood warning"). The following three procedures were performed: (i) tagging—we tagged each word's part-of-speech (POS) by using *TweetNLP*, a dedicated programming library to analyze tweets (Owoputi et al., 2013); (ii) chunking—based on each word's POS tag, we extracted multiple-word noun phrases by grouping consecutive nouns and nouns with adjectives. We defined such patterns by using regular expressions; (iii) then we combined each tweet's original words with extracted noun phrases. For example, when a disaster tweet contains "flash flood warning," we added "flash flood warning" to its unigram words of "flash," "flood," and "warning." It was reported that topic models with multiple-word phrases produce more reliable and interpretable results than those with only unigram words (Wang, McCallum, & Wei, 2007). We excluded stopwords for topic modeling based on *MALLET*'s stop-word list, because these words convey little topical content (e.g., "a," "the," "etc") (Debortoli, Müller, Junglas, & vom Brocke, 2016). In addition, we also filtered typos (e.g., "informacion," "peopl") and uninterpretable words (e.g., "agr'd," "+sja") by relying on *TweetNLP's* POS tag of "G"—foreign or "garbage" words.

Topic modeling is a clustering method, in the sense that documents are grouped together by the similarity of topics in each document (Blei et al., 2003). Consequently, finding the optimal number of topics is an important task for the LDA topic modeling. To achieve this goal, we generated 199 topic models by increasing the number of topics from 2 to 200, calculated each topic model's

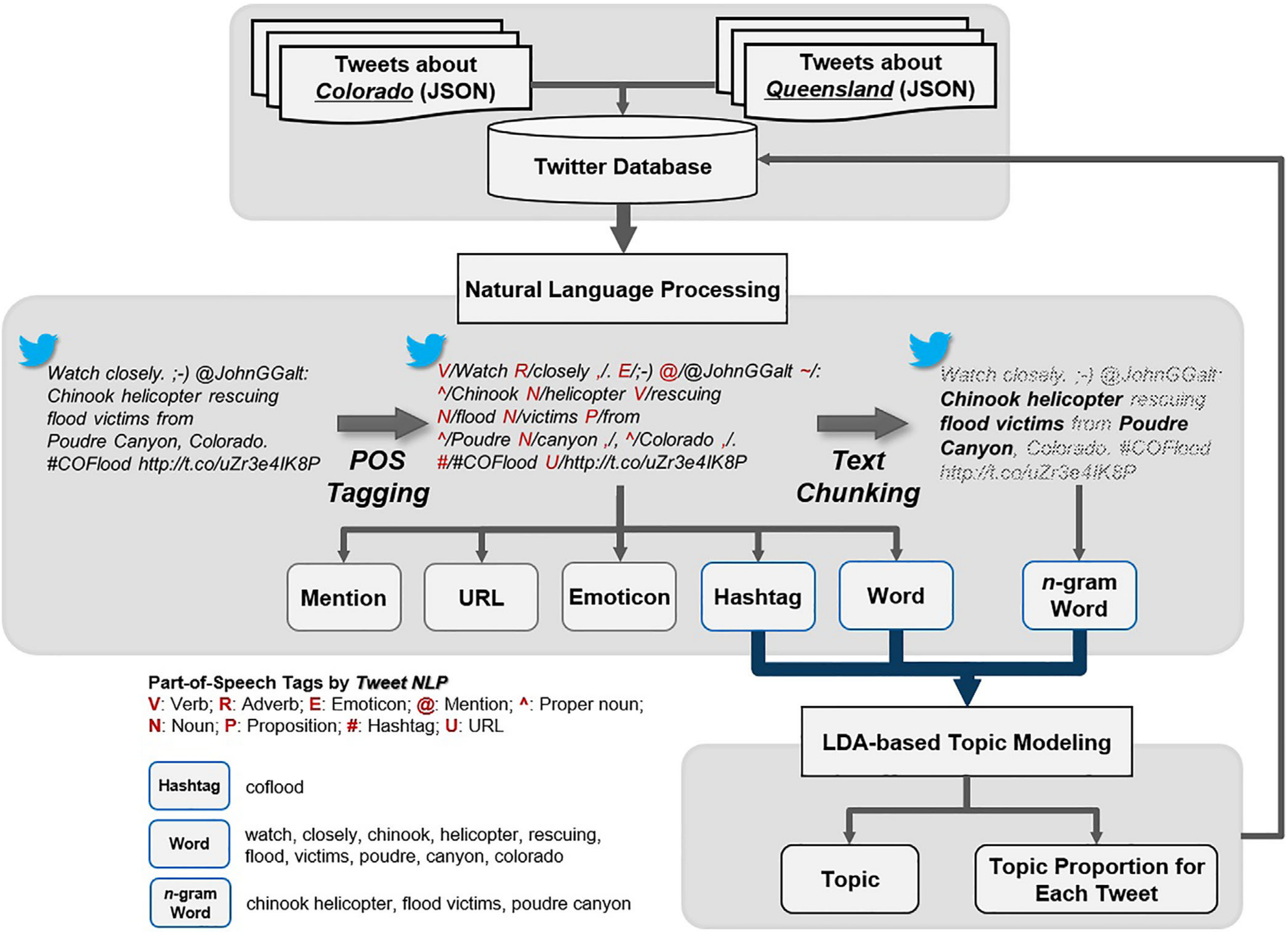


**FIGURE 1** The framework for processing tweets [Color figure can be viewed at wileyonlinelibrary.com]

goodness of fit, and evaluated the generalizability of each topic model in terms of its perplexity score that was calculated based on the equation below, where $M$ refers to the number of documents in the testing data set, $w_d$ refers to the words in document $d$, and $N_d$ refers to the number of words in document $d$ (Blei et al., 2003).

