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From the sky to the smartphone: Communicating weather information in a digital age

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As new technology has emerged in the digital era, the public can now choose from a variety of new media from which to get weather information. Weather applications (apps) and social media have emerged as some of the popular new media. This study sought to understand the extent to which these new media are used, how weather apps are perceived, how the news media used Twitter during Hurricane Irma, and how the public engaged with the news media's tweets. A survey and dataset of tweets were used to evaluate the research questions and hypotheses of this research. The study found that most survey participants used digital sources for weather information, even in severe weather. The weather app was the most used source of all age brackets, though held a stronger majority amongst younger demographics. Numerous relationships were found between weather app usage and gender, smartphone brand and reliance, time of app usage, and app usage frequency. Participants who downloaded a non-standard weather app onto their phone had higher self-perceived weather knowledge and interest.

Weather app users perceived their app to be accurate and sometimes inconsistent, which were both found to be correlated to trust. Perceived app accuracy was also moderately correlated with other aspects of the field of meteorology. Respondents indicated that they accounted for

uncertainty in a forecast with time and for regional variability of weather when determining if the forecast verified. However, both conclusions will require further research.

The final study of this dissertation found that content, frequency, and engagement with news media tweets during Irma fluctuated over the storm’s duration and a relationship was found between content and engagement. Smaller television markets showed less coverage and overall change in coverage and engagement compared to larger markets. Finally, a meteorologist’s tweeting of personal content prior to the storm was found to be weakly correlated with the number of retweets received during the storm.

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"O Lord, you are my God; I will exalt you; I will praise your name, for you have done wonderful things, plans formed of old, faithful and sure."

(English Standard Version Bible, 2017, Isaiah 25:1)

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CHAPTER I

INTRODUCTION

1.1 Introduction

The landscape by which the public receives its weather information has vastly changed over the last fifteen years and continues to change at a rapid pace. Social science has long been applied to meteorology to better understand how the public is acquiring and using weather forecasts. However, new methods of acquiring weather information necessitate new applications of previous research concepts and conclusions regarding the adoption of the new technology; how, when, and why the new technology is used; and whether the new technology actually proves to be useful. The invention of digital media including smartphone applications (apps) and social media have revolutionized the way humans communicate. This revolution has touched weather forecasting as well.

Traditionally, the public has used television as means to get a weather forecast, but work in recent years has noted a trend suggesting that this habit may have changed in favor of using digital technology like weather apps or social media to get a weather forecast (Lazo et al. 2009; Demuth et al. 2011; Phan et al. 2018; Nunley & Sherman-Morris, 2020). With this change comes new questions surrounding the usage of new technologies by both the public and media for the dissemination and reception of weather information, in addition to the trust in and perceptions about the new technology and its effectiveness at delivering a weather forecast.

This dissertation aims to answer or contribute to the answers to the above questions. Two methodologies were used to better understand this shift in technology that has occurred. A survey was conducted regarding the public's usage and perceptions of weather apps and their features. Secondly, a dataset of news media tweets—messages published on the social media platform Twitter—was used to evaluate how the public reacted to messaging from the news media during a hurricane and how the news media conducted its coverage of the storm.

This paper comprises three projects. The first focuses on understanding the public's usage of weather apps, the second focuses on understanding the public's perception of weather apps, and the third focuses on understanding the performance of local broadcast media Twitter accounts during Hurricane Irma of 2017. Chapters two through four are each dedicated to one of these projects. In them exists a short introduction to the project, a comprehensive literature review of previous research relating to the project, an explanation of the methodology, a discussion section, and a concluding statement. The dissertation closes with a broader conclusion section regarding the paper as a whole.

The field of meteorology and even the whole scientific industry should take interest in this subject. Better understanding the public's usage of and interaction with digital media for weather information will allow for adaptations to be made to the presentation of the information, ultimately affecting the public's understanding of what to expect. Weather forecasts are easily verifiable by the public (Morss et al. 2008), and their trust in them is on the line if they perceive them to be inaccurate or unvaluable. While the interpretation of the forecast is not solely in the hands of the forecaster, it is essential that forecasts are properly communicated in order to make sure the public has the proper idea of what to expect. With a better communicated forecast and better public understanding of weather, inconvenience can be avoided, money can be saved, and lives can be better protected.

CHAPTER II

UNDERSTANDING PUBLIC USAGE OF WEATHER APPS

2.1 Introduction

This project sought to examine how individuals use their weather apps and to understand what influences their usage of the app. Within the last fifteen years, the weather app has become a common way to get a weather forecast and has helped disintegrate the monopoly on weather forecast consumption that television once held (Nunley & Sherman-Morris, 2020). This project investigates what source people use for weather information for both severe weather and normal times, for those who use a weather app, it also examines the weather app's main user demographics, and when and how it is being used. The following research questions and hypotheses were used to accomplish this:

- RQ1: To what extent does the public use the television or a weather app for general forecast information?
  - Hypothesis 1: The weather app will be the primary way the public gets general forecast information.
- RQ2: To what extent does the public use the television or a weather app for severe weather information?
  - Hypothesis 2: The television will be the primary way the public gets severe weather information.
- RQ3: What are the demographics of those who are most likely to use a weather app?

    - Hypothesis 3: Lower age brackets will be more likely to use the weather app than higher age brackets.
- RQ4: Do the majority of weather app users have notifications turned on?
- RQ5: Do users who download a weather app instead of using the predownloaded one have a higher interest in or knowledge about weather?
    - Hypothesis 4a: Individuals who consider themselves to be more knowledgeable about weather will be more likely to use another app besides the pre-downloaded one.
    - Hypothesis 4b: Individuals who consider themselves to have a higher interest in weather will be more likely to use another app besides the pre-downloaded one.
- RQ6: Are there any relationships between weather app usage, device type, device usage, gender, age, location, or time of day?

2.2 Literature Review

2.2.1 Invention of smartphone and applications

Prior to 2008, less than ten percent of the mobile phone market had a smartphone, and this was even after the release of the Apple iPhone (Comscore, 2017). By 2019, eighty-one percent of Americans owned a smartphone (PewResearch, 2019). This explosion of technology brought about many changes to the way most people live life. Phone calls and text messages had already brought a new form of connectivity to the world prior to this time, but the smartphone changed the mobile phone into a small computer. With that change, came the ability to use the internet while on the go.

A smartphone app is software that accomplishes a task on the smartphone. Weather apps provide users with an up-to-date weather forecast for their location. Most smartphones now have a weather app already downloaded and ready for use before the consumer even buys and uses the phone. In just over a decade, a method for acquiring weather information went from virtually nonexistent to almost universal.

However, just because the weather app is now available to most people, that does not necessarily mean that most people will adopt the new technology. According to the Technology Acceptance Model (TAM), in order for technology to be adopted it needs to be considered easy to use and useful to the consumer (Davis, 1989). The usefulness referred to by Davis is not the usefulness of the forecast, but rather of the new technological medium. For a weather app to be adopted, the consumer will have to consider the app both a useful way of getting the weather forecast and easy to use.

2.2.2 Shift in Weather Forecast Sources

In the recent past, television was considered to be the primary way that the public received weather information (Lazo et al., 2009, Demuth et al., 2011). While these studies occurred shortly after the invention of the smartphone, the massive expansion of smartphone usage had not yet happened. Thus, the full effect of the smartphone on the weather forecast market had not yet been felt.

More recent studies are limited; however, they do seem to show a change in how the public is receiving its weather forecasts. A study of college students found that the app was their primary way of getting weather information (Phan et al. 2018). Older age groups are typically slower to adopt new technology (Charness & Bosman, 1992). However, with over eighty percent of Americans having a smartphone (PewResearch, 2019), the new technology is clearly penetrating far beyond college students. More research is needed to understand if older generations are using a weather app instead of watching a television weather forecast. This study expands weather app usage research to include all age demographics.

While it is likely that many differences exist between smartphone usage in North America and Eastern Asia, a study in Hong Kong found that those aged 45-64 also preferred a smartphone as their source for weather information (Chan et al. 2017). As of the late 2010s, Nunley and Sherman-Morris (2020) found that the weather app was strongly challenging the television as the dominant medium for weather information. Due to the lack of vast literature in this area, a clear conclusion cannot be formulated. But based on the previously mentioned studies in addition to the overall decline in local television viewing (Nix-Crawford, 2017), indications would suggest that the weather app is becoming a very popular, if not the most popular method by which to receive weather information. Answering the question of which information medium is most prevalently used is very important to the field of meteorology to understand how best to reach the public with weather information. This study answers this question.

While it is reasonable to assume that the weather app is potentially the most common way to get weather forecast information, this assumption breaks down in severe weather. Numerous studies have shown that severe weather and disaster situations still drive people to the television for information (Reuter & Spielhofer, 2017; Sherman-Morris et al. 2020a; Sherman-Morris, 2010; Perreault et al. 2014; Stokes & Senkbeil, 2017; Silva et al. 2017). However, the weather app or smartphone notification can still play an important role in alerting individuals of the threat even if they are likely to do most of their information gathering from the television (Jauernic & Van Den Broeke, 2017, Sherman-Morris, 2010, Perreault et al. 2014; Silva et al. 2017).

2.2.3 Advantages of Weather Apps

There are many reasons why the weather app is gaining so much traction, and many of these reasons make the app superior to television when considered in light of TAM. Weather apps contain location-based services (LBS) which give a forecast for either your local town or even your specific GPS location. This was found to be attractive simply because it was more personalized to an individual (Kaasinen, 2005). Television weather forecasts are generally given for a region or for the main towns of the region. When it comes to specificity of location and personalization, television cannot match the app.

Convenience is another advantage for the weather app (Phan et al. 2018). Users can access the forecast at any time and virtually any location, instead of being confined to a certain time and place for a television forecast (Kaasinen, 2005).

