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Weather Communication on Twitter: Identifying Popular Content and Optimal Warning Format Via Case Studies and a Survey Analysis

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WEATHER COMMUNICATION ON TWITTER:
IDENTIFYING POPULAR CONTENT AND OPTIMAL WARNING
FORMAT VIA CASE STUDIES AND A SURVEY ANALYSIS

A Dissertation

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
In partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

in

The Department of Geography and Anthropology

by
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December 2017
For Jaimee and her unconstrained love and support

For Mom and Shane and their love and encouragement

For Barry and his belief in me and invaluable guidance

For Pat, Rocky, WBRZ and the opportunity to come to this special city of Baton Rouge

For Doug and his everlasting friendship
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ABSTRACT

The use of Twitter as a channel for weather information inspires a deeper analysis of key information nodes during episodes of high impact weather, especially local meteorologists. To optimize communication on the channel, it is important to understand what kinds of messages produce exposure and attention among users—which translates to knowledge that could improve the reach of a warning. Literature identifies two key models that well describe the cognitive processing of tweets and warnings. The Protective Action Decision Model (PADM) describes risk perception and the factors that enable or disable one from acting on a warning. Particularly through environmental and social cues, the first steps of the PADM could be aided or impeded by a tweet. The Extended Parallel Process Model (EEPM) describes the components of an effective warning message. Even in a tweet, ignoring one or both of the two critical components of a warning—threat and efficacy—could inhibit a user from taking the correct protective action, if any at all. Through two case studies of tweets during high impact weather events in southeast Louisiana, messages containing photos and videos are most likely to appear in Twitter timelines and therefore generate the greatest exposure. Similarly, followers of a local meteorologist Twitter account will be most likely to retweet and therefore pay attention to messages containing photos and videos. The case studies also revealed that, particularly with warnings, tweets containing equal levels of threat and efficacy, as well as some personalizing factor such as a map or geographic indicator generate more retweets and therefore attention. In a subsequent survey, case study results were not duplicated via self-reported interests from respondents. An example photo was less popular and an example warning with minimal actionable information was most popular. The survey also revealed that Louisianans prefer websites and Facebook to receive weather information, while mobile phone apps and Twitter scored lower preferences.
CHAPTER 1. BACKGROUND AND THIS STUDY

1.1 INTRODUCTION

Where print, radio and television are modern channels that imply credibility, Twitter and other social media are post-modern unfiltered channels where any “enthusiast” can post information—credible, official, or not. Author and professor Tom Nichols (2017) may have been on to something when discussing these social media shortcomings in his book “The Death of Expertise.” For the sciences, especially those in mainstream media like meteorology, there are an overwhelming number of amateur sources that inundate social media with questionable information. Not only does this present obvious safety concerns, but also creates an array of communication issues.

Recent amalgamations of meteorology and social science have led to tremendous improvement in weather communication. As of January 2016, the Pew Research Center reported that 21 percent of adult Americans use Twitter and 42 percent of users check it daily (Greenwood et al. 2016). Internet estimates are that more than 500 million unique tweets are sent on a daily basis (Lowe 2017). More specifically, Twitter has even been gauged as a metric for heightened public attention during severe weather (Ripberger 2014). Twitter, with other post-modern electronic channels, continues to modify communication strategies of practitioners. Scholars have provided comprehensive analyses of specific hazard warning processes (Brotzge and Donner 2013, Carr et al. 2015, Morss et al. 2015), but also call for further scrutiny of effective weather warning communication through social media. Field leaders have begun acknowledging social media and establishing guidelines for use. Both the American Meteorology Society and National Weather Association recommend additional study of channels like Twitter (AMS 2017, Bunting and Muzio 2014).
Literature for this research encompasses an array of fields, but some key works include: communication studies and the Extended Parallel Process Model (EPPM) (Witte 1992, Hoang 2015), risk perception (Quarantelli and Dynes 1977, Mileti and Sorenson 1991, Trainor and McNeil 2008, Sutton et al. 2014) and the Protective Action Decision Model (PADM) (Lindell and Perry 2012), social media and informatics (Kogan et al. 2015, Palen and Anderson 2016) and finally social science and meteorology (Lazo et al. 2009, Demuth et al. 2012, Ripberger 2014). One integrative study to compliment and contribute to existing literature would be scrutiny of risk perception, warning communication, and social media on a small scale. Rather than broad examination of weather communication, this study focuses on a specific channel used for weather communication from one specific source during one specific event.

Twitter timelines are chronological and therefore of greater benefit to the dispersal of time sensitive weather information. Additionally, since it has been proven as metric for attention to severe weather (Ripberger 2014), this research has given Twitter a closer look for message improvement. Research was segmented into three chapters. While previous studies on Twitter and disaster have amassed voluminous data sets to identify geographic usage trends (Kogan et al. 2015), linguistic features (Verma 2011) and content (Suh 2010, Hong 2011), there has yet to be an in-depth look at a single, key information node for weather information (Kogan et al. 2015)—a local meteorologist.

Chapter 2 is a case study of tweets passing through local meteorologist accounts during an episode of high impact weather. Tweets were collected for a given time period during the southeast Louisiana tornado outbreak of February 2016 to identify what types of tweets are most likely to travel through the Twitter network of a local meteorologist during high impact weather events. Reasoned a good fit to describe the flow of information through Twitter, the PADM
(Lindell and Perry 2012), components of exposure and attention were measured via impressions, retweets and likes. In addition to that, warning tweets were partitioned into a different data set and compared to warning tweets from another source to evaluate the ability of different warning tweet formats to travel through a network. The EPPM (Witte 1992) posits warnings providing a balance of threat and efficacy that are most likely to inspire adaptive responses. Thus, it was used as a basis to predict the most successful warning format.

Chapter 3 tests the findings of the tornado outbreak case study to look for differing trends during a longer duration, high impact weather event in the same region from the same local meteorologist. Floods evolve on much different temporal scales than tornadoes, hence exposure and attention to messages and therefore protective action may unfold differently as well. River flood warnings are communicated with expected inundation levels, determined by what occurred at key geographic locations during previous floods. The southeast Louisiana flood of August 2016 left forecasters with little precedent to project inundation levels and it was therefore a difficult weather communication scenario. While tornado warnings can vary slightly from region to region, flood warnings can vary in the same area on a case by case basis. Residents may be warned to stay alert, stay in place or evacuate. The use of Twitter by weather communicators, especially during a flood, taps into two known needs of warning communication—speed and social network “milling” or confirming of information (Quarantelli and Dynes 1977, Sutton et al. 2014). During an event of the magnitude of the flood of August 2016, many residents may be displaced, without power and therefore with limited access to information. Having strong connections with various social networks such as Twitter increases the chances of receiving a warning message (Donner et al. 2012). This study will follow the same methodology as chapter 2 for a much different type of disaster in the same geographic region. Data analysis identified types
of tweets most likely to travel through the network of a local meteorologist and evaluated the ability of different warning tweet formats to travel through a network.

Chapter 4 takes a different look at Twitter. The most recent academic survey assessing American’s channel preferences for weather information found television as the top choice (Demuth et al. 2012). With many new channels gaining popularity since then, including Twitter, the standing of each must be reevaluated. In this study, survey respondents ranked preferred channels for weather information as well as preferred channels for watches and warnings. Respondents were asked to rank interest in four types of weather tweets. Later in the survey, respondents were shown example tweets of those four types to compare self-reported interest to possible interaction with a tweet, a retweet, a like, scrolling past, or clicking a link. The survey also collected information about weather watches and warnings to gauge the understanding of terminology and the types of weather for which respondents want more information. Finally, the EPPM’s assertion that warning messages structured with threat and efficacy will spread most effectively through a social network will be tested again. Respondents were shown one of four example warning tweets with varying levels of threat and efficacy and asked to rate their likelihood of various interactions with that tweet. The full survey provides insight to preferred channels for weather information, how different types of weather information are valued by Twitter users, and how Twitter users interact with various warning tweet formats.

Twitter affords weather communicators the capability of reaching an increasingly mobile society at any time of the day. Weather messages need to be accurate but also timely, making the rapid release and serial transmission capabilities of the channel a potentially reliable partner for weather communicators (Ferrell 2012). However, with multiple sources converging on the same channel there can be overlapping, conflicting and inadequate information. Credible sources tweet
an array of content. Different sources may tweet the same content at the exact same time, but different wording may lead followers to varying interpretations. Disagreeing forecasters may tweet and create more uncertainty for a follower trying to make a decision. Public and private entities may send warning tweets providing varying levels of completeness.

Via gaps in the literature, and initiatives of organizations such as the American Meteorological Society (AMS) and National Weather Association (NWA) (AMS 2017, Bunting and Muzio 2014), the weather community has displayed need for a case study. Useful information could be extracted from a close-up look at local meteorologist Twitter account and new survey data assessing Twitter as a weather communication channel from the perspective of a Twitter user. We hope this research helps answer three important questions for weather communicators. What types of tweets does my audience want? To what types of tweets will my audience respond to? Are weather warning tweets as effective as possible?

Existing practices are built on good intentions but outcomes still have varying levels of success. There has been work to understand the key components of a successful message (Trainor and McNeil 2008, Lindell and Perry 2012) with modern electronic channels like print, radio and television broadcasting. However, multiple studies have identified that internet users find web sources to be just as, if not more, credible than modern channels (Johnson and Kaye 2004, MacDougall 2005). Credible or not, if that perception exists, practitioners must take the post-modern electronic channels, such as Twitter, seriously as delivery channels. Social media, and specifically Twitter, are no longer tertiary tools. It is time to optimize the 140 character message—often the first place where big weather messages are brought to being.
1.2 REFERENCES


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CHAPTER 2 – TWITTER STORM: ANALYSIS OF TWEET PERFORMANCE DURING THE SOUTHEAST LOUISIANA TORNADO OUTBREAK OF FEBRUARY 2016

2.1 INTRODUCTION

The largest tornado outbreak for southeast Louisiana since 1989 occurred on 23 February 2016 (NCEI 2016). In that 27-year period, weather warning communication had drastically evolved from channels such as television, radio, and print to internet and social media such as Facebook and Twitter. Since then, southeastern Louisiana has experienced high-impact weather events, including major hurricanes and tornadoes. However, unlike tropical storms which often allow days of lead time to prepare, tornado warning lead times are in the range of 15 minutes (Simmons and Sutter 2008). Therefore, the protective actions of people evolve on much more urgent temporal scales. This places high importance on the effectiveness and efficiency of tornado warning messages across all media channels.

Especially during high impact weather events, messages need to be accurate and timely. Having access to updated information, and strong connections with various social networks increases the chances one will receive a warning message (Donner and Diaz 2012). The rapid release and viral capabilities of Twitter make the channel an ally to weather communicators (Ferrell 2012), hoping to reach people outside of scheduled daily print and television or radio programming times.

Researchers have evaluated Twitter as a communication tool for weather, disasters, and hazards. Scholars have used Twitter as a metric for public attention (Ripberger 2014) and have provided comprehensive analyses of the tornado warning process (Brotzge and Donner 2013). Some have even analyzed the linguistic features common to popular messages (Verma et al. 2011). Many of these studies considered content trends from a large population. We wanted to
examine specifically what content comes from key messengers during high impact weather events - in this case, local meteorologists. Therefore, this research is a case study of Twitter communication from local broadcast meteorology accounts.

To optimize weather communication on Twitter, it is necessary to understand what types of tweets and what format of warning tweets spread more rapidly through these social media networks. For this research, our intentions were multifaceted. The data set consists of tweets from three local broadcast meteorology accounts during the southeast Louisiana tornado outbreak of February 2016. A tweet typology was defined and tweets passing through a single local meteorologist account were classified. The analysis identified tweet types from the event that garnered a high level of exposure and attention per the Protective Action Decision Model (PADM) (Lindell and Perry 2012) and looked for characteristics common to popular content. In addition, we evaluate warning tweets specifically to test the Extended Parallel Process Model (EPPM) (Witte 1992) as an effective predictor of warning tweet performance. To do this, we needed to use two additional local accounts, with differently formatted warning messages. The key nomenclature used with Twitter is highlighted in Table 2.1.

Table 2.1. Key terms and definitions of this research.

<table>
<thead>
<tr>
<th>TWITTER TERMINOLOGY</th>
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<tr>
<td>Tweet</td>
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2.2 METEOROLOGICAL REVIEW

On 23 February 2016 an upper level trough and associated surface low pressure system produced 13 tornadoes in southeast Louisiana and south Mississippi. One day prior to the event,
the National Weather Service (NWS) - Storm Prediction Center (SPC) placed parts of the central Gulf Coast under a “moderate risk” for severe weather, which heightened public awareness for the event. In all, the local NWS office, which includes the entire area of study for this event, issued 25 tornado warnings. The 13 tornadoes that touched down ranged in strength from EF0 to EF3 after storm surveys were completed (Fig. 2.1). Two deaths and 92 injuries were reported, while 75 of those injuries occurred in St. James Parish where a mobile home community was struck by an EF2 tornado (NCEI 2017, NWS 2016).

![SPC Storm Reports for 02/23/16](image)

**Figure 2.1.** Storm reports for 23 February 2016. Graphic is from the Storm Prediction Center and can be found at [www.spc.noaa.gov](http://www.spc.noaa.gov).

### 2.3. LITERATURE REVIEW

#### 2.3.1. Risk Perception and the Protective Action Decision Model

To develop useful weather communication protocols, it is important to understand how people respond to warnings as disasters unfold (Peacock et al. 1997). Risk perception is a key
The Protective Action Decision Model (PADM) (Lindell and Perry 2012) (Fig. 2.2) is a conceptualization of the risk perception process from the environmental and social context, to psychological process to protective action in response to disaster stimuli. According to the PADM, protective action will be implemented when the receiver determines the immediacy of the threat, effectiveness of the action to justify disruption of normal behavior, and has all of the information needed to do so (Lindell and Perry 2012). In the example of a tornado warning, this would mark the point where a person shelters in a study building or low-lying area.

The process of protective action decision-making begins with environmental cues, social cues, and warnings. Warnings are messages transmitted from a source via a channel to receivers. For the purposes of this study, local meteorologists are the sources and Twitter is the 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).

![Figure 2.2. Protective Action Decision Model (Lindell and Perry 2012)](image)

As is evident throughout the PADM, numerous obstacles stand in the way of these processes. Consider some of the obstacles presented in a tornado event. As one’s residence is often viewed
as a safe, comforting place under duress, heeding advice to leave a mobile home for sturdier
refuge becomes challenging. One must perceive great danger to leave comfort (Mileti and
Sorensen 1991). Environmental cues such as dark skies, funnel clouds, or perhaps even a
developed tornado may be necessary for a receiver to heed warnings. Additionally, despite
availability of various government and media sources and channels distributing warning
information, many people place their highest trust in family and friends and social networks are
used to confirm, personalize, and understand threats (West and Orr 2007). Even if a warning
message meets all the criteria deemed effective, if reaction from one’s social network is not also
strong, action may not be taken.

Simply put, if a receiver is not adequately exposed to environmental and social cues of a
warning, action will not be taken. If a receiver cannot or does not devote attention to a warning
message, action will not be taken. Finally, if a user cannot comprehend a warning due to
language barriers or technical jargon, action will not be taken (Lindell and Perry 2012). Even if
effective messages are created, it is difficult to know whether a message receiver pays attention
to or acts on those messages (Ripberger 2014).

Situational perceptions then facilitate or impede protective action decision-making. Each
receiver will have different threat perceptions based on beliefs that a hazard will or will not cause
harm to life or property (Lindell and Perry 2012). The dread factor (Slovic et al. 1982), “crying-
wolf effect” (Barnes et al. 2007), and false alarm ratio (FAR) (Simmons and Sutter 2008), may
all have an impact on perceptions of a particular environmental threat. Intrusiveness of a hazard
and previous experience may influence perceptions and actions (Trainor and McNeil 2008). It is
possible for one to be under a tornado warning multiple times without actually experiencing a
tornado. Therefore, specificity is an important characteristic of a message (Trainor and McNeil
Receivers must also have positive perceptions of the protective actions being advised (Lindell and Perry 2012).

A receiver then transitions into protective action decision making, risks are identified and available actions are assessed. People will identify and assess risks at hand and identify and assess available actions. Threats more proximal in time and distance tend to inspire preparedness, or in other words, if a situation becomes real, then real action will be taken (Tierney 1995).

The model remains relevant to Twitter through this point, as receivers may reach a need to further assess information. People will seek verification of official warning messages by discussing the warning with members of their social network (Quarantelli and Dynes 1977). This action has been called “milling,” and Twitter offers one way for social networks to verify official messages (Sutton et al. 2014). Milling makes it necessary that warnings include information such as graphics and web links that further inspire protective action (Sutton et al. 2014). Furthermore, this reinforces the need for multiple sources (emergency management, media, NWS) to issue the same message, as individuals perceive different levels of credibility from various sources (Carr et al. 2015, Mileti and Sorenson 1991). A clear, repeated message communicated with specificities such as locations helps to personalize risk and generate action (Mileti and Sorensen 1991, Su et al. 2010, Starbird and Palen 2012).

The need for additional information may instigate a feedback loop where receivers begin the whole process anew via a new source or channel in search of new environmental or social cues. Some people may want more information on the threat or the possible actions that can be taken and some receivers may chose to relay the information to others (Lindell and Perry 2012)—a retweet in the case of Twitter.
2.3.2. Social Media and Informatics

From February 2004 to June 2007, the world was introduced to the smartphone and social media applications like Twitter (Phillips 2007, Ritchie 2015, Twitter 2016). Social media applications on smartphones allow constant connectivity to a social network with access to multiple information sources on multiple channels. For example, by the end of February 2016, there were 320 million active Twitter users (Twitter 2016). Serial transmission (Sutton et al. 2014) of messages allows a network of dozens, hundreds, or thousands to spread information rapidly. Thus, a channel such as Twitter becomes a valuable asset to meteorologists and others with an objective of getting and reinforcing messages to as many people as possible during high impact weather events.