$$\mathrm{Perplexity}(\mathrm{D_{test}}) = \exp\left\{\frac{\sum_{d=1}^{M}\log p(w_d)}{\sum_{d=1}^{M} N_d}\right\}$$

Each topic model's generalizability is inversely related to its perplexity score—a lower perplexity indicates a higher generalizability. By applying the cumulative sum procedure on the perplexity score of topic models per Twitter data set (Ellaway, 1978), we found the optimal topic model for each Twitter data set at which the changes in the perplexity scores are negligible, signifying that additional topics do not substantially improve futher topic models' generalizability (see Figure 2). As a result, we obtained the optimal topic model with 72 topics for the Queensland floods and with 57 topics for the Colorado floods (see Appendix A).

To take concrete examples of how each tweet's entropy is calculated based on the number of topics and each topic's proportion, we consider the actual tweets about the Colorado floods shown in Table 1 and their topics in Table 2.

The results of LDA indicate that Tweet A has the topic of #51 with the topic proportion of 99.3% (e.g., higher ground, immediately, water, coming, move, creek), resulting in its entropy of 0.007. Unlike Tweet A, Tweets B, C, and D describe more than one topic. The major topic of Tweet B is #51 with the proportion of 77.9% (e.g., wall, water, coming, emerson gulch, higher ground), and its second topic is #20 with the proportion of 21.3% (e.g., pray, people, safe). Obviously, Tweet B's entropy of 0.524 is higher than that of Tweet A. Although Tweet C has two topics of #20 (e.g., loved, pray, rain) and #51 (e.g., move, higher ground), its entropy of 0.685 is higher than that of Tweet B due to the topic proportion of 56.8% for #20 and 42.5% for #51. Last, Tweet D's entropy is highest, at 1.012, as it conveys three topics—#51 (45.8%; e.g., higher ground), #20 (38.2%; e.g., stay, safe, people), and #45 (15.3%; e.g., boulder creek).

## 4.3 | Statistical analysis

This study's unit of analysis is a tweet, and the dependent variable is each tweet's retweet count. We aggregated a tweet's retweets made within 24 hours after posting, which accounted for over 93% of the total number of retweets in both Twitter data sets. Due to a count-dependent variable's discrete distribution, regression models using ordinary least squares produce inconsistent, biased results (Cameron & Trivedi, 2013). Statistical procedures, such as Poisson or negative binomial models, should be employed (O'Hara & Kotze, 2010). A negative binomial model is preferred to a Poisson model when a count-dependent variable shows the presence of greater variability or overdispersion, possibly causing similar consequences to the violation of the homoscedasticity assumption in linear regression analysis (Hilbe, 2011). We confirmed that our Twitter data sets have a substantially larger variance than its mean, and the likelihood-ratio test of alpha suggests the use of the negative binomial model over the Poisson model.

Prior research has revealed factors affecting tweets' retweeting. Sutton et al. (2014) observed that hashtags, followers, and followees were positively associated with the retweet count. Suh et al. (2010) showed that both twitterers' status (or past tweets) and whether tweets included a mention (or "@") were negatively related to the retweet count. We included these characteristics in our empirical models as control variables by applying a