Weather apps also make use of notifications which take advantage of both convenience and LBS. This means that instead of consumers even needing to seek out a forecast or weather information, the information comes to them (Zabini, 2016; Sherman-Morris et al. 2020b). The notification can contain forecast information or a severe weather alert that pops up on the screen of their smartphone. Since the frequency and deployment of notifications can be controlled by app developers and app managers, this can be used to encourage app usage.

In times of crisis or urgent situations, “getting the right information to the right person at the right time” is invaluable (Hagar, 2015, pp. 10). With notifications, the weather app has the ability to target specific information to specific people at specific times in a way that television cannot. This makes the app a very valuable tool when severe weather situations arise. However, if notifications are not enabled, some of the value of the app is lost.

2.2.4 Weather App Usage

After the adoption of the app comes the usage--the regular or even irregular interaction the consumer has with the app. The Technology Acceptance Model for Mobile Services extended Davis' TAM by proposing that adoption would turn into usage if there is perceived value, perceived ease of use, trust, and perceived ease of adoption (Kaasinen, 2005). Trust and perceived value take the place of usefulness, as a weather app would not be useful or appear to have value without being able to trust its output (Bryant et al. 2017). Thus, the usefulness and value of a weather app are tied to trust which depends on accuracy, reliability, and security (Bryant et al. 2017). Thus, in addition to being easy to use and useful, a weather app has to be dependable and trustworthy in order for usage to occur.

There are many different aspects that affect app usage behavior. Perceived value is mentioned by Kaasinen (2005) as "the key features of the product that are appreciated by the users" (p. 73). Phan et al. (2018) found the hourly and 5-day forecasts, severe weather alerts, chance of rain, and current conditions to be in the top five features of the app. This indicates that the app is used for both general forecast information and severe weather. However, it is possible that the usage could look different between the two different situations in terms of usage session length, features used, and the frequency of usage. Further research is needed to understand this.

Usage may also be affected by the type of app being used. As mentioned previously, most smartphones come with weather apps predownloaded. However, Bryant et al. (2016) found that a slim majority of their respondents downloaded a different weather app. With hundreds of weather apps on the market, there are plenty of options for consumers to find exactly what they want. Consumers that download a weather app want more data (Phan et al., 2018) and have greater trust in it than those who use the predownloaded app (Bryant et al. 2017). Research has also shown that individuals who access specialty weather websites have a higher perceived knowledge about the weather (Nunley & Sherman-Morris, 2020). Further research is needed to understand if consumers who download their own app rate their weather knowledge or interest higher than those who use the predownloaded app.

Many additional influencers may directly or indirectly impact app usage including the user's device type, personality, gender, age (Anshari et al. 2016; Van Deursen et al. 2015), location, as well as time of day (Qiao et al. 2016).

Location and the broader social context will impact not only what type of app is used, but also if it is even being used at all. Qiao et al. (2016) described entertainment and connectivity apps, such as YouTube and Facebook, as being used often at home. Commuting may involve a mix of getting ready for the workday with emails, as well as entertainment similar to home. At work, communication apps and business or market related apps are common, in addition to weather apps. Social media is often used when at an entertainment establishment or when relaxing. However, the social context is important to consider along with location (Shepard et al. 2010). If consumers are busy, traveling, shopping, or with a group of people, they may not use their phone as much which in turn affects app usage (Oulasvirta et al. 2005). Even if the social context does not affect a consumer's app usage, it may affect their response to any information gleaned from the app (Bean et al. 2015). For example, if a severe weather alert pops up on the phone, the consumer may see it, but reacting to the message by taking action could be altered if the person is with friends, busy, or perhaps feels safe at home and does not take action despite actually receiving the warning (Bean et al. 2015).

Time of day has also been shown to heavily influence what apps are used. Qiao et al. (2016) points out that each type of app has a distribution of usage throughout the day that typically has a resemblance from day to day, though tends to be different for different types of apps. Temporally, app usage transitions from news and information gathering early in the day to business and communication during the day to entertainment by the end of the day (Qiao et al., 2016). News and weather app usage have been found to typically occur in the morning (Böhmer et al. 2011). The typical amount of time that an app is used in one usage session is less than one minute (Böhmer et al., 2011).

While all of this research is not necessarily cohesive, each of these factors are likely to affect app usage as well as interact with each other and the characteristics of the consumer to produce results—even if they are not always the same results from person to person. This makes all of these factors important in studying this subject.

2.3 Methodology

Two main methods for this type of study emerge from the literature—survey and smartphone measuring. Smartphone measuring involves an app or software on a consumer's smartphone that tracks their app usage (Raento et al. 2009). While a very accurate way of retrieving app usage information, it comes with a host of privacy concerns in addition to an overall low willingness to participate by consumers (Shepard et al. 2010; Reuver et al. 2012).

For this reason, this project makes use of a survey asking participants about their app usage habits. This has been done in many other projects similar to this one (Anshari et al. 2016; Phan et al., 2018; Bryant et al., 2016; Chan et al., 2017). The survey did not include solely app users but attempted to obtain a representative sample of the public in order to gauge how many participants use the app versus those who use television or another means to get weather information. The survey gathered demographic information—age, gender, race, ethnicity, education level, zip code, and urban/rural classification—in addition to asking about participants' weather knowledge and interest in weather. Participants were also asked about their smartphone ownership and usage as well as their main source for weather information. This included questions about the type of smartphone they own, how long they have owned a smartphone, their regular smartphone usage habits, as well as their source for weather information both in and out of severe weather situations.

The survey then asked about the participants' specific weather app, their usage of it, their perceived accuracy of the app, and whether or not it is the pre-downloaded app on their phone. The survey avoids extensively asking about what a participant would most likely do in hypothetical situations but focuses on asking about app usage behavior that has occurred in the past in addition to regular app usage habits.

Questions regarding TAM were also included in the survey because it was investigating a potential switch in media sources for forecast information. This model was laid out by Davis in 1989 and was adapted by Kaasinen in 2005 to include mobile services. Davis (1989) theorized that acceptance of technology would take place if it was easy to use and showed usefulness. Kaasinen (2005) replaced usefulness with ease of adoption, perceived value, and trust.

However, given the previous literature mentioned, it appears the acceptance of weather apps and other digital sources for weather information has largely already occurred. This survey was designed under this assumption, making questions about ease of adoption and perceived value less necessary. Instead, respondents were asked about the usefulness of a weather app forecast and television forecast respectively to gauge the value and usefulness that each medium held.

The survey was published in Qualtrics and distributed via Prolific—a survey panel that includes individuals from all over the world who participate in surveys for compensation.

Recruitment requirements included only that the survey sample be nationally representative of the United States demographics as well as that it only contain participants from within the U.S. The use of Prolific meant that participants had to be technologically savvy enough to operate a computer and to register as a participant with the company. This could have resulted in a more technologically savvy survey sample for this study as compared to the U.S. population. Prolific participants also have the option to choose which surveys they take. Thus, individuals may have chosen to participate in this study because it interested them. This may have resulted in a sample of people who have a higher interest in or knowledge about the weather than would be typical.

Table 2.1 shows the statistical methods used for each hypothesis or research question. Hypotheses 1 and 2 were evaluated by comparing the number of people that answered in each category of the question. The sample was bootstrapped to increase the confidence in the results and a confidence interval produced for each category. Research question 3 looked for relation between weather app usage and numerous demographic characteristics. A Kruskal Wallis and Fisher's Exact test were used to check for relationships among the different levels of variables. Hypothesis 3 was evaluated using the Kruskal Wallis test to see if age is related to weather app usage. Research question 4 used a survey question simply asking which notifications (if any) are received on the respondent's smartphone. Percentages of those who answer with one of the notification options and those who answer "none" were compared to see how many people in this sample have some form of notification turned on compared to those who do not. Hypotheses 4a and 4b used a Mann Whitney U test to check for a significant difference in the mean weather knowledge and interest scores between those who use a pre-downloaded app and those who find their own app to download. Finally, research question 6 again used a combination of a Kruskal

Wallis and Fisher's exact test to check for association between app usage and the other demographics.

Table 2.1 Statistical analyses performed for chapter two

Research Question or Hypothesis	Statistical Test
Hypothesis 1 The weather app will be the primary way the public gets general forecast information.	Boot-strapped Confidence Interval
Hypothesis 2 The television will be the primary way the public gets severe weather information.	Boot-strapped Confidence Interval
Research Question 3 What are the demographics of those who are most likely to use a weather app?	Fisher's Exact Test
Hypothesis 3 Lower age brackets are more likely to use the weather app than higher age brackets.	Kruskal Wallis
Research Question 4 Do the majority of weather app users have notifications turned on?	Boot-strapped Confidence Interval
Hypothesis 4a Individuals who consider themselves to be more knowledgeable about weather will be more likely to use another app besides the pre-downloaded one.	Mann Whitney U
Hypothesis 4b Individuals who consider themselves to have a higher interest in weather will be more likely to use another app besides the pre-downloaded one.	Mann Whitney U
Research Question 6 Are there any relationships between weather app usage, device type, device reliance, gender, age, location, or time of day?	Kruskal Wallis/Fisher's Exact Test

2.4 Results

The sample size was 600 people from across the United States. The sample obtained from Prolific had some variation from what would be considered nationally representative of the U.S. Results of the demographic related questions are presented in Table 2.2. The only major differences between the survey demographics and the 2019 U.S. Census existed in race and ethnicity data, education attainment, and age distribution. There were fewer individuals who identified as white in the survey than in the census, and there were more who identified as Hispanic or Latino. Despite being given the option to check all races or ethnicities that they identified with, no participant checked more than one option. In the census, participants are asked to identify their race as well as whether they are Hispanic or non-Hispanic. This could explain the discrepancy. The survey participants were more educated, with more respondents having a bachelor's degree or some college experience compared to census data. Another major discrepancy occurred in age distribution. The survey results are based on a significantly younger population than the U.S. population.

