Natural Hazards (2020) 103:2207–2229
https://doi.org/10.1007/s11069-020-04078-6

ORIGINAL PAPER

Content driving exposure and attention to tweets during local, high-impact weather events

Joshua D. Eachus[1] · **Barry D. Keim**[1]

Received: 7 May 2019 / Accepted: 18 May 2020 / Published online: 28 May 2020

Abstract
The use of Twitter to disseminate weather information presents need for the analysis of what types of messages, and specifically warning messages, incur exposure and attention. Having this knowledge could increase exposure and attention to messages and perhaps increase retransmission through Twitter. Two models describe the cognitive processing of tweets and warnings. The extended parallel process model describes components of an effective warning message. Even in a tweet, ignoring one or both critical components of a warning—threat and efficacy—could inhibit a user from taking the correct protective action. The protective action decision model (PADM) describes risk perception and factors that enable or disable one from giving attention to a message. The PADM also helps to define impressions, retweets or likes as metrics of exposure or attention to a tweet. Tweets from three Twitter accounts within one television market during two high-impact weather events were examined. From an individual account, impressions, retweets and likes were collected to identify commonalities to tweets with much exposure and attention. Results indicate photographs and geographically specific messages were popular. Second, from two competing television weather accounts, warning tweet formats were compared to identify exposure and attention to each. Warning tweets providing threat and efficacy performed best. The purpose of this work is twofold. First is to identify local trends to compliment findings from studies with large sample sizes. Second is to apply existing theory on warning message content to Twitter. This approach should benefit communication strategies of key information nodes—local meteorologists—during high-impact weather events.

Keywords Weather · Twitter · Communication · Meteorologists · Warnings · Messaging

1 Introduction

Weather forecasts are not limited to television. In 2020, weather messages are communicated on channels including, but not limited to radio, newspaper, the Internet, mobile phones, Facebook and Twitter. Urgent weather warning communication begins with

✉ Joshua D. Eachus
joshua.d.eachus@gmail.com

[1] Department of Geography and Anthropology, Louisiana State University, 13451 Country Meadow Ave., Baton Rouge, LA 70816, USA

issuance from the official source (National Weather Service in the USA) and then travels through any number of channels and social networks. Research has shown that having strong connections with a variety of social networks increases the chances of receiving a warning message (Donner et al. 2012). No matter the channel or social network, weather messages in high-impact events need to be accurate and timely; making the rapid transmission capabilities of social media posts an intriguing ally to weather forecasters (Ferrell 2012).

Twitter is just one social media platform on which individuals receiving warnings. Twitter has an unfiltered, chronological flow of information that has become an integral part of weather warning communication. In January 2009, there were less than 30 million users worldwide, but by the end of February 2020, there were 330 million monthly active users. In that 11-year period, how individuals receive weather information has changed. Twitter reaches people outside of the traditional daily television, radio and print schedules. Through a network of followers, dozens, hundreds or thousands of people can receive and spread information almost instantaneously.

Researchers have evaluated Twitter as a communication tool during severe weather events. Some have used it as a metric for public attention (Ripberger 2014). Other scholars have provided comprehensive analyses of specific hazard warning processes (Brotzge and Donner 2013; Carr et al. 2015; Morss et al. 2015), some of which called for further scrutiny of effective warning communication through social media. Many of these studies considered content trends from large populations.

This research addresses a subset of the population in the form of local broadcast meteorologists, described as key messengers during high-impact weather events (Kogan et al. 2015). These communicators may be able to improve their strategies with insights into what Twitter content proves popular during high-impact weather events.

Using a case study approach, three local broadcast meteorologist profiles were examined after two separate high-impact weather events in the same region. The relatively small data set consists of tweets from one personal broadcast meteorologist (an author of this paper) and two local news stations. Tweets from these accounts were analyzed after the February 2016 southeast Louisiana tornado outbreak that killed two people and injured 92 and the August 2016 southeast Louisiana flood that set state records for rainfall totals; it inundated 140,000 structures (including 50,000 homes) and killed 13 people (Brown et al. 2020).

While trying to understand which content receives the most attention and exposure and spreads more rapidly; the goal of the tweet content analysis in this study was twofold. First, the personal account was used to identify traits similar to tweets that had much exposure and attention during two separate high-impact weather events. Second, the two local news station accounts were used to compare and contrast warning tweets to identify the most effective message format per existing literature. Key nomenclature used with Twitter and in this study is highlighted in Table 1.

2 Literature review

This study aims to add understanding to the transmission of tweets during high-impact weather events by identifying trends in exposure and attention to weather content and warnings messages. To develop useful weather communication strategies, it is important to have knowledge of risk perception, the channel through which a message is being

Table 1 Key terms and definitions of this research

Twitter terminology	
Tweet	Message appearing chronologically on Twitter timeline
Retweet	Sharing of a tweet from another user
Like	Acknowledgement of a tweet
Reply	Comment about a tweet directed to its creator
Impression	Times a user is served a Tweet in timeline or search results
Follower	User following a specific account
Handle	@ symbol followed by a name, which is a specific user's account

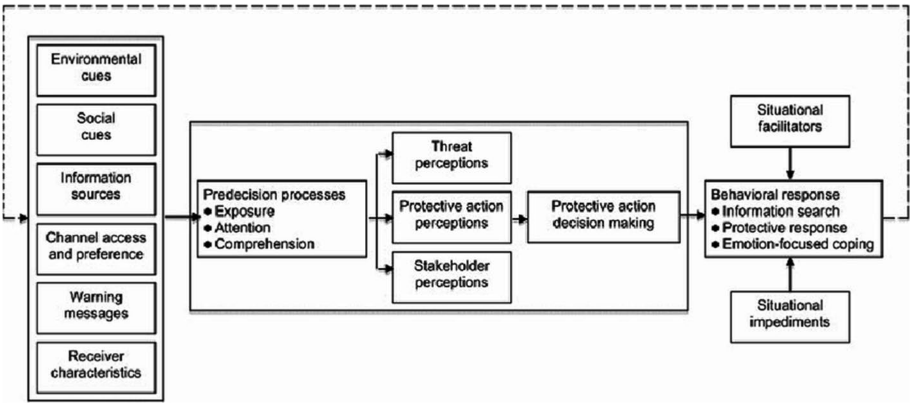


Fig. 1 Protective action decision model (Lindell and Perry 2012)

communicated, factors that determine what content will be retransmitted and effective warning messaging.

2.1 Risk perception

Effective weather communication on any channel, including Twitter, requires an understanding of how people respond to disasters as they unfold (Peacock et al. 1997). The protective action decision model (PADM) (Lindell and Perry 2012) (Fig. 1) is a modern and seminal conceptualization of the risk perception process from the initial message and external factors, to pre-decision psychological processes, to protective action decision making to behavioral response. Action is taken if the message receiver determines a threat significant enough and the recommended action effective enough to justify disruption of normal behavior (Lindell and Perry 2012).

Protective action decision making begins with environmental cues, social cues and information sources. One must perceive great danger to abandon comfort, such as home (Mileti and Sorensen 1991). Therefore, in tornado or flash flood warning situation, environmental cues such as dark skies or rising rivers may be necessary for a receiver to heed warnings. However, these visualizations may not always be present, even when a threat is imminent. Social networks such as family, friends, neighbors and online channels like

Twitter serve as social cues to confirm, personalize and understand threats (West and Orr 2007). Even if a warning message meets all appropriate criteria, if reaction by one's social network is not also strong, action may not be taken. Another obstacle to protective action may be the source of information. Despite availability of government and media sources and channels distributing warning information, many people place their highest trust in family and friends (West and Orr 2007).