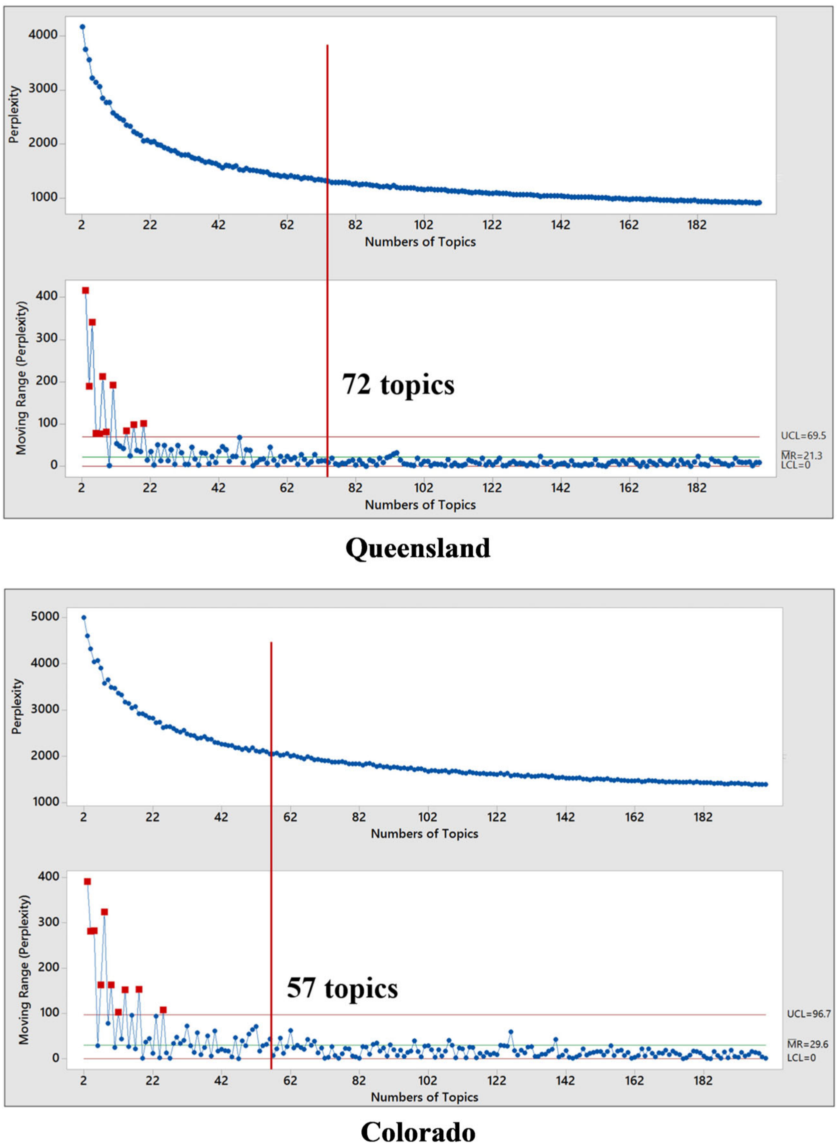


**FIGURE 2** Perplexity values and moving ranges [Color figure can be viewed at wileyonlinelibrary.com]

**TABLE 1** Example tweets[a]

| | Content | Retweet count | Topic number: proportion | Entropy |
|---|---|---|---|---|
| Tweet A | SEEK HIGHER GROUND IMMEDIATELY: Wall of water coming down Boulder Canyon. Move away from Boulder Creek! #BoulderFlood | 272 | #51: 0.993 | 0.007 |
| Tweet B | Praying for people in #Boulder. Hearing a lg wall of water is coming down from Emerson Gulch. Please be safe & go to higher ground. #coflood | 0 | #51: 0.779<br>#20: 0.213 | 0.524 |
| Tweet C | Move to higher ground. Hold your loved ones close & pray this rain shows mercy, cleanly washing away this town. #coflood #GoodnightNightvale | 1 | #20: 0.568<br>#51: 0.425 | 0.685 |
| Tweet D | Boulder creek running at 5,000 cubic feet per second. Stay safe people get to higher ground. #boulderflood | 0 | #51: 0.458<br>#20: 0.382<br>#45: 0.153 | 1.012 |

[a]These tweets can be accessed at https://twitter.com/CUBoulder/statuses/378210912693264385, https://twitter.com/CarrieKintz/statuses/378391344898535424, https://twitter.com/IncrediSquish/statuses/379036515742916608, and https://twitter.com/1DancingCrane/statuses/378369601215545345.

**TABLE 2** Topics corresponding to the four tweets

| Topic number | Top 20 keywords |
|---|---|
| #20 | safe, boulder, stay, rain, friends, prayers, thoughts, people, hope, affected, home, good, dry, family, love, raining, bad, crazy, victims, house |
| #45 | creek, boulder creek, boulder, water, flow, wall, usgs, official, denver, term, experts, tsunami, experts term, readings, creek flow readings, sensor, fourmile, usgs sensor, observed, massive wall |
| #51 | canyon, boulder, water, ground, higher, higher ground, wall, coming, boulder canyon, creek, immediately, move, boulder creek, gulch, emerson gulch, emerson, seek, debris, pearl, vehicles |

natural logarithm transformation for better normality (Judd, McClelland, & Ryan, 2011). We also controlled the effect of the tweet length to better evaluate tweets' entropy by including the numbers of words and hashtags. Additionally, each Twitter data set was contrast-coded to control for different characteristics of the two flood incidents. Table 3 summarizes the descriptive statistics of the dependent, control, and independent variables.

We established the hierarchical regression models to examine whether entropy constantly influences the retweet count over and above the other variables. Model 1 includes entropy and the control variables. Model 2 adds Model 1 URLs and emoticons. Model 3 adds Model 2 to the two interaction terms of entropy with URLs and emoticons. To examine the interaction relationships, all numerical variables were centered from their means (Aiken, West, & Reno, 1991). Model 3 shown, in Figure 3, is the main empirical model to evaluate the research hypotheses. Models 4-1 and 4-2 represent Queensland and Colorado, respectively.

The variance information factor (VIF) analysis in Model 3 showed that none of the VIFs exceeded the acceptable level of 5, indicating that multicollinearity is not a concern (Belsley, 1991). Table 4 presents the results of the empirical models. Through Models 1 to 4, we confirmed that the effect of entropy on the retweet count was significant and constant.

The results support H1, which assumes a negative relationship between entropy and the retweet count. Given that the other variables are held constant, a 10% increase in entropy decreased the retweet count by 14.7% on average ($\beta_{Entropy}$ = -1.677*** or Incident Rate Ratio [IRR] = 0.187). We also found the similar negative effects of entropy on the retweet count in Models 4-1 and 4-2 (see Figure 4).

We theorized URLs' positive effect on the retweet count (H2a) and its conditional effect on the relationship between entropy and the retweet count (H2b). H2a is supported, in the sense that URLs increased the retweet count by 26.1% per URL on average, while holding the other variables constant ($\beta_{URLs}$ = 0.232*** or IRR = 1.261). As we expected in H2b, URLs significantly alleviated the negative effect of entropy on the retweet count by a factor of 1.774 ($\beta_{Entropy \times URLs}$ = 0.573*** or IRR = 1.774). That is, an additional URL mitigated a decrease in the retweet count to 9.95% from 15.4% per 10% increase in entropy. Therefore, H2b is also supported. In H3a, H3b-1, and H3b-2, we mainly dealt with emoticons. While the results support the negative effect of emoticons on the retweet count ($\beta_{Emotions}$ = -0.102*** or IRR = 0.0969), emoticons were not conditional on the relationship between entropy and the retweet count ($\beta_{Entropy \times Emotions}$ = −0.0005, $p$ = .990).