Table 2.2 Comparison of survey sample demographics with U.S. Census demographics

	Demographic Characteristics	Survey Participants	2019 Census Data (U.S. Census Bureau, n.d.)
Gender N = 600	Male	289 (48.2%)	49.2%
	Female	292 (48.7%)	50.8%
	Transgender Male	3 (0.5%)	-
	Transgender Female	1 (0.2%)	-
	Gender Variant/Non-Conforming	14 (2.3%)	-
	Prefer not to identify	1 (0.2%)	-
Race & Ethnicity N = 600	White	424 (70.7%)	77.5%
	Black or African American	74 (12.3%)	13.0%
	Asian	39 (6.5%)	6.1%
	Hispanic or Latino	39 (6.5%)	16.4%
	Mixed race	19 (3.2%)	2.0%
	Middle Eastern or North African	3 (0.5%)	-
	American Indian or Alaska Native	1 (0.2%)	1.2%
	Other	1 (0.2%)	-
Education Level N = 600	Some High School	7 (1.2%)	7.1%
	High School Graduate	90 (15.0%)	28.3%
	Some College	189 (31.5%)	18.0%
	Associate's Degree	53 (8.8%)	9.8%
	Bachelor's Degree	176 (29.3%)	21.3%
	Advanced Degree	82 (13.7%)	12.0%

Table 2.2 (continued)

	Demographic Characteristics	Survey Participants	2019 Census Data (U.S. Census Bureau, n.d.)
Urban/ Rural Living Area N = 600	Urban area	183 (30.5%)	Urban 80.7%*
	Suburban area	320 (53.3%)	
	Rural small town	65 (10.8%)	Rural 19.3%*
	Rural outside of town	29 (4.8%)	
	Not sure	3 (0.5%)	
Age N = 600	18-29	334 (55.7%)	21.1%
	30-39	147 (24.5%)	17.3%
	40-49	58 (9.7%)	15.8%
	50-59	46 (7.7%)	16.6%
	60+	15 (2.5%)	29.3%

(*) 2010 Census data (U.S. Census Bureau, 2016)

One limitation of the survey sample's characteristics should be mentioned. The survey sample was close to being nationally representative of the United States' population. However, this sample was likely well acquainted with the online environment, and this may have affected the results as the sample may have been more technologically savvy than would accurately be observed in the U.S population. This survey would not have even been available to people who do not use computers of some form.

2.4.1 Survey Results Unrelated to Research Questions or Hypotheses

Below is a summary of the results of survey questions that did not specifically pertain to a research question or hypothesis. The summary is followed by the statistical tests performed to evaluate the research questions and hypotheses.

Questions 1-4 investigated the sources people use for both general forecast data and severe weather information. Question 1 (Table 2.3) showed that most respondents reported using an app or widget for a general weather forecast, with over 9 in 10 individuals using a digital source of some kind. Question 2 (Table 2.4) underscored these findings by showing that most people had received a weather forecast from a digital source in the last 24 hours.

Table 2.3 Survey Question 1

Q1. What would you describe as your main source for getting a weather forecast?

		95% Confidence Interval	
N = 600	**Frequency**	**Lower**	**Upper**
Weather App or Widget	464	74.0%	80.5%
A Website on the Internet	87	11.7%	17.3%
Television	37	4.3%	8.2%
Social Media	7	0.3%	2.0%
Other	5	0.2%	1.0%
Radio	0	0.0%	0.0%

Table 2.4 Survey Question 2

Q2. Where in the last 24 hours have you obtained a weather forecast? (Check all that apply.)

		95% Confidence Interval	
N = 598	**Frequency**	**Lower**	**Upper**
Weather App or Widget	472	75.3%	81.8%
A Website on the Internet	125	17.5%	24.2%
Television	90	12.2%	17.8%
Social Media	40	4.7%	8.8%
Radio	21	2.2%	5.2%
Other	24	2.5%	5.8%
None	29	3.2%	6.7%

Questions 1-4 investigated the sources people use for both general forecast data and severe weather information. Question 1 (Table 2.3) showed that most respondents reported using an app or widget for a general weather forecast, with over 9 in 10 individuals using a digital source of some kind. Question 2 (Table 2.4) underscored these findings by showing that most people had received a weather forecast from a digital source in the last 24 hours.

Table 2.5 Survey Question 3

Q3. Which source is typically the first source to alert you that severe weather is occurring near you?

N = 600	Frequency	95% Confidence Interval Lower	Upper
Weather App Notification	261	39.2%	47.3%
Mobile Phone Emergency Alert	166	23.7%	31.5%
Television	48	6.0%	10.2%
Friends or Family	47	5.7%	10.2%
A website on the internet	33	3.8%	7.3%
Social Media	24	2.5%	5.7%
Other	7	0.3%	2.2%
Tornado Siren	5	0.2%	1.7%
NOAA Weather Radio	5	0.2%	1.7%
Radio	4	0.2%	1.3%

This trend carried over into severe weather information as well. Not only was a mobile phone emergency alert or weather app the primary way people were alerted about severe weather near them (Q3) (Table 2.5), but digital sources were also the primary information media for garnering more information about the severe weather after being alerted (Q4) as will be seen when testing hypothesis two.

Table 2.6 Survey Question 12

Q12. Do you have a smartphone?
N = 600

	Frequency	Percentage
Yes	595	99.2%
No	5	0.8%

Most of the questions in the survey were only relevant for those who used a smartphone and weather app. Thus, question 12 (Table 2.6) asked participants whether they had a smartphone. Of the 600 responses, 595 had a smartphone (99.2%). Question 13 (Table 2.7) continued eliminating those to whom the bulk of the survey would not apply by asking how often respondents used a weather app. If they answered “never”, then they were asked about their smartphone usage and demographics and were then taken to the end of the survey.

Table 2.7 Survey Question 13

Q13. How often do you use a weather app?
N = 594

	Frequency	**Percentage**
Multiple times per day	163	27.2%
Once per day	223	37.2%
More than once per week, but not daily	111	18.5%
Once per week	28	4.7%
Less frequently than once per week	37	6.2%
Never	32	5.3%

Table 2.8 Survey Question 14

Q14. How many weather apps do you have on your phone?
N = 557

	Frequency	**Percentage**
0	3	0.5%
1	413	74.1%
2	119	21.4%
3	19	3.4%
4	3	0.5%

Non-smartphone owners followed the same course without being asked about their smartphone usage. Thirty-two individuals reported never using a weather app. This left 37 respondents total that were not asked the bulk of the questions related to weather apps. More than two-thirds (65.0%) of weather app users reported using their app at least once per day (Q13). Question 14 (Table 2.8) clarified that a large majority (74.1%) of people only have one weather app on their phone, and it is most often used at some point in the morning hours (Q15) (Table 2.9). Only a small majority (56.8%) stated that they had downloaded a weather app before (Q16) (Table 2.10) which would indicate that a sizable share of the population is using the weather app that came on their smartphone. Interestingly, more than a third of people who had downloaded an app still preferred the pre-downloaded app instead of the one they chose (Q17) (Table 2.11). The most frequent apps chosen for download (Q18) (Table 2.12) included The Weather Channel (47.5%), Accuweather (31.8%), Weather Underground (10.7%), and local news station apps (9.7%).

Table 2.9 Survey Question 15

Q15. What time of day do you most frequently use your weather app?
N = 563

	Frequency	**Percentage**
Overnight (Midnight - 6am)	3	0.5%
Early Morning (6am - 9am)	232	38.7%
Late Morning (9am - Noon)	167	27.8%
Early Afternoon (Noon - 3pm)	47	7.8%
Late Afternoon (3pm - 6pm)	26	4.3%
Early Evening (6pm - 9pm)	24	4.0%
Late Evening (9pm - Midnight)	24	4.0%
Anytime you are bored	40	6.7%

Table 2.10 Survey Question 16

Q16. Most smartphones come with a weather app already on them. However, some people choose to download a different weather app onto their smartphone. Have you ever downloaded a weather app?
N = 562

	Frequency	**Percentage**
Yes	319	56.8%
No	243	43.2%

Table 2.11 Survey Question 17

Q17. Do you prefer to use the weather app you downloaded or the one that came on your phone?

N = 319

	Frequency	Percentage
The weather app I downloaded	198	62.1%
The weather app that came on my phone	121	37.9%

Table 2.12 Survey Question 18

Q18. From the list of weather apps below, please select any of the apps that you use regularly? (Check all that apply.)

N = 318

	Frequency	Percentage
The Weather Channel	151	47.5%
Accuweather	101	31.8%
Local News Station's Weather App	31	9.7%
WeatherBug	29	9.1%
Weather Underground	34	10.7%
Other	73	23.0%

Notifications go hand in hand with smartphones and every weather app user reported receiving at least one type of weather notification on their phone (Q19) (Table 2.13). Severe weather alerts were the most common notifications being received. Yet, caution must be used when interpreting these results as confusion is likely to exist as to whether a severe weather alert is a Wireless Emergency Alert (WEA) or a weather app notification. Thus, while 79.9% of people reported getting severe weather notifications on their phones, that does not mean that they are coming from the weather app they use.

Regardless of where the alert came from, 380 of the 450 people who reported getting severe weather notifications, said that they typically see severe weather when they get alerted that severe weather is near (Q20) (Table 2.14). This is encouraging for those concerned about false-alarm effects, though it also raises questions regarding whether a participant truly understands what severe weather is as opposed to just a bad storm as it is unlikely that such a strong majority receives severe weather conditions as defined by the National Weather Service each time they get a severe weather notification.

Table 2.13 Survey Question 19

Q19. Which notifications do you get on your smartphone about the weather? (Check all that apply.)

		95% Confidence Interval	
N = 563	**Frequency**	**Lower**	**Upper**
Severe Weather	450	76.9%	83.1%
Rain is close to you	148	22.7%	30.4%
Weather headlines	141	21.5%	28.6%
Lightning is close to you	99	14.7%	20.8%
Other	24	2.7%	6.0%
None	84	11.9%	17.9%

Table 2.14 Survey Question 20

Q20. When your phone gives you a severe weather alert notification, do you normally see severe weather?