As a social media platform, Twitter has the ability to enhance situational awareness during an emergency (Hughes et al. 2014) similar to the environmental and social cues outlined in review of the PADM. In researching Twitter content during high impact weather events, it must be understood that an entire geographic population is not likely uniformly represented. However, the Twitter population of that geographic area is likely to represent a range of behaviors and ideas (Palen and Anderson 2016).

Ripberger (2014) provided some evidence for this by finding that Twitter is a viable metric of public attention during high impact weather. In a statistical analysis of six-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 emanated from infrequent severe weather commentators in the public
rather than experts. Additionally, messages such as watches and warnings correlated with high social media volume (Ripberger 2014).

Since Twitter has been identified as a channel where traffic increases during times of severe weather and can provide retransmission and reinforcement of weather messages, 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 type of content being shared. There was little to no relationship between the number of previous posts and “retweetability” of a post. Tweets that contain weblinks to additional data garnered a high retweet rate (Suh 2010). This showed some validity to the desirability of “hidden content” or links included in a tweet. Additionally, use of a hashtag (#) appeared 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.

2.3.3. Warnings and the Extended Parallel Process Model

In disaster situations, users have been found to favor messages that are specific, clear and themed toward public safety (Sutton et al. 2014). People in the path of disaster favor locally-created tweets and those with locally-actionable information (Kogan et al. 2015, Starbird and Palen 2010). Those tweeting or retweeting information during a disaster, are most commonly those geographically affected by the disaster, while the local media serve as key centers of information (Kogan et. al 2012).

As critical information nodes during weather related disasters (Kogan et al. 2015), local meteorologists communicating warnings should be providing messages with a balance of threat
and efficacy. The Extended Parallel Process Model (EPPM) (Fig. 2.3) describes the cognitive processes that follow warning messages. Fear appeals are persuasive messages designed to imply harm to people if recommended actions are not taken (Witte 1992). Fear appeals 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). Threat and efficacy exist as external variables that a person must perceive (Rogers 1983, Witte 1992). From the viewpoint of a forecast user, threat is perceived susceptibility and severity while efficacy is user capacity to take action and the perceived effectiveness of that action (Witte 1992). If a threat is determined to be high, fear will initiate a person to begin evaluation of efficacy of the recommended response. However, if the threat is gauged as low, no further cognitive processing occurs (Witte 1992). Messages are rejected if themed toward threat with an absence of efficacy.

Figure 2.3. Extended Parallel Process Model (derived from: Witte 1992)

Receivers of that message may respond to 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). Messages are often accepted if balanced with a high level of threat and efficacy. Receivers of that message will then attempt to mitigate danger
and hopefully adapt 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 as disaster impacts near (Hoang 2015). Messages that only convey threat are more likely to inspire fear appeals, which are likely to fail (Witte 1992). Message receivers responding to fear, may feel helplessness and may take the wrong protective action or no action at all.

2.3.4. Summary and Research Questions

I believe the PADM is well suited to describe the cognitive processing of tweets during a weather disaster, where an impression implies that a follower has been exposed to a message and a retweet, like or reply suggests some level of attention to the message. Furthermore, the EPPM seems a good fit to describe the most effective format of a weather warning tweet, one that provides both threat and efficacy. Though limited by characters (140 to 280 in 2017), including links, tweets can feasibly be constructed to meet all appeals of the EPPM. Previous literature suggested an implied obligation to “big data” can obscure the necessity for a good research question from the start. Big data may reveal more truths about Twitter if then given an analytical and even ethnographical approach (Palen and Anderson 2016). My review has found most studies do not specifically focus on information coming from local broadcast meteorologists, opening a niche for this research. Indeed, this particular study does not reveal a sample size that would be considered big data. The case study approach was utilized to identify any underlying trends in the data at hand, if nothing more than to validate existing literature and 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 a specific case (Yin 2013).

This study addresses four research questions to contribute to the understanding of social media for weather communication.

- First, what was the general level of exposure and attention to tweets from one television weather station during the February 2016 southeast Louisiana tornado outbreak?
- Second, how did tweet type affect exposure and attention to tweets during this event?
- Third, what aspects of specific tweets led them to perform exceedingly well compared to other tweets?
- Finally, how did threat and efficacy in official warning message tweets affect exposure and attention to tweets?

2.4 METHODS AND HYPOTHESES

2.4.1. Data

This work provides a case study of Twitter messaging from the southeast Louisiana tornado outbreak of February 2016. Tweets come from two local broadcast television news affiliates in the Baton Rouge Designated Market Area (DMA). Specifically, we collected Tweets created between 22-24 February 2016 from three Twitter accounts: one local meteorologist’s professional account (@meteorologist) and two accounts that are operated by local broadcast meteorology teams (@TeamWeather1; @TeamWeather2). @meteorologist account had approximately 2,300 followers at the time of the event, and represents one individual meteorologist’s public following on Twitter. This data set will be used for a content and statistical analysis of tweets. @TeamWeather1 and @TeamWeather2 immediately disseminated
NWS warnings during the event, and represented a television weather team. @TeamWeather1 and @TeamWeather2 had a number of followers proximal to each other but greater than @meteorologist. The addition of these two accounts allowed statistical analyses of specifically warning tweets.

We aimed to assess performance of @meteorologist tweets that occurred over a three day period. Retweets, likes, and replies are tweet performance data available to the public, but only account owners have access to full metrics of each individual tweet, including impressions (defined below). An author of this work owned @meteorologist. Twitter allows account owners to download a complete history of tweets sorted by year and month. Retrieving tweets from non-owned accounts is a bit more cumbersome, especially in the competitive space of broadcast television. One can use Twitter’s Application Program Interface (API) to retrieve tweets with specific words, phrases and hashtags from any public account during a specified date and time. However, this method has two limitations. First, it is plausible that some tweets pertinent to the study will lack the words, phrases, or hashtags used for API data collection. Second, the API feature returns a sample of tweets, which may not reflect the full body of tweets especially when the topic is less common (e.g., one regionally-confined tornado outbreak) (Morstatter et al. 2013). Thus to collect every tweet originating or passing through an account required manually collecting tweets and available metrics. For this research, through owned (@meteorologist) and non-owned accounts (@TeamWeather1 and @TeamWeather2), we manually entered tweets into a spreadsheet for content analysis of tweet type and statistical analysis of the performance measures. For content and statistical analysis, we first provide a breakout of tweets originating from @meteorologist to examine the account as a source of information. Next, we included retweets that @meteorologist passed along to examine it as aggregator of information. For
exposure and attention to warning messages, we included @TeamWeather1 and 
@TeamWeather2.

2.4.2. Content Analysis, Tweet Types

To extract useful information from this analysis for practitioners, tweets of similar 
content were assigned a type. Three types were identified and tweets analyzed were inductively 
assigned based on source of information, nature of content, and language used.

1) Official statement tweets are content issued by government entities such as NWS or 
city leaders. Official statements include outlooks, watches, warnings or notices about 
road and school closures.

2) Value-added tweets are content from private entities such as broadcast media or the 
public. Television news consultants stress uniqueness and therefore local broadcast 
meteorologists are expected to provide original content and analysis, which is deemed 
“value-added.” Value-added tweets include independent analyses of a scenario, technical 
jargon and information not part of an official statement.

3) Engagement and observation tweets are photos, reports and interactions from user 
accounts. Engagements and observations include images of storms, damage or disaster 
response.

These three types were determined to adequately encompass variations in content during high 
impact weather event without bogging down the case study with too many subtypes. In addition, 
the definitions we presented do not allow much room for crossover within types. For instance, if 
a picture is tweeted by NWS, it is still considered an engagement and observation; if an NWS 
warning is tweeted by a private entity, it is still considered an official statement.
2.4.3. Statistical Analysis, Measuring Exposure and Attention

Per the PADM, exposure and attention are critical phases of protective action decision making. As such, meteorologists tweeting weather information during impact events hope to illicit such behaviors by improving the exposure and attention to their messages. We examined the level of exposure and attention to tweets and retweets from @meteorologist by assessing 1) impressions, 2) retweets, and 3) 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 often a tweet is viewed. 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). However, a retweet or like signifies interaction with the tweet indicating some level of attention, more than simple exposure to a tweet. @TeamWeather1 and @TeamWeather2 had a comparable number of followers during the tornado event and were used to evaluate the effect of warning format on attention to messages (retweets). However, the retweet count alone would be insufficient to evaluate attention due to the disparities in associated, retweeting accounts. To make the most accurate comparison possible, only tornado warning tweets from each weather account subsequently retweeted by the associated television station accounts were considered. Still, this left an uneven comparison as one station had approximately 39,000 more followers at the time—almost double the other. Therefore, to soundly identify the performance of one warning tweet format versus another, each tweet’s retweet count was divided by the number of followers on the main account to calculate an average number of followers needed to achieve a retweet. Lower numbers would then suggest fewer people within that particular social network are needed to generate a retweet.
and that would point toward more attention and potentially a more effective formatting of the warning tweet.

2.4.4. Hypotheses

Based on our research questions, we developed four hypotheses related to tweet content and levels of exposure and attention. Some tweets are thoroughly retransmitted and others are not. Despite message importance or quality, unknown factors such as time of day, users online and salience of a topic may affect the number of impressions, retweets or likes of a tweet.

**H1. Tweets will vary widely in their exposure and attention.**

Given the PADM, tweets containing images of the risky environment and making mention to geography provide “environmental cues” should have a higher level of exposure (impression) and attention (retweet or like). Further, tweets with reports from residents or affected individuals provide “social cues” that should increase the level of exposure and attention. Tweets with images also potentially acquiesce to research that attention to online news media is increased by sensational images and text (Zhang et al. 2012).

**H2. Engagement and observation tweets will have the highest level of exposure and attention.**

Official statements from government agencies are messages that are often shared through multiple sources. Value-added tweets offer information beyond what may be included in an official statement and have a greater possibility of being unique to one source. Since official statements are likely to be repeated across many sources, we expect this to limit the number of retweets on official statements compared to the more unique value-added tweets.

**H3. Value-added tweets will have more exposure and attention than official statements**

Retransmission of warning messages through social networks is vital to reach as many people as possible and represents social cues and milling activity known to happen in the
preparedness period of an emergency. It is possible that an increased level of attention to warning tweets can be expected by formatting tweets with respect to the EPPM; that is, they will provoke more attention by including both threat and efficacy. Thus, using the retweet metric, we expect that:

\[ H4. \text{Official warning statements which focus on threat and efficacy will be retweeted more than other warning tweets} \]

Hypotheses 1, 2, and 3 address how message type affects exposure and attention to a message and will be addressed with data analysis on the @meteorologist account. Hypothesis 4 focuses specifically on official statements to understand how format of a warning tweet translates into levels of attention and will draw from @TeamWeather1 and @TeamWeather2 data.

2.5. RESULTS

2.5.1. Exposure and Attention by Tweet Type

2.5.1.1. @meteorologist tweets

During this tornado event, there were 60 original tweets from the @meteorologist account. Among the 60 original tweets, there were 2,224 average impressions per tweet (Table 2.2) with a standard deviation of 1,656. Nine tweets were one standard deviation above the mean and six tweets were one standard deviation below the mean in impressions. Original tweets from @meteorologist received an average of 3.8 retweets and 2.7 likes but the standard deviations were 4.3 and 3.5 indicating positively-skewed distributions. Seven tweets had zero retweets and eight tweets had zero likes. These results suggest that tweet exposure and attention varied widely per tweet, supporting H1, and that the data set contained a large number of tweets with low exposure and attention.
Table 2.2. @meteorologist tweet statistics for 22 – 24 Feb. 2016 (highlight denotes highest value per statistic)

<table>
<thead>
<tr>
<th>TWEET TYPE</th>
<th>ORIGINAL CONTENT</th>
<th>Impressions</th>
<th>Retweets</th>
<th>Likes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Total (SD)</td>
<td>Mean (SD)</td>
<td>Median</td>
</tr>
<tr>
<td>All</td>
<td>60</td>
<td>423413</td>
<td>7177 (6314)</td>
<td>6099</td>
</tr>
<tr>
<td>Official Statements</td>
<td>13</td>
<td>73386</td>
<td>5645 (3295)</td>
<td>5175</td>
</tr>
<tr>
<td>Value-Added</td>
<td>24</td>
<td>112740</td>
<td>4698 (3350)</td>
<td>4417</td>
</tr>
<tr>
<td>Engagements &amp; Observations</td>
<td>23</td>
<td>237287</td>
<td>10786 (8194)</td>
<td>7947</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>RETWEETS</th>
<th>N</th>
<th>Total (SD)</th>
<th>Mean (SD)</th>
<th>Median</th>
<th>Total (SD)</th>
<th>Mean (SD)</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>85</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>2686</td>
<td>21.9 (41.2)</td>
<td>7</td>
</tr>
<tr>
<td>Official Statements</td>
<td>24</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>522</td>
<td>12.1 (21.4)</td>
<td>8</td>
</tr>
<tr>
<td>Value-Added</td>
<td>19</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>374</td>
<td>11.0 (25.2)</td>
<td>4</td>
</tr>
<tr>
<td>Engagements &amp; Observations</td>
<td>45</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>4728</td>
<td>26.6 (56.5)</td>
<td>8</td>
</tr>
</tbody>
</table>

Value-added tweets were the most common tweet type from @meteorologist making up 80% of the data set while engagements/observations and official statements each made up 10% of the set (Table 2.2). Value-added tweets made the most impressions in sum, but this is skewed by higher volume of tweets. Therefore, we examined the average number of impressions by each tweet type. With 3,191, official statements had the largest average number of impressions per tweet followed by engagements and observations with 2,568 and value-added statements with 2,059. Official statements also had the highest average number of retweets with 6.7, followed by
engagements and observations with 5.5 and value-added with 3.2. In contrast, value-added
tweets had the highest average number of likes with 2.7 followed by 2.3 for engagements and
observations then official statements with 2.0. Statistics suggest the highest level of exposure and
attention is for the official statements tweet type for tweets from @meteorologist. These findings
do not support H2 or H3.

One cannot give attention to a message if they are not exposed to it. Since retweets and likes
indicate attention, by dividing these metrics by the impressions metric, which indicates exposure,
we can provide an estimate for this account during this event as to the average number of
impressions needed to achieve attention. For the @meteorologist account, there was an average
of 814 impressions needed for each retweet and 1,145 impressions needed for each like. This
suggests fewer people needed to be exposed to a message to retweet it than to like it.

 Tweets with a large N for retweets and likes indicate a high level of attention. These outlier
tweets, those with the highest number of retweets, likes, or impressions, were examined
specifically to understand how they differed qualitatively from other tweets. A picture of a
recliner sitting in the middle of a destroyed home garnered the most retweets by a wide-margin
(n = 24) with 12 more than the second most retweeted message (Fig. 2.4).

The tweet stated that an elderly man was in the chair as a tornado destroyed his home. While
on average, official statements received more retweets, the large number of retweets for this
particular engagement and observation tweet offers marginal support for H2 that engagements
and observations can garner high exposure and attention.

The most liked tweet was a reflection of gratitude that more lives were not lost during the
event. With a tweeted image relaying an actual email sent in by a thankful viewer, the tweet

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received 20 likes and made 4,539 impressions, but this is only partial support for H3 that value-added tweets will have more exposure and attention than official statements.

The tweet with the most impressions (n = 7,265) was of a value-added tweet with an image showing rotation in a tornadic thunderstorm (Fig. 2.5). There is one element that separates this tweet from others—four well-known geographic indicators. Four of the top nine tweets referred to a geographic location. Mentioning town names and key thoroughfares seemed to contextualize the tweet to an extent beyond more common geographical references to a parish.

![Figure 2.4. Most retweeted message by @meteorologist account 22 – 24 Feb. 2016](image1)

![Figure 2.5. Most impressions by @meteorologist tweet 22 – 24 Feb. 2016](image2)

2.5.1.2. @meteorologist retweets included

By introducing retweets through @meteorologist, an additional 130 tweets became available but 45 were removed due to irrelevance to this analysis. As previously noted, impressions data are only available to the originator of a tweet, and therefore will not be included for the remainder of the analysis.

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1 Forty-five tweets were excluded as they were reply messages or retweets of miscellaneous remarks from followers that are irrelevant to this data analysis. Excluded tweets include retweets of complimentary messages from followers or reply messages serving as communication between other organizations done via Twitter in lieu of phone/email.
Among the 85 retweets that passed through @meteorologist, most were retweeted less than 20 times, but a minority garnered much attention. Messages retweeted by the @meteorologist account averaged 28.9 retweets compared to just 3.8 retweets for original content (Table 2.2). The large difference between mean (28.9) and median (9) again indicated a highly skewed distribution. 13 tweets were one standard deviation above the mean with anywhere from 64 to 350 retweets (Fig. 2.6).

![Number of Retweets Frequency](image)

**Figure 2.6.** Histogram showing frequency of select ranges of retweets through @meteorologist account

Statistics on the retweeted content from @meteorologist supported H2 that engagement and observation tweet types will be retweeted the most (mean = 44.2), indicating the highest level of exposure and attention, followed by official statements (mean = 17.3) and value-added tweets (mean = 6.7). There was not strong support for H3. In fact, no value-added tweets had retweet numbers at least one standard deviation above the mean. Of the 13 most retweeted messages, 11 were engagement and observation tweets. The other two were official statements.
What about the 13 most retweeted messages explained their resonance? Again, we qualitatively evaluated these tweets for content. The most popular tweet did entail damage—the most devastating of the event, from what turned out to be the strongest tornado (although that was unknown at the time of the tweet).

Several nuances likely increased the exposure and attention to this tweet. While there had been several photos of severely damaged homes, downed infrastructure, and toppled trees, very few photos offered a wider scope of damage. The picture from Convent, Louisiana (Fig. 2.7) was one of the first of the day to show multiple structures in ruin. Also, for the first time that day, this tweet suggested serious harm to people. Human compassion for those hurt or trapped may have sensationalized an already upsetting image. In addition, the breaking news element of this tweet may have carried weight.

The next three most popular messages, all with more than 150 retweets, contained video or photos of actual tornadoes, which provided environmental cues confirming the forecasted threat. A photo of a waterspout very early in the day was the first image to verify threats that had been disseminated many days in advance.