**TABLE 3** Variable description

| Variables | | Queensland Mean | Queensland SD | Queensland Range | Colorado Mean | Colorado SD | Colorado Range |
|---|---|---|---|---|---|---|---|
| **Dependent** | | | | | | | |
| *Retweets_24h$_i$* | The number of retweets of tweet *i* within 24 hr after its posting | 0.803 | 9.276 | 0–1684 | 1.227 | 6.74 | 0–741 |
| **Independent** | | | | | | | |
| *Entropy$_i$* | The entropy of tweet *i* | 0.316 | 0.343 | 0–1.64 | 0.238 | 0.317 | 0–1.6 |
| *URLs$_i$* | The number of URLs in tweet *i* | 0.432 | 0.546 | 0–5 | 0.616 | 0.543 | 0–4 |
| *Emoticons$_i$* | The number of emoticons in tweet *i* | 0.059 | 0.059 | 0–9 | 0.013 | 0.114 | 0–3 |
| **Control** | | | | | | | |
| *Words$_i$* | The number of words in tweet *i* | 9.45 | 4.00 | 0–26 | 8.52 | 3.93 | 0–24 |
| *Hashtags$_i$* | The number of hashtags in tweet *i* | 1.23 | 0.810 | 0–13 | 1.34 | 1.19 | 0–15 |
| *Ln(Followers$_{i,t}$)* | The log-transformed number of followers of tweet *i*'s author at time *t* | 5.399 | 1.785 | 0–14.5 | 6.031 | 2.323 | 0–16.4 |
| *Ln(Followees$_{i,t}$)* | The log-transformed number of followers of tweet *i*'s author at time *t* | 5.36 | 1.54 | 0–12.1 | 5.815 | 1.939 | 0–12.7 |
| *Ln(Likes$_{i,t}$)* | The log-transformed number of favorites of tweet *i*'s author at time *t* | 1.83 | 1.97 | 0–8.97 | 3.432 | 2.611 | 0–13.6 |
| *Ln(Status$_{i,t}$)* | The log-transformed total number of past tweets of tweet *i*'s author at time *t* | 7.44 | 1.97 | 0–12.7 | 8.044 | 2.258 | 0–14.1 |
| *Mention_YN$_i$* | A contrast code to indicate whether tweet *i* includes other twitterers (1 for "Yes,"−1 for "No") | | | | | | |
| *Flood_Cases* | A contrast code to distinguish two flood incidents (1 for "Colorado," −1 for "Queensland") | | | | | | |

$$
\begin{aligned}
Retweets\_24h_i = \beta_0 &+ \underbrace{\underbrace{\beta_1 Entropy_i}_{Tweet\ Content} + \underbrace{\beta_2 URLs_i + \beta_3 Emoticons_i}_{Supplmental\ Information}}_{Main\ Effects} \\
&+ \underbrace{\beta_4 Entrpy_i \times URLs_i + \beta_5 Entrpy_i \times Emoticons_i}_{Moderation\ Effects} \\
&+ \underbrace{\beta_6 Words_i + \beta_7 Hashatgs_i + \beta_8 Mention\_YN_i}_{Controls\ about\ Tweets} \\
&+ \underbrace{\beta_9 Ln(Followers_{i,t}) + \beta_{10} Ln(Followees_{i,t}) + \beta_{11} Ln(Likes_{i,t}) + \beta_{12} Ln(Status_{i,t})}_{Controls\ about\ Twitterers} \\
&+ \underbrace{\beta_{13} Flood\_Cases}_{Control-Floods} \\
&+ \varepsilon_i
\end{aligned}
$$

**FIGURE 3** The empirical model

To put it differently, an additional emoticon decreased the retweet count by 9.69% on average, but this negativity did not significantly influence the relationship between entropy and the retweet count. Consequently, H3a is supported, but neither H3b-1 nor H3b-2 is supported. The empirical results that we found in Model 3 were replicated in Models 4-1 and 4-2. In summary, except for H3b-1 and H3b-2, the other hypotheses are supported.

## 4.4 | Predictive modeling

By utilizing the notion of predictive analytics (e.g., supervised learning or the classification approach) we corroborate additional evidence for entropy as a reliable factor to significantly affect disaster tweets' retweeting. Through the exploratory statistical analysis, we demonstrated the expected relationships of entropy with