Warning messages are transmitted from a source via a channel to receivers. Local broadcast meteorologists are one such source and Twitter is one such channel. Receivers' characteristics such as physical and mental abilities and social and economic resources influence whether the message enters the pre-decision phase of exposure, attention and comprehension (Lindell and Perry 2012). Metrics provided by Twitter can provide a measurement of exposure and, to a limited extent, attention to message. The greater the number of people exposed to a message, the more likely that message will be given attention and retransmitted (Sutton et al. 2015)

Even if Twitter metrics allow us to assess some level of exposure and attention to messages, it is difficult to know if a receiver acts on those messages (Ripberger 2014). After a series of cognitive processes, that are unmeasurable by Twitter, there are situational facilitators or impediments related to the channel that can influence protective action. Receivers may feel a need to reassess information. People may use social networks, such as Twitter, to seek verification of official warning messages in an action called milling (Quarantelli and Dynes 1977). Due to milling and previously discussed social cues, Twitter can certainly enhance awareness during an emergency (Hughes et al. 2014). Thus, it is important that the multitude of sources (emergency management, media, NWS) issue specific, consistent messages, as individuals perceive different levels of credibility from various sources (Carr et al. 2015; Mileti and Sorensen 1991). Emotional processing based on previous experience or level of preparedness could affect protective action. Language barriers and technical jargon may also stand in the way of comprehension (Lindell and Perry 2012).

2.2 Twitter

From February 2004 to June 2007, society was introduced to smartphones and social media channels such as Twitter with easier access to multiple information sources (Phillips 2007; Ritchie 2015; Twitter 2016). By the end of February 2020, there were 330 million active Twitter users. These channels afforded users constant connectivity to a social network.

Twitter is a social media application that emergency management agencies and weather forecasters have added to their communication strategy. Twitter users "microblog" by publishing 280 character limit messages[1] that appear on a chronological timeline of other users that have chosen to "follow" the message publisher. A follower may choose to reply to the messenger, like the message or retweet, which shares the message with their own followers. Serial transmission or retweets (Sutton et al. 2014) of Twitter messages can allow dozens, hundreds or thousands of people to rapidly consume and spread information. Such a platform may be considered valuable to those tasked with communication during high-impact weather events. Twitter may even provide the warning message verification that people usually seek (see *milling* on page 4) in times of disaster, by allowing the public to confirm the accuracy of the warning within one of their social networks (Sutton et al. 2014).

[1] 140-character limit messages at the time of the two weather events in this study.

Ripberger (2014) provided some evidence that Twitter is a viable metric of public attention during high-impact weather. In a statistical analysis of 6 months of tweets, it was found that 94 percent of over 1.7 million unique accounts used the word “tornado” less than 3 times. Models then verified that Twitter traffic increased on days where a high number of watches and warnings were issued and/or a large population was affected. Such numbers indicate that a majority of posts are emanating from infrequent severe weather commentators in the public rather than experts (Ripberger 2014). Additionally, messages such as watches and warnings correlated with high social media volume (Ripberger 2014). Many studies of Twitter during high-impact weather events focus on big data sets from a large pool of accounts and not specifically on tweets coming from broadcast meteorologists. A case study approach may help identify trends during a localized weather event to validate the existing literature and establish questions for further examination.

2.3 Tweet content

Since Twitter has been identified as a channel where traffic increases during times of severe weather (Ripberger 2014) and can provide retransmission and reinforcement of weather messages (Hughes et al. 2014), practitioners should like to know what affects the likelihood that weather information will be retweeted. Suh et al. (2010) scoured 74 million tweets to determine what type of content is being shared. There was little to no relationship between the number of previous posts and retweetability of a post. It was originally believed that tweets containing web links to additional data garnered a high retweet rate (Suh et al. 2010). However, newer studies found that messages including links to more information are less likely to be retransmitted (Sutton et al. 2015). Also, the use of a hashtag (#) appears commonly in retweeted information. Hashtags serve to mark tweets relevant to certain topics (Bruns and Burgess 2011). Topical communities and ad hoc publics develop thanks to tweets that contain hashtags (Bruns and Burgess 2011). By including a hashtag, Twitter users interested in the topic referenced by a hashtag may discover tweets from those not followed as part of their network.

When used for the research of high-impact weather events, it must be understood that an entire *geographic population* is not likely uniformly represented on Twitter. However, the *Twitter population* of a geographic area is likely to represent their range of behaviors and ideas (Palen and Anderson 2016).

People in the path of disaster prefer locally created tweets and those with locally actionable information (Kogan et al. 2015; Starbird and Palen 2010). Receivers also favor messages themed toward public safety (Sutton et al. 2014) that are clear and repetitive with specificities such as locations to help personalize the risk and generate action (Mileti and Sorensen 1991; Suh et al. 2010, Starbird and Palen 2010). In disaster situations, milling (Quarantelli and Dynes 1977) makes it necessary that warnings include information such as graphics and web links that further inspire protective action (Sutton et al. 2014). Those tweeting or retweeting information during a disaster are most commonly those geographically affected by the disaster, while local media serve as key centers of information (Kogan et al. 2012).

2.4 Effective warning messaging

As critical information nodes during weather-related disasters (Kogan et al. 2015), local meteorologists communicating warnings should provide messages with a balance of threat

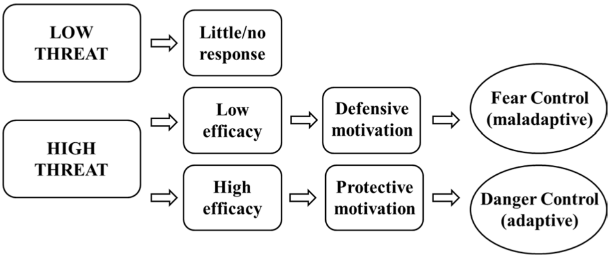


Fig. 2 Extended parallel process model (derived from: Witte 1992)

and efficacy. Threat and efficacy exist as external factors that a person must perceive (Rogers 1983). From the viewpoint of a forecast user, threat is perceived susceptibility and severity, while efficacy is user capacity to take action and perceived effectiveness of that action (Rogers 1983).

The extended parallel process model (EPPM) (Fig. 2) describes how threat and efficacy play a role in the cognitive processes that follow reception of warning messages. Fear appeals, such as weather warnings, are persuasive messages designed to imply harm to people if recommended actions are not taken (Witte 1992). These often contain vivid content and language, e.g., a smoking cessation public service announcement that shows human lung damage and verbalizes connections with cancer (Witte 1992). If a threat is determined to be high, fear will initiate a person to begin evaluating efficacy of the recommended response. However, if the threat is gauged as low, no further cognitive processing occurs (Witte 1992). Messages are often rejected if presented as a high threat with an absence of efficacy. Receivers of such as message may respond to their own fear, which could incur a maladaptive response to the situation. Fear control processes are often involuntary and an attempt to control that fear rather than respond to the danger at hand (Witte 1992). On the other hand, messages are often accepted if balanced with a high level of efficacy. Receivers of that message will then attempt to mitigate danger and (hopefully) implement the recommended safety measures. Danger control processes are cognitive and rational thoughts to evaluate danger and the appropriate response (Witte 1992).