Of the last two messages to get over 100 retweets, one was actually a repeat of the most popular—a link to an online news story that detailed the breaking news of search and rescue happening in Convent. The other was another damage photo (Fig. 2.8). While this one was less impressive than many others from that day, it was one of the first photos of the day to show any damage whatsoever. In addition, the damage was to a recognizable business in a populated area. Finally, it contained a humorous hashtag—not necessarily inappropriate since nobody was hurt. Five of the seven remaining retweets landing one standard deviation above the mean were damage pictures from locations that had experienced the most intense tornadoes—EF2 or higher.
The other common trait to all of these tweets was that they came very soon after the tornadoes had struck, not grouped in with dozens of images tweeted the following day, after mass media converged on the scene increasing the number of information sources and amount of content available to share.

The final two tweets receiving high amounts of exposure and attention were official statements. Surprisingly, neither of these were weather warnings on the day of the event. Retweeted 99 times, the most popular official message was a depiction of all damage paths overlaid on Google Maps by the NWS. This was the earliest day-after tweet bringing scope and magnitude of the entire event into light. One day prior to the event, a television news reporter broke news that the entire school system of a parish would be closed due to the impending
weather. Simply put, this message personalized the situation for families in the area contributing to overall exposure and attention.

Statistical performance of retweets provides reinforcement of H2 that engagement and observation tweets will have the greatest exposure and attention. Not only did engagements and observations account for the most retweets in sum, but also the highest average retweets by type. Results continue to work against H3 that value-added messages will have more exposure and attention than official statements. Not only did value-added statements receive fewer retweets than official statements, but also had a lower average number of retweets. Official statements accumulated over 150 more retweets than value-added statements despite having 37 less tweets to do so.

2.5.2. Attention to Warning Messages

@TeamWeather1 and @TeamWeather2, which automatically tweet NWS warnings provide statistics to assess attention to warning tweets. Both @TeamWeather1 and @TeamWeather2 sent out nearly 20 warning tweets on 23 February 2016—some of which were duplicates or warning updates. Comparison allowed evaluation of the EPPM as a model for formatting warning tweets. @TeamWeather1 tweeted warning messages identified tornado threat, provided efficacy (or a mitigating action) and included a map of the warned area (Fig. 2.9). @TeamWeather2 tweeted a text only warning message that identified the tornado threat, did not provide efficacy and named the threatened area—by parish/county (Fig. 2.10).

There were five tornado warnings retweeted from both main station accounts at the same time. Though the data set is small, some statistical evidence indicated inclusion of threat and efficacy components of the EPPM increased attention to warning messages (Table 2.3). While @TeamWeather2 had a higher average number of retweets (15.8) than @TeamWeather1 (10.6),
when adjusted for number of followers by retweeting accounts, the @TeamWeather1 account demonstrated a more efficient social network. @TeamWeather1 averaged 5,148 followers per retweet compared to 5,898 followers per retweet from @TeamWeather2. H4 predicted that official warning statements focused on both threat and efficacy as suggested by the EPPM would be retweeted more than other warning tweets. Given the lower average number of followers

**Table 2.3.** By tornado warning, retweets per account (left), number of followers per retweet (right) (highlight denotes highest value per statistic)

<table>
<thead>
<tr>
<th>Time of Warning</th>
<th>Total Retweets by Account</th>
<th>Followers per Retweet by Account</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>@TeamWeather1</td>
<td>@TeamWeather2</td>
</tr>
<tr>
<td>1146a</td>
<td>16</td>
<td>15</td>
</tr>
<tr>
<td>1240p</td>
<td>5</td>
<td>20</td>
</tr>
<tr>
<td>103p</td>
<td>15</td>
<td>19</td>
</tr>
<tr>
<td>311p</td>
<td>10</td>
<td>16</td>
</tr>
<tr>
<td>406p</td>
<td>7</td>
<td>9</td>
</tr>
<tr>
<td>Total</td>
<td>53</td>
<td>79</td>
</tr>
<tr>
<td>Average</td>
<td>10.6</td>
<td>15.8</td>
</tr>
</tbody>
</table>
needed for a retweet, warning tweets designed with respect to the EPPM did seem to indicate a greater potential to generate attention.

While not part of the studied data set, a glance at local NWS tornado warning tweets during the event showed higher retweet numbers than @TeamWeather1 and @TeamWeather2 with threat only messaging (Fig. 11). It is possible those numbers result from a more weather savvy Twitter following. Given what we know about threat messaging and fear appeals though (Witte 1992), those retweet numbers should not be viewed as a success for the NWS. Messages that focus on threat without efficacy can inspire irrational decision-making (Witte 1992). Per the EPPM and findings presented here, it might be possible for NWS warning tweets to get more attention (retweets) with a revised message format.

Figure 2.11. National Weather Service warning tweet format, tornado warning #1 on 23 Feb. 2016
2.6. DISCUSSION, LIMITATIONS AND FUTURE STUDY, CONCLUSIONS

2.6.1. Discussion

This research aimed to add to the literature on social media and warning communication using a case study of local meteorologist Twitter accounts during a tornado outbreak in southeastern Louisiana. Through content analysis of tweets and statistical analysis of tweet performance, we provided an assessment of how exposure and attention varied by tweet content. Results contribute to use of two models as tools for risk perception and warning communication. Content analysis suggests the PADM is a good fit to describe the flow of information on Twitter through pre-decision processes. Statistical analysis indicated that the EPPM is good predictor of attention to warning tweets. H1 expected significant variation in exposure and attention to tweets. Indeed, a few tweets had more than 100 retweets, while others had zero.

In the overall data set, engagements and observations scored more retweets by an overwhelming number, which offered some support for H2 that engagements and observations would have the most exposure and attention. However, with the smaller @meteorologist data set, engagements and observations did not have more retweets or impressions. This could possibly be attributed to the vast majority of @meteorologist tweets being value-added. In addition, compelling photos are difficult for a broadcast meteorologist to personally produce with limited access to the outside environment during live television coverage of high impact weather events. Combining practical observation with results of this study, it is evident that Twitter users seeking weather information are highly interested in messages containing real photographs. Despite variance in specific content—storm damage, storms themselves, and relief efforts—engagements and observations almost unanimously make more impressions, produce more retweets and therefore result in greater exposure and attention. Within the PADM, photographs (not to be
confused with computer generated images and maps), provide a way to communicate environmental and possibly even social cues that can help instigate protective action. Those disseminating weather messages might consider a way to make photographs a focus of social media content strategy or even utilize real photographs to reach more people with the most important messages.

Marginal support was evident for H3, which expected value-added tweets to have more exposure and attention than official statements. Some of the single largest numbers of impressions and retweets on the @meteorologist account were value-added statements. A few of these made clear reference to geographical features. The literature does widely agree that a key component of the warning message is to “personalize the threat” (Mileti and Sorensen 1991, Tierney 1995, Trainor and McNeil 2008). Naming nearby landmarks likely helped appease this need. However, numbers from @meteorologist, including retweets, show value-added messages to have the lowest average impressions and retweets. H3 was initially formed with the assumption that because official statements are uniform and disseminated via a large number of Twitter accounts, the retweet numbers from any one account would be lower. Comparatively, value-added statements are often unique to only one account, thus the most interesting would only stem from one source resulting in more retweets. This was not the case. Official statements, such as tornado warnings, are the most basic but often most important messages during such an event and showed higher exposure and attention in this study. Such tweets seem to have language that is easier to discern and resonant 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 as well as some media (Trainor and McNeil 2008). Value-added statements certainly can be important, allowing for clarification and specification.
However, value-added tweets may also contain a bit more jargon than official statements, such as velocity signatures and correlation coefficients. This is one explanation as to why they did not travel as well as expected; they appeal to a smaller segment of users. The volume of value-added tweets may also bring the effects of social media fatigue into play (Bright et al. 2015). 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. Whether the weather enterprise should consider limiting the number of value-added messages produced is a question for future research.

Previous literature has noted that both large followership and specific message content will contribute to more exposure for a message (Sutton et al. 2014). Perhaps there is some preliminary evidence here that suggests message content plays a stronger role than number of followers for likelihood of retweet and therefore attention to a tweet.

A comparison of same storm warning tweets containing different levels of threat and efficacy on different accounts offered support for H4 that warning tweets with both threat and efficacy messaging would garner the most attention (retweets). Observations from this study, and the literature suggest that warning tweets could continue improving by incorporating both threat and efficacy components of a warning per the EPPM (Witte 1992, Hoang 2015). @TeamWeather1 containing threat and efficacy in warning tweets was a more efficient message style than the threat only wording used by @TeamWeather2. With the advent of storm-based tornado warning polygons, naming entire parishes or counties could create confusion, as it is possible that only part of a parish/county is actually under the warning.

2.6.2. Limitations and Future Study

To reiterate, a small data set is the biggest limitation to this study, but the case study approach to local information nodes during impact weather is a beneficial component to related
“big data” findings. Studying tweets individually can potentially eliminate the context of a situation (Palen and Anderson 2016). However, given the narrowed focus of weather specific Twitter accounts and a chronological stream of tweets, the context of this study is a bit firmer.

Meteorologists will benefit from continued research collaboration with social scientists to develop messaging strategy on Twitter. Furthermore, messages tailored to a more regional or local audience will likely be more personalized and therefore even more effective (Trainor and McNeil 2008). Why were more Twitter accounts not examined? First, this particular event was nearly exclusive to the Baton Rouge DMA. Within that market, there are only two television stations that consistently tweet warnings as they are issued. Second, as has been addressed, accessing full tweet history and metrics is only possible for account owners. Twitter API does allow for partial lists of tweets from specific accounts on specific dates but does not show retweets through those accounts. Therefore, several omissions of tweets with high impression, retweet and like numbers would have made for poor comparison to the @meteorologist account analyzed. Future researchers could select high impact weather events in a variety of different geographic regions, contact multiple 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 as to 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.

Whereas one might assume that older tweets would naturally have more time to collect retweets, this Twitter archive was not analyzed until a full month after the event. Some researchers have developed algorithms to predict lifespan of a tweet (Bae at al. 2014), but in
practical use, communications and marketing specialists note the average lifespan of a tweet to be quite short, on the order of 15 to 30 minutes (Wenstrom 2017). Future research could include time analyses on tweets. Instead of tweets being compared at one simultaneous point in time, a cohort type of analysis could analyze tweets at select time intervals such as first hour, second hour, first 24 hours or first 72 hours. This also will help practitioners understand if pertinent weather information is reaching the target audience on time, or later.

Another critique of the methodology might be that each individual tweet’s metrics inflated or deflated based on the wide range of social network sizes to which it may have been exposed. However, increased followership does not necessarily result in more retweets (Hong et al. 2011). In this case study, some of the tweets with the greatest numbers of impressions or retweets emanated from accounts with low followership. Additionally, impression, retweet and like numbers from this specific event could potentially be polluted because in times of disaster, users from a much broader geographical area converge on the topic (Hughes et al. 2014). Whether this inflates numbers or even if it does so uniformly is difficult to determine.

As for the Twitter metrics that were measured—there does seem to be some room for expansion. The “engagements” metric offers more certainty that attention is given to a message. An engagement identifies that a tweet was clicked on or enlarged to further view the contents. This would possibly better signify attention given to messages but would require researchers to be given account owner access to any Twitter handles being studied.

Finally, this case study provides insight as to what type of content results in exposure and attention. These findings could be synthesized with survey data using mock tweets to assess self-reported message type and warning format preferences.
2.6.3. Conclusions

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). We hope that this work contributed to those objectives.

The growing volume and increasing percentage of time users spend on social media is contributing to information overload (Hughes et al. 2014). As timelines bulge with information, research suggests mental resources to process information are reaching a maximum (Bright et. al 2015). Additional research found that coping with the volume of information, blurs one’s ability to act and pay attention to most messages (Bright et. al 2015). This gives reason for practitioners to increase quality of tweets and possibly decrease quantity.

Individuals will have their own network on Twitter. Since the quality and breadth of these networks is hugely difficult to determine, those responsible for communicating important weather messages such as warnings should focus on consistency across sources (Trainor and McNeil 2008, Lindell and Perry 2012).

Counting on Twitter alone as a weather messaging and warning medium is not expected. However, Twitter has a heightened value among other social media mediums as a message and warning tool because it offers chronological display of information. 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 be familiar with the “crying wolf effect” and the “false alarm ratio” (Barnes et. al 2007, Simmons and Sutter 2008). If not designed carefully, tweets may spread geographically ambiguous or temporally inaccurate messages and warnings. Such poor practice would only further contribute to some of the ongoing industry wide issues.
We found that during a localized tornado outbreak, key information nodes such as a broadcast meteorologist had large exposure and attention to tweets containing photographs and videos. Official statements such as warning tweets were also relatively popular content within a social network, but value-added tweets received the lowest amount of exposure and attention. Reference to geographic features such as locations or roads was prevalent among many popular tweets. Finally, we found that warning messages that contained both threat and efficacy needed fewer followers to generate attention (retweet). We hope this study continued a conversation on optimizing messaging on Twitter and other forms of social media across the weather enterprise.²

2.7. REFERENCES


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 photos 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 2013). Unlike Twitter, Facebook is not chronological. Posts of urgent nature, such as tornado warnings could appear hours later, long after expiry—once interaction reaches a critical level.


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CHAPTER 3 – TWITTER STORM 2: ANALYSIS OF TWEET PERFORMANCE DURING THE SOUTHEAST LOUISIANA FLOOD OF AUGUST 2016

3.1. INTRODUCTION

From 10-14 August 2016, a tropical low pressure system brought record rain and flash flooding to southeast Louisiana, while in many some cases exceeding 100, 200 and 1,000 year two-day totals at multiple gauging sites. Resulting runoff produced historic flood crests along the Amite, Comite, Tangipahoa and Tickfaw Rivers. Parishes within, and surrounding the Baton Rouge Metropolitan Area, reported over 30,000 water rescues, over 60,000 homes damaged totaling over $30 million (Yan 2016).

Floods evolve on much different temporal scales than tornadoes, hurricanes or snowstorms, meaning warnings are disseminated and protective actions are taken differently as well. Not to be mistaken with a flash flood warning, a (river) flood warning is issued when a specific river is expected to exceed flood stage or overtop its banks at one or more points along the river. River flood warnings are communicated with expected inundation levels, determined by what occurred at key geographic locations during previous floods. The flood event of August 2016 left forecasters with little precedent to project inundation levels and therefore a difficult risk communication scenario for affected forecast users. Residents may or may not be warned to move to higher ground, stay alert or evacuate. Among many other channels, flood warnings and inundation levels can be communicated through social media such as Twitter.

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 2016 there were 320 million active users (Twitter 2016). In that time, how individuals receive weather information has changed. Twitter reaches people
outside of the traditional daily print and scheduled television or radio programming. Through a social network of followers and friends, dozens, hundreds, or thousands of people can receive and spread information almost instantaneously.

Use of social media taps into two known needs in weather warning communication: speed and social network “milling” or confirming of information (Quarantelli and Dynes 1977, Sutton et al. 2014). During high impact weather events like floods, providing real-time information can save lives. Weather messages need to be accurate and timely, making the rapid release and viral spread of social media posts a strong partner for weather forecasters (Ferrell 2012).

Weather warning communication begins with issuance from the official source (National Weather Service in the United States) and then travels through social networks possibly reaching audiences who did not receive the original message. Research has shown that having strong connections with various social networks increases the chances of receiving a warning message (Donner et al. 2012). Twitter is just one social network that increases the likelihood of individuals receiving warnings.

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.

To optimize weather communication on Twitter, it is necessary to understand what types of content result in more exposure and attention to messages and therefore spread more rapidly through social networks. We addressed this need via a case study of Tweets during the southeast Louisiana flood of August 2016. Following methodology from a previous study on the southeast
Louisiana tornado outbreak of February 2016, this analysis contributes to understanding of how tweet content can affect exposure and attention to weather messages. The key nomenclature used with Twitter is highlighted in Table 3.1.

**Table 3.1.** Key terms and definitions of this research.

<table>
<thead>
<tr>
<th>TWITTER TERMINOLOGY</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Tweet</strong></td>
</tr>
<tr>
<td><strong>Retweet</strong></td>
</tr>
<tr>
<td><strong>Like</strong></td>
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<tr>
<td><strong>Reply</strong></td>
</tr>
<tr>
<td><strong>Impression</strong></td>
</tr>
<tr>
<td><strong>Follower</strong></td>
</tr>
<tr>
<td><strong>Handle</strong></td>
</tr>
</tbody>
</table>

**3.2. METEOROLOGICAL REVIEW**

On 8 August 2016 a weak tropical low pressure system was positioned along the northeastern Gulf Coast. A surface high pressure system in the Eastern United States was providing southeasterly wind flow and thus an ongoing stream of moisture from the Gulf of Mexico. By 10 August, the surface low had drifted westward along the Gulf Coast centering just south of Gulfport, Mississippi. The National Weather Service (NWS) Weather Prediction Center (WPC) issued a moderate risk for flash flooding on day 2 (12 Aug) with a forecast of over 250 mm.

On 11 August, the surface low pressure center shifted northwest and settled in southwest Mississippi. WPC rain forecasts actually scaled back to a 200-230 mm range for much of Louisiana and south Mississippi. The morning excessive rain outlook maintained a moderate risk for flash flooding. However, new guidance prompted the afternoon outlook to encircle a high risk area west to east from approximately Lafayette, La. To Slidell, La. and north to south from McComb, Ms. to Houma, La (Fig. 3.1). This meant that there was a greater than 15 percent chance of rainfall exceeding flash flood guidance.
After a few rounds of moderate to heavy rain over the previous two days, a shield of heavy rain associated with the surface low developed during the early morning hours of 12 August. Record precipitable water values (579 mm) contributed to rainfall rates of 20-50 mm per hour. Later that morning, WPC maintained a high risk for flash flooding and expected rainfall rates of 75 to 125 mm per hour over portions of Ascension, East Baton Rouge, East Feliciana, Livingston, St. Helena and Tangipahoa Parishes. A weak surface low squeezed between high pressure to the east and a cold front to the northwest. With little motion in the upper levels and ongoing moisture convergence at the surface low pressure center, a moist adiabatic, warm layer process provided nearly continuous rain through the morning. By dawn, dual-pol radar estimated 250 mm of rain had fallen in some areas of southeastern Louisiana and southwestern Mississippi. WPC noted ongoing strong low to mid level forcing and high resolution models showed a
(conservative) additional 250 mm of rain. For the first time, WPC MPD mentioned that “life-threatening runoff and/or flash flooding” was expected. On the morning of 12 August, the NWS New Orleans Weather Forecast Office (WFO) put a message on Twitter noting that record flood crests would occur.