**TABLE 4** The statistical results

| Variables | Model 1 | Model 2 | Model 3 | Model 4-1 (Queensland) | Model 4-2 (Colorado) |
|---|---|---|---|---|---|
| **Main** | | | | | |
| $Entropy_i$ | −1.704*** (0.0405) | −1.699*** (0.0408) | −1.677*** (0.0398) | −1.922*** (0.0595) | −1.456*** (0.0463) |
| $URLs_i$ | — | 0.183*** (0.0240) | 0.232*** (0.0224) | 0.337*** (0.0379) | 0.166*** (0.0265) |
| $Emoticons_i$ | — | −0.0982*** (0.0151) | −0.102*** (0.0140) | −0.0889*** (0.0203) | −0.103*** (0.0187) |
| **Interaction** | | | | | |
| $Entropy_i \times URLs_i$ | — | — | 0.573*** (0.0705) | 0.422*** (0.105) | 0.507*** (0.0841) |
| $Entropy_i \times Emoticons_i$ | — | — | −0.000524 (0.0398) | 0.00815 (0.0569) | 0.03110 (0.0534) |
| **Control** | | | | | |
| $Words_i$ | 0.0554*** (0.00357) | 0.0677*** (0.00351) | 0.0690*** (0.00349) | 0.0770*** (0.00507) | 0.0629*** (0.00418) |
| $Hashtags_i$ | 0.254*** (0.0159) | 0.265*** (0.0165) | 0.265*** (0.0159) | 0.232*** (0.0364) | 0.258*** (0.0116) |
| *Flood_Cases* | −0.115*** (0.0190) | −0.128*** (0.0188) | −0.129*** (0.0184) | — | — |
| $Ln(Followers_{i,t})$ | 0.681*** (0.0107) | 0.679*** (0.0106) | 0.676*** (0.0104) | 0.612*** (0.0190) | 0.718*** (0.0111) |
| $Ln(Followees_{i,t})$ | −0.118*** (0.00950) | −0.117*** (0.00958) | −0.115*** (0.00931) | −0.137*** (0.0162) | −0.0798*** (0.00928) |
| $Ln(Likes_{i,t})$ | 0.0851*** (0.0106) | 0.0859*** (0.0104) | 0.0851*** (0.0100) | 0.0387 (0.0225) | 0.112*** (0.00641) |
| $Ln(Status_{i,t})$ | −0.308*** (0.0116) | −0.302*** (0.0117) | −0.300*** (0.0114) | −0.157*** (0.0241) | −0.422*** (0.0110) |
| $Mention\_YN_i$ | −0.119*** (0.0146) | −0.102*** (0.0154) | −0.0997*** (0.0154) | −0.208*** (0.0229) | −0.0119 (0.0189) |
| *Constant* | −0.854*** (0.0154) | −0.857*** (0.0149) | −0.847*** (0.0150) | −0.792*** (0.0294) | −0.963*** (0.0207) |
| **Inalpha** | | | | | |
| *Constant* | 1.250*** (0.0227) | 1.244*** (0.0225) | 1.241*** (0.0223) | 1.441*** (0.0352) | 1.041*** (0.0242) |
| **Model Summary** | | | | | |
| *Log-likelihood Ratio* | 30736.31*** | 37383.62*** | 37603.27*** | 14588.69*** | 23723.45*** |
| *McFadden's* $R^2$ | 0.110 | 0.111 | 0.111 | 0.098 | 0.126 |
| *n* | 157111 | | | 79213 | 77898 |

*Note:* $*p < .05$; $**p < .01$; $***p < .001$; standard errors in parentheses.