Evidence from a case study about weather blogs prior to disaster suggests messages have a propensity to be dominated by threat centric messaging as disaster impacts near (Hoang 2015). Again, messages that only convey threat are more likely to inspire fear appeals and are more likely to fail. Message receivers responding to fear may feel helplessness and may take the wrong protective action or no action at all according to the EPPM. More recent research, specific to Twitter, examined these findings to find that messages providing hazard impact and protective action guidance were highly retransmitted (Sutton et al. 2015).

3 Research questions

The previous literature on Twitter and weather information has taken a "big data" approach. Though extremely important, big data may reveal even more truths about Twitter if complimented with an analytical or even ethnographical approach (Palen and Anderson 2016). Most studies do not specifically focus on information coming from local broadcast meteorologists, opening a niche for the research presented here. We took a case study approach to identify any underlying trends in the data at hand, to validate the existing literature and to establish questions for further examination. Case study research offers the ability to combine qualitative and quantitative methods, as well as provide in-depth information about specific events (Yin 2013), that may be missed in analyses of large data sets. This study addresses two research questions to contribute to the understanding of Twitter in weather communication.

Using the cognitive processes described by the PADM as a guide, certain behaviors (available metrics) on Twitter (Table 1) can identify exposure and attention. Impressions indicate exposure to a message, while retweets or likes suggest some level of attention to a message. Furthermore, the EPPM is a good fit to describe the most effective format of a weather warning tweet, one that provides both threat and efficacy. Though with character limits (140 until recently changed to 280 in late 2017), including links, tweets can be constructed to meet all appeals of the EPPM. With this reasoning, we ask:

1. Comparing warning format of tweets between two different television station weather accounts, do the retweets and likes reveal any trends in receiver preference? How do these trends fit within the existing literature on warning messages?
2. Analyzing the tweets from a single meteorologist's Twitter account during two different disasters, what traits are similar to tweets with the most impressions, retweets and likes? How do these trends fit within the existing literature on popular tweet content?

4 Methods and data

4.1 Data

Tweets from the February 2016 tornado outbreak and August 2016 flood come from two local broadcast television news affiliates in the Baton Rouge, Louisiana Designated Market Area (DMA). Specifically, we collected Tweets created between February 22–24, 2016, and then August 11–15, 2016, from three Twitter accounts: two accounts that are operated by local broadcast meteorology teams (herein referred to as @TeamWeather1; @TeamWeather2) and one local meteorologist's professional account (herein referred to as @meteorologist). @TeamWeather1 and @TeamWeather2 were the only two unique television weather teams in the DMA that immediately disseminated NWS warnings during the events. @TeamWeather1 and @TeamWeather2 had a number of followers proximal to each other. The use of these two accounts allowed for specific analyses of warning tweets. The @meteorologist account had approximately 2700 followers at the time of the events and represents one individual meteorologist's public following on Twitter. These data were used to identify (other) popular tweet content.

4.2 Measuring exposure and attention to tweets

Since exposure and attention are critical steps of protective action decision making, we measured each by assessing impressions (where available), retweets and likes. An impression means a message appeared in a user's timeline indicating a finite level of exposure. An impression is not a measure of followers, but indicates how many users may see a tweet. Thus, impressions vary because not all followers of an account are on Twitter at the same time to see a specific tweet (Rosenman 2012; Sullivan 2014). A retweet or like signifies interaction with the tweet indicating some level of attention, more than simple exposure to a tweet.

Retweets and likes are publicly available, but only account owners have access to full data on each tweet, including impressions. An author of this work owned the @meteorologist account (and was affiliated with @TeamWeather1). Twitter allows account owners to download a complete history of tweets sorted by year and month. Twitter's Application Program Interface (API) can also be used to retrieve tweets with specific words, phrases and hashtags from any public account during a specified date and time. For this research, through owned (@meteorologist) and non-owned accounts (@TeamWeather1 and @TeamWeather2), tweets were entered into a spreadsheet. To identify traits common to popular tweets on the @meteorologist account, those that were one standard deviation above the mean number of impressions, retweets and likes were chosen for a content discussion.

To determine which format of warning messages garnered more attention, we used retweets and likes data from @TeamWeather1 and @TeamWeather2. Although @TeamWeather1 and @TeamWeather2 had comparable numbers of followers during the events, followership disparities in associated, frequently retweeting main television station accounts made for an uneven comparison. In both events, one station almost doubled the other in followership. To make the most even comparison possible, only tornado warning and flash flood warning tweets from each weather account subsequently retweeted by associated main television station accounts were considered. From that set, each retweet total was divided by the number of followers on the main account to calculate an average number of followers needed to achieve one retweet or like. Lower numbers would suggest fewer people within that particular social network are needed to generate a retweet or like and that would point toward more attention and potentially a more effective formatting of the warning tweet.

5 Results

5.1 Warning tweets

5.1.1 Tornado outbreak—February 23, 2016

@TeamWeather1 and @TeamWeather2, which automatically tweet NWS warnings, provide a way to assess attention to warning tweets. Both @TeamWeather1 and @TeamWeather2 sent out nearly 20 warning tweets on February 23, 2016—some of which were duplicates or warning updates. Comparison allowed evaluation of the EPPM as a model for formatting warning tweets. The warning messages from @TeamWeather1 identified the tornado *threat*, provided *efficacy* (or a mitigating action) and included a map of the warned area (Fig. 3). The @TeamWeather2 warning messages only included text that identified the tornado *threat* only, no mitigating actions, and then named the threatened area—by parish/county without a map (Fig. 4).

There were five tornado warnings that were retweeted from the main television station accounts. First glance at the numbers indicated that inclusion of threat and efficacy components of the EPPM increased attention to warning messages (Table 2). While @TeamWeather2 had a higher average number of retweets (15.8) than @TeamWeather1 (10.6), when adjusted for the number of followers by retweeting main station accounts, the @TeamWeather1 account demonstrated a more efficient social network. @TeamWeather1 averaged 5148 followers needed for one retweet compared to 5898 followers needed for one retweet from @TeamWeather2. While the other attention metric of likes

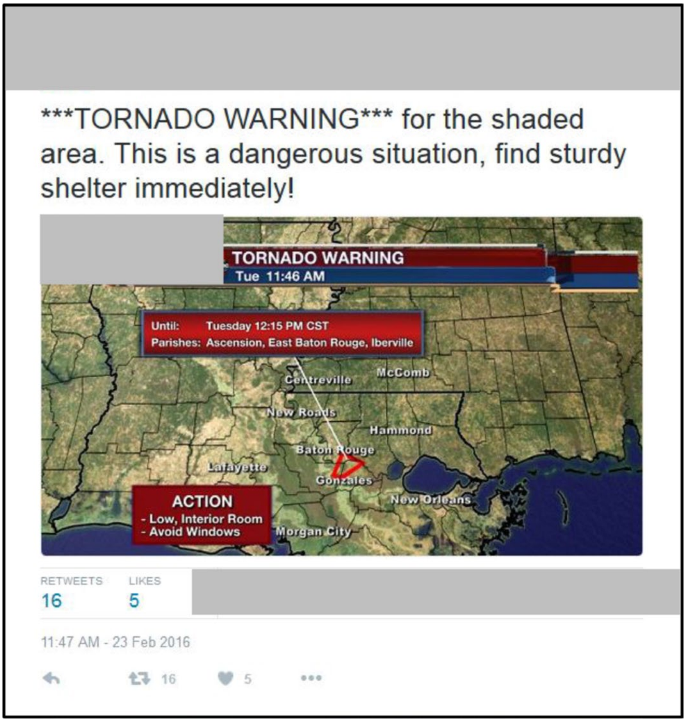
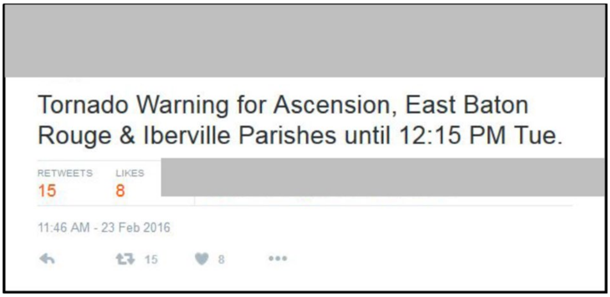


Fig. 3 @TeamWeather1 warning tweet format, tornado warning #1 on February 23, 2016

Fig. 4 @TeamWeather2 warning tweet format, tornado warning #1 on February 23, 2016



came in smaller number, the same general trend is observed. The distributions of followers per retweet and like between @TeamWeather1 and @TeamWeather2 were tested using the Wilcoxon signed-rank test, and neither were found to be statistically significant (followers per retweet, p 0.59; followers per like, $p = 0.28$), though these insignificant results are not totally surprising given the small sample sizes (5) of original tweets from the two accounts.