After subsiding briefly, the low pressure system drifted mere kilometers west and steady rain regenerated within multiple convective bands on the morning of 13 August. WPC predicted that low level confluent flow in a deep tropical air mass with precipitable water values over 60 mm would lead to another several hours of heavy rain. Amounts from 12 August were, on average, doubled on 13 August leaving behind two day totals exceeding 500 mm over parts of at least three parishes in southeast Louisiana. On 14 and 15 August, the low pressure system was absorbed by a cold front to the northwest essentially ending the rain event in Louisiana. Associated runoff and river flooding would continue with crests moving downstream through 15 August.

3.3. LITERATURE REVIEW

3.3.1. Risk Perception and the Protective Action Decision Model

Effective weather communication protocols require an understanding of risk perception and how people respond to disasters as they unfold (Peacock et al. 1997). The Protective Action Decision Model (PADM) (Lindell and Perry 2012) (Fig. 3.2) is a 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 warnings. Warnings are messages transmitted from a source via a channel to receivers. For the purposes of this study, local broadcast meteorologists will be the sources and Twitter will be the 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).

There are obstacles to taking protective action. One must perceive great danger to leave comfort, such as home (Mileti and Sorensen 1991). Environmental cues such as seeing flooded roads or rising rivers may be necessary for a receiver to heed warnings. 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). Social networks are used to confirm, personalize, and understand threats (West and Orr 2007). Even if a warning message meets all appropriate criteria, if reaction of a social network is not also strong, action may not be taken.
Key to research on Twitter messaging is pre-decision processes of exposure and attention. A receiver must be exposed to an environmental or social cue to take action. Next, attention must be devoted to those cues, or more importantly, the message, in order to take action (Lindell and Perry 2012). Via these cues, Twitter can enhance situational awareness during an emergency (Hughes et al 2014). 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).

Receivers then transition into protective action decision making. People will identify and assess risks at hand and identify and assess available actions. Threats more proximal in time and distance tend to inspire preparedness, or in other words, if a situation becomes real than real action will be taken (Tierney 1995). Intrusiveness of a hazard and previous experience may influence perceptions and actions making specificity an important characteristic of a message (Trainor and McNeil 2008). While protective action cannot be assessed via Twitter, the PADM literature remains relevant to Twitter because during this process, receivers may reach a need for additional information. People will seek verification of official warning messages by discussing the warning with members of their social network (Quarantelli and Dynes 1977). This action has been called “milling,” and Twitter offers one way for social networks to verify official messages (Sutton et al. 2014). Milling makes it necessary that warnings include information such as graphics and web links that further inspire protective action (Sutton et al. 2014). Furthermore, this reinforces the need for multiple sources (emergency management, media, NWS) to issue the same message as individuals will perceive different levels of credibility from various sources (Carr et al. 2015, Mileti and Sorensen 1991). A clear, repeated message communicated with
specificities such as locations helps to personalize risk and generate action (Mileti and Sorensen 1991, Suh et al. 2010, Starbird and Palen 2010).

3.3.2. Social Media and Informatics

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 2016, there were 320 million active Twitter users (Twitter 2016). 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 protocols. Twitter users “microblog” by publishing 140 character messages that appear on a chronological timeline of other users that have chosen to “follow” the message publisher. A follower may choose to like a message, reply to the messenger, or retweet which shares the message with their own followers. Serial transmission, or retweets, (Sutton et al. 2014) of Twitter messages through a social network can allow dozens, hundreds, or thousands of people to rapidly spread information. Such a platform is valuable to those tasked with communication during high impact weather events. Twitter may even provide the warning message verification that people usually seek in times of disaster, by allowing the public to confirm the accuracy of the warning within their social network (Sutton et. al 2014).

Ripberger (2014) provided some evidence for this by finding that Twitter is a viable metric of public attention during high impact weather. In a statistical analysis of six-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).

Since Twitter has been identified as a channel where traffic increases during times of severe weather and can provide retransmission and reinforcement of weather messages, 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. Tweets that contain weblinks to additional data garner a high retweet rate (Suh et al. 2010). This shows some validity to the desirability of “hidden content” or links that may be in addition to the text of a tweet. Also, 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 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).

3.3.3. Warnings and the Extended Parallel Process Model

In disaster situations, users have been found to favor messages that are locally created, actionable (Kogan et al. 2015, Starbird and Palen 2010), clear, specific and themed toward public safety (Sutton et al. 2014). Most commonly, information during a disaster has come from those
geographically affected by the disaster, while local media serve as key nodes of information (Kogan et. al 2012).

As critical information centers during weather related disasters, local broadcast meteorologists communicating weather warnings should be providing messages with a balance of threat and efficacy. Threats may be communicated with fear appeals, which are vivid, persuasive messages designed to imply harm to people if recommended actions are not taken (Witte 1992). Threat and efficacy exist as external variables that a person must perceive (Rogers 1983, Witte 1992). In the EPPM (Fig. 3.3), from the viewpoint of a forecast user, threat is perceived susceptibility and severity while efficacy is user capacity to take action and the perceived effectiveness of that action (Witte 1992).

Figure 3.3. Extended Parallel Process Model (derived from: Witte 1992)

If a threat is determined to be high, fear will initiate a person to begin evaluation of efficacy of the recommended response. However, if threat is gauged as low, no further cognitive processing occurs (Witte 1992). Messages are rejected if themed toward threat with an absence of efficacy. Receivers of that message may respond to 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). Messages are often accepted if
balanced with a high level of threat and efficacy. Receivers of that message will then attempt to mitigate danger and hopefully take the recommended safety measures. Danger control processes are cognitive and rational thoughts to evaluate danger and the appropriate response (Witte 1992).

A case study of weather blogs prior to Hurricane Ike found that messages were dominated by threat as impact neared (Hoang 2015). Per the EPPM, threat only messages can cause receivers to respond to fear, feel helplessness and take the wrong protective action or no action at all (Witte 1992, Hoang 2015). Though limited by 140 characters, including links, tweets can feasibly be constructed to meet all appeals of the EPPM.

3.3.4. Summary and Research Questions

The PADM was used to outline the cognitive processing of tweets during a high impact weather event as an impression implies that a follower has been exposed to a message and a retweet, like or reply suggests attention to the message. The EPPM is a good fit to describe the most effective format of a weather warning tweets, one that provides both threat and efficacy. 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 local broadcast meteorologists, opening a niche for this research. The case study approach was utilized to identify any underlying trends in the data at hand, if nothing more than to validate findings from previous studies, existing literature and establish additional research points for the weather enterprise.

This study addresses two research questions to contribute to the optimization of Twitter as a weather communication channel.

- First, how did tweet type affect exposure and attention to messages during a flood event compared to a tornado event?
Second, how did threat and efficacy in official warning message tweets affect attention to tweets?

3.4. METHODS AND HYPOTHESES

3.4.1. Data

Following methodology from a previous study on the southeast Louisiana tornado outbreak of February 2016, a different type of event is analyzed to determine if findings were anomalous or part of a trend. To do so we examine tweets from 11 August to 15 August during the southeast Louisiana flood of August 2016. This timeframe included the day before heavy rain began through the final river crest. Tweets emanate from two local broadcast television news affiliates in the Baton Rouge Designated Market Area (DMA), one of which employed an author of this work. Three accounts were used for the analysis, one meteorologist’s professional account (@meteorologist) and two accounts that are operated by local broadcast meteorology teams (@TeamWeather1; @TeamWeather2). @meteorologist account had approximately 3,000 followers at the time of the event, and represents one individual meteorologist’s public following on Twitter. @TeamWeather1 and @TeamWeather2 accounts are used to immediately disseminate NWS warnings during impact weather events, and are not specifically tied to a specific individual. @TeamWeather1 and @TeamWeather2 had a number of followers proximal to each other but greater than @meteorologist. The addition of these two accounts allowed statistical analyses of warning tweets.

Only the @meteorologist account was analyzed in full. While retweets, likes and replies are available to the public, only account owners can access full metrics of each individual tweet. Impressions (defined below) were needed to gauge exposure of tweets over the five day period, but are not freely available.
Twitter allows account owners to download a complete history of tweets sorted by year and month. Twitter’s Application Program Interface (API) allows retrieval of tweets with specific words, phrases and hashtags from any public account during a specified date and time. However, this method has two limitations. First, it is plausible that some tweets pertinent to the study will lack the words, phrases, or hashtags used for API data collection. Second, the API feature returns a sample of tweets, which may not reflect the full body of tweets especially when the topic is less common (e.g., one regionally-confined flood) (Morstatter et al. 2013).

For this research, through owned (@meteorologist) and non-owned accounts (@TeamWeather1 and @TeamWeather2), tweets were manually entered into a spreadsheet for content analysis of tweet type and statistical analysis of the performance measures. For content and statistical analyses, we first provided a breakout of tweets originating from @meteorologist to examine it as a source of information. Next, we included retweets through @meteorologist to examine it as aggregator of information. Then, to assess exposure and attention to warning messages, we include @TeamWeather1 and @TeamWeather2.

3.4.2. Content Analysis, Tweet Types

To analyze differences in tweet performance by content, three types were identified and tweets analyzed were inductively assigned based on source of information, nature of content, and language used. The same typology established in the tornado event case study, is as follows:

1) *Official statements* tweets are content issued by government entities such as NWS or city leaders. Official statements include outlooks, watches, warnings or notices about road and school closures.

2) *Value-added* tweets are content from private entities such as broadcast media or the public. Television news consultants stress uniqueness and therefore local broadcast
meteorologists are expected to provide original content and analysis, which is deemed “value-added.” Value-added tweets include independent analyses of a scenario, technical jargon and information not part of an official statement.

3) Engagements and observations tweets are photos, reports, and interactions from user accounts. Engagements and observations include images of storms, damage or disaster response.

These three types encompass variations in content during an impact weather event without paralysis by analysis. A small number of types allowed more information to be extracted from an already small data set. In addition, the type definitions do not allow crossover between types. For instance, even if a photograph comes from government entity, it is still considered an engagement and observation type.

3.4.3. Statistical Analysis, Measuring Exposure and Attention

In the PADM, exposure and attention are critical phases of protective action decision making. Meteorologists tweeting weather information during high impact weather events aim to illicit protective action, but need exposure and attention to messages for that to happen. We examined the level of exposure and attention to tweets and retweets from @meteorologist by assessing 1) impressions, 2) retweets, and 3) likes.

An impression counts the number of times a tweet has been served in a user timeline, indicating exposure to the message. 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 is the number of times a message has been shared and likes are the number of times a viewer clicks the like button for the message. A retweet or like signifies interaction with the tweet, indicating more than just exposure, and therefore some level of attention to a tweet. Since @TeamWeather1 and @TeamWeather2 had a comparable number of followers during the flood, they were used to
appraise the effect of warning format on attention to messages (retweets). However, retweets alone were insufficient to measure attention because of disparities in associated retweeting accounts. To make the most accurate comparison possible, only warning tweets from each weather account subsequently retweeted by the associated television station accounts were considered. Still, this left an uneven comparison as one station had approximately 40,000 more followers at the time—almost double the other. Therefore, to truly identify the performance of one warning tweet format versus another, each tweet’s retweet count was divided by the number of followers on the associated television station account to calculate an average number of followers needed to achieve a retweet. Lower numbers would then suggest fewer people within that particular social network are needed to generate a retweet and such would point toward more attention and potentially a more effective formatting of the warning tweet.

3.4.4. Hypotheses

Based on our research questions, we developed two hypotheses related to tweet content and levels of exposure and attention. While weather communicators may view some messages as more important, factors such as time of day, users online and salience of the topic also affect impressions, retweets and likes. Some tweets are thoroughly retransmitted and others are not, but pictures seem to be a prevalent feature of highly retweeted and liked messages. Tweets containing images of the risky environment and making mention to geography provide “environmental cues” should have a higher level of exposure (impression) and attention (retweet or like). Further, tweets with reports from residents or affected individuals provide social cues that should increase the level of exposure and attention.

\textit{H1. Engagements and observations will have the highest level of exposure and attention}
Retransmission of warning messages through social networks is vital to reach as many people as possible and represents social cues and milling activity known to happen in the preparedness period of an emergency. It is possible that an increased level of attention to warning tweets can be expected by formatting tweets with respect to the EPPM; that is, they will provoke more attention by including both threat and efficacy. Thus, using the retweet metric, we expect that:

**H2. Official statements which focus on threat and efficacy will be retweeted most**

Hypothesis 1 uses the @meteorologist tweet data to address how message content affects exposure and attention within the PADM and if trends vary based on the weather hazard. Hypothesis 2 uses @TeamWeather1 and @TeamWeather2 to understand effectiveness of the EPPM as a model for weather warning communication, and how format of a warning tweet translates into levels of attention.

### 3.5. RESULTS

#### 3.5.1. @meteorologist original content only

**3.5.1.1. Statistical Summary**

Among the 60 original tweets, there were 7,177 average impressions per tweet (Table 3.2). However, the standard deviation was very large (6,314 impressions) indicating a wide range of exposure in tweets from this account. Fourteen tweets were one standard deviation above the mean with just eight tweets one standard deviation below the mean.

Original tweets from @meteorologist had a negatively skewed distribution of retweets (mean = 11.9, S.D. = 18.1) and likes (mean = 5.0, S.D. = 8.1). In other words, many tweets received very little attention, but a few tweets received very much attention.
3.5.1.2. Analysis

The tweet data set for @meteorologist offered support for H1. Engagement and observations tweets averaged 10,786 impressions—more exposure than value added and official statements combined (Table 3.2). Engagements and observations tweets (21 retweets, 10 likes) also averaged more attention than value added (6 retweets, 2 likes) and official statements (7 retweets, 2 likes). There was little difference in metrics between value added and official statements.

Table 3.2. @meteorologist tweet statistics for 2016 southeast Louisiana flood (highlight denotes highest value per statistic)
The @meteorologist tweet that received the most impressions (exposure) with 32,149 was an engagement and observation from 12 August at approximately 11:24pm (Fig. 3.4), very early during the event. This occurred prior to the time of river crests, possibly allowing more devices to be in use instead responding to rising water. Compared to tweets with the top five most impressions, this side-by-side comparison of a backyard before and after the heavy rain had the fewest retweets and likes.

The @meteorologist tweet with the most retweets (attention) with 107 was an engagement and observation from 13 August at approximately 9:53am (Fig. 3.5), more than 24 hours into the event. This tweet showed flooding of a very recognizable area in the most populated city of the forecast area, setting geographic reference and personalization very high.

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 and therefore retweets.
3.5.2. @meteorologist retweets

3.5.2.1. Statistical Summary

By introducing retweeted messages via @meteorologist, a broader data set becomes available—however, as noted previously, the ability to analyze tweet impressions data was lost, because the impressions metric is only available for original content. A total of 197 retweets were available for analysis (Table 3.2).

This content averaged 27 retweets with a standard deviation of 57 meaning most tweets were retweeted fewer times but a minority garnered much attention. The large difference between mean and median again indicated a highly skewed distribution (Table 3.2). Eighteen retweets were one standard deviation above the mean with anywhere from 78 and 417 retweets.

All 18 of the retweets one standard deviation above the mean were of the engagements and observation type, lending more support to H1. Similar to @meteorologist original tweets, retweets supported H1 showing engagements and observations to average the most retweets (27) and likes (14) and therefore the most attention. Here though, the margin is not as staggering with value added which averaged 11 retweets, 4 likes and official statements 12 retweets, and 5 likes.

3.5.2.2. Analysis

Five messages were retweeted over 200 times—again all engagements and observations. The most retweeted message gained 459 retweets and was posted on 14 August at 8:42pm (Fig. 3.6). Aerial video of cars driving on flooded roads was accompanied by message text, “Please pray for Baton Rouge, Denham Springs Louisiana. #Flood2016.” The call to pray may have been an action driver in and of itself and responsible for added retweets. In similar instances, some retweeting may be acknowledging that they too support those affected. The other four messages
with between 202 and 351 retweets also contained unique visual perspectives, wide scope photos or aerial images, and showed devastation in well-recognized or highly populated areas.

Unlike @meteorologist original tweets, there were far fewer value added (n=11) than official statements (n=29). However, the value added averaged significantly more retweets whereas the numbers were nearly identical for original content. The offset here was clearly caused by two very large outliers, particularly a message of “more rain approaching” the flood stricken areas that was retweeted 144 times.

![Image](https://example.com/image.png)

**Figure 3.6.** Most retweeted message through @meteorologist during southeast Louisiana flood of August 2016

3.5.3. Warnings

During the heavy rain and flood event, @TeamWeather1 sent over 50 warning tweets—some of which were duplicates or warning updates. Warnings were formatted with threat and efficacy as well as a map to identify location (Fig. 3.7). @TeamWeather2 sent 23 warning tweets, no duplicates or updates and excluded areal flood warnings. A text-only, threat-only format was
used. (Fig. 3.8). Within the 23 warnings available for comparison, just three remained that were either both retweeted or both not retweeted by the main station accounts.

Despite a small data set, numbers suggest that inclusion of the threat and efficacy components increased attention to warning messages. While @TeamWeather2 account had higher average number of retweets (14.7 compared to 11.0), when controlling for number of followers, @TeamWeather1 (which used content with threat and efficacy) showed greater effectiveness with an average of 5,357 followers per retweet compared to 8,445 followers per retweet from @TeamWeather2 (Table 3.3). Previous literature noted that both threat and efficacy in a message with geography and personalization play a large role in attention to a message. Perhaps there is some preliminary evidence here that suggests message format plays a stronger role in generating retweets than number of followers.