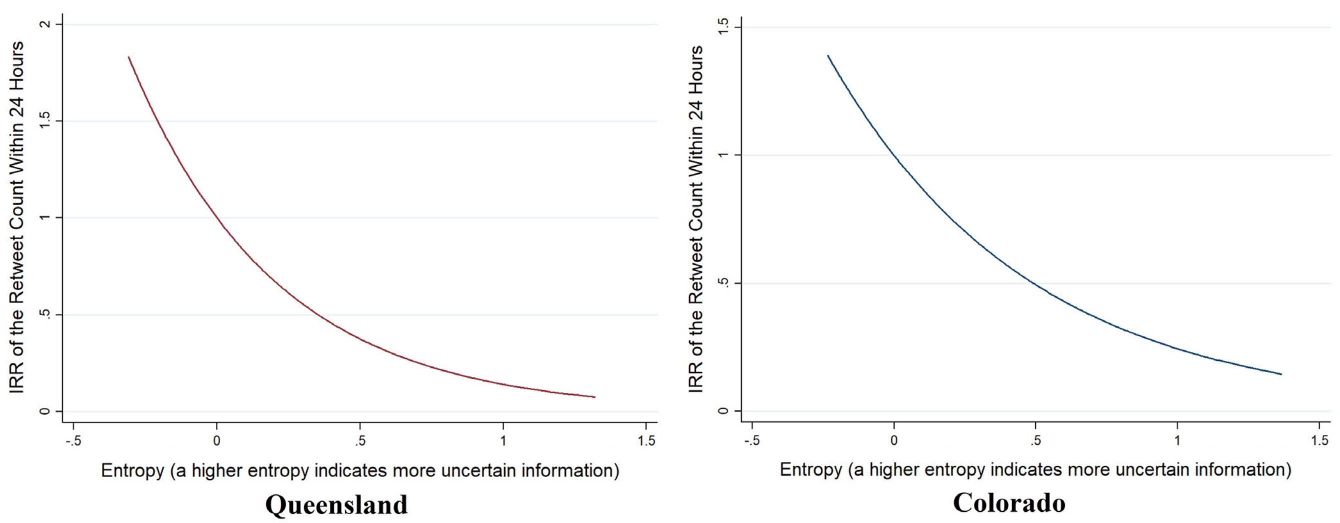


**FIGURE 4** The main effect plots of entropy [Color figure can be viewed at wileyonlinelibrary.com]

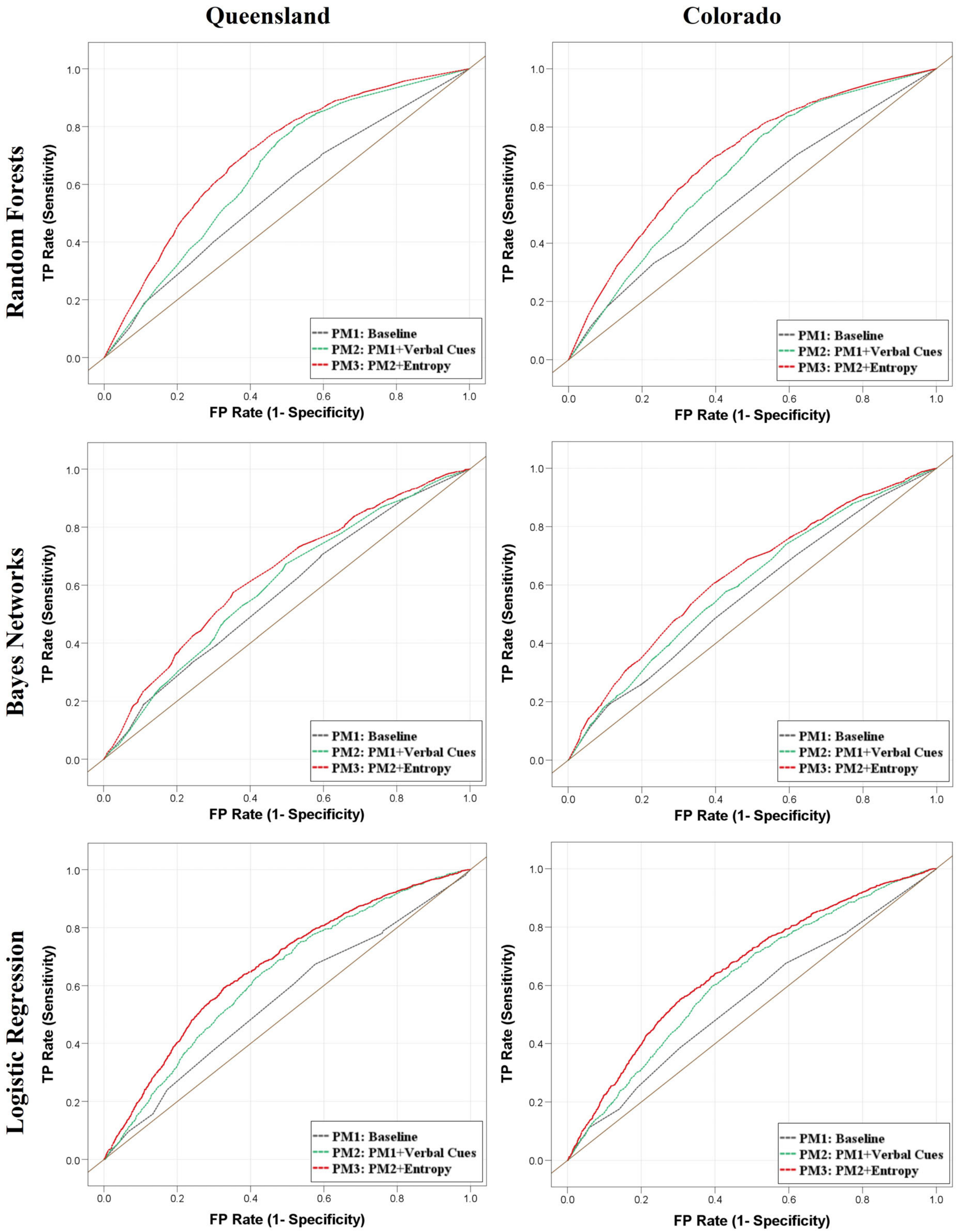


**FIGURE 5** The ROC graphs of classifiers (5 minutes) [Color figure can be viewed at wileyonlinelibrary.com]

the retweet count. We now switch to a predictive study to gauge the predictive capability of entropy in classifying *unobserved* tweets' retweet probability. Using tweets' symbolic elements (Son et al., 2019), we defined the following three models: Predictive Model 1 (PM1) as a baseline model includes *URLs*, *Emoticons*, and *Mention_YN*. Predictive Model 2 (PM2) adds PM1 *Words* and *Hashtags* as Twitter conventions to convey information. Predictive Model 3 (PM3) adds PM2 *Entropy* as an indicator of a tweet's uncertainty. To enhance the