5.1.2 Flood event—August 2016

During the flood event of mid-August 2016, @TeamWeather1 sent over 50 warning tweets—some of which were duplicates or warning updates. Warnings were formatted

Table 2 Individual tornado warnings from @TeamWeather1 and @TeamWeather2 subsequently retweeted by associated main station accounts; at time of event @TeamWeather1 main station account had 45,000 followers, @TeamWeather2 main station account had 86,000 followers, retweets/likes from each account (left), adjusted number of followers per retweet/like (right)

Time of warning	Retweets/likes		Followers per retweet/like	
	@TeamWeather1	@TeamWeather2	@TeamWeather1	@TeamWeather2
2/23/16 11:46am	16/6	15/7	2813/7500	5733/12,285
2/23/16 12:40 pm	5/3	20/8	9000/15,000	4300/10,750
2/23/16 1:03 pm	15/6	19/8	3000/7500	4526/10,750
2/23/16 3:11 pm	10/8	16/2	4500/5625	5375/43,000
2/23/16 4:06 pm	7/1	9/2	6429/45,000	9556/43,000
Total	53/24	79/27	849/1875	1089/3185
Average	10.6/4.8	15.8/5.4	5148/9375	5898/15,926

Fig. 5 @TeamWeather1 flash flood warning format, 5:54 pm August 13, 2016

with a threat, a mitigating action and a map to identify location (Fig. 5). @TeamWeather2 sent 23 warning tweets, no duplicates or updates and excluded areal flood warnings. A text-only, threat-only format was used (Fig. 6). Within the 23 warnings available for comparison, just three remained that were either both retweeted or both not retweeted by the main station accounts.

Fig. 6 @TeamWeather2 flash flood warning format, 5:54 pm August 13. 2016

Table 3 Individual flash flood warnings from @TeamWeather1 and @TeamWeather2 subsequently retweeted by associated main station accounts; at time of event @TeamWeather1 main station account had 54,000 followers, @TeamWeather2 main station account had 99,000 followers retweets/likes from each account (left), adjusted number of followers per retweet/like (right)

Time of warning	Retweets/likes		Followers per retweet/like	
	@TeamWeather1	@TeamWeather2	@TeamWeather1	@TeamWeather2
8/12/16 4:23 am	7/3	11/5	7714/18,000	9000/19,800
8/13/16 8:14 am	12/4	25/2	4500/13,500	3960/49,500
8/13/16 5:53 pm	14/2	8/4	3857/27,000	12,375/24,750
Total	33/9	44/11	1636/6000	2250/9000
Average	11/3	14.7/3.7	4909/18,000	6735/26,757

Similar to what occurred during the tornado outbreak, numbers suggest that inclusion of the threat and efficacy components as well as a supporting map increased attention to warning messages. @TeamWeather2 again had higher average number of retweets (14.7 compared to 11.0), but when controlling for the number of accessible followers, @TeamWeather1 showed greater effectiveness with an average of 5357 followers needed for one retweet compared to 8445 followers needed for one retweet from @TeamWeather2 (Table 3). Again, as in the case with the tornado outbreak, likes produced smaller numbers, but the same trend. The distributions of followers per retweet and like between @TeamWeather1 and @TeamWeather2 were again tested using the Wilcoxon signed-rank test and neither were found to be statistically significant (followers per retweet, $p=0.42$; followers per like, $p=0.79$). These insignificant results are once again not totally surprising given the small sample sizes (in this case—3) of original tweets from the two accounts.

5.2 Exposure and attention to tweets from a single account

5.2.1 Quantitative analysis

Both the tornado and flood events resulted in 60 tweets from @meteorologist. Despite putting out exactly the same number of tweets in each event, content during the flood event had much higher exposure and attention—evidenced by higher numbers of impressions, retweets and likes. During the tornado outbreak, there was an average of 2224 impressions compared to 7176 for the flood event. The tornado outbreak averaged 3 likes per tweet

Table 4 @meteorologist tweet statistics for February 22–24, 2016 tornado event and August 11–15, 2016 flood event

@meteorologist		Impressions			Retweets			Likes		
Event	*N*	Total	Mean (SD)	Median	Total	Mean (SD)	Median	Total	Mean (SD)	Median
Tornado	60	133,429	2224 (1656)	1756	226	4 (4)	2	161	3 (3)	2
Flood	60	423,413	7176 (6314)	6099	714	12 (18)	8	295	5 (8)	2

versus 5 for the flood event. There was an even greater difference in retweets. The tornado outbreak averaged just 4 retweets per tweet, while the flood event average 12. Both events also produced a positively skewed distributions for retweets (means = 4/12, medians = 2/8, S.D.s = 4/18) and likes (means = 3/5, medians = 2/2, SDs = 3/8). In other words, many tweets received little attention, but a few tweets received much attention (Table 4).

5.2.2 Qualitative analysis

Tweets with a large total of impressions indicate a high level of exposure, while many retweets and likes indicate a high level of attention. Tweets that had a number of impressions, retweets and likes one standard deviation above their respective means were examined to understand how they differed (or compared) qualitatively from other tweets. This resulted in 12 unique tweets from the tornado outbreak and 7 from the flood event. (Many were above one standard deviation across two or all three metrics.)

5.2.2.1 Tornado outbreak The tweet with the most impressions (exposure) ($n = 7265$) was a computer-generated weather graphics showing rotation in a tornadic thunderstorm (Fig. 7). There is one element that separates this tweet from others—four well-known geographic indicators. Four of the top 13 tweets all contained radar images of tornado signatures and referred to a geographic location. Mentioning town names and key thoroughfares seemed to contextualize the tweet to an extent beyond more common geographic references to a parish (county).

A day after the tornadoes, a photograph of a recliner sitting in the middle of a destroyed home garnered the most retweets (attention) of the outbreak by a wide margin ($n = 24$), with 12 more than the second most retweeted message (Fig. 8). The tweet stated that an elderly man was in the chair as a tornado destroyed his home. This tweet was 1 of just 6 during the entire outbreak to be accompanied by a photograph and the only to provide a very close look at damage. Other photographs were aerial or much wider in scope.

The most liked tweet was a reflection of gratitude that more lives were not lost during the outbreak. With a tweeted image relaying an actual email sent by a thankful viewer, the tweet received 20 likes and made 4539 impressions. There is some evidence that emotive content can be more highly retransmitted (Sutton et al. 2015). Also, this tweet may tap into the parasocial relationship existent between broadcasters and viewers, or in this case, Twitter followers (Giles 2002). Two other tweets may fall into this category—one showing a behind the scenes look at the TV weather center during storm coverage and the other from @meteorologist acknowledging the hard work from colleagues reporting in the field.