N = 450

	Frequency	**Percentage**
Yes	380	84.4%
No	70	15.6%

Question 21 (Table 2.15) was taken from Phan et al. who used this question to understand what features of a weather app were most important to its users (2018). Their question style was a likert scale of importance for each feature. The present study altered it by asking participants to check all features that they felt more most important. The top five features are as follows: hourly

forecast (67.9%), chance of precipitation (66.8%), severe weather alerts (63.6%), 5-day forecast (52.4%), and current information (49.4%).

Table 2.15 Survey Question 21

Q21. What would you say are the most important features of your weather app? (Check all that apply.)
N = 563

	Frequency	Percentage
Hourly Forecast	382	67.9%
Chance of Precipitation	376	66.8%
Severe Weather Alerts	358	63.6%
5-Day Forecast	295	52.4%
Current Information	278	49.4%
10-Day Forecast	174	30.9%
Satellite and Radar	161	28.6%
UV Index	100	17.8%
Pollen Count	71	12.6%
Lightning Detection	61	10.8%
10+ Day Forecast	58	10.3%
News Headlines	42	7.5%
Airport Delays	30	5.3%
Weather Videos	9	1.6%
Advertisements	1	0.2%

Question 21 (Table 2.15) was taken from Phan et al. who used this question to understand what features of a weather app were most important to its users (2018). Their question style was a likert scale of importance for each feature. The present study altered it by asking participants to check all features that they felt more most important. The top five features are as follows: hourly forecast (67.9%), chance of precipitation (66.8%), severe weather alerts (63.6%), 5-day forecast (52.4%), and current information (49.4%).

Questions 22-25 were used to understand “why” people use an app versus the television for a weather forecast. Questions 22 and 24, shown in Tables 2.16 and 2.17 respectively, asked how convenient the respondent considered their weather app or television forecast to be.

Table 2.16 Survey Question 22

Q22. How convenient do you consider your weather app to be?
N = 560, Mean = 4.44

	Frequency
Very convenient (5)	309
Convenient (4)	196
Somewhat convenient (3)	50
Not very convenient (2)	3
Not convenient (1)	2

Table 2.17 Survey Question 23

Q23. How useful do you consider your weather app to be?
N = 563, Mean = 4.49

	Frequency
Very useful (5)	319
Useful (4)	203
Somewhat useful (3)	38
Not very useful (2)	2
Not useful (1)	1

Questions 23 and 25 (Tables 2.18 & 2.19) then asked how useful each of these media were. Questions 22-25 were Likert style questions and were recoded to 1-5 interval data. The means for weather app convenience and usefulness were 4.44 and 4.49 respectively (N = 560, N = 563). The respective means for television forecast convenience and usefulness were 2.98 and 3.59 (N = 563). Wilcoxon Sign Rank tests were performed on the differences in the corresponding means. Weather app convenience ($Z = -17.926$, $p < 0.001$) (Table 2.20) and usefulness ($Z = -15.628$, $p < 0.001$) (Table 2.21) were found to be significantly greater than that of television.

When turning to perceptions of app forecast accuracy, question 31 (Table 2.22) asks how many days per week respondents felt their app got the forecast correct. Upon averaging out the dataset's response, the mean was 4.96 days (N = 560). Only 5.5% of the people that answered the question thought that their weather app was right seven days a week.

Table 2.18 Survey Question 24

Q24. How convenient do you consider a TV weather forecast to be?
N = 563, Mean = 2.98

	Frequency
Very convenient (5)	46
Convenient (4)	140
Somewhat convenient (3)	172
Not very convenient (2)	168
Not convenient (1)	37

Table 2.19 Survey Question 25

Q25. How useful do you consider a TV weather forecast to be?
N = 563, Mean = 3.59

	Frequency
Very useful (5)	94
Useful (4)	236
Somewhat useful (3)	160
Not very useful (2)	53
Not useful (1)	20

Table 2.20 Wilcoxon Sign Rank test for convenience of weather app vs. television

	N = 560 **Weather App**		N = 563 **Television**			**Wilcoxon Sign Rank Test Probability**
	Mean	SD	Mean	SD	Z	
Convenience Rating	4.44	0.71	2.98	1.07	-17.93	<0.001

Table 2.21 Wilcoxon Sign Rank test for usefulness of weather app vs. television

	N = 563 Weather App		N = 563 Television			Wilcoxon Sign Rank Test Probability
	Mean	SD	Mean	SD	Z	
Usefulness Rating	4.49	0.65	3.59	0.99	-15.63	<0.001

Weather app forecasts are largely driven by computers. Yet, it is unclear if the public knows this. If not, blame from a perceived or legitimately inaccurate forecast could be projected onto a meteorologist or "meteorologists" as a whole. Questions 38 (Table 2.23) and 39 (Table 2.24) asked likert style questions regarding how involved a meteorologist and computer are in formulating the weather app's forecast. Upon recoding the data into 1-5 interval data, the mean for meteorologist involvement was 3.33 (N = 563), and the mean for computer involvement was 4.34 (N = 563). This indicates that the public overall perceives more involvement from a computer than a human meteorologist. However, the most common responses on a meteorologist's involvement in formulating a weather app's forecast were "somewhat involved" and "involved". This suggests that the public perceives there to be a higher degree of human involvement than is real.

Table 2.22 Survey Question 31

Q31. On average, how many days of the week do you think the weather app you use most frequently gets the forecast correct?
N = 560, Mean = 4.96 days

	Frequency	Percentage
1 day	1	<0.1%
2 days	8	0.1%
3 days	47	8.4%
4 days	112	20.0%
5 days	212	37.9%
6 days	149	26.6%
7 days	31	5.5%

Table 2.23 Survey Question 38

Q38. How involved do you think a meteorologist is in formulating the forecast for your weather app?
N = 563, Mean = 3.33

	Frequency
Very involved (5)	54
Involved (4)	199
Somewhat involved (3)	206
Not very involved (2)	87
Not involved (1)	17

The next block of survey questions was for those who reported using a weather app associated with a local news station. Per question 18, this is only 31 of the 600 respondents in the dataset. The goal was to understand what type of relationship the respondent had with the local news station and meteorologists.

Question 40 (Table 2.25) asked if participants had ever watched one of the meteorologists responsible for formulating the forecast in their weather app. The intention was to gauge whether they thought the meteorologists on camera at the news station were responsible for developing the forecast. Fourteen of the thirty responses said “yes”. Those 14 then moved to question 41 (Table 2.26) and were asked how often they watched that meteorologist. Responses ranged, though 10 of the 14 watched them only “a few times per week”, “a few times per month”, or “almost never”. Seven of the fourteen claimed that they followed that meteorologist on social media (Q42) (Table 2.27). Ten of the same fourteen participants also said that the meteorologist was partially responsible for a wrong forecast on the app (Q43) (Table 2.28). For all 31 individuals who used a local news station’s weather app, more than half watched it a few times per month or less (Q44) (Table 2.29), and 83.8% had a moderate or high trust in the news station (Q45) (Table 2.30).

Table 2.24 Survey Question 39

Q39. How involved do you think a computer is in formulating the forecast for your weather app?

N = 563, Mean = 4.34

	Frequency
Very involved (5)	299
Involved (4)	172
Somewhat involved (3)	78
Not very involved (2)	12
Not involved (1)	2

Table 2.25 Survey Question 40

Q40. Have you ever watched one of the meteorologists that put the forecast in your weather app deliver the forecast on TV?

N = 30

	Frequency
Yes	14
No	6
Not that I know of	10

Table 2.26 Survey Question 41

Q41. How often do you watch that meteorologist on TV?

N = 14

	Frequency
Multiple times per day	1
Every day	3
A few times per week	4
A few times per month	2
Almost never	4

Table 2.27 Survey Question 42

Q42. Do you follow that meteorologist on social media?

N = 14

	Frequency
Yes	7
No	7

Table 2.28 Survey Question 43

Q43. Think about a time when your weather app got the forecast wrong. How responsible do you think that meteorologist was for the poor forecast?

N = 14

	Frequency
Fully responsible	0
Partially responsible	10
Not responsible	4

Table 2.29 Survey Question 44

Q44. How often do you watch the TV channel or news station that makes your weather app?

N = 31

	Frequency
Multiple times per day	2
Every day	6
A few times per week	6
A few times per month	7
Almost never	10

Table 2.30 Survey Question 45

Q45. How would you rate your trust in that news station or TV channel?

N = 31, Mean = 3.35

	Frequency
Very High	2
High	12
Moderate	14
Low	1
Very Low	2

Questions 46-49 asked about respondents’ smartphone and usage habits. The majority of the smartphone-owning portion of the sample had Apple smartphones (63.0%), but 23.0% owned a Samsung, 5.4% owned a Google, and 8.6% owned some other brand (Q46) (Table 2.31).

Table 2.31 Survey Question 46

Q46. What brand is your smartphone?
N = 595

	Frequency
Apple	375
Samsung	137
Google	32
Other	51

Table 2.32 Survey Question 47

Q47. How long has it been since you got your very first smartphone?
N = 595

	Frequency
0 – 1 years	17
2 – 3 years	26
4 – 5 years	68
6 – 8 years	182
9 – 12 years	221
13 years or more	81

Table 2.33 Survey Question 48

Q48. When is the first time you typically use your smartphone after waking up?
N = 595

	Frequency
Before getting out of bed	390
Right after getting out of bed	149
After being out of bed for an hour or so	46
A long time after waking up	10

Table 2.34 Survey Question 49

Q49. How easily could you function without your smartphone for a day?
N = 594

	Frequency
Very Easily	56
Easily	93
Somewhat Easily	167
Not Easily	196
Not at all Easily	82

Two-thirds said that they got their very first smartphone six to twelve years ago, and 81.3% have had a smartphone for six years or longer (Q47) (Table 2.32). Over 65% of the respondents used their smartphone before even getting out of bed in the morning (Q48) (Table 2.33). Almost half of the sample stated that they could not easily or not at all easily function without their smartphone for the day (Q49) (Table 2.34).