**TABLE 5** The AUC values of classifiers

| Retweet period | | Algorithms / 5-fold cross-validation | Random forests PM1 | Random forests PM2 | Random forests PM3 | Bayes networks PM1 | Bayes networks PM2 | Bayes networks PM3 | Logistic regression PM1 | Logistic regression PM2 | Logistic regression PM3 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Queensland | 5 min | 1 | 0.574 | 0.659 | 0.701 | 0.573 | 0.598 | 0.629 | 0.554 | 0.632 | 0.658 |
| | | 2 | 0.564 | 0.649 | 0.708 | 0.568 | 0.601 | 0.646 | 0.548 | 0.626 | 0.672 |
| | | 3 | 0.565 | 0.649 | 0.714 | 0.570 | 0.602 | 0.649 | 0.553 | 0.633 | 0.675 |
| | | 4 | 0.574 | 0.665 | 0.716 | 0.570 | 0.609 | 0.645 | 0.556 | 0.64 | 0.668 |
| | | 5 | 0.561 | 0.664 | 0.711 | 0.565 | 0.596 | 0.631 | 0.550 | 0.633 | 0.665 |
| | | Average | 0.568 | 0.657 | 0.710 | 0.569 | 0.601 | 0.640 | 0.552 | 0.633 | 0.668 |
| | | **Difference**[a] | — | — | **0.053** | — | — | **0.039** | — | — | **0.035** |
| | 1 hr | 1 | 0.559 | 0.665 | 0.712 | 0.562 | 0.601 | 0.635 | 0.536 | 0.636 | 0.667 |
| | | 2 | 0.563 | 0.662 | 0.718 | 0.563 | 0.600 | 0.648 | 0.545 | 0.638 | 0.679 |
| | | 3 | 0.571 | 0.681 | 0.728 | 0.572 | 0.607 | 0.637 | 0.552 | 0.648 | 0.674 |
| | | 4 | 0.573 | 0.665 | 0.716 | 0.58 | 0.608 | 0.645 | 0.551 | 0.646 | 0.677 |
| | | 5 | 0.564 | 0.676 | 0.724 | 0.569 | 0.607 | 0.646 | 0.551 | 0.641 | 0.676 |
| | | Average | 0.567 | 0.670 | 0.720 | 0.569 | 0.605 | 0.642 | 0.547 | 0.642 | 0.675 |
| | | **Difference**[a] | — | — | **0.050** | — | — | **0.038** | — | — | **0.033** |
| Colorado | 5 min | 1 | 0.581 | 0.667 | 0.71 | 0.576 | 0.612 | 0.643 | 0.561 | 0.644 | 0.677 |
| | | 2 | 0.564 | 0.661 | 0.711 | 0.57 | 0.607 | 0.64 | 0.555 | 0.633 | 0.665 |
| | | 3 | 0.561 | 0.654 | 0.702 | 0.564 | 0.598 | 0.638 | 0.548 | 0.628 | 0.666 |
| | | 4 | 0.576 | 0.666 | 0.715 | 0.577 | 0.614 | 0.655 | 0.559 | 0.641 | 0.68 |
| | | 5 | 0.561 | 0.654 | 0.708 | 0.57 | 0.602 | 0.65 | 0.552 | 0.619 | 0.665 |
| | | Average | 0.569 | 0.660 | 0.710 | 0.571 | 0.607 | 0.645 | 0.555 | 0.633 | 0.671 |
| | | **Difference**[a] | — | — | **0.049** | — | — | **0.039** | — | — | **0.038** |
| | 1 hr | 1 | 0.560 | 0.669 | 0.723 | 0.564 | 0.600 | 0.649 | 0.545 | 0.646 | 0.682 |
| | | 2 | 0.568 | 0.657 | 0.713 | 0.573 | 0.610 | 0.645 | 0.549 | 0.644 | 0.680 |
| | | 3 | 0.560 | 0.662 | 0.708 | 0.570 | 0.601 | 0.642 | 0.545 | 0.632 | 0.674 |
| | | 4 | 0.573 | 0.673 | 0.718 | 0.572 | 0.596 | 0.635 | 0.548 | 0.650 | 0.676 |
| | | 5 | 0.570 | 0.680 | 0.733 | 0.572 | 0.603 | 0.645 | 0.551 | 0.657 | 0.691 |
| | | Average | 0.567 | 0.668 | 0.720 | 0.570 | 0.602 | 0.643 | 0.548 | 0.646 | 0.681 |
| | | **Difference**[a] | — | — | **0.051** | — | — | **0.041** | — | — | **0.035** |

[a]*Entropy*'s contribution to the retweet probability in a given time period is captured by comparing PM3 with PM2.

generalizability of the predictive models, three classification algorithms of random forests, Bayes networks, and logistic regression were used to build classifiers to foretell the retweet probability within (i) 5 minutes (i.e., quick retweeting) and (ii) 1 hour (i.e., general retweeting) after posting.

In each time period, the following procedures were conducted. First, 20,000 tweets were chosen by stratified sampling to train unbiased classifiers (Kotsiantis, Zaharakis, & Pintelas, 2007)—randomly selected 10,000 tweets with at least one retweet and randomly selected 10,000 tweets with no retweets. Second, a random sample of 70% of the 20,000 tweets were used to train classifiers, and the rest were utilized to evaluate the performance of classifiers by the area under the ROC curve (AUC). While an ROC (or receiver operating characteristic) curve uses true and false positives to evaluate the performance of classifiers,[5] an AUC resulting from an ROC curve is a single measure of goodness of fit whose values range from 0 to 1—a higher AUC value represents a more accurate classifier; a 0.5 AUC value indicates random guessing (Fawcett, 2006). Last, the above two procedures were repeated five times, or 5-fold cross-validation, to calculate a range of the prediction accuracies across randomly sampled data sets (Wendler & Gröttrup, 2016).

In Figure 5, we show the ROC curves of the classifiers predicting the retweet probability within the 5-minute period. All ROC curves through the six plots are above the diagonal line (or random guessing), demonstrating that tweet content is an important predictor of retweeting. Especially, PM3's classifiers that include *Entropy* outperform the other two classifiers regardless of the algorithms and Twitter data sets. The importance of Entropy is further investigated based on each classifier's AUC.

Each classifier's AUC values after 5-fold cross-validation are summarized in Table 5. It is noteworthy that Entropy constantly increased the prediction accuracy over and above the other content features of tweets, such as URLs, Emoticons, Mention_YN, Words, and Hashtags. Without exception, we observed consistent improvement across two Twitter data sets, two time periods, and three classification algorithms. On average, Entropy contributed to enhancing the classifier accuracy on unseen disaster tweets' retweet probability by 5.3% at maximum and 3.3% at minimum in the Queensland floods, and by 5.0 and 3.5% (respectively) in the Colorado floods. Therefore, we confirm that Entropy is a reliable factor of disaster tweets that significantly influences retweet probability.

## 5 | DISCUSSION

Through the statistical analyses, we validated that entropy behaves as proposed with respect to the retweet count. By employing the predictive analytics, we corroborated the empirical evidence by revealing entropy as a reliable content feature of disaster tweets.