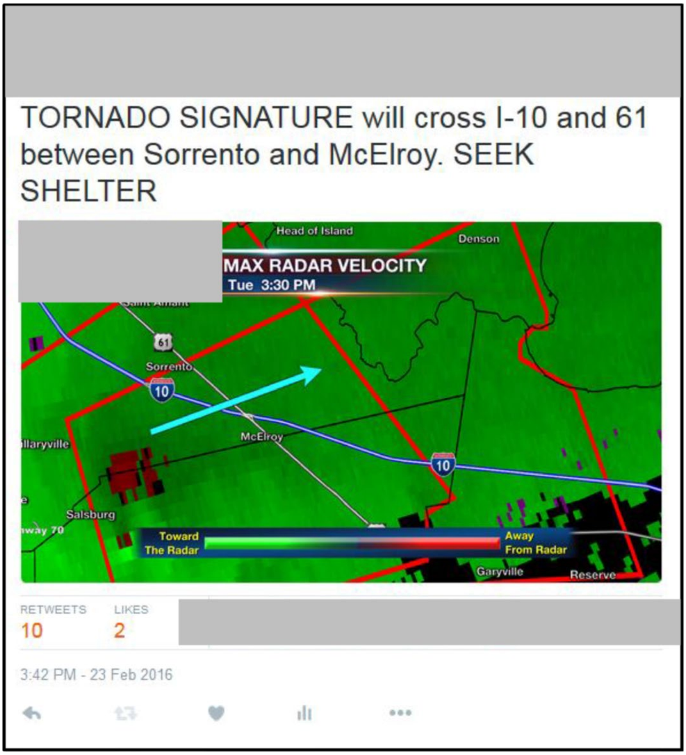


Fig. 7 Most impressions by @meteorologist tweet February 22–24, 2016

Two tweets were safety reminders leading to the outbreak. One tweet was a video interview with the local NWS meteorologist-in-charge discussing storm surveys. The last tweet not discussed was of probabilistic tornado forecast graphic, but did not any characteristics that distinguished it from other top tweets or many from the entire population for that matter.

5.2.2.2 Flood event The tweet with the most impressions (exposure) ($n = 32{,}149$) was a photograph from 12 August at approximately 11:24 am, very early during the event (Fig. 9). The side-by-side comparison of a backyard before and after torrential rain was tweeted prior to the time of river crests and water entering homes, possibly allowing more devices to be in use instead of people being distracted by responding to rising water.

The most retweeted (attention) ($n = 107$) and liked ($n = 47$) message was a photograph (Fig. 10) from 13 August at approximately 9:53 am, more than 24 h into the event. This tweet showed flooding of a very recognizable spot in the most populated city of the forecast area, providing a geographic reference point and a level of personalization relevant to many. By this time, river flooding was occurring and it is therefore possible that fewer Twitter timelines were open for exposure. On the other hand, salience of the event may have increased attention for those that were online and therefore retweets.

Four of the five remaining tweets with higher exposure and attention were photographs. These included a picture of a home completely submerged, cars stalled on a busy road in

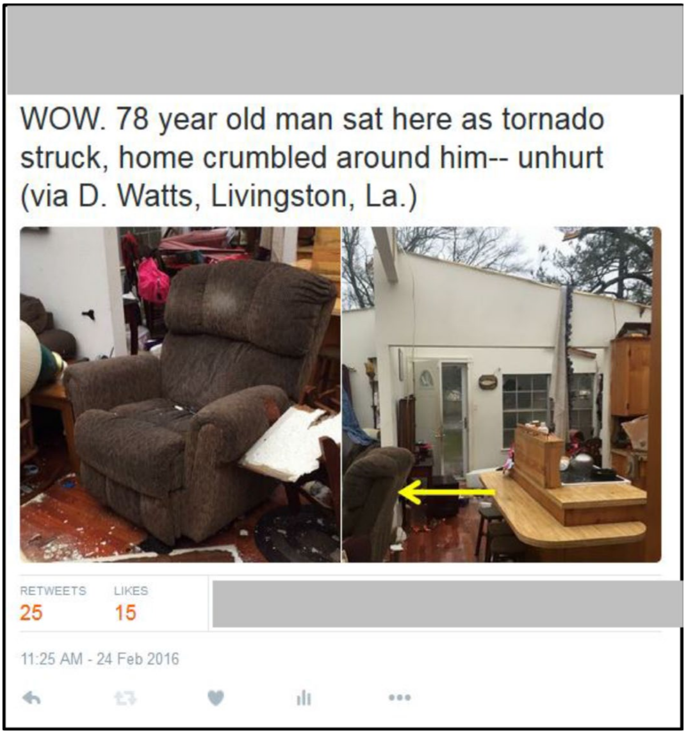


Fig. 8 Most retweeted message by @meteorologist account February 22–24, 2016

the city, flooding near LSU and a bayou overtaking a bridge on another busy road in the city. Each of these photographs provided unique environmental context clues that may have served as a part of the pre-decision processes of protective action. Therefore, it is no surprise that, much more than computer-generated graphics, tweets with photographs garner more exposure and attention.

The remaining tweet not yet discussed was a map outlining a continuing “flash flood emergency” for part of the forecast area. Like photographs, warning messages also play an important role ahead of one taking protective action. This message came at a time when water rescues were being performed by emergency managers, and may have reinforced the gravity of the situation for receivers.

6 Limitations, discussion and further considerations

Using tweets from three local television weather Twitter accounts during a tornado outbreak and flood event in southeastern Louisiana, this research provided a case study analysis to help understand messaging on Twitter during high-impact weather. In addition, the research applied principles of existing theory to message content and warnings. The following section will provide limitations to this approach and methodology. Discussion of results will be segmented by looking at each research question individually. The last

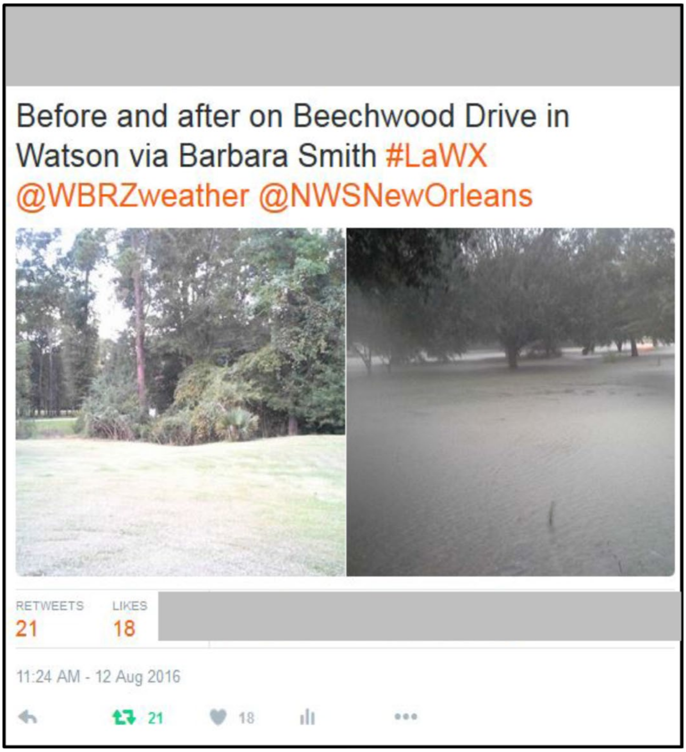


Fig. 9 @meteorologist tweet with most impressions during southeast Louisiana flood of August 2016

section will provide some overall takeaways, future research opportunities and recommendations for concerned fields.