2.4.2 Primary Weather Information Source

RQ1: To what extent does the public use the television or a weather app for general forecast information?

This research question was asked based on findings from recent literature that suggest a growing trend toward using digital sources to get weather information (Nunley & Sherman-Morris, 2020; Phan et al. 2018). Question 1 of the survey asked about respondents' main source for a weather forecast. It was hypothesized that the weather app would be the most frequently selected source.

H1: The weather app will be the primary way the public gets general forecast information.

This hypothesis was evaluated using a bootstrapped confidence interval with a 95% confidence level and a 1000 re-sample bootstrap in SPSS. The results showed that between 74.0% and 80.5% of the population use a weather app or widget to get their forecast (Table 2.35). This far exceeded the next most common source—a website on the internet. Television did not even account for 10% of the sample. This led to the conclusion that the weather app (or widget) is the primary way that the public gets a weather forecast, a change from research near 2010 that showed television as the primary source (Lazo et al., 2009; Demuth et al., 2011).

Table 2.35 Survey Question 1

Q1. What would you describe as your main source for getting a weather forecast?

		95% Confidence Interval	
N = 600	**Frequency**	**Lower**	**Upper**
Weather App or Widget	464	74.0%	80.5%
A Website on the Internet	87	11.7%	17.3%
Television	37	4.3%	8.2%
Social Media	7	0.3%	2.0%
Other	5	0.2%	1.0%
Radio	0	0.0%	0.0%

2.4.3 Weather Information Sources during Severe Weather

RQ2: To what extent does the public use the television or a weather app for severe weather information?

While research suggests a growth in the use of digital sources for receiving a weather forecast, severe weather still tends to encourage the use of the television for forecast information (Sherman-Morris et al. 2020; Silva et al. 2017, Stokes & Senkbeil, 2017). Therefore, it was hypothesized that television would remain the primary source for getting severe weather information.

H2: The television will be the primary way the public gets severe weather information.

Question 4 asked participants to check all of the sources they turn to during severe weather after having been alerted about it. This provided the possibility of multiple responses. The hypothesis was evaluated by performing another 95% confidence interval with a 1000 re-sample bootstrap in SPSS. The most common response was a website on the internet followed closely by a weather app (Table 2.36). Television was chosen more frequently as a source for severe weather information compared to general forecast information, though it was still a distant third source on the list. Interestingly, social media saw more popularity during severe weather potentially due to citizens looking for severe weather reports and pictures or messages from friends or family. These results do not lend credence to hypothesis two. Thus, the television may in fact not be the primary way that the public gets severe weather information. This would contrast with many recent research findings. Attention should also be drawn to subtle differences in studies that seek to understand the most used source for information and the most important source for information, as these may not be the same. More research would also be beneficial in understanding if information sources change for different types of active or severe weather.

Table 2.36 Survey Question 4

Q4. After you have been alerted about the severe weather by (pipe above answer), what source or sources do you typically go to next for more information? Check all that apply.

		95% Confidence Interval	
N = 599	**Frequency**	**Lower**	**Upper**
Weather App or Widget	277	42.2%	50.0%
A Website on the Internet	305	46.8%	54.8%
Television	137	19.5%	26.0%
Social Media	108	15.2%	21.2%
Radio	18	1.7%	4.3%
Other	6	0.3%	1.8%

2.4.4 Weather App User Demographics

RQ3: What are the demographics of those who are most likely to use a weather app?

Several demographic characteristics were asked of participants in the survey including age, gender, race and ethnicity, education level, and urban/rural living environment. Since age was the only interval level variable, a Kruskal Wallis (KW) test was performed to determine if there were any significant differences in the mean age for each type of weather information source listed in question 1. The KW was significant and led to rejection of the null hypothesis ($H = 38.315$, $p < 0.001$). Dunn-Bonferroni post-hoc tests determined that the only significant differences in the mean age of each source were between weather app or widget and a website as well as weather app or widget and television ($p = 0.003$, $p < 0.001$). Bonferroni correction was used to test significance. The mean age for weather app or widget users was significantly lower than the mean age of television and website users (Table 2.37).

Table 2.37 Mean age of each weather information source category

Primary Weather Information Source N = 599	**Mean Age**
Weather App or Widget	29.64
A Website on the Internet	33.87
Television	40.51
Social Media	28.29
Other	44.60

The other demographic variables examined were nominal level, thus a chi-square analysis was desired. Due to row and column percentages below the acceptable level, a Fisher's Exact test was used (Table 2.38). The results of the Fisher's Exact test for gender and weather information source were statistically significant ($N = 582$, $p < .001$). Websites and television are used by more males, and the weather app is used by slightly more females.

Table 2.38 Fisher’s exact test and distribution of respondents by age bracket

Table	Demographic Characteristics	Weather App N (% of demographic characteristic using source)	Website	Television	Social Media	Radio	Other	Fisher Test Value	p-value
Gender N = 582	Male	195 (67.5%)	62 (21.5%)	26 (9.0%)	4 (1.4%)	0 (0%)	2 (0.7%)	40.323	<.001*
	Female	253 (86.6%)	23 (7.9%)	11 (3.8%)	2 (0.7%)	0 (0%)	3 (1.0%)		
Race & Ethnicity N = 600	White	323 (76.2%)	67 (15.8%)	24 (5.7%)	5 (1.2%)	0 (0%)	5 (1.2%)	37.809	.371
	Black or African American	55 (74.3%)	7 (9.5%)	11 (14.9%)	1 (1.4%)	0 (0%)	0 (0%)		
	Asian	33 (84.6%)	6 (15.4%)	0 (0.0%)	0 (0%)	0 (0%)	0 (0%)		
	Hispanic or Latino	32 (82.1%)	4 (10.3%)	2 (5.1%)	1 (2.6%)	0 (0%)	0 (0%)		
	Mixed race	17 (89).5%)	2 (10.5%)	0 (0.0%)	0 (0%)	0 (0%)	0 (0%)		
	Middle Eastern or North African	3 (100.0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)		
	American Indian or Alaska Native	1 (100.0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)		
	Other	0 (0%)	1 (100.0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)		
Edu. Level N = 597	High School	74 (76.3%)	15 (15.5%)	6 (6.2%)	2 (2.1%)	0 (0%)	0 (0%)	14.484	.468
	Some College	147 (77.8%)	30 (15.9%)	10 (5.3%)	1 (0.5%)	0 (0%)	1 (0.5%)		
	Associate’s Degree	37 (69.8%)	10 (18.9%)	5 (9.4%)	1 (1.9%)	0 (0%)	0 (0%)		
	Bachelor’s Degree	143 (81.3%)	22 (12.5%)	8 (4.5%)	2 (1.1%)	0 (0%)	1 (0.6%)		
	Advanced Degree	60 (73.2%)	10 (12.2%)	8 (9.8%)	1 (1.2%)	0 (0%)	3 (3.7%)		
Urban/ Rural Living Area N = 600	Urban area	143 (78.1%)	27 (14.8%)	10 (5.5%)	3 (1.6%)	0 (0%)	0 (0%)	17.671	.365
	Suburban area	251 (78.4%)	45 (14.1%)	20 (6.3%)	2 (0.6%)	0 (0%)	2 (0.6%)		
	Rural small town	48 (73.8%)	9 (13.8%)	5 (7.7%)	1 (1.5%)	0 (0%)	2 (3.1%)		
	Rural outside of town	20 (69.0%)	5 (17.2%)	2 (6.9%)	1 (3.4%)	0 (0%)	1 (3.4%)		
	Not sure	2 (66.7%)	1 (33.3%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)		
Age N = 600	18-30	299 (83.5%)	40 (11.2%)	13 (3.6%)	4 (1.1%)	0 (0%)	2 (0.6%)	-	-
	31-40	99 (74.4%)	25 (18.8%)	6 (4.5%)	3 (2.3%)	0 (0%)	0 (0%)		
	41-50	36 (64.3%)	10 (17.9%)	8 (14.3%)	0 (0%)	0 (0%)	2 (3.6%)		
	51-60	23 (60.5%)	8 (21.1%)	7 (18.4%)	0 (0%)	0 (0%)	0 (0%)		
	61+	7 (46.7%)	4 (26.7%)	3 (20.0%)	0 (0%)	0 (0%)	1 (6.7%)		

(*) Indicates significance

The Fisher’s Exact test for race and ethnicity and weather information source was not significant (N = 600, p = .371). Due to the number of categories in each variable, a Monte Carlo estimate was performed using a 99.9% confidence level and 10,000 samples. Despite a lack of significance, further investigation showed that Black and African American individuals were more likely to use television and white and Asian individuals were more likely to use a website than the other race and ethnicity categories. These two observations were not likely enough to make the whole test come back as significant.

Education levels “high school graduate” and “some high school” were combined in the Fisher’s exact test between education level and weather information source. This was done due to similarities between the two categories and the small number of “some high school” respondents in this sample. A Monte Carlo estimate was also used on this test with a 99.9% confidence level and 10,000 samples. The test was insignificant, indicating no relationship between education level and source type (N = 597, p = .468).

Finally, the effect of urban/rural classification on weather information source was examined using a Fisher’s exact test. A Monte Carlo estimate was again used on this test with a confidence level of 99.9% and 10,000 samples. The test showed no significance (N = 600, p = .378).

Age and gender were the only demographic characteristics found to have an association with which weather source was used. The results of the Fisher’s exact test are listed in the table below (Table 2.38).

H3: Lower age brackets are more likely to use the weather app than higher age brackets.