The empirical findings support entropy as a valid measure of uncertainty. First, as a disaster tweet's entropy increases, its retweet count decreases—uncertain tweets are likely to be less clearly communicated (Bergeron & Friedman, 2015) and thought to convey less sufficient information (Mileti & Sorensen, 1990), negatively influencing retweeting. This result demonstrates that entropy captures the essential characteristic of uncertainty in the context of Twitter for disaster communication. Second, the negative relationship between entropy and retweet count is mitigated by URLs, as URLs can convey additional information beyond words and hashtags, further strengthening the validity of entropy. We inherently assumed that tweets' uncertainty is caused by the restricted amount of information; therefore, such restriction must be alleviated by further information provided by URLs. This finding establishes a plausible foothold for addressing the conflicting effects of URLs on retweeting. Third, as we posited in H3a, emoticons' valueless or marginal situational information decreases the retweet count. However, unlike URLs' interactive relationship with entropy, emoticons neither significantly mitigate nor aggravate uncertainty. According to the confidence interval of the interaction term, the low and high levels are −0.0785 and 0.0775, each of which is very close to 0. As the confidence interval is narrowly defined near 0, a barely significant correlation or relationship is implied (Schmidt & Hunter, 1997). Hence, we conclude that there is insufficient evidence to support a significant relationship between emoticons and entropy (e.g., Johnson, 1999). As entropy is supposed to react only with Twitter's conventions manifesting information, this insignificant relationship does not weaken the validity of entropy; it adds further evidence that is not as strong as what we obtained from URLs.

From the predictive analytics, we confirm that entropy is a unique, distinct characteristic of disaster tweets. Entropy constantly improves the prediction accuracy of the retweet probability in both Twitter data sets regardless of the retweet time periods (i.e., 10 minute or 1 hour) and the classification algorithms (i.e., random forests, Bayes networks, and logistic regression). Therefore, we find that entropy is a reliable feature of disaster tweets, and expect it will be included in future studies on disaster communication via Twitter.

Twitter has changed the way in which the affected public understands disaster situations and plans protective actions. Its improvised communication networks and the capped-length tweets are two factors that allow the public to quickly craft and update warnings and alerts. However, how the 140-character limit affects Twitter communication during disasters is largely unexplored. By taking tweet length into consideration, we offer entropy as a valid and reliable measure of the uncertainty of disaster tweets.

This study contributes to URT by applying its theoretical implementation on Twitter to enhance our understanding of disaster communication. Uncertainty defined in URT provides a suitable criterion to evaluate disaster messages, such as clarity and sufficiency of information, and establishes the foothold of entropy to assess a disaster tweet's uncertainty. Consequently, URT facilitates revealing the hidden truth of disaster tweets: the more topics in a disaster tweet, the higher the uncertainty—and the lower the retweet count. The empirical findings contribute to the literature on Twitter for disaster communication. First, during a disaster, a tweet's uncertainty matters, as it prevents its conveyed information from being more widely shared. Second, such uncertainty can be alleviated by additional information furnished by URLs. That said, URLs are better evaluated by considering uncertainty. Hence, the uncertainty of a tweet plays a critical role in elucidating inconsistent results regarding URLs (Burnap et al., 2014; Pervin et al., 2014).

Based on the empirical findings, we can offer agencies and individuals evidence-based strategies for designing disaster tweets and terse messages such as WEAs. First, one topic per tweet (or message) is recommended to minimize or avoid uncertainty; a series of related disaster tweets can be used to raise multiple topics. Second, URLs are a reliably effective means to convey additional information beyond tweets' words and hashtags, and they can mitigate uncertainty. Third, although emoticons make disaster tweets friendlier and more emotive, they barely update twitterers' situational awareness; twitterers should be thoughtful about including emoticons. Last but not least, entropy can be of importance for Twitter, as it can foretell which disaster tweets will be more widely propagated. Twitter can leverage the meaning and application of entropy to find significant disaster tweets in advance for timely sharing with the affected public.

## 6 | LIMITATIONS

This study has limitations that open opportunities for future research. First, entropy was examined in cases of floods; to enhance the entropy's generalizability, future studies should apply entropy in other disaster contexts. Second, disaster tweets' uncertainty was assessed by two algorithmic methods of entropy and the LDA technique. It would be useful to explore the extent to which actual twitterers would agree with entropy when evaluating disaster tweets. Third, we have raised an untouched aspect of emoticons—information value. As convenient means of expressing feeling, emoticons have been studied in the domains of politics (Stieglitz & Dang-Xuan, 2013) and sentiment analysis (Liu, Li, & Guo, 2012). However, how emoticons help the affected public during disasters is mostly unknown. Future research may perform in-depth analysis on emoticons as a conveyance of information in disaster contexts. Last, Twitter recently extended its character limit to 280; one concern with this change is whether the extended length affects the current findings. We are informed from the Twitter data sets that on average 33% of the total characters were unused (i.e., 47 characters). We extended Model 3 by including the interaction between entropy and individual tweet length. The results indicate that as the tweet length increased, the negative effect of entropy on the retweet count strengthened ($\beta_{\text{Entropy×Length}} = -0.1137^{***}$). Therefore, it is highly probable that the current findings will be maintained even with the 280-character limit.

## 7 | CONCLUSION

Overall, this study offers entropy as a measure for a disaster tweet's uncertainty. The results of the statistical and predictive analyses support the validity and reliability of entropy. Therefore, we conclude that entropy is an important feature of disaster tweets that can enhance the current understanding of Twitter's role during disasters.

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## ENDNOTES

[1] Followers are twitterers who follow the person; followees are twitterers whom the person follows.

[2] We discuss the implication of these hypotheses in the Discussion section.

[3] Gnip—https://support.gnip.com/apis/

[4] **E**mpowering the **P**ublic with **I**nformation in **C**risis—https://epic.cs.colorado.edu/

[5] True positive: a tweet is predicted to be retweeted, when it is retweeted in a given time period. False positive: a tweet is predicted to be retweeted, when it is *not* retweeted in a given time period.

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## SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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