Figure 3.7. @TeamWeather1 Flash Flood Warning format, 5:54pm 13 August 2016

Figure 3.8. @TeamWeather2 Flash Flood Warning format, 5:54pm 13 August 2016
Table 3.3. Retweets per account sorted by individual flash flood warnings (left), number of followers per retweet (right) (highlight denotes highest value per statistic)

<table>
<thead>
<tr>
<th>Time of Warning</th>
<th>Total Retweets by Account</th>
<th>Followers per Retweet by Account</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>@TeamWeather1</td>
<td>@TeamWeather2</td>
</tr>
<tr>
<td>8/12/16 4:23am</td>
<td>7</td>
<td>11</td>
</tr>
<tr>
<td>8/13/16 8:14am</td>
<td>12</td>
<td>25</td>
</tr>
<tr>
<td>8/13/16 5:53pm</td>
<td>14</td>
<td>8</td>
</tr>
<tr>
<td>Total</td>
<td>33</td>
<td>44</td>
</tr>
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</table>

3.6. DISCUSSION, LIMITATIONS, CONCLUSIONS

3.6.1. Discussion

This work duplicated methodology from a previous case study on tweet exposure (impressions) and attention (retweets and likes) during a tornado event. Hypotheses were based on findings of the southeast Louisiana tornado outbreak of February 2016 case study. First, it was expected that the engagement and observations tweet type would generate the most exposure and attention. Second, it was expected that warning tweets containing threat and efficacy would be retweeted most, signaling greater attention. Results reinforced findings of the tornado outbreak study, largely confirming both hypotheses.

3.6.1.1. Tweet Type

The first hypothesis that engagement and observation messages will have the greatest reach (H1) was supported. In both subsets of the data (@meteorologist original and @meteorologist retweets), engagements and observations scored more retweets than the other two types combined. While there may be exceptions, by their nature, videos offer more content than a single image. The two most retweeted messages were both videos. Text accompanying any image or video is also an important component of well-performing messages. Additionally, literature suggests added attention to online news media is increased by sensational images and text (Zhang et al. 2012). Highly retweeted messages met several other characteristics of popular
tweets identified in previous studies: video content was included, the geographical scope personalized the message for a large audience and there was an appeal to human compassion from both the text and visual perspective (Mileti and Sorenson 1991, Tierney 1995, Trainor and McNeil 2008).

The most retweeted message expressed human compassion for those affected. Due the milling behaviors associated with social media and Twitter, there are 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 are being 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. More evidence 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.

In the tornado outbreak case study, official statements far outperformed value-added tweets. In this case study of a flood event, the difference was negligible. Identifying exposure and attention to official statements and value added tweets remains confounded. Each has a strong argument for and against being more popular. With official statements, uniformity and commonality across multiple accounts might water down the retweet numbers, but on the other hand, official statements are basic and appeal to a broader audience. The uniqueness of value added messages would seemingly give the message an advantage in the retweet count, but at the same time could contain jargon and appeal to a narrower audience. While official statements are crucial to the warning process, value added messages have a place as well. With a much higher standard deviation than official statements in impressions and retweets, value added messages
have proven potential to be very effective. However, ambiguous numbers suggest this type should be used cautiously during impact weather events to avoid potentially contributing to social media fatigue (Bright et al. 2015).

Interestingly, despite differences in geographic and temporal scope between the tornado outbreak and flood, the amount of exposure needed to gain attention only varied a little from case to case. In each event, approximately 825 impressions (814 and 842 respectively) were needed to gain a retweet. The disparity was a little greater for the number of impressions needed to gain a like with 1,145 in the tornado outbreak to 2,142 in the flood event. Followship for the @meteorologist account had nominally increased from the tornado event to the flood event 6 months later. More analyses should be performed to determine if these are baseline numbers for the @meteorologist account, or hold true for other local broadcast meteorologist accounts during impact weather events.

What role did followership play on exposure and attention? While the top two most retweeted messages were shared through highly followed accounts, some of the most popular tweets emanated from accounts with low followership. However, reach was boosted through tagging accounts with high followership or through use of a common hashtag-- #LaWX or #LaFlood for this scenario.

What role did time play on exposure and attention? 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 and data or power outages began. 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). There are a couple of factors that complicate both assertions. First, Twitter analytics
experts have suggested the prime time for retweets, and thus attention, is deeper into the afternoon hours (Fontein 2016). Second, in practical use, communications and marketing specialists note the average lifespan of a tweet to be quite short, about 15 to 30 minutes (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) and therefore less attention.

3.6.1.2. Warnings

This research followed the tornado outbreak case study in providing support for H2, or the idea that warnings with a high level of threat and efficacy will perform better than those without. For instance, when eliminating the qualification that warning tweets must include a retweet from the associated television station account, @TeamWeather2 with threat-only text-only messaging outperformed @TeamWeather1 in sheer number of retweets despite having lower followership. However, results indicated that fewer followers were needed to generate retweets for the threat and efficacy messaging of @TeamWeather2.

3.6.2. Limitations and Further Study

It is suggested that an implied obligation to “big data” can obscure the necessity for a good research question from the start. Big data may reveal more truths about Twitter if then given an analytical and even ethnographical approach (Palen and Anderson 2016). Studying tweets individually can potentially eliminate the context of the situation (Palen and Anderson 2016).
However, given the narrowed focus of weather specific Twitter accounts and a chronological stream of tweets, the context of this study is a bit firmer.

While a small data set was desirable for this case study on tweet types, it diminished available evidence to make determinations about warning messages. Comparing same storm warning messages containing different levels of threat and efficacy on different accounts seemed to offer the best real time example of whether existing literature on risk perception and warning communication holds true for social media. These methods could benefit from comparisons of tweets from more than two accounts during the same weather event in the same regions and then perhaps be broadened to identify trends from one geographic region to another. Researchers might consider an array of different weather events and Twitter accounts from across multiple sectors such as public and private forecasters as well as emergency management.

The impressions metric provided an assessment of exposure to a tweet but it is unknown if any attention was actually given to the message, or if the user scrolled right past. In the weather warning arena, exposure to a message means less without attention and subsequent action. Retweets and likes allow some measure of attention. Future research on social media and warning messages should further work to determine how different Twitter metrics can be used as a measure of not just attention, but possibly action.

Finally, given the high volume of tweets in a long duration event, more research is needed to determine if Twitter users are affected by 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.
3.6.3. Conclusions

Weather events that cause greater impact to society generate a greater need for information and an increase of information flow. Some weather events simply lead to more social media volume than others (Hong et al. 2011). Overall, the southeast Louisiana flood event of August 2016 occurred over a longer time period, affected more people, had a much larger number of tweets, impressions and retweets requiring user attention span for a much longer time than did the southeast Louisiana tornado outbreak of February 2016. Spatially, a much larger area was affected and likely a higher number of Twitter users either was affected, or knew somebody that was. Dramatic photos 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.

Researchers should continue to evaluate Twitter as a tool for weather communication. As weather communicators must make the most of the 140 character limited tweet during high impact weather events, content and warning format was brought to the forefront of this inquiry.

Even more than in a previous the tornado outbreak case study, engagements and observations garnered the most exposure and attention (impressions, retweets and likes). Photographs and video provided a way to communicate environmental and social cues within a weather message. Perhaps a previously received warning message has been reinforced by the image. Reference to geography and location was prevalent among the most popular messages. Weather warning communicators should make this idea a focus of social media content strategy or even utilize real photographs to reach more people with the most important messages.

Exposure to a warning is important to generate appropriate action, but too many warnings or conflicting warnings may cause maladaptive responses—and Twitter is especially vulnerable to
these shortcomings. Given the uniqueness of each individual’s Twitter network, weather communicators must be consistent across sources (Trainor and McNeil 2008, Lindell and Perry 2012). If not designed carefully, tweets may spread geographically ambiguous or temporally inaccurate messages and warnings. Such poor practice would only further contribute to some of the ongoing industry-wide issues. In addition, individual threat perceptions may also be affected by the dread factor (Slovic 1982), “crying-wolf effect” (Barnes et. al 2007), false alarm ratio (FAR) (Simmons and Sutter 2008), and social media fatigue (Bright et al. 2015) and Twitter research on weather communication should overlap these factors with future study.

Despite limited data, findings continue to show greater attention to warning messages that includes threat and efficacy. Warnings on Twitter should continue to present both to encourage adaptive responses and protective action. Furthermore, practitioners should continue to develop strategies with an understanding of risk perception, the PADM and EPPM to optimize weather communication on Twitter.

3.7. REFERENCES


CHAPTER 4 – WEATHER INFORMATION CHANNEL AND CONTENT PREFERENCES: A SURVEY

4.1. INTRODUCTION

As the old adage goes, time is money—social media and smartphones are big earners when information is time sensitive. That holds particularly true with weather information where immediacy saves lives. The urgency of weather has driven immediacy to a priority for information sources and has created additional streams of advertising revenues for these sources. While competition has been healthy for the advancement of technology, it has been a hindrance to the spread of information.

Post-modern electronic mediums, or channels, such as Facebook, Twitter and smartphone applications continue to accelerate the pace at which weather information is distributed. Most weather communicators are now able to reach an increasingly mobile society at any time of the day. Weather messages need to be accurate, but also timely, making the rapid release and serial transmission capabilities of social media a perfect partner for weather communicators (Ferrell 2012).

However, with multiple sources converging on the same channel, it sometimes produces overlapping, conflicting, and inadequate information. Never mind the viral, internet fame-seekers have also adopted Twitter to spread inaccurate, but buzzworthy information. In addition, credible sources are also tweeting an array of content in the face of increasing competition. Furthermore, varying sources may be tweeting the same subject matter at the exact same time, but variations in wording could lead followers to interpret different messages. Disagreeing forecasters may also tweet and create more uncertainty for a follower trying to make a decision. Public and private entities may send warning tweets providing varying levels of completeness. In assessing Twitter as part of protocols, weather communication sources should be asking several questions. What
types of tweets does my audience want? To what types of tweets will my audience respond? Are weather warning tweets as effective as possible?

Existing practices were built with good intentions, but outcomes still have varying levels of success. There has been work to understand the key components of a successful message (Lindell and Perry 2012, Trainor and McNeil 2008) with modern electronic channels like print, radio, and television broadcasting. However, multiple studies have identified that internet users find web sources to be just as, if not more, credible than modern channels like traditional print, radio, and television (Johnson and Kaye, 2004, MacDougall, 2005). If that perception exists, practitioners must take the post-modern electronic mediums seriously as delivery channels. Social media, and specifically Twitter, are no longer tertiary tools. It is time to optimize the 140 character message—often the first place where big weather messages are brought into existence.

The most recent academic survey assessing American’s channel preferences for weather information comes from 2010, when television was still the top choice (Demuth et al. 2010). With many new channels gaining popularity since then, including Twitter, we must reevaluate where each stands. Through survey data, we asked respondents to rank preferred channels for weather information as well as watches and warnings. Respondents were asked to rank interest in four types of weather information on Twitter. Later in the survey, respondents were shown example tweets of those four types of weather information to see if self-reported interest can predict interaction with a tweet. The survey also collected information about weather watches and warnings to gauge the understanding of terminology and the types of weather for which respondents wanted more information. Finally, we expand upon previous work(s) that contends that warning tweets structured with respect to the Extended Parallel Process Model (EPPM) will spread most effectively through a social network. Each respondent was shown one of four
example warning tweets with varying levels of threat and efficacy and asked to rate their likelihood of various interactions with that tweet. After collecting pilot data, this study expanded the respondent pool to assess Twitter as a tool for transmission of weather information and the EPPM as a guide for the formatting of weather watches and warnings on Twitter. In addition, a more robust survey allowed sorting of respondents by various demographics including geographic location.

The objectives for this research were to:

1) gain insight to preferred channels for weather information,

2) gain insight as to how different types of weather information are valued by Twitter users, and

3) gain insight to Twitter user reactions to various warning tweet formats.

Mean scores of respondent rankings will be used to identify collective preferences in the content provided.

4.2. LITERATURE REVIEW

4.2.1. Twitter Use

Having strong connections to various social networks, including Twitter, increases the chance one will receive a message (Donner et al. 2012). Twitter is one social network or channel available to those tasked with public safety and spreading warning messages. A proper warning message may inspire protective action through a series of cognitive processes (Lindell and Perry 2012). One of the biggest hindrances to protective action is simply exposure of warning messages. Given available research on social media, warning messaging and risk perception, message exposure is a continuing challenge for weather communicators.
As of January 2016, the Pew Research Center reported that 21 percent of adult Americans use Twitter and 42 percent of users check it daily (Greenwood et al. 2016). In addition, Internet estimates are that more than 500 million unique tweets are sent on a daily basis. More specifically to this study, Twitter has been gauged as a metric for heightened public attention during severe weather (Ripberger 2014). Case studies have found reporting (secondhand) information as the main use of Twitter during impact weather (Takahashi et al. 2015). Even by segmenting populations of the data set, and eliminating journalists, important information was still transmitted. Individuals used the channel for reporting 33 percent of the time and for memorializing affected people and communities 55 percent of the time (Takahashi et al. 2015). As is true with any large populations, while exact usage numbers will remain unknown, these statistics suggest that a significant segment of the population is using Twitter during impact weather events.

Many studies have analyzed large data sets of tweets and/or hashtags to identify patterns in content during disasters or impact weather events (Lachlan et al. 2014, Kogan et al. 2015, Romero et al. 2011, Verma et al. 2011, Bruns and Burgess 2011, St. Denis et al. 2014). While findings from these studies are important to weather communication strategies, they may only be a part of the puzzle. What seems to be lacking in the literature is recent survey work on what Twitter users report about their habits and desires during high impact weather events. An understanding of what content proves resonant with users, may help to perpetuate the most important information through social networks, such as Twitter.

4.2.2. Threat and Efficacy & the Extended Parallel Process Model

Threat and efficacy frame the key components of an adequate warning message. Where weather threats are often communicated in terms of likelihood and magnitude, weather efficacy
deals with an individual’s ability to take protective action and the positive outcome that action could create (Hoang 2015). Threat influences an individual’s attitude and efficacy determines the positive or negative orientation of that attitude (Hoang 2015).

The extended parallel process model (EPPM) places the motivations of fear at the center of cognitive processing. If responsible weather warning messages are intended to motivate protective action, one containing a clear representation of significant threat along with an achievable mitigating action could be reasoned as sufficient (Hoang 2015). The EPPM has been applied in studies focused on anti-smoking and safe sex—predicting that messages communicating high threat and low efficacy will cause individuals to react to their own fear rather than the danger at hand (Hoang 2015). While fear instigates maladaptive responses, when framed with efficacy, productive and protective actions can be inspired (Witte 1992). The EPPM underscores that one is coping with an event rather than escaping from an unpleasant emotional state (Hoang 2015).”

As has been proven in the health community (Witte 1992), the EPPM may guide formatting of successful weather warning messages. Considering perceived susceptibility, perceived severity, response efficacy and self-efficacy, an examination of national and local blog posts prior to the landfall of Hurricane Ike found that many did not include all components. Additionally, threat components outweighed efficacy components which according to the EPPM would cause fear rather than danger response processes (Gore and Bracken 2005). The research also found that efficacy messaging showed up with decreasing frequency as landfall approached (Hoang 2015). While troubling, it is possible to reason that from a meteorological and emergency response perspective that some actions simply can no longer be taken past a critical time.
The EPPM is certainly not without some opposition—as principles may not apply across the board. As is often the case, outcomes will vary based on the individual. In examining thresholds for proactive decision making based on probabilistic weather forecast information, research has found that messages delivered to inhomogeneous groups inspired different actions (Morss 2010). With this outcome, it has been suggested that forecasts should provide information that can be acted on, such as probability and confidence, rather than specific actions (Morss 2010). This would certainly leave room for some ambiguity in several components of an EPPM based message.

Geographical location has been shown to play a role in weather warning situations as well. Like individuals, each community is unique and weather messaging needs to be tailored as such. Rather than strictly scientific, a societal perspective to weather warnings should be considered (Donner et al. 2012).

### 4.2.3. Previous Surveys

As of 2006, a poll of Americans found that a majority was getting weather forecasts from local television (36%) and newspaper (24%) (Lazo et al. 2009). Researchers then noted that growing digital space would likely change the way people consume weather forecasts. In 2010, the same research team added a few new channels for forecast information to a similar survey including social media and cell phones. For a daily forecast, television remained the primary channel preference with 43% of respondents consulting either local or cable networks more than twice daily (Demuth et al. 2012). Less than 9% of respondents consulted mobile phones and social media more than twice a day for their forecast (Demuth et al. 2012). Still, aside from inclusion on the survey with other minority preferences, there was no trend toward post-modern electronic channels for weather information.
There has also been some survey work as to warning message wording and source (Perrault et al. 2014). Traditional television tornado warnings were found to be more credible than radio warnings, however the newest impact based, high threat, “scary” warnings were viewed as least credible (Perrault et al. 2014).

As noted, threat and efficacy must both be high in a situation for a user to take action.

Different from the 2014 study, rather than comparing mock video and radio messages and assessing perceived credibility, we used mock warning tweets from one source. Our intentions were to assess Twitter specifically and what format of a warning message inspires interactions such as retweets, information sharing (telling others), information seeking (clicking web links) and ignoring (scrolling past). We also used survey data to understand what type of content is desirable to Twitter users and where the platform stands as a weather communication channel.

4.3. METHODS

To examine preferred channels for weather information, we examined data from survey respondents. Key objectives of the survey were to gain insight about preferred channels for weather information, how different types of weather information are valued by Twitter users, and Twitter user reactions to various warning tweet formats. Channels chosen for evaluation included those commonly provided by broadcast media outlets: television, website, Facebook, Twitter and mobile phone app. In addition to collecting some demographic information, questions also assessed respondent understanding of weather watch and warning terminology as well as the specific hazards for which they want information.

Question design was optimized through consultation with experienced weather related survey administrators at the University of Alabama-Huntsville and California University of Pennsylvania. Created and administered through Qualtrics, the survey was pretested with people.
not considered weather communicators as one final quality check for clarity. The full survey can be found in Appendix A.