While there were weather app or widget users of all ages, the mean age (29.64) was lower than all other sources except social media (28.29). The survey data was divided into different age categories (18-30, 31-40, 41-50, 51-60, 61+), and the use of different sources was then compared. Overall, weather apps or widgets still dominated every age group. However, the percentage of people in each age group that used weather apps decreased with age. Contrastingly, use of websites and television increased with age.

2.4.5 Weather App Notifications Usage

RQ4: Do the majority of weather app users have notifications turned on?

Question 19 (Table 2.39) told participants to choose all notifications listed in the responses that they had turned on. This question intentionally refrained from asking what weather app notifications a person received, as there is likely to be confusion amongst participants as to whether a notification is coming from an app or if it is a Wireless Emergency Alert (WEA). With the unlikelihood of avoiding this confusion, question 19 was phrased to include any type of weather notification. This allowed the researcher to see how many people were getting weather information pushed to them.

The most likely notification to be confused with WEA is a severe weather alert. Nearly 80% of the sample reported getting severe weather notifications on their smartphones (Table 2.39). Beyond that, the usage of notifications dropped off markedly. Approximately a quarter of the sample got notifications about weather headlines and nearby rain. These two notifications are most likely coming from a weather app or potentially a news app and are not likely confused with WEA. There was still a small group of people (14.9%) that reported not getting any weather notifications on their phone. Thus, the utility of the smartphone as a "weather alert system" is not absolute, as there are still some people who are not affected by WEA and weather app notifications.

Given the confusion surrounding severe weather alert notifications and what source is responsible for them, it is unclear whether a majority of weather app users have their notifications turned on. When excluding severe weather notifications from the list, 41.3% of respondents said they got at least one of the other notifications on the list. Furthermore, it can be said that a large majority of weather app users do report receiving a notification of some kind on their smartphone regarding severe weather.

Table 2.39 Survey Question 19

Q19. Which notifications do you get on your smartphone about the weather? (Check all that apply.)

		95% Confidence Interval	
N = 563	**Frequency**	**Lower**	**Upper**
Severe Weather	450	76.9%	83.1%
Rain is close to you	148	22.7%	30.4%
Weather headlines	141	21.5%	28.6%
Lightning is close to you	99	14.7%	20.8%
Other	24	2.7%	6.0%
None	84	11.9%	17.9%

2.4.6 Weather Knowledge and Interest of Weather App Users

RQ5: Do users who download a weather app instead of using the predownloaded one have a higher interest in or knowledge about weather?

This research question was inspired by previous research that suggests people who download a weather app different from the one that came on their phone want additional and potentially more specialized data (Phan et al. 2018). Nunley and Sherman-Morris (2020) showed that higher perceived weather knowledge was associated with the use of specialized weather websites. Thus, the following hypotheses were created.

H4a: Individuals who consider themselves to be more knowledgeable about weather will be more likely to use another app besides the pre-downloaded one.

H4b: Individuals who consider themselves to have a higher interest in weather will be more likely to use another app besides the pre-downloaded one.

The sample was divided into two groups—those who had downloaded a weather app and those who had not—based on the results from question 16. Question 56 asked respondents to rate their weather knowledge on a Likert scale, and question 57 asked about weather interest. The data from these two questions were recoded as 1-5 interval data. A mean score was then calculated for each recode for both groups of people—those who had downloaded an app and those who had not. Mann Whitney U tests were then run to compare the means.

The mean self-assessed weather knowledge rating of those who had not downloaded a weather app (2.94, $N = 243$) was lower than that of people who had downloaded an app (3.17, $N = 318$). Mean weather interest was also lower for the group that had not downloaded an app (3.03, $N = 243$), in comparison to its counterpart (3.38, $N = 319$). The Mann Whitney U test for weather knowledge led to the rejection of the null hypothesis and went to show that those who download a weather app do have a higher weather knowledge rating ($U = 4.128$, $p < 0.001$). Similarly, the Mann Whitney U test rejected the null hypothesis for weather interest, indicating that those who download an app have a higher interest in weather than those who did not download a weather app ($U = 4.932$, $p < 0.001$).

2.4.7 Factors influencing Weather App Usage and User Demographics

RQ6: Are there any relationships between weather app usage frequency, device brand, device reliance, gender, age, or time of day of usage?

A Kruskal Wallis test was run with each variable to check for its relationship with age. Age was only related to smartphone brand ($H = 60.723$, $p <.001$), time of day of app usage ($H = 19.443$, $p = .007$), and smartphone reliance ($H = 9.658$, $p = .047$) (Table 2.40). Apple smartphone users are significantly younger than users of other brands ($p <.001$) (Table 2.41), and early morning app users tend to be older than late morning app users ($p = .007$). The KW test indicated that there was significant difference between mean ages of people in different device reliance categories, but post-hoc pairwise comparisons did not show any significance once the Bonferroni correction was implemented. It is likely that the overall significance of the Kruskal Wallis is driven by difference in mean ages of those in the "somewhat easily" versus "not easily" comparison, the "somewhat easily" versus "easily", and the "somewhat easily" versus "very easily" comparison as those were the lowest p-values.

Table 2.40 Kruskal Wallis test results

Age's effect on…	**H**	**p-value**
Frequency of weather app usage N = 594	9.027	.108
Smartphone brand N = 595	60.723	<.001*
Smartphone reliance N = 594	9.658	.047*
Time of day of weather app usage N = 563	19.443	.007*

(*) Indicates significance ($\alpha = 0.05$)

Table 2.41 Mean age of smartphone users by brand

Smartphone Brand	**Mean Age**
Apple N = 375	28.7
Samsung N = 137	33.8
Google N = 32	35.6
Other N = 51	36.5
No Smartphone N = 5	46.6

Fisher’s exact tests were used to test all other relationships between weather app usage frequency, smartphone brand, smartphone reliance, gender, and time of day of app usage. Monte Carlo estimates with 99.9% confidence levels and 10,000 samples were used for all tests except those where gender was one of the variables.

Weather app usage frequency was found to have a significant relationship with smartphone brand, gender, and time of day of usage. Apple smartphone users are more likely to check their weather app multiple times per day compared to other brands’ users (Table 2.42). Furthermore, females tended to use their weather app slightly more often than males (Table 2.43). Those who check their weather app in the early morning or late morning are more likely to check the app more frequently too as opposed to those who check it later in the day. This is a logical conclusion. Those who check their app in the morning, early or late, consider weather information important enough to check it earlier in their day. Similarly, those who check a weather app frequently likely also consider a weather forecast to be important information. Those who check the forecast late in the day or less frequently are more likely to put less importance or interest in that type of information.

Apple smartphone users were found to be more likely to say they could not easily function without their smartphone for a day than other brands’ users (Table 2.42). Google and Samsung users more frequently said they could easily or very easily function without their smartphone for a day than Apple users did. This indicates that Apple users perceive that they are more reliant on their smartphones than Google and Samsung users. Furthermore, a strong relationship was found between smartphone brand and gender. Females make up 62.6% of Apple’s smartphone users, whereas males make up 86.2% of Google users and 64.4% of

Samsung users. Smartphone brand however did not influence the time of day at which people used their weather app.

Males indicated that they could more easily function without a smartphone for a day than females did (Table 2.44). However, device reliance was not related to time of day of app usage. Similarly, gender did not influence what time of day people used their weather apps (Table 2.45).

Table 2.42 Results of Fisher's exact test for smartphone brand

		Smartphone Brand									
		Apple		Samsung		Google		Other			
Table	Characteristics	N (% of Apple users with that characteristic)		N (% of Samsung users with that characteristic)		N (% of Google users with that characteristic)		N (% of "Other" users with that characteristic)		Fisher Test Value	p-value
Weather app usage frequency N = 594	Multiple times per day	120	(33.1%)	23	(18.7%)	9	(29.0%)	11	(23.9%)	23.393	0.018*
	Once per day	141	(39.0%)	57	(46.3%)	8	(25.8%)	17	(37.0%)		
	More than once per week, but not daily	66	(18.2%)	24	(19.5%)	11	(35.5%)	10	(21.7%)		
	Once per week	15	(4.1%)	10	(8.1%)	2	(6.5%)	1	(2.2%)		
	Less frequently than once per week	20	(5.5bn c%)	9	(7.3%)	1	(3.2%)	7	(15.2%)		
Smartphone Reliance N = 594	Very Easily	25	(44.6%)	13	(23.2%)	7	(12.5%)	11	(19.6%)	27.612	0.005*
	Easily	54	(58.1%)	31	(33.3%)	3	(3.2%)	5	(5.4%)		
	Somewhat Easily	111	(66.5%)	34	(20.4%)	8	(4.8%)	14	(8.4%)		
	Not Easily	124	(63.3%)	43	(21.9%)	10	(5.1%)	19	(9.7%)		
	Not at all Easily	61	(74.4%)	16	(19.5%)	3	(3.7%)	2	(2.4%)		
Gender N = (576)	Male	137	(48.1%)	85	(29.8%)	25	(8.8%)	38	(13.3%)	65.890	<.001*
	Female	229	(78.7%)	47	(16.2%)	4	(1.4%)	11	(3.8%)		
Time of day of weather app usage N = (563)	Early Morning (6-9am)	161	(69.4%)	42	(18.1%)	9	(3.9%)	20	(8.6%)	28.894	0.069
	Late Morning (9am-Noon)	110	(65.9%)	37	(22.2%)	8	(4.8%)	12	(7.2%)		
	Early Afternoon (Noon-3pm)	23	(48.9%)	16	(34.0%)	3	(6.4%)	5	(10.6%)		
	Late Afternoon (3pm-6pm)	18	(69.2%)	5	(19.2%)	2	(7.7%)	1	(3.8%)		
	Early Evening (6-9pm)	14	(58.3%)	6	(25.0%)	0	(0%)	4	(16.7%)		
	Late Evening(9pm-Midnight)	12	(50.0%)	8	(33.3%)	4	(16.7%)	0	(0%)		
	Overnight (Midnight-6am)	1	(33.3%)	1	(33.3%)	1	(33.3%)	0	(0%)		
	Anytime I'm bored	23	(57.5%)	9	(22.5%)	4	(10.0%)	4	(10.0%)		