6.1 Limitations

A small data set may be considered the biggest limitation to this research. However, feeling obligated to a robust data set can obscure the necessity for a good research question from the start. Big data may reveal even more truths about Twitter if complimented with an analytical and even ethnographical approach (Palen and Anderson 2016), such as in this work. Furthermore, as has been addressed, accessing full tweet history with measurable metrics is only possible for account owners. However, the case study approach does provide communication insights into key local information nodes during impact weather events. Understanding how Twitter use varies in specific case studies compared to larger, non-geographic specific data sets helps elucidate distinctions that local weather communicators need to optimize their messages.

This Twitter archive was not analyzed until several weeks to months after the events. Whereas one might assume that older tweets would naturally have more time to collect retweets, researchers have developed algorithms to predict life span of a tweet (Bae et al. 2014), and in practical use, communications, and marketing specialists note that the average life span of a tweet is quite short—about 15–30 min (Wenstrom 2017).

Fig. 10 @meteorologist tweet with most retweets during southeast Louisiana flood of August 2016

It is arguable that each individual tweet's metrics were inflated or deflated based on the wide range of social network sizes to which it may have been exposed. Increased followership does not necessarily result in more retweets (Hong et al. 2011). Additionally, impression, retweet and like numbers from this specific event could potentially be augmented because in times of disaster, users from a much broader geographic area converge on the topic (Hughes et al. 2014). Whether this inflates numbers or even if it does so uniformly is difficult to determine.

With regard to the metrics chosen, impressions imply that a user was shown a tweet in their timeline, but it is unknown whether the user scrolled through their timeline too rapidly to actually be exposed to the message. It can be said with more confidence that a retweet or like implies some level of attention to the tweet, such as reading the message, unless the user blindly retweets and likes messages. In the weather warning arena, exposure to a message means little without attention and subsequent action. However, action may not be taken if a receiver is not adequately exposed to environmental and social cues of a warning, or if a receiver cannot or does not devote attention to a warning message. These are all cognitive processes that cannot be measured through a database of tweets.

6.2 Discussion

To begin, there is a broad point to be made regarding the @meteorologist tweets versus the @TeamWeather1/2 warning tweets. In high-impact weather events, National Weather Service warnings are disseminated via a large number and variety of Twitter accounts. With regard to warnings, one may suppose there would be a "watering down" effect limiting the number of retweets from any one account. On the other hand, tweets from a single meteorologist are unique to only one account, so one might expect more retweets. This was not the case. The average number of retweets for tornado and flash flood warnings was higher than the average number of retweets for the selected top performing tweets (let alone the entire set) from the @meteorologist account in this study (Tables 1, 2, 3).

Higher exposure and attention suggest tornado and flash flood "warning" tweets are the most important messages during such events. These tweets may have language that is easier to discern and resonates better with a broader audience. They also may indicate the importance of credibility in warning disseminators, as receivers are more likely to trust an official source such as government and some media (Mileti and Sorensen 1991; Trainor and McNeil 2008; Carr et al. 2015).

Additional messages from individual meteorologists certainly have a place, providing reinforcement and specification to followers. Conversely, these tweets may also contain a bit more jargon than warnings, e.g., velocity signatures and correlation coefficients. This may provide explanation as to why these tweets did not show as high of numbers of impressions, retweets and likes compared to warnings; they simply appeal to a smaller segment of users.

This case study of local television weather Twitter accounts during a tornado outbreak and a flood event addressed two questions. First, do the numbers of retweets and likes in warning tweets reveal any trends in receiver preference and how do these trends fit within the existing literature on warning messages? Second, what traits are similar to tweets with the most impressions, retweets and likes and how do these trends fit within the existing literature on popular tweet content?

6.2.1 Warning tweets

Warning messages that contained threat and efficacy (a mitigating action) as well as a supporting map needed fewer followers to generate attention (retweet or like). Tweets tailored to a more regional or local audience will likely feel more personalized to a receiver and therefore be even more effective (Trainor and McNeil 2008). These particular events were nearly exclusive to the Baton Rouge DMA, where just two television stations consistently tweet warnings as they are issued. Comparing same storm warning messages from @TeamWeather1 and @TeamWeather2, which offered two very different types of tweets, offered a real-time example of whether the existing literature on risk perception and warning communication could hold true for social media. When eliminating the qualification that warning tweets must include a retweet from the associated television station account, @TeamWeather2 with threat-only text-only messaging actually outperformed @TeamWeather1 in sheer number of retweets/likes due to having access to higher followership. However, when adjusted to account for uneven followership, the results suggested that @TeamWeather1 warning tweets containing both threat and efficacy messaging, as well as an accompanying map, required fewer followers to generate a retweet/like, even though the statistical analysis was insignificant. This is a complimentary finding to the EPPM (Witte 1992) literature, which would suggest @TeamWeather1 uses a more effective warning message. It is worth noting that the @TeamWeather2 account used in this study lacked the specificity of a map or storm-based tornado and flash flood warning polygons. Sources naming entire parishes or counties could create confusion, as it is possible that only part of a parish/county is actually under the warning.

6.2.2 Exposure and attention to tweets from a single account

The general level of exposure and attention to different types of tweets was highly variable. It was evident in the available tweets that those containing pictures gained more exposure (impressions) and attention (retweets and likes). With regard to the literature, namely that on the PADM, photographs provide a way to communicate environmental and possibly even social cues that can help instigate protective action (Lindell and Perry 2012). The interest in photographs may show that Twitter followers of @meteorologist are performing milling activity and discovery of real photographs provides message verification (Quarantelli and Dynes 1977) or the fact that attention to online news media has been shown to increase with sensational images and text (Zhang et al. 2012). Of course, compelling photographs are difficult for a broadcast meteorologist to, personally, produce due to limited access to the outside environment during live television coverage of high-impact weather events.

Less prevalent in this study was exposure and attention paid to tweets without a photograph. A few tweets such as live storm analysis and associated radar images did have many impressions, retweets and likes. These made clear reference to geographic features and literature does widely agree that a key component of the warning message is to "personalize the threat" (Mileti and Sorensen 1991; Tierney 1995; Starbird and Palen 2010). Naming nearby landmarks likely helped appease this need and provided greater specificity (Trainor and McNeil 2008).

Some tweets also made an appeal to human compassion from both a text and visual perspective (Mileti and Sorensen 1991; Tierney 1995; Trainor and McNeil 2008). Related, some tweets metrics could have been boosted due to the use of a hashtag during these events, such as #LaWX or #LaFlood. This component of messages bears out implications that practitioners must consider. Given the use of common hashtags (Bruns and Burgess 2011), and the increased volume of compassionate tweets utilizing these hashtags, it is possible that some hashtags can be "hijacked" from those hoping to spread resourceful information. The stream of any particular hashtag related to a disaster may be overwhelmed by those offering support for victims and possibly from accounts not local to the disaster.