Surveys were distributed via the social media accounts and websites of colleagues in meteorology, climatology, and emergency management. An email was sent to each broadcast meteorologist listed on local television station websites and each office of emergency management in the state of Louisiana. Several NWS meteorologists also shared the links on their personal social media accounts. For those willing to take part in distribution, a link to the survey was provided along with suggested prompts for websites, Facebook and Twitter. While internet reach inevitably extends beyond a confined geographic area, survey design consultants advised partitioning response data by state to allow geographic homogeneity when evaluating results and making recommendations to practitioners. Of course, using social media and internet platforms as a distribution tool can be prohibitive to collecting a full sample of the population. In this case, we specifically aim to understand the habits of those with access to post-modern traditional channels in addition to modern channels to assess preferred channels.

Questions 1-6 asked qualifying and demographic information with multiple choice. Questions 7-8 used a Likert scale from strongly disagree (1) to strongly agree (5) to assess respondent reasoning for following weather accounts on Twitter and preferences in getting a weather forecast. Question 9 asked respondents to arrange a list of channels from most preferred (5) to least preferred (1). Questions 10-11 repeated the design for questions 8-9 but dealt with preferences for weather watches and warnings. Questions 12-19 gathered respondent beliefs about watches and warnings. Respondents were asked to match phrases with watches or warnings, select watches and warnings that they want to know about and/or receive push
notifications to their mobile devices, and also answer some multiple choice questions about their recent experiences with watches and warnings.

Question 20 A-D provided mock tweets of four varying content types—forecast, explainer, watch, and photo. To assess interactions with types, respondents rated their likelihood to retweet, tell others, scroll past, or click a link associated with the message. For these questions, responses were rated from very unlikely (1) to very likely (5).

Question 21 A-D provided mock warning tweets with four varying message formats—one contained threat and efficacy with a picture, one contained threat in only text, one contained threat with an image, and one contained efficacy. These tweets, used to test the EPPM with threat and efficacy, were not shown to the entire survey segment. Rather, the four messages were evenly and randomly distributed among the respondents to avoid any comparative biases or priming. Again, to assess interactions by warning format, respondents rated their likelihood to retweet, tell others, scroll past or click a link associated with the message. We will refer to these Twitter behaviors as interactions. Of course, other than scrolling past, the interactions are considered favorable to the goal of information sharing. For these questions, responses were rated from very unlikely (1) to very likely (5).

For questions that contained example tweets, a series of Twitter images was designed. The images were created by using an original Twitter message as a template and then altering the content in Microsoft Paint using Twitter’s Arial font. Associated weather images were designed using the Weather Services International (WSI) Max graphic suite. Weather information pertained to geographic location non-specific to the target survey audience of Louisiana residents. No identifying “source,” such as a television station or the National Weather Service, was provided to avoid any biases that may cause.
For several questions, we used the qualtrics survey software to calculate a mean score. These scores indicate overall respondent rankings. As a 1 to 5 ranking scale was used throughout the survey, higher scores lean toward 5 which was the affirmative ranking and lower scales lean toward 1 which was the negative ranking.

4.4. RATIONALE AND HYPOTHESES

Compared to 2006 and 2009, when the last similar surveys were taken, modern mediums, or channels, such as television, radio and newspaper are now delivering information in tandem with post-modern electronic mediums, or channels, such as social media and smartphones. We suspect the preference for television as a weather information source will be lower in this survey. Furthermore, a category unavailable in 2009, the smartphone application, may capture some percentage of the channel preference.

**H1: Respondents will self-report a preference for post-modern electronic channels**

As a prelude to this study, a pilot survey collected data from 50 respondents attending a large University in the southeastern United States. Casual Twitter users were asked to gauge their interest in specific channels. They were also asked to scale interest in specific types of content and then shown examples of content types to see if “self-reported” interest levels matched interactions with example content. To recap key findings of the pilot survey:

1. People wanted a daily forecast.
2. Twitter was not a preferred channel for weather information.
3. Weather photos were self-reported as undesirable, but examples were most retweeted.
4. Weather warnings were self-reported as undesirable, but examples were more retweeted.
5. Mock warning tweets most likely to be retweeted included threat and efficacy.
Findings suggested that there is not a parallel between ranked interest and interaction. While people may want a daily forecast, it may not be something they are likely to retweet or tell others. While people may not want warnings, the urgency of such messages may inspire interactions—retweeting, telling others and clicking a link for more information.

\textit{H2: Photo tweet interactions will score higher than respondent self-reported interest}

\textit{H3: Alert tweet interactions will score higher than respondent self-reported interest}

\textit{H4: Forecast tweet interactions will score lower than respondent self-reported interest}

Messages indicating not only threat, but also efficacy have been modeled and proven to have greater effect on proactive decision making (Hoang 2015). Many watches, warnings and other urgent messages will present a threat or hazard without any action that can be taken to mitigate the risk. This often has counterproductive consequences, perhaps due to generating a helpless mentality (Lang 2000). Specifically in the era of storm-based warning polygons, not considering county and parish borders necessitates the need for a visual accompaniment. Pilot data for this research suggested a message providing threat, efficacy and visual representation of a warning would be retweeted and told to others most.

\textit{H5: Warning messages that include threat and efficacy will score more likely to be retweeted than those that do not}

\textit{H6: Warning messages that include threat and efficacy will score more likely to tell others than those that do not}

4.5. RESULTS AND ANALYSIS

From 23 March 2017 to 1 August 2017, the survey collected 276 completed responses (Table 4.1). 16 respondents answered that they worked in meteorology or climatology so were excluded for possible pre-existing biases and insights to the questions. A total of 47 respondents were not from Louisiana and these were not retained in this analysis. However, these surveys
Table 4.1. Survey respondent demographics

<table>
<thead>
<tr>
<th></th>
<th>LOUISIANA</th>
<th>OTHER</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>69</td>
<td>26</td>
</tr>
<tr>
<td>Female</td>
<td>127</td>
<td>21</td>
</tr>
<tr>
<td>18-21</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>22-34</td>
<td>52</td>
<td>22</td>
</tr>
<tr>
<td>35-44</td>
<td>44</td>
<td>6</td>
</tr>
<tr>
<td>45-54</td>
<td>34</td>
<td>10</td>
</tr>
<tr>
<td>55-65</td>
<td>43</td>
<td>5</td>
</tr>
<tr>
<td>65+</td>
<td>20</td>
<td>1</td>
</tr>
</tbody>
</table>

will be kept for analysis of other states in a later study. In total, 196 survey remained for analysis. The entire survey report has been attached (Appendix A). Not all respondents answered every question, so total responses for any given question will be equal to or less than 196. We analyzed the results in four sections—weather information channel preferences, information desired, watches and warnings information, and warning format.

4.5.1. Weather Information Channel Preferences

Before making any efforts at message optimization, those providing weather information need to know the preferred channels of forecast users. Respondents (N=166) were asked to rank five channels from most preferred (5) to least preferred (1) for getting weather information. Table 4.2 shows a summary of responses, from first choice (5) to fifth choice (1) including the number (n) of times each channel was chosen as a ranked preference as well as the percentage relative to other channels. Interestingly, phone applications were the most common first choice and the most common fifth choice. A few of the write-in submissions for the channel “other” included newspaper (n=1), NOAA Weather Radio (n=1), radio station (n=1) and text message (n=1). Including the mean score of each channel for all responses ranks the channels from most to least preferred as website, Facebook, television, Twitter, phone app. Sorting by mean score of
first choice, post-modern electronic channels (phone app., Facebook, Twitter) were preferred over modern electronic (television) which supports H1.

Table 4.2. Respondent rankings of weather information channel preferences

<table>
<thead>
<tr>
<th>CHANNEL</th>
<th>FIFTH CHOICE</th>
<th>FOURTH CHOICE</th>
<th>THIRD CHOICE</th>
<th>SECOND CHOICE</th>
<th>FIRST CHOICE</th>
<th>MEAN</th>
</tr>
</thead>
<tbody>
<tr>
<td>TWITTER</td>
<td>29.70%</td>
<td>15.76%</td>
<td>15.15%</td>
<td>13.94%</td>
<td>18.79%</td>
<td>31.51</td>
</tr>
<tr>
<td>TELEVISION</td>
<td>12.12%</td>
<td>29.70%</td>
<td>20.00%</td>
<td>18.79%</td>
<td>17.58%</td>
<td>29.35</td>
</tr>
<tr>
<td>FACEBOOK</td>
<td>18.79%</td>
<td>15.15%</td>
<td>18.79%</td>
<td>21.21%</td>
<td>22.42%</td>
<td>29.32</td>
</tr>
<tr>
<td>WEBSITE</td>
<td>6.06%</td>
<td>18.79%</td>
<td>32.73%</td>
<td>27.88%</td>
<td>12.73%</td>
<td>21.30</td>
</tr>
<tr>
<td>PHONE APP.</td>
<td>30.30%</td>
<td>16.97%</td>
<td>12.73%</td>
<td>15.15%</td>
<td>23.03%</td>
<td>31.39</td>
</tr>
<tr>
<td>OTHER</td>
<td>3.03%</td>
<td>3.03%</td>
<td>1.21%</td>
<td>3.03%</td>
<td>5.45%</td>
<td>9.38</td>
</tr>
</tbody>
</table>

4.5.2. Weather Information Desired on Twitter

Table 4.3 tells more about what respondents want in a forecast and weather information on Twitter. On the same 1-5 Likert scale, more than 80% of respondents agree or strongly agree that they want to have a weather forecast updated every day (n=137). When asked about reasons for following weather accounts on Twitter, mean scores showed watches and warnings as the most likely reason (n=114) and photos and videos as the least likely reason (n=50).

Table 4.3. Respondent rankings of weather information preferences

<table>
<thead>
<tr>
<th>PREFERENCES IN GETTING A WEATHER FORECAST</th>
<th>MEAN</th>
</tr>
</thead>
<tbody>
<tr>
<td>UPDATED EVERY DAY</td>
<td>4.31</td>
</tr>
<tr>
<td>ONLY WHEN THE WEATHER IS THREATENING</td>
<td>2.99</td>
</tr>
<tr>
<td>I FOLLOW WEATHER ACCOUNTS ON TWITTER BECAUSE...</td>
<td>MEAN</td>
</tr>
<tr>
<td>I NEED TO HAVE A FORECAST</td>
<td>3.75</td>
</tr>
<tr>
<td>I AM INTERESTED IN WEATHER</td>
<td>3.80</td>
</tr>
<tr>
<td>I WANT WATCHES &amp; WARNINGS</td>
<td>4.43</td>
</tr>
<tr>
<td>I WANT PICTURES/VIDEO OF NATURE AND WEATHER</td>
<td>3.40</td>
</tr>
</tbody>
</table>

In a later section of the survey, respondents were shown example tweets for each of the four message types in Table 4.3. They were asked to rank the likelihood for each tweet type that they would retweet, tell others, scroll past or click a link. Mean scores from the example tweets show no support for H2 or H3 that photos and alerts would score higher than self-reported interest.
Watch and warning tweets and photo tweets had higher scores for respondent interest (Table 4.3) than for respondent favorable interactions (retweet, tell others, click link) with example tweets (Table 4.4). However, respondents did demonstrate a lower interest in a general forecast tweet than what was self-reported, which supported H4.

Table 4.4. Mean scores of respondent response to example tweet types

<table>
<thead>
<tr>
<th></th>
<th>Retweet</th>
<th>Tell Others</th>
<th>Scroll Past</th>
<th>Click Link</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast</td>
<td>1.41</td>
<td>1.92</td>
<td>3.13</td>
<td>1.86</td>
</tr>
<tr>
<td>Explainer</td>
<td>2.25</td>
<td>3.03</td>
<td>2.09</td>
<td>3.13</td>
</tr>
<tr>
<td>Watch</td>
<td>2.30</td>
<td>3.24</td>
<td>2.07</td>
<td>3.06</td>
</tr>
<tr>
<td>Photo</td>
<td>1.88</td>
<td>1.74</td>
<td>2.70</td>
<td>1.99</td>
</tr>
</tbody>
</table>

4.5.3. Watches and Warnings

Before analyzing the effectiveness of different formats of warning tweets, we gathered a general assessment of respondent understanding of weather watches and warnings. Responses indicate that 94.2% and 94.8% respectively matched “have a plan in place” and “significant weather may occur at a later time” with the term “watch.” Also, 96.1% and 94.8% respectively matched “take action now” and “significant weather is occurring” with the term “warning.” All except one respondent reported being under a weather warning within one year of taking the survey. This respondent must not have gotten notification as the Iowa Environmental Mesonet shows that every parish in Louisiana had been under some sort of weather watch or warning during the one year period (IEM 2017). A total of 87.9% (n=147) of respondents said they took action as a result of a warning within the last year.

92% (n=150) of respondents said that they like to have watches and warnings as soon as they are issued. Respondents were also asked to rank channel preferences for getting watches and warnings. Television had the highest mean score followed by website, Facebook, phone app. and Twitter (Table 4.5).
Respondents were asked what watches and warnings they want to know about and then for what watches and warnings they would like push notifications to their mobile phones (Figs. 4.1 and 4.2). A total of 166 of 167 wanted to know about tornado warnings and 161 said they would like a push notification to their mobile phone in the event of a tornado warning. More than 75% of respondents also would like to know about severe thunderstorm warnings (N=161) and flash flood warnings (N=137), but a slightly lower percentage want those warnings pushed to their mobile phones.

### Table 4.5. Respondent selections of weather watches and warnings channel preferences

<table>
<thead>
<tr>
<th>CHANNEL</th>
<th>FIFTH CHOICE</th>
<th>FOURTH CHOICE</th>
<th>THIRD CHOICE</th>
<th>SECOND CHOICE</th>
<th>FIRST CHOICE</th>
<th>MEAN</th>
</tr>
</thead>
<tbody>
<tr>
<td>TWITTER</td>
<td>35.03%</td>
<td>17.83%</td>
<td>9.55%</td>
<td>12.74%</td>
<td>19.11%</td>
<td>2.80</td>
</tr>
<tr>
<td>TELEVISION</td>
<td>8.28%</td>
<td>25.48%</td>
<td>23.57%</td>
<td>20.38%</td>
<td>17.20%</td>
<td>3.28</td>
</tr>
<tr>
<td>WEBSITE</td>
<td>3.82%</td>
<td>22.93%</td>
<td>35.03%</td>
<td>25.48%</td>
<td>12.74%</td>
<td>3.20</td>
</tr>
<tr>
<td>FACEBOOK</td>
<td>14.65%</td>
<td>18.47%</td>
<td>22.29%</td>
<td>22.29%</td>
<td>21.02%</td>
<td>3.20</td>
</tr>
<tr>
<td>PHONE APP.</td>
<td>34.39%</td>
<td>12.74%</td>
<td>8.28%</td>
<td>16.56%</td>
<td>24.84%</td>
<td>2.94</td>
</tr>
<tr>
<td>OTHER</td>
<td>3.82%</td>
<td>2.55%</td>
<td>1.27%</td>
<td>2.55%</td>
<td>5.10%</td>
<td>8.00</td>
</tr>
</tbody>
</table>

**Figure 4.1.** Respondent selections of watches and warnings they want to know about (N=167)
mobile phones. While nearly half of respondents want to know about river flooding, winter storms, extreme temperatures and dense fog, less than 30% want those alerts pushed to their mobile phones.

![Watches & Warnings - Want Push Notifications](image)

**Figure 4.2.** Respondent selections of watches and warnings for which they want push notification to their mobile phone (N=167)

### 4.5.4. Warning format

At the end of the survey, each respondent was randomly shown one of four possible warning formats. Responses produced unexpected results, contrary to data from the pilot survey and contrary to what literature suggested we would find (Table 4.6).

### Table 4.6. Mean scores of respondent response to example warning tweet formats

<table>
<thead>
<tr>
<th>Warning format (sample size)</th>
<th>Retweet</th>
<th>Tell Others</th>
<th>Scroll Past</th>
<th>Click Link</th>
</tr>
</thead>
<tbody>
<tr>
<td>Threat, Efficacy, (Graphic) (n=33)</td>
<td>2.79</td>
<td>4.09</td>
<td>1.64</td>
<td>3.27</td>
</tr>
<tr>
<td>Threat Only (Just Text) (n=38)</td>
<td>3.51</td>
<td>4.23</td>
<td>1.51</td>
<td>4.03</td>
</tr>
<tr>
<td>Threat Only (Graphic) (n=39)</td>
<td>3.37</td>
<td>4.33</td>
<td>1.47</td>
<td>4.37</td>
</tr>
<tr>
<td>Efficacy Only (Graphic) (n=44)</td>
<td>2.93</td>
<td>3.98</td>
<td>1.80</td>
<td>3.66</td>
</tr>
</tbody>
</table>
The warning tweet format most likely to be retweeted was threat only with just text. The warning tweet format that respondents would most likely cause them to tell others was threat only with a graphic included. Further working against H5 and H6, the warning tweet format expected to score best, threat and efficacy with a graphic, was the least likely to be retweeted and the second least likely to cause respondents to tell others.

4.6. DISCUSSION, LIMITATIONS, CONCLUSIONS AND FUTURE STUDY

4.6.1. Discussion

Compared to 2006 and 2010 surveys (Lazo et al. 2009, Demuth et al. 2012), our findings did not show television as the most preferred channel for weather information (Table 4.1). Considering the rankings top to bottom with mean scores, it was the third ranked channel. Websites ranked just ahead of Facebook for the top spot. The relatively high ranking for Facebook is somewhat unsettling from a weather information perspective as the application is designed to place popular, and not necessarily timely, content in user timelines. Those responsible for sharing weather information should post to Facebook carefully, making sure that dates and times are a clear part of any such content to avoid confusion. Twitter ranked fourth and phone apps last.

Phone apps did claim most of the first choice preference at 23%, but also had most of the fifth (last) choice preference at 30% which was enough to skew it to last place overall. Sorting for age did not reveal any significant trends. Despite having spent a larger portion of their adult lives without post-modern electronic channels, older respondents showed no less preference for these channels than did younger respondents.