(*) Indicates significance ($\alpha = 0.05$)

Table 2.43 Results of Fisher's exact test for weather app usage frequency

		Weather app usage frequency													
		Multiple times per day N (% of of these people with that characteristic)		Once per day N (% of of these people with that characteristic)		More than once per week, but not daily N (% of of these people with that characteristic)		Once per week N (% of of these people with that characteristic)		Less frequently than once per week N (% of of these people with that characteristic)		Never N (% of of these people with that characteristic)		Fisher Test Value	p-value
Smartphone Reliance N = (594)	Very Easily	18	(32.1%)	21	(37.5%)	6	(10.7%)	2	(3.6%)	4	(7.1%)	5	(8.9%)	24.515	0.582
	Easily	20	(21.5%)	35	(37.6%)	14	(15.1%)	8	(8.6%)	9	(9.7%)	7	(7.5%)		
	Somewhat Easily	41	(24.7%)	68	(41.0%)	31	(18.7%)	7	(4.2%)	10	(6.0%)	9	(5.4%)		
	Not Easily	59	(30.1%)	66	(33.7%)	43	(21.9%)	8	(4.1%)	11	(5.6%)	9	(4.6%)		
	Not at all Easily	25	(30.5%)	33	(40.2%)	16	(19.5%)	3	(3.7%)	3	(3.7%)	2	(2.4%)		
Gender N = (575)	Male	68	(23.9%)	105	(36.8%)	55	(19.3%)	15	(5.3%)	25	(8.8%)	17	(6.0%)	11.470	0.042*
	Female	92	(31.7%)	112	(38.6%)	52	(17.9%)	11	(3.8%)	10	(3.4%)	13	(4.5%)		
Time of day of weather app usage N = (562)	Early Morning (6-9am)	85	(36.6%)	93	(40.1%)	38	(16.4%)	6	(2.6%)	10	(4.3%)	-	-	66.750	<.001*
	Late Morning (9am-Noon)	37	(22.2%)	85	(50.9%)	33	(19.8%)	9	(5.4%)	3	(1.8%)	-	-		
	Early Afternoon (Noon-3pm)	13	(27.7%)	10	(21.3%)	13	(27.7%)	3	(6.4%)	8	(17.0%)	-	-		
	Late Afternoon (3pm-6pm)	7	(28.0%)	7	(28.0%)	6	(24.0%)	3	(12.0%)	2	(8.0%)	-	-		
	Early Evening (6-9pm)	5	(20.8%)	9	(37.5%)	4	(16.7%)	1	(4.2%)	5	(20.8%)	-	-		
	Late Evening (9pm-Midnight)	5	(20.8%)	9	(37.5%)	5	(20.8%)	3	(12.5%)	2	(8.3%)	-	-		
	Overnight (Midnight-6am)	1	(33.3%)	2	(66.7%)	0	(0.0%)	0	(0.0%)	0	(0.0%)	-	-		
	Anytime I'm bored	10	(25.0%)	8	(20.0%)	12	(30.0%)	3	(7.5%)	7	(17.5%)	-	-		

(*) Indicates significance ($\alpha = 0.05$)

Table 2.44 Results of Fisher's exact test for smartphone reliance

		Smartphone Reliance: Very Easily N (% of of these people with that characteristic)		Easily N (% of of these people with that characteristic)		Somewhat Easily N (% of of these people with that characteristic)		Not Easily N (% of of these people with that characteristic)		Not at all Easily N (% of of these people with that characteristic)		Fisher Test Value	p-value
Gender N = (575)	Male	34	(11.9%)	51	(17.9%)	80	(28.1%)	87	(30.5%)	33	(11.6%)	9.737	0.044*
	Female	19	(6.6%)	39	(13.4%)	81	(27.9%)	104	(35.9%)	47	(16.2%)		
Time of day of weather app usage N = (562)	Early Morning (6-9am)	16	(6.9%)	35	(15.1%)	76	(32.8%)	74	(31.9%)	31	(13.4%)	32.328	0.187
	Late Morning (9am-Noon)	17	(10.2%)	24	(14.4%)	46	(27.5%)	55	(32.9%)	25	(15.0%)		
	Early Afternoon (Noon-3pm)	4	(8.7%)	7	(15.2%)	9	(19.6%)	19	(41.3%)	7	(15.2%)		
	Late Afternoon (3pm-6pm)	0	(0.0%)	5	(19.2%)	6	(23.1%)	6	(23.1%)	9	(34.6%)		
	Early Evening (6-9pm)	3	(12.5%)	5	(20.8%)	8	(33.3%)	8	(33.3%)	0	(0.0%)		
	Late Evening (9pm-Midnight)	2	(8.3%)	4	(4.7%)	6	(25.0%)	10	(41.7%)	2	(2.5%)		
	Overnight (Midnight-6am)	1	(33.3%)	1	(33.3%)	0	(0.0%)	1	(33.3%)	0	(0.0%)		
	Anytime I'm bored	8	(20.0%)	5	(12.5%)	7	(18%)	14	(35.0%)	6	(15.0%)		

(*) Indicates significance (α = 0.05)

Table 2.45 Results of Fisher's exact test for gender

		Gender: Female N (% of of these people with that characteristic)		Male N (% of of these people with that characteristic)		Fisher Test Value	p-value
Time of day of weather app usage N = (546)	Early Morning (6-9am)	108	(47.4%)	120	(52.6%)	10.835	0.135
	Late Morning (9am-Noon)	100	(61.3%)	63	(38.7%)		
	Early Afternoon (Noon-3pm)	18	(43.9%)	23	(56.1%)		
	Late Afternoon (3pm-6pm)	12	(48.0%)	13	(54.2%)		
	Early Evening (6-9pm)	11	(45.8%)	13	(52.0%)		
	Late Evening (9pm-Midnight)	11	(47.8%)	12	(52.2%)		
	Overnight (Midnight-6am)	1	(33.3%)	2	(66.7%)		
	Anytime I'm bored	17	(43.6%)	22	(56.4%)		

2.5 Discussion

This research found that digital sources are dominating more traditional sources for weather information, building on the findings of Phan et al. (2018), Chan et al. (2017), and Nunley and Sherman-Morris (2020). The weather app was clearly identified as the primary source for weather information, especially in lower age brackets. This is consistent with Phan et al.'s (2018) findings in a college aged group of individuals. Questions existed surrounding how far this truth extended into older age brackets. The results of this research indicate that weather apps are dominant even amongst older groups, though to a lesser extent.

Interestingly, this study broke away from much of the literature focusing on weather information sources during severe weather. Several studies from 2017 found that television was the most common source used for alerting or information during a tornado warning (Stokes & Senkbeil, 2017; Silva et al. 2017) and emergency situations (Reuter & Spielhofer, 2017). Sherman-Morris et al. (2020a) found that local television was the most important source for information during a hurricane. These studies still presented a strong indication that other sources were used, including digital sources, but they found television to be dominant. This survey did not specify a type of situation or severe weather, it simply asked for the most common source used to gather information during severe weather. The lack of specificity about the situation may have affected the results as the definition of severe weather is broad and may be interpreted differently from person to person. This may explain the deviation, though reliance on digital sources during severe weather situations may truly be a growing. This survey was administered to an online audience which may make them more likely to use an online or digital source and may affect average age of the participants. The four studies mentioned above also used online survey methods (Stokes & Senkbeil, 2017; Silva et al. 2017; Reuter & Spielhofer, 2017; Sherman-Morris et al. 2020a). Though only Silva et al. (2017) indicated that their sample was representative of the U.S. population by age. Stokes and Senkbeil (2017) as well as Reuter and Spielhofer (2017) had small percentages of respondents in age brackets over 50 years of age similar to this study. More research will be needed on older age brackets to better understand the generalizability of this conclusion.

Similar to Bryant et al. (2016), a slight majority of the survey sample downloaded a different weather app than the pre-downloaded one on their phone. Interestingly, this group was not very diverse in the apps they chose as a large percentage of them chose either The Weather Channel or Accuweather. These individuals also rated their weather knowledge and interest higher than the alternative group which expands the findings of Nunley and Sherman-Morris (2020) into weather apps in addition to websites.

The sample rated the top five features of their weather app as 1) hourly forecast, 2) chance of precipitation, 3) severe weather alerts, 4) 5-day forecast, and 5) current information. Though minor ordinal differences occur, this is the same top five important features that Phan et al. (2018) found. Severe weather alerts were found to be widely used, though it was unclear if these alerts originated from an app or WEA. Due to the uncertainty, it was not concluded that most app users have notifications turned on. Additional research into this will be important to truly understand the acceptance of notifications. As such a useful feature from a risk information perspective, perhaps more education for the public would be wise to make sure that either weather app alerts or WEA notifications are enabled.

Only around 5% of survey respondents said they used a local news station's weather app. While limited, this seemed adequate to examine some of the questions by the researcher. Approximately, half of this group said that they had seen the meteorologist on TV who was responsible for inputting the forecast into their app. Most thought that if the forecast was wrong, the meteorologist was at least partially responsible. Though most of these respondents did not indicate frequent viewership of either the meteorologist or news channels. Furthermore, only half indicated following the meteorologist on social media. The only thing that pointed to strong evidence of a relationship between the consumer and the news station was that 83.8% of the news station app users indicated moderate or high trust in that news station. Thus, this may be more of a relationship with the brand of the news station or simply their position as a media authority in the market. Further research is needed to understand how the public perceives the relationship between a news station's weather app and that news station's brand and personalities and how this may influence their weather app choice.

Usefulness and convenience were both significantly higher for weather apps than television, which according to the TAMMS explains the growth of the medium (Kaasinen, 2005). However, the usage of the weather app varied amongst demographics. Females were more likely to be app users than males. Females were also more likely to own Apple smartphones. These users were more likely to check their weather app more frequently and be more reliant on their phones. Overall, weather app usage was found to typically occur in the morning hours, consistent with previous research (Böhmer et al. 2011).