Identifying the role time played on tweet popularity (or lack thereof) is somewhat ambiguous. One could argue that tweets with high exposure and attention from early in the event were a sign that more people were on Twitter, before personal circumstances became dire due to power outages or rising water. In contrast, one could also argue that tweets with high exposure and attention later in the event were a sign of increased salience of the disaster and participation from outside of the region (Kogan et al. 2015). Several factors complicate both of those assertions. First, Twitter analytics experts have suggested the prime time for retweets, and thus attention, is during the later afternoon hours (Fontein 2016). Second, in practical use, communications and marketing specialists note the average life span of a tweet to be quite short, about 15–30 min (Wenstrom 17). Given the chronological nature of Twitter, tweets move further down timelines each second as users come and go on the platform (Wenstrom 17). Third, as humans have a limited amount of mental resources to process information (Lang 2000), recall and comprehension can be adversely affected by an over-abundance of information (Bright et al. 2015). Simply, tweet volume may have increased and contributed to what is known as social media fatigue (Bright et al. 2015), thereby resulting in less attention.

Weather events that cause greater impact to society generate a greater need for information and an increase in the information flow. Some weather events simply lead to more social media volume than others (Hong et al. 2011). Compared to the tornado event, the flood event occurred over a longer period and affected more people, requiring user attention span for much more time. Spatially, a larger area was affected, and likely, a higher number of Twitter users either were affected themselves or knew people that were affected. Dramatic photographs of flooded roads, submerged cars and overflowed streams became more and more common as the event progressed, but there were no identifiable temporal trends in the reach of such messages.

6.3 Further considerations

This type of study would be a prudent undertaking for researchers and local meteorologists wanting to gain better understanding of their local audience message preferences. Studies could benefit from comparisons of tweets from more than two accounts during the same weather event in the same regions. The methods could then be broadened to identify trends from one geographic region to another. Researchers might consider an array of different types of weather events and Twitter accounts from across multiple sectors such as public and private forecasters as well as emergency management. Discovery of trends in more effective tweets may help to optimize content and make for more efficient social networks.

Future research on social media and warning messages should work to determine how different Twitter metrics can be used as a measure of exposure, attention and possibly action. While factors such as time of day, users online and salience of the topic may affect impressions, retweets and likes, research agrees that photographs and specificity such as geographic locations are integral to inspire action.

Given the high volume of tweets in a long duration event, more research is needed to determine if Twitter users are affected by a concept known as social media fatigue (Bright et al. 2015) and to what level. Social media fatigue accounts for the limited mental processing capacity of people (Lang 2000) and the fact that at some point, the breadth of information becomes overwhelming as is therefore missed or ignored. The complications social media fatigue could present government, private and public sector forecasters during high-impact weather events are immense. More evidence of this phenomenon might inspire coordination with Twitter to allow users in need of information during a disaster to have an option to exclude information not pertinent to the disaster or the region affected.

Especially in large media markets, as many as five television stations with three or more meteorologists each could be providing analyses of the same situation. Future researchers could select high-impact weather events in a variety of different geographic regions, contact multiple local meteorologist Twitter account owners and request full archives. Due to the competitive nature of broadcast media, researchers from outside of the media industry or at least outside of the market under scrutiny may have better success at attaining these archives. This would allow further insight into types of tweets that receive the most exposure and attention (impressions, retweet and likes) and if trends in tweet type vary by region or type of weather event.

Exposure and attention to warnings are important to generate appropriate action, but too many warnings or conflicting warnings may cause maladaptive responses—and Twitter is especially vulnerable to these shortcomings. Warning messages need to be carefully tailored by region and coordinated among varying sources. Presenting warnings without identifying the threat, the proper actionable information and the spatial–temporal scope could lead to poor decision making from the end user. This is important because individuals will have their own network on Twitter, and will receive messages from any number of different sources. For communicators, quality and breadth of these networks are difficult to determine, reinforcing the need for weather messages such as warnings to be consistent across sources (Trainor and McNeil 2008; Lindell and Perry 2012).

To add layers to the work, future research could include time analyses of tweets. Instead of tweets being compared at one simultaneous point in time, a cohort analysis could analyze tweets at select time intervals such as first hour, second hour, first 24 h or first 72 h. This also will help practitioners understand whether pertinent weather information is reaching the target audience on time or later.

The reason Twitter has a heightened value among other social media mediums as a message and warning tool is because it has an ability to offer a chronological display of information. At the time of these events, that was the case. However, Twitter has since implemented a "top tweets" option that uses an algorithm to serves timelines with popular tweets. This algorithm, like Facebook[2], adds a new layer for future researchers to consider. Future questions may ask what is needed to make a tweet popular and move it up in timelines. It is possible, if not likely based on other recent work about tweet popularity (Sutton et al. 2015), that the same findings will hold true.

Case studies like this in addition to a thorough understanding of risk perception and warning communication literature are necessary for improved Twitter messaging and warning efforts. Those using Twitter as part of messaging and warning protocols should also be familiar with the "crying wolf effect" and the "false alarm ratio" (Barnes et al. 2007; Simmons and Sutter 2008).

For all of these reasons, haphazardly curated tweets may spread geographically vague or temporally inaccurate messages and warnings. Such poor practice would only further contribute to some ongoing industry wide issues.

Not only in weather, but in emergency management, there is a call for more research as to understanding how social media works and forming best practices (Hughes et al. 2014). Given the identification of local meteorologists as key information nodes during high-impact weather, more should be done to understand how these communicators can best reach their audiences with critical information. Hopefully, these findings provide a different scale and provoke future studies to understand the possible value of Twitter for warning communication. Key communicators in high-impact weather events, such as local broadcasters, may use these methods and findings to tailor their use of Twitter in similar events. While this study identified exposure and attention to actual tweets, synthesis with survey data could further portend what type of information is wanted by users. Overall, this work should continue a conversation on optimizing messaging on Twitter and other forms of social media across the weather enterprise.[2]

[2] Unfortunately, this study may have very little application to Facebook. Social media, like all technology, is adapting to users for platform optimization. Facebook previously provided a personalized newsfeed of updates from those with who you were associated. Minor adjustments were made to favor photographs over text. Now, over 100,000 individual criteria weigh on Facebook's newsfeed algorithm. Existing actions on the post, relationship to the source and time decay all factor into position of an item on a news feed (McGee

References

Bae Y, Ryu PM, Kim H (2014) Predicting the lifespan and retweet times of tweets based on multiple feature analysis. ETRI J 36(3):418–428. https://doi.org/10.4218/etrij.14.0113.0657

Barnes LR, Gruntfest EC, Hayden MH, Schultz DM, Benight C (2007) False alarms and close calls: a conceptual model of warning accuracy. Weather Forecast 22(5):1140–1147. https://doi.org/10.1175/WAF1031.1

Bright LF, Kleiser SB, Grau SL (2015) Too much Facebook? An exploratory examination of social media fatigue. Comput Hum Behav 44:148–155. https://doi.org/10.1016/j.chb.2014.11.048

Brotzge J, Donner W (2013) The tornado warning process: a review of current research, challenges, and opportunities. Bull Am Meteorol Soc 94(11):1715–1733

Brown VM, Keim BD, Kappel WD, Hultstrand DM, Peyrefitte AG, Black AW, Steinbilber KM, Muhlestein GA (2020) How rare was the August 2016 South-Central Louisiana heavy rainfall event? J Hydrometeorol 21:773–790

Bruns A, Burgess J (2011) The use of Twitter hashtags in the formation of ad hoc publics. In: 6th European consortium for political research general conference (ECPR 2011), August, pp 1–9

Carr RH, Montz B, Maxfield K, Hoekstra S, Semmens K, Goldman E (2015) Effectively communicating risk and uncertainty to the public: assessing the national weather service's flood forecast and warning tools. In: Bulletin of the American Meteorological Society (September), pp 1–44. http://doi.org/10.1175/BAMS-D-14-00248.1