Respondents indicated that receiving a daily weather forecast was important to them. As expected though, respondents mean scores were between strongly disagree and disagree for likelihood to retweet, tell others about or click a link on a tweet of a daily forecast. Respondents
agreed that they followed Twitter accounts for watches and warnings and the mock watch tweet did receive the highest mean score for likelihood to retweet and likelihood to tell others. Curious, given literature and previous studies, was the rejection of H2 that photo tweet interactions would score higher than self-reported interest. The mean score for interactions with the mock photo tweet were lower than self-reported interest in weather photos. While we would not necessarily expect people to tell others about a photo they saw, or click a link when a photo is the key piece of information, photos have proven to be the most retweeted content in previous research and pilot studies. Photo content may have played a role in this study. The mock tweet photo of a sunset may have been underwhelming compared to highly retweeted photos of tornado and flood damage in previous case studies.

When provided with definitions and terms associated with both weather watches and warnings, more than 95 percent of respondents were able to correctly drag and drop the definitions and terms next to the corresponding word. Respondents weighted interest in tornado, severe thunderstorm, and flash flooding alerts well above that of others presented. However, across the board, respondents scored knowing about an alert higher than wanting a push notification to their mobile device for that alert. These findings lend important insight to weather communicators as even a digitally inclined sample of the population may become apathetic with an overabundance of alerts, causing desensitization or perhaps cry-wolf syndrome (Barnes et al. 2007) to decrease effectiveness of future alerts. A push notification is currently the most intrusive form of channel to receiver communication. Through the NWS Wireless Emergency Alert (WEA) system, or any private sector mobile weather application, a watch or warning may be forced to a device. Somebody away from home, away from television or even away from a computer may be interrupted with an alert. While this has clear, potentially life-saving benefits,
especially private sector weather communicators need to consider the ramifications of overuse. For instance, if an application pushes less threatening alerts for dense fog and wind, perhaps a user will not react to the indication or read the bulletin when a more life-threatening tornado warning is pushed through.

Less than 70 percent of respondents wanted push notifications for flash flooding, yet over 80 percent of respondents wanted push notifications for severe thunderstorms and up to 90 percent for tornadoes. Less than 30 percent of respondents wanted push notifications for temperature related hazards. The lower percentages that wanted push notifications for flash flood warnings or extreme temperatures suggests a lower dread factor (Slovic et al. 1982) associated with these hazards—which each have killed more people per year in the United States on a 30-year average than tornadoes, wind or lightning (NWS 2016). Perhaps better outreach is needed to make these dangers more salient. Recent flood disasters, such as Hurricane Harvey in Houston, TX, and subsequent media attention may serve to increase the dread factor associated with flooding.

Phone app was also polarizing in ranking preferences for receiving watches and warnings. It had the most first choice rankings and the second most (by one vote) last choice rankings. Twitter had the most last choice rankings. Combined, phone app and Twitter accounted for approximately 50% of the fourth and fifth choice rankings. Weather communicators should consider more outreach and awareness for both channels as they are arguably the most timely in distributing information. While we just considered potential pitfalls of phone apps, when used correctly, they certainly are capable of being the first channel to deliver information to a large segment of the population who may not be actively searching for weather watches or warnings. Consider the alternatives; television, websites, Facebook and even Twitter require one to be actively using that channel to receive the information. In many cases, some form of secondary
human intervention is needed to initiate watches and warnings on these channels as well. Apps are typically triggered instantaneously via the primary NWS issuance. Some sources also have arrangements that automatically transmit watches and warnings to the other channels but again, a person must be actively using that channel to receive a warning.

We argue that Twitter has an advantage over websites, Facebook and television as it still allows one to be mobile while seeking information via the channel’s smartphone interface. In addition, one can chose to receive notifications when a selected weather source tweets information, such as a preferred weather source. While Facebook may be configured similarly, from a content seeking standpoint, there are still algorithm issues. With the exception of a recently added “in case you missed it” section atop timelines (a feature that can be turned off), Twitter displays information chronologically, meaning that the latest information will be seen first.

The finding in this survey most worthy of further scrutiny was the respondent preference in warning tweet format. Most literature would suggest that the most effective format for a warning message would include threat, efficacy and some way of personalizing a message—such as a map of the threatened area. Examination of actual events has shown receiver preference for the properly formatted warning tweet with threat, efficacy and an image. Why then, did that message format not yield the most favorable interactions (likelihood to retweet, tell others, click link)? It is possible that the example tweets were not personal enough. Perhaps Louisiana respondents did not empathize with a tornado warning for the Philadelphia area—selected as a geographically neutral location for the survey. It is possible that respondents from Louisiana assumed geographic insularity and if they knew nobody from the Philadelphia area that would be affected by the tornado warning, then they would have no reason to spread that warning message through
their social network or gather more information. Furthermore, it is possible that knowing they were not actually affected, there would be no reason to share the tweets containing actionable information.

Threat only tweets had high mean scores for both likelihood to retweet and likelihood to tell others. While warning communicators may see this as a route to take for warning formatting, interpret the results with caution. By issuing a threat only statement and having that message retransmitted through a social network, we are assuming that message receivers know the proper mitigation strategies for that threat. We must remember that a retweet of a threat-only message could be a reaction to fear rather than danger which is often a much less rational process (Witte 1992). This could produce similar, possibly deadly results in taking action on the warning.

Weather communicators should focus less on analytics such as retweets, and more on the content being provided so that warnings are complete, personal, and actionable to the receiver.

4.6.2. Limitations

While this survey could stand to benefit from a large respondent pool, it was intentionally limited geographically to allow cross comparison and expansion of localized weather communication research. State-by-state or even city-by-city surveys may help weather communicators understand the needs of their populations. Distribution methods could be altered to achieve a desired sample of the population. In this case, because we aimed to understand more about Twitter as a weather information and weather warning channel, survey distribution primarily on social media likely yielded a more digitally fluent respondent pool. It is possible though that this distribution method reached an audience less inclined to rely on television as an information channel. Therefore, speculation about preference for television as a weather information channel for a wide segment of the population may be reserved for another study.
4.6.3. Conclusions and Future Study

Much like work done by Lazo et al. (2009) and Demuth at al. (2012), research could go beyond simple channel preferences and incorporate situational channel preferences. For instance, when do people prefer television over a website? What type of weather information do people prefer on Facebook versus Twitter and vice versa? How are different segments of the population using these channels? Surveys like this should be performed more often (Lazo et al. 2009) and more regionally. Weather communicators would benefit from understanding changes in channel preference over time and geographically. It is possible, if not likely, that Midwest residents would react differently to tornado warnings than Gulf Coast residents. It is also possible that Midwest residents’ perceptions of tornadoes have changed with time. We also encourage similar studies on warning formatting on Twitter and other channels. Warnings are the most critical weather messages regarding protection of life and property and should be prioritized in studies as such.

Twitter has become a vast social network where many walks of life interact on the same playing field. Among many subgroups, there is the weather expert and the layperson. Of course, there is little limitation as to who one can follow. A layperson highly interested by, but not necessarily formally educated about weather, could follow a very large number of weather related accounts. It is also likely that many of these weather accounts are tweeting conflicting or confusing information and jargon. Natural competition for social equity and peer approval on Twitter may lead to conversations and content that cause one to lose trust in weather communicators or misinterpret information. Inevitably, some weather events will lead to more Twitter content than others. This allows a presumption that even somebody with a small but homogenous, or weather-centric, social network could be inundated with information (Hong et
al. 2011). The volume of use during high impact weather could be making Twitter its own obstacle to effective information spread.

Social media fatigue deals with a user tendency to trim usage after becoming overwhelmed with content (Bright 2015). The Limited Capacity Model (LCM) states that “people have a limited amount of mental resources to process information.” Under the assumption that people are information consumers with a limited capacity to do so, there must be compromises as the amount of data continues to overwhelm available attention (Lang 2000). Distractions will limit attention to and retention of information (Lang 2000). Recall and comprehension are also adversely affected by an over-abundance of information (Bright 2015). While this study did not test particularly for social media fatigue, the concept is significant enough that it may be considered by future research specifically with regard to weather information on Facebook and Twitter.

Previous research identified a need to understand weather communication on a variety of platforms (Lazo et al. 2009). This research aimed to identify Twitter’s place as a warning channel and continue a discussion about optimizing use of the platform. While it is not the top choice for weather information, it remains a choice for receivers. We may use the channel rankings found in this survey as a way to perhaps prioritize the distribution of information but we do not consider it a reason to excuse any single channel from weather information protocol. In fact, an increasingly diverse and mobile society will likely continue to use a multitude of channels to gather information, based on availability, convenience, type of weather and other situational factors. Each channel arguably has advantages in different scenarios, so scholars should continue to work with practitioners to optimize communication on all channels, including Twitter.
4.7. REFERENCES


CHAPTER 5 – CONCLUSION AND RECOMMENDATIONS

5.1. SUMMARY OF FINDINGS

This work aimed to learn more about Twitter as a weather communication channel. Specifically, insight was sought to understand the transmission of messages from key information nodes during high impact weather events, including content type and warning format. A pair of case studies, and a survey were conducted to support this investigation.

Two case studies of a local meteorologist Twitter account during high impact weather revealed that pictures and video are the most desirable content to followers. Environmental and social cues, presented as important components of risk perception (Lindell and Perry 2012), seemed to be strong predictors of exposure and attention to a tweet and an increased number of impressions and retweets. Personalization of a message was another component of risk perception literature (Trainor and McNeil 2008) that emerged as a theme among highly transmitted tweets. No matter the tweet type, reference to geographical location generally resulted in more exposure and attention. Testing for likelihood of attention (or a retweet) based on warning format, both studies indicated that warning tweets formatted with equal levels of threat and efficacy needed fewer followers per retweet, just as literature and the Extended Parallel Process Model (EPPM) (Witte 1992) suggested. In each case, the data sets were limited, and a more robust sampling of accounts across multiple regions during differing high impact weather events would assist in developing this theory.

A sample of Louisianans with digital connectedness found that among five channels—Twitter ranked as the fourth preference for weather information and the fifth choice for watches and warnings. Respondents reported interest in a daily weather forecast but did not indicate likelihood to favorably interact—retweet, like, click on a link—with a forecast on Twitter.
Watches and warnings were reportedly the main reason respondents follow weather accounts on Twitter and a watch scored as the most likely tweet to gain interaction from respondents. Contrary to findings in the case studies of high impact weather events, respondents did not indicate likelihood to interact with photos. However, the context of an actual event may have inspired much more interaction than the example photo provided in a survey.

For preferred warning tweet format, the survey returned an unexpected result and one much different from the two case studies. Respondents reported being most likely to favorably interact with a text-based, threat-only warning. Case studies predicted that a warning tweet with a balance of threat and efficacy and an image to increase personalization would be most effective at generating attention. The surprising survey result could have occurred for many reasons, including lack of an actual threat when compared to the case studies or absence of geographical personalization due to a neutral location being chosen for example tweets.

5.2. RECOMMENDATIONS

To continue increasing message effectiveness, weather communicators must understand first risk perception and second what content and language generates exposure and attention on a variety of channels, including Twitter. This work examined Twitter specifically to find that local meteorologists should expect photos and video to gain the most exposure and attention on Twitter during high impact weather events followed by weather watches and warnings. Warnings especially, need to be formatted with equal levels of threat and efficacy to have the highest likelihood of inspiring protective action. Finally, forecasts, analyses and technical jargon may be least desirable to receivers.

During high impact weather events, time and resources dwindle for key information nodes such as local meteorologists. Messaging on multiple channels must be calculated and prioritized.
Given the lower preference of Twitter as a weather information channel, communicators should have a content plan so not to detract from time spent on other channels. Attaching important messages, with content likely to achieve high levels of exposure and attention, such as a photo, may increase retransmission of a message. Taking time to offer technical expertise or further analysis may be better performed on a channel more preferred to audiences such as a website, Facebook, or television.

While results of the survey may have been discouraging for advocates of Twitter, the channel can still be advantageous to receivers. Twitter allows one to be mobile while seeking information via a smartphone interface. In addition, one can chose to receive notifications when a specific source tweets information, such as a preferred weather source. Unlike Facebook, Twitter displays information chronologically meaning that the latest information will be seen first. Given the temporal benefits of Twitter to some of the other channels considered in this work, weather communicators may consider more outreach to help users understand the benefit of a chronological flow of information. Preferred channels like websites, Facebook, and television may even be used to raise awareness about the communication advantages of the other channels. Again, being connected to multiple social networks increases the likelihood one will receive information (Donner et al. 2012).

Despite the low overall preference of Twitter among survey respondents, watches and warnings ranked as the main reason for use. That offered additional credence to the necessity of understanding ideal warning tweet format and to what format users respond.

Survey respondents unexpectedly chose a text-based, threat-only warning tweet as the most likely to gain an interaction. This, by scholarly standards, would be the least effective warning format. Providing minimal information may encourage milling (Quarantelli and Dynes 1977,
Sutton et al. (2014)—or a search for additional information when time could be critically low. Providing no protective action may cause fear response processes and therefore maladaptive responses (Witte 1992). Providing no personalization of the threat via geography or specificity in locations may cause a threat to be taken less seriously. Even if respondents believe the text-based, threat-only warning was sufficient, pursuing this as a strategy would mean that weather communicators assume all Twitter users are adept in understanding weather threats and protective actions, an assumption that could be deadly. In the case studies, the recommended warning format proved to be the tweet format that garnered the most exposure and attention. As asserted in the literature (Trainor and McNeil 2008), practitioners should make every effort to structure warning tweets with threat, efficacy and geographical context.

Each high impact weather event presents an opportunity to perform case studies of select Twitter accounts. Warnings are the most critical weather messages regarding protection of life and property and should be prioritized in studies as such. Despite the many sectors and sources involved in warning communication, measuring attention to warnings and identifying a format resonant among large social networks will increase chances of retransmission. Targeted studies may also seek to uncover content preferences of different demographic groups. Twitter weather warning format and message type could be examined on any geographic level and any weather event. Message exposure and attention could even be analyzed in benign weather scenarios.

As Lazo et al. (2009) recommended, more survey work such as this should be performed more frequently. Especially with rapid changes in digital information, weather communicators need to have a constant gauge for preferences of those they serve. In addition to frequency, surveys should be administrated regionally as weather hazards will be perceived differently depending on the location of respondents.
Weather communicators must also consider the deficiencies of Twitter during impact weather events. An increased volume of tweets may more easily lead to conflicting information. An increased level of information during high impact weather events may lead to more jargon passing from atypical weather communicators—such as researchers and scientists—through accounts of typical weather communicators—such as broadcasters and bloggers—therefore creating confusion in a social network. There have been well-publicized instances of amateur weather communicators producing inaccurate or intentionally misleading content for viral fame on the internet or social media (Mersereau 2015). In fact, some of the topics covered in this work are often openly, sometimes hastily, debated by members of the weather enterprise on Twitter. In and of itself this could be a deficiency of Twitter, as lack of official tone and expressed uncertainty may cause a follower to lose trust in Twitter as a weather communication channel. Of course, there are many more shortcomings that should be identified and addressed.

In conclusion, while the ability of Twitter to provide timely, chronological information may make it a gainful channel for weather communicators, more must be understood about the preferences of message receivers. Furthermore, weather communicators need to understand more about their social networks, their own strengths and their own limitations in content and warning messaging on Twitter. Researchers might consider partnerships with broadcast media consulting firms to see if recommended practices perform well in focus groups. Collaborations with social scientists in the National Weather Service might also improve message content and warning format from the primary source of United States weather information. With these additional insights, a more expansive group of scholars might consider working with industry leaders in the American Meteorological Society, National Weather Association and even National Weather Service to hone best practices for weather communication on Twitter.
5.3. REFERENCES


APPENDIX A. I.R.B. Correspondence

From: Institutional R Board
Sent: Friday, March 17, 2017 3:09 PM
To: Barry D Keim <keim@lsu.edu>; 'Josh Eachus' <jeachus@wbrz.com>
Subject: IRB Application

Hi,

The IRB chair reviewed your application, Optimizing the Message: Weather Information on Twitter, and determined IRB approval for this specific application (IRB# 3855) is not needed. There is no manipulation of, nor intervention with, human subjects. Should you subsequently devise a project which does involve the use of human subjects, then IRB review and approval will be needed. Please include in your recruiting statements or intro to your survey, the IRB looked at the project and determined it did not need a formal review.

You can still conduct your study. It falls under a certain category that does not need IRB approval.

Elizabeth

Elizabeth Cadarette
IRB Coordinator
Office of Research and Economic Development
Louisiana State University
130 David Boyd Hall, Baton Rouge, LA 70803
office 225-578-8692 | fax 225-578-5983
eantol1@lsu.edu | lsu.edu | www.research.lsu.edu

LSU Research - The Constant Pursuit of Discovery
APPENDIX B. FULL SURVEY

Weather Information
August 21st 2017, 8:22 am MDT

Welcome - Lead Investigator: Dr. Barry Keim  E327 Howe-Russell-Kniffen Geoscience Complex  Louisiana State University  Baton Rouge, LA 70803  Phone: 225-578-6170  keim@lsu.edu  The Geography and Anthropology Department at Louisiana State University is conducting research about the use of weather information on social media. This study will collect data from willing survey participants on a state by state basis, around the United States. By taking the time to fill-out a brief survey you will help the research team understand specific user preferences and trends with regard to weather information on Twitter. In addition, a portion of the survey is geared toward improving warning messages transmitted during potentially life-threatening weather events. The survey should only take 5-10 minutes to complete and little to no writing or typing is required. Participation is completely optional. If you wish to provide contact information for participation in future research, such as additional surveys or focus groups, you may do so, but this optional. You will be asked a few demographic questions to ensure we are getting responses from a full sample of the population. You must be at least 18 years of age to participate in the study. The information you provide will remain confidential and no names or contact information will be used in printed findings. The Institutional Review Board examined this study and determined formal review was not needed. As such, there are no risks to participating in this survey. Questions pertain to weather information and the channels through which they are transmitted. If you have questions, concerns, or complaints about your rights as a participant in this research study, you may contact Dennis Landin, PhD, Chair or Elizabeth Cadarette, IRB Coordinator at:

130 David Boyd Hall
Louisiana State University
Baton Rouge, LA 70803
Email: irb@lsu.edu
Phone: 225-578-8692
Fax: 225-578-5983
<table>
<thead>
<tr>
<th>#</th>
<th>Answer</th>
<th>%</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>I would like to participate</td>
<td>100.00%</td>
<td>194</td>
</tr>
<tr>
<td>5</td>
<td>I would NOT like to participate</td>
<td>0.00%</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>100%</td>
<td>194</td>
</tr>
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</table>
1/22 - I am 18 years of age or older.