Donner WR, Rodriguez H, Diaz W (2012) Tornado warnings in three southern states: a qualitative analysis of public response patterns. J Homel Secur Emerg Manag 9(2):15–20. https://doi.org/10.1515/1547-7355.1955

Ferrell J (2012) Social media: a new horizon for forecasting. In: Weatherwise, August, pp 12–18

Fontein D (2016) The best time to post on Facebook, Twitter, and Instagram in 2016. https://blog.hootsuite.com/best-time-to-post-on-facebook-twitter-instagram/. Accessed 21 Nov 2016

Giles DC (2002) Parasocial interaction: a review of the literature and a model for future research. Media Psychol 4(3):279–305. https://doi.org/10.1207/S1532785XMEP0403_04

Hoang TS (2015) Blogging during a crisis: threat and efficacy in online communication during a hurricane. Online J Commun Media Technol 5(2):1–30

Hong L, Dan O, Davison BD (2011) Predicting popular messages in Twitter. In: Proceedings of the 20th international conference on world wide web (www), pp 57–58. http://doi.org/10.1145/1963192.1963222

Kogan M, Palen L, Anderson KM (2015) Think local, retweet global : retweeting by the geographically—vulnerable during hurricane sandy. In: Proceedings of the 18th ACM conference on computer supported cooperative work & social computing, Vancouver, pp 981–993

Lang A (2000) The limited capacity model of mediated message processing. J Commun (Winter) 50:46–70

Lindell MK, Perry RW (2012) The protective action decision model: theoretical modifications and additional evidence. Risk Anal 32(4):616–632. https://doi.org/10.1111/j.1539-6924.2011.01647.x

McGee M (2013) Edgerank is dead: Facebook's news feed algorithm now has close to 100 k weight factors. Social Media Marketing. Marketing Land. http://marketingland.com/edgerank-is-dead-facebooks-news-feed-algorithm-now-has-close-to-100k-weight-factors-55908. Accessed 3 Nov 2015

Mileti D, Sorensen J (1991) Communicating risks to the public: international perspectives. In: Kasperson RE, Stallen PJM (eds). Springer, Dordrecht, pp 367–392 Netherlands

Footnote 2 (continued)

2013). Posts of urgent nature, such as tornado warnings, could appear hours later, long after expiry—once interaction reaches a critical level.

Morss RE, Mulder KJ, Lazo JK, Demuth JL (2015) How do people perceive, understand, and anticipate responding to flash flood risks and warnings? Results from a public survey in Boulder, Colorado, USA. J Hydrol 541:649–664. https://doi.org/10.1016/j.jhydrol.2015.11.047
NCEI (2017) Storm events database. https://www.ncdc.noaa.gov/stormevents/listevents.jsp?eventType=%28C%29+Tornado&beginDate_mm=02&beginDate_dd=22&beginDate_yyyy=2016&endDate_mm=02&endDate_dd=24&endDate_yyyy=2016&county=ALL&hailfilter=0.00&tornfilter=0&windfilter=000&sort=DT&submitbutton=Search&statefips=22%2CLOUISIANA#. Accessed 31 Aug 2017
NWS (2016) Severe weather event of February 23, 2016. https://www.weather.gov/lix/02232016severe. Accessed 5 Sept 2017
Palen L, Anderson KM (2016) Crisis informatics: new data for extraordinary times. Science 353(6296):224–225. https://doi.org/10.1126/science.aag2579
Peacock WG, Morrow BH, Gladwin H (1997) Hurricane Andrew: ethnicity, gender and the sociology of disaster. Texas A&M University, Hazard Reduction and Recovery Center, Texas
Hughes AL, Peterson S, LP (2014) Social media and emergency management. In: Critical issues in disaster science and management: a dialogue between scientists and emergency managers, pp 349–392
Phillips S (2007) A brief history of Facebook. https://www.theguardian.com/technology/2007/jul/25/media.newmedia. Accessed 30 June 2016
Quarantelli EL, Dynes RR (1977) Response to social crisis and disasters. Annu Rev Sociol 3(Janowitz 1968):23–49. https://doi.org/10.1146/annurev.so.03.080177.000323
Ripberger JT (2014) Social media and severe weather: do tweets provide a valid indicator of public attention to severe weather risk communication? Weather Clim Soc 6(4):520
Ritchie R (2015) History of iPhone: Apple reinvents the phone. http://www.imore.com/history-iphone-original. Accessed 30 June 2016
Rogers RW (1983) Cognitive and physiological processes in fear appeals and attitude change : a revised theory of protection motivation. Soc Psychophysiol Source Book 19(November):469–573. https://doi.org/10.1093/deafed/ent031
Rosenman ETR (2012) Retweets—but Not Just Retweets: quantifying and predicting influence on Twitter, 1–86. Retrieved from http://evanrosenman.com/Rosenman_thesis.pdf
Simmons KM, Sutter D (2008) Tornado warnings, lead times, and tornado casualties: an empirical investigation. Weather Forecast 23(2):246–258
Starbird K, Palen L (2010) Pass it on? Retweeting in mass emergency. In: Proceeding of ISCRAM (2010), pp 1–10
Suh B, Hong L, Pirolli P, Chi EH (2010) Want to be retweeted? Large-scale analytics on factors impacting retweet in twitter network. In: 2010 IEEE second international conference on social computing (Socialcom), pp 177–184. http://doi.org/10.1109/SocialCom.2010.33
Sullivan D (2014) Just like Facebook, Twitter's new impression stats suggest few followers see what's tweeted.http://marketingland.com/facebook-twitter-impressions-90878. Accessed 5 Sept 2017
Sutton J, Chi ES, Johnson B, Fitzhugh S, Gibson B, Butts CT (2014) Warning tweets: serial transmission of messages during the warning phase of a disaster event. Inf Commun Soc 17(6):765–787. https://doi.org/10.1080/1369118X.2013.862561
Sutton J, Ben Gibson C, Phillips NE, Spiro ES, League C, Johnson B, Butts CT (2015) A cross-hazard analysis of terse message retransmission on Twitter. Proc Natl Acad Sci USA 112(48):14793–14798. https://doi.org/10.1073/pnas.1508916112
Tierney KJ (1995) Getting ready: research on disaster preparedness. In: Tierney K, Lindell M, Perry R (eds) Facing the unexpected: disaster preparedness and response in the United States. National Academies Press, Washington, DC, pp 28–79
Trainor J, McNeil S (2008) A brief summary of social science warning and response literature: a report to COT, The Netherlands
Twitter Milestones (2016) https://about.twitter.com/. Accessed 30 June 2016
Wenstrom E (2017) The life span of a tweet. http://stantoncomm.com/life-span-tweet
West DM, Orr M (2007) Race, gender, and communications in natural disasters. Policy Stud J 35(4):569–586. https://doi.org/10.1111/j.1541-0072.2007.00237.x
Witte K (1992) Putting the fear back into fear appeals: the extended parallel process model. Commun Monographs. https://doi.org/10.1080/03637759209376276
Yan H (2016) Louisiana's mammoth flooding: by the numbers. http://www.cnn.com/2016/08/16/us/louisiana-flooding-by-the-numbers/. Accessed 25 Nov 2016
Yin RK (2013) Case study research: design and methods, 5th edn. Sage Publications, New York
Zhang C, Meadows C, Zhou S (2012) Online news sensationalism: the effects of sensational levels of online news stories and photographs on viewers' attention, arousal, and information recall. In: Annual meeting of the international communication association, May, pp 24–28