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<th>Answer</th>
<th>%</th>
<th>Count</th>
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</thead>
<tbody>
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<td>Yes</td>
<td>100.00%</td>
<td>195</td>
</tr>
<tr>
<td>2</td>
<td>No</td>
<td>0.00%</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>100%</td>
<td>195</td>
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</tbody>
</table>
2/22 - Do you get weather information on Twitter? For example... you follow a local television weathercaster, the National Weather Service, the Weather Channel or another account that shares weather information.

<table>
<thead>
<tr>
<th>#</th>
<th>Answer</th>
<th>%</th>
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<td>Yes</td>
<td>57.65%</td>
<td>113</td>
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<td>2</td>
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<tr>
<td></td>
<td>Total</td>
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</table>
3/22 - Are you a student or employee in the field/s of meteorology or climatology?

<table>
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<tr>
<th>#</th>
<th>Answer</th>
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</thead>
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<tr>
<td></td>
<td>Total</td>
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### 4/22 - What has been your primary state of residence for the last 12 months?

<table>
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<tr>
<td></td>
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<td>196</td>
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</table>
5/22 - I am...

<table>
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<th>#</th>
<th>Answer</th>
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<td>1</td>
<td>Male</td>
<td>35.20%</td>
<td>69</td>
</tr>
<tr>
<td>2</td>
<td>Female</td>
<td>64.80%</td>
<td>127</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>100%</td>
<td>196</td>
</tr>
</tbody>
</table>
### 6/22 - My age is...

<table>
<thead>
<tr>
<th>#</th>
<th>Answer</th>
<th>%</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>21 or under</td>
<td>1.53%</td>
<td>3</td>
</tr>
<tr>
<td>2</td>
<td>22-34</td>
<td>26.53%</td>
<td>52</td>
</tr>
<tr>
<td>3</td>
<td>35-44</td>
<td>22.45%</td>
<td>44</td>
</tr>
<tr>
<td>4</td>
<td>45-54</td>
<td>17.35%</td>
<td>34</td>
</tr>
<tr>
<td>5</td>
<td>55-64</td>
<td>21.94%</td>
<td>43</td>
</tr>
<tr>
<td>6</td>
<td>65 or over</td>
<td>10.20%</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>100%</td>
<td>196</td>
</tr>
</tbody>
</table>
These statements rate your reasoning for following weather accounts on Twitter on a scale of 1 to 5. 1 means you strongly disagree with the statement, 5 means you strongly agree with the statement. I follow weather accounts because...

<table>
<thead>
<tr>
<th>#</th>
<th>Question</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>I need to have a forecast</td>
<td>28.17%</td>
<td>20</td>
<td>22.73%</td>
<td>10</td>
<td>27.00%</td>
</tr>
<tr>
<td>#</td>
<td>I am interested in weather</td>
<td>22.54%</td>
<td>16</td>
<td>31.82%</td>
<td>14</td>
<td>29.00%</td>
</tr>
<tr>
<td>----</td>
<td>--------------------------------</td>
<td>--------</td>
<td>------</td>
<td>--------</td>
<td>------</td>
<td>--------</td>
</tr>
<tr>
<td>3</td>
<td>I want watches &amp; warnings</td>
<td>16.90%</td>
<td>12</td>
<td>0.00%</td>
<td>0</td>
<td>8.00%</td>
</tr>
<tr>
<td>4</td>
<td>I want pictures/video of nature and weather</td>
<td>32.39%</td>
<td>23</td>
<td>45.45%</td>
<td>20</td>
<td>36.00%</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>Total</td>
<td>71</td>
<td>Total</td>
<td>44</td>
<td>Total</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>#</th>
<th>I need to have a forecast</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>I need to have a forecast</td>
<td>3.76</td>
</tr>
<tr>
<td>2</td>
<td>I am interested in weather</td>
<td>3.81</td>
</tr>
<tr>
<td>3</td>
<td>I want watches &amp; warnings</td>
<td>4.43</td>
</tr>
<tr>
<td>4</td>
<td>I want pictures/video of nature and weather</td>
<td>3.41</td>
</tr>
</tbody>
</table>
8/22 - These questions tell us about your preferences in getting a weather forecast. Rate the following on

<table>
<thead>
<tr>
<th>#</th>
<th>Question</th>
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<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Updated every day</td>
<td>3.83%</td>
<td>8</td>
<td>5.26%</td>
<td>12.27%</td>
<td>20</td>
</tr>
<tr>
<td>2</td>
<td>Only when the weather is</td>
<td>21.05%</td>
<td>44</td>
<td>29.47%</td>
<td>28</td>
<td>16.56%</td>
</tr>
<tr>
<td>#</td>
<td>On Twitter</td>
<td>On television</td>
<td>On a website</td>
<td>On Facebook</td>
<td>On a cell phone app.</td>
<td>Total</td>
</tr>
<tr>
<td>----</td>
<td>------------</td>
<td>---------------</td>
<td>--------------</td>
<td>-------------</td>
<td>----------------------</td>
<td>-------</td>
</tr>
<tr>
<td>3</td>
<td>26.32%</td>
<td>11.96%</td>
<td>8.13%</td>
<td>23.44%</td>
<td>5.26%</td>
<td>209</td>
</tr>
<tr>
<td>4</td>
<td>16.84%</td>
<td>13.68%</td>
<td>10.53%</td>
<td>15.79%</td>
<td>8.42%</td>
<td>95</td>
</tr>
<tr>
<td>5</td>
<td>11.66%</td>
<td>20.25%</td>
<td>22.09%</td>
<td>9.20%</td>
<td>7.98%</td>
<td>163</td>
</tr>
<tr>
<td>6</td>
<td>14.89%</td>
<td>15.43%</td>
<td>18.09%</td>
<td>12.23%</td>
<td>11.70%</td>
<td>188</td>
</tr>
<tr>
<td>7</td>
<td>8.70%</td>
<td>13.04%</td>
<td>13.80%</td>
<td>12.67%</td>
<td>22.50%</td>
<td>529</td>
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<tr>
<td></td>
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<td>Total</td>
<td>Total</td>
<td>Total</td>
<td>Total</td>
<td></td>
</tr>
</tbody>
</table>

- Updated every day
- Only when the weather is threatening
- On Twitter
- On television
- On a website
- On Facebook
- On a cell phone app.

### Updated every day

<table>
<thead>
<tr>
<th>Updated every day</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Updated every day</td>
<td>4.32</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>--------------------------------</td>
</tr>
<tr>
<td>2</td>
<td>Only when the weather is threatening</td>
</tr>
<tr>
<td>3</td>
<td>On Twitter</td>
</tr>
<tr>
<td>4</td>
<td>On television</td>
</tr>
<tr>
<td>5</td>
<td>On a website</td>
</tr>
<tr>
<td>6</td>
<td>On Facebook</td>
</tr>
<tr>
<td>7</td>
<td>On a cell phone app.</td>
</tr>
</tbody>
</table>
9/22 - Rank each platform to show your preference in getting weather forecasts. 1 means the platform is your least preferred, 5 means the platform is your most preferred.
<table>
<thead>
<tr>
<th>Rank</th>
<th>Source</th>
<th>Used</th>
<th>Found</th>
<th>Total</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Television</td>
<td>2</td>
<td>20</td>
<td>49</td>
<td>20.48%</td>
</tr>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Facebook</td>
<td>3</td>
<td>32</td>
<td>26</td>
<td>15.66%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Website</td>
<td>4</td>
<td>10</td>
<td>32</td>
<td>19.28%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Phone App.</td>
<td>5</td>
<td>50</td>
<td>28</td>
<td>16.87%</td>
</tr>
<tr>
<td></td>
<td></td>
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<td>Other</td>
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<td>5</td>
<td>3.01%</td>
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<td></td>
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</tr>
<tr>
<td>Total</td>
<td></td>
<td>16</td>
<td>16</td>
<td>16</td>
<td>100%</td>
</tr>
</tbody>
</table>

9/22_6_TEXT - Other

Other

Paper

Can't rank these

NOAA Weather Radio

radio

Text

friend

printed info from Safety and Health Dept. at work.

Combination of ForeFlighr and AviationWeather.com

Radio

Public Early Warning System
<table>
<thead>
<tr>
<th></th>
<th></th>
<th>Twitter</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td>Twitter</td>
<td>2.98</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>Television</td>
<td>3.05</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>Facebook</td>
<td>3.22</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>Website</td>
<td>3.27</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>Phone App.</td>
<td>2.90</td>
</tr>
</tbody>
</table>
10/22 - These statements rate your preferences for getting weather watches and warnings on a scale of 1 to 5. 1 means you strongly disagree with the statement, 5 means you strongly agree with the statement. I like to get weather watches and warnings...

[Bar chart with categories labeled as they are issued, on Twitter, on television, on a website, on Facebook, and on a cell phone app.]

127
<table>
<thead>
<tr>
<th>#</th>
<th>Question</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>As soon as they are</td>
<td>1.38%</td>
<td>2</td>
<td>0.00%</td>
<td>0</td>
<td>1.04%</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>On Twitter</td>
<td>39.31%</td>
<td>57</td>
<td>20.00%</td>
<td>10</td>
<td>17.71%</td>
<td>17</td>
</tr>
<tr>
<td>3</td>
<td>On television</td>
<td>12.41%</td>
<td>18</td>
<td>16.00%</td>
<td>8</td>
<td>23.96%</td>
<td>23</td>
</tr>
<tr>
<td>4</td>
<td>On a website</td>
<td>10.34%</td>
<td>15</td>
<td>30.00%</td>
<td>15</td>
<td>30.21%</td>
<td>29</td>
</tr>
<tr>
<td>5</td>
<td>On Facebook</td>
<td>31.72%</td>
<td>46</td>
<td>22.00%</td>
<td>11</td>
<td>14.58%</td>
<td>14</td>
</tr>
<tr>
<td>6</td>
<td>On a cell phone app.</td>
<td>4.83%</td>
<td>7</td>
<td>12.00%</td>
<td>6</td>
<td>12.50%</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>Total 145</td>
<td>Total 50</td>
<td>Total 96</td>
<td>Total 156</td>
<td>Total 537</td>
<td></td>
</tr>
</tbody>
</table>
11/22 - Rank each platform to show your preference for getting weather watches and warnings. 1 means the platform is your least preferred, 5 means the platform is your most preferred.

<table>
<thead>
<tr>
<th>#</th>
<th>Question</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Twitter</td>
<td>34.81%</td>
<td>55</td>
<td>17.72%</td>
<td>28</td>
<td>9.49%</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>Televisio n</td>
<td>8.23%</td>
<td>13</td>
<td>25.32%</td>
<td>40</td>
<td>24.05%</td>
<td>38</td>
</tr>
<tr>
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<td>-------------</td>
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<td>--------</td>
<td>----</td>
<td>--------</td>
<td>----</td>
</tr>
<tr>
<td>3</td>
<td>Website</td>
<td>3.80%</td>
<td>6</td>
<td>23.42%</td>
<td>37</td>
<td>34.81%</td>
<td>55</td>
</tr>
<tr>
<td>4</td>
<td>Facebook</td>
<td>15.19%</td>
<td>24</td>
<td>18.35%</td>
<td>29</td>
<td>22.15%</td>
<td>35</td>
</tr>
<tr>
<td>5</td>
<td>Phone App.</td>
<td>34.18%</td>
<td>54</td>
<td>12.66%</td>
<td>20</td>
<td>8.23%</td>
<td>13</td>
</tr>
<tr>
<td>6</td>
<td>Other</td>
<td>3.80%</td>
<td>6</td>
<td>2.53%</td>
<td>4</td>
<td>1.27%</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>Total</td>
<td>15</td>
<td>Total</td>
<td>15</td>
<td>Total</td>
<td>15</td>
</tr>
</tbody>
</table>

Other

Other

Radio

Can't Rank

Scan not figure out how to make the numbers move

Push alert on phone

radio

Cell phone

Radio

iPad

<table>
<thead>
<tr>
<th>#</th>
<th></th>
<th>Twitter</th>
<th>Mean</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td></td>
<td>Twitter</td>
<td>2.82</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>Television</td>
<td>3.28</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>Website</td>
<td>3.20</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>Facebook</td>
<td>3.19</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Phone App.</td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>------------</td>
<td>---</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>2.95</td>
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<tr>
<td>6</td>
<td></td>
<td>Other</td>
<td>5.56</td>
</tr>
</tbody>
</table>
12/22 - What weather watches and warnings do you like to know about? Check all that apply.

<table>
<thead>
<tr>
<th>#</th>
<th>Answer</th>
<th>%</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Tornado</td>
<td>18.10%</td>
<td>166</td>
</tr>
<tr>
<td>2</td>
<td>Severe Thunderstorm</td>
<td>17.56%</td>
<td>161</td>
</tr>
<tr>
<td>3</td>
<td>Flash Flooding</td>
<td>14.94%</td>
<td>137</td>
</tr>
<tr>
<td>4</td>
<td>River Flooding</td>
<td>8.62%</td>
<td>79</td>
</tr>
<tr>
<td>5</td>
<td>Winter Storm</td>
<td>8.83%</td>
<td>81</td>
</tr>
<tr>
<td></td>
<td>Extreme Temperatures</td>
<td></td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>----------------------</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>6</td>
<td>Extreme Temperatures</td>
<td>9.27%</td>
<td>85</td>
</tr>
<tr>
<td>7</td>
<td>Dense Fog</td>
<td>9.49%</td>
<td>87</td>
</tr>
<tr>
<td>8</td>
<td>Wind</td>
<td>10.14%</td>
<td>93</td>
</tr>
<tr>
<td>9</td>
<td>Other</td>
<td>3.05%</td>
<td>28</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>100%</td>
<td>917</td>
</tr>
</tbody>
</table>

**Other**

- Other
- Hurricane watches and warnings
- Hurricane/Tropical Weather
- Only severe weather
- Hurricane
- Hurricanes
- Tropical weather
- Hail
- All
- Hurricane
- Hail
- Ice, hurricanes
- Tropical and winter related
- Heat advisories
- Severe weather like hail and strong winds
- Lighting strikes
- Hurricane
- High Winds, Hail, Hurricane
What weather watches and warnings do you like to know about? Check all that apply. - Selected Choice
13/22 - For what weather watches and warnings would you like to receive automated push notifications to your mobile device? Check all that apply.

<table>
<thead>
<tr>
<th>#</th>
<th>Answer</th>
<th>%</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Tornado</td>
<td>24.36%</td>
<td>161</td>
</tr>
<tr>
<td>2</td>
<td>Severe Thunderstorm</td>
<td>21.63%</td>
<td>143</td>
</tr>
<tr>
<td>3</td>
<td>Flash Flooding</td>
<td>16.04%</td>
<td>106</td>
</tr>
<tr>
<td>4</td>
<td>River Flooding</td>
<td>5.90%</td>
<td>39</td>
</tr>
<tr>
<td>5</td>
<td>Winter Storm</td>
<td>6.35%</td>
<td>42</td>
</tr>
</tbody>
</table>

**Other**
<table>
<thead>
<tr>
<th></th>
<th>Extreme Temperatures</th>
<th></th>
<th>Dense Fog</th>
<th>7.41%</th>
<th></th>
<th>Wind</th>
<th>8.93%</th>
<th></th>
<th>Other</th>
<th>2.42%</th>
<th></th>
<th>Total</th>
<th>100%</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Other**

- **Hurricane**
  - Phone off except 1 hour on Monday no computer iPad off except some times so I would not get any weather info from these only TV constantly on
- **Hurricane**
- **Hurricane/Tropical Weather**
- **Hurricane**
- **Tropical weather**
- **Hail**
- **Hail**
- **Hurricane**
- **Hurricane**
- **Hurricane**
- **Coastal Flooding**
14/22 - What is the difference between a weather watch and a weather warning?

QID9 - Groups

- Have a Plan in Place
- Take Action Now
- Significant weather event is occurring
- Significant weather event may occur at a later time

[Diagram showing the difference between watch and warning for different scenarios]
What is the difference between a weather watch and a weather warning?

- Have a Plan in Place
- Take Action Now
- Significant weather event is occurring
- Significant weather event may occur at a later time
What is the difference between a weather watch and a weather warning?
15/22 - Have you been in a weather watch or warning within the last year?

### Survey Results

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16/22 - Have you taken action as a result of a weather watch or warning within the last year?

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Do you live near (within 5 miles) a body of water?

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18/22 - Do you believe a flash flood warning is a serious situation?

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19/22 - What type of flooding poses the greatest threat to you?

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VITA

Joshua David Eachus was born in 1986 in Media, Pennsylvania. Josh graduated from the California University of Pennsylvania with a Bachelor’s of Science degree in Meteorology in May 2009. While in that program, Josh researched teleconnections and northeast weather patterns and participated in a two-week-long summer storm chase across the country for credited coursework. Through August 2010, Josh completed a Master of Science degree in Sports Management from California University of Pennsylvania. After graduation, Josh began a career in broadcast meteorology, working in Steubenville, Ohio until 2013 when he relocated to Baton Rouge, Louisiana to work for WBRZ. During his broadcast career, Josh became a facilitator of local Integrated Warning Team workshops bringing together local media, emergency managers and the National Weather Service to improve weather communication. In addition, Josh was an active member of the American Meteorological Society and National Weather Association presenting research at serving on expert panels at annual conferences. Josh has also contributed to wxshift.com and created thewxsocial.com, a blog site dedicated to better weather communication. In 2015, the Associated Press voted Josh as having the “Best Weathercast” in Baton Rouge. Josh enrolled in the doctoral program of Louisiana State University’s Department of Geography and Anthropology in the fall of 2015 and began coursework and research in geography, communication and sociology. Studies at LSU have fundamentally changed and shaped Josh’s approach to communicating weather. Upon graduation from the program, Josh continued to apply these principles as chief meteorologist for WBRZ.