2.6 Conclusion

As the media landscape continues to rapidly evolve, the sources that the public turn to for weather information are also changing. This study used a diverse sample to show that the weather app was now the primary source for people to get weather information. With this change comes adjustments in when and how people are getting a forecast and forces a consideration on what factors influence when, where, and why they get weather information. This research provided a necessary step forward for the weather communication community to better understand the public's new habits for learning about the weather. It confirmed and expanded previous research findings from existent literature. One major deviation occurred regarding information sources during severe weather, and continued research will be necessary to understand where the public is turning to during those scenarios.

CHAPTER III

UNDERSTANDING PUBLIC PERCEPTION OF WEATHER APPS

3.1 Introduction

This project sought to understand the public's perceived accuracy and consistency of their choice weather app and how that impacts their trust in the app and trust in meteorology. The study also examined the perceptions of some weather features and messaging techniques. The following research questions and hypotheses were the focus of this study:

- RQ7: What is the public's perceived accuracy of a weather app?
- RQ8: How does the perceived accuracy of a weather app affect the trust in the weather app?
    - Hypothesis 5: The higher the perceived accuracy, the greater the trust in the app.
- RQ9: What is the public's perceived consistency of a weather app?
- RQ10: How does the perceived inconsistency of a weather app affect the trust in the weather app?
    - Hypothesis 6: The lower the perceived inconsistency, the greater the trust in the app.
- RQ11: How does the public interpret the quantification of uncertainty from their weather app?

- RQ12: Does the public consider regional variability when getting a forecast from their weather app?
- RQ13: Are there any relationships between perceived accuracy and the trust put in weather apps, meteorologists, news stations, and the field of meteorology?

3.2 Literature Review

For much of recent history, the television has been the avenue by which people chose to get a weather forecast (Corso, 2007; Demuth et al. 2011; Grotticelli, 2011). While it may not have been their sole source for weather information (Demuth et al. 2011), it was the most common.

3.2.1 Forecast Value

Getting a weather forecast is usually promoted by wanting to know when to plan activities, how to dress, or even simply just for the sake of knowing the forecast (Demuth et al. 2011). Forecast information is valuable if the user's decision making is improved, and if the decision they made based on the forecast information was a good decision (Millner, 2008; Voulgaris, 2019). The usefulness of a forecast is based on the user having at least moderate confidence that the forecast information will be accurate and useful (Demuth et al. 2011; Kay et al. 2015; Bryant et al. 2017). Accuracy has long been considered an important factor in forecast value (Murphy, 1993).

However, a distinction exists between accuracy and what this project calls "perceived accuracy"—whether or not the consumer perceives the forecast to be accurate. A forecast may have been "accurate" according to a forecaster, but it may be interpreted as "inaccurate" by the consumer because they were measuring it with two different standards (Murphy, 1993). A forecast may call for scattered showers, and as long as showers were scattered about the area, the forecaster was right. However, if rain did not fall at the forecast user's house, they may interpret the forecast as having been wrong. When asking about the accuracy of the forecast they use, consumers are not expected to be keeping logs of forecast versus observation, nor are they expected to research the accuracy. Their version of accuracy will originate in what they heard, what they then expected, and what they then observed. Close resemblance of observation and forecast are not expected to be noticed; however, large differences between the two especially involving precipitation are likely to be noticed and perceived as inaccurate (Murphy, 1993; Morrow, 2008). Perceived accuracy is more subjective than accuracy because it is dependent on an individual's own expectations and observations—two things that are likely to vary from person to person. Thus, in the mind of the forecast user, perceived accuracy is accuracy. This idea has been used in other research (Sherman-Morris, 2005).

3.2.2 Invention of Weather Apps

The advent of the 2010s came with widespread explosion of smartphone technology and the apps that run on these devices. By the middle of the decade, mixed results were found as to whether the weather app or television was the primary way to receive a forecast (Silver, 2015; Hickey, 2015). By 2018, college students listed the weather app as their primary way of getting weather information (Phan et al. 2018). However, near the same time, it was found that those fifty-five and older relied on television much more heavily for news consumption (Pew Research Center, 2018). While this is specifically for news, it does delineate a distinction between younger and older people as to how they get their information.

Research over the last several years indicates a positive attitude toward the accuracy and usefulness of weather apps (Bryant et al. 2017). Most smartphones come with a form of weather app predownloaded on the phone; however, many people choose to download a different weather app (Bryant et. al 2017). Higher accuracy and more information was expected out of an app that was not predownloaded on the phone (Bryant et al. 2017; Phan et al. 2018). Phan et al. (2018) found that a majority of college students have only one weather app on their phone, with males being more likely than females to have multiple weather apps. Multiple weather apps could be desired or needed on account of unique weather features in particular regions of the world, activities that require more information than a traditional app offers, or simply for more information (Guo et al. 2018).

The weather app has made very large gains in the weather forecast market since its inception a little over a decade ago. Weather apps are consistently rated in the top seven apps on the market (Khamaj et al. 2019; Purcell, 2011), and ninety-one percent of smartphone users have a weather app (Khamaj et al. 2019). Given the ubiquity of smartphones and weather apps, “it would be hard to imagine a better device for distributing weather information” (Mass, 2012, pp. 800). The public appears to agree with this as Phan et al. (2018) found that four in five of their participants not only had a weather app but used it on a daily basis. Convenience in the form of immediate information was a big reason most people chose the app as their forecast medium (Nix-Crawford, 2017; Phan et al, 2018). Immediate information is not generally available on the television, at least not in the way that it is on an app, social media, or the internet (Nix-Crawford, 2017).

3.2.3 Trust in the Forecast: Developing Trust

Weather apps are popular, quickly gaining ground on television, and mostly considered accurate. However, the effect that perceived inaccuracy of an app has on trust in the app, a meteorologist, a news station, or even in the field of meteorology as a whole has gone largely unaddressed in modern research. In order to understand the connection between inaccuracy and trust, an understanding of trust has to be established.

In television, trust is vital in both acquiring and keeping viewers (Nix-Crawford, 2017). It is “defined as the willingness of a person, group or community to defer to or tolerate, without fear, the judgements or actions of another person or institution that directly affect one’s own actions or welfare” (Crease, 2004, pp. 18). There are three primary components that have been identified in the development of trust—benevolence, integrity, and competence (McKnight & Chervany, 2001). McKnight and Chervany (2001) give a lengthy review of trust definitions. Benevolence contributes to the development of trust-related feelings if the person doing the trusting perceives that the other party cares about them and acts in their interest. Integrity can also foster trust by promoting honesty and acting in good faith. Competency is simply having the ability to do something. In the case of a forecast, trust is shown by a person if they are willing to use the forecast when making decisions about their life. They would trust in a forecast if they perceived it to be for the furthering of their own interest, if they thought it was honest or at least in good faith, if they perceived it to be accurate and made by a competent forecaster, and if a weather forecast is actually possible. Competency and whether a forecast predicts beyond what is actually known will be discussed later. But benevolence and integrity will be discussed below with accuracy, consistency, reliability, and relationships.

First, trust can be developed through accuracy (Murphy, 1993; Burgeno & Joslyn, 2020), consistency (Murphy, 1993; Losee & Joslyn, 2018), and reliability (Kaasinen et al. 2011). Or, trust can be pre-existing based on previous experience or relationships (MSG Management Study guide, 2017; Wall et al. 2017; Nix-Crawford, 2017). An example of a previous relationship influencing trust would be a viewer's parasocial relationship with a news station's weathercaster. This is discussed below.

Other factors that can influence trust include easy-to-understand communication (Nix-Crawford, 2017), timely delivery of information (Nix-Crawford, 2017), and high severity of a forecast. The more severe a forecast is, the more trust an individual may put in the forecast (Losee & Joslyn, 2018).

3.2.4 Trust in the Forecast: Parasocial Relationship

Sherman-Morris (2005) found that television viewers developed a relationship with their local weathercaster known as a para-social relationship--a one-sided relationship that is nurtured by the viewers' frequently seeing the weathercaster on television. Because of this, the viewer comes to think of the weathercaster as a friend and displays a higher trust in the weathercaster and what they say (Sherman-Morris, 2005). Sherman-Morris (2005) showed that a viewer will look at forecast and severe weather information differently and possibly take a different action than they would otherwise simply because the weathercaster is the one giving the information. Sherman-Morris et al. (2020a) found more recently that para-social relationship with a local news personality is less prominent today and may play a greater role in day-to-day weather information seeking as opposed to decision making.

Klotz (2011) has found that parasocial relationships associated with television do carry over into the digital realm such as social media. He found that social media actually worked to enhance pre-existing parasocial relationships because it increased the interaction between the personality and the viewer (Klotz, 2011). Given that the relationship carried over into social media, a viewer may make choices regarding other digital media, such as weather apps, that are also influenced by the pre-existent parasocial relationship.

Suppose a person is in the habit of watching a particular weathercaster and that person has developed a trust in them. When downloading a weather app, the viewer chooses the app offered by the news station the weathercaster works for and trusts its output. This trust, at least initially, is not based on the accuracy, consistency, or reliability of the app, but rather it is an extension of the parasocial relationship developed previously with the weathercaster. Thus, pre-existent parasocial relationships could work beneficially for the development of trust in a weather app.

Additionally, a weather app user's relationship with a weathercaster could affect perceived accuracy of the forecast as Sherman-Morris (2005) showed that trust, perceived accuracy, and parasocial interaction were related. It is possible that a weather app could be viewed as more trustworthy and accurate simply because of its association with a trusted person in the consumer's life. This makes it important to understand what type of relationship the consumer has with their local news media when studying their perceived accuracy of their weather app.

However, if a parasocial relationship is absent and if the weather app has replaced the television as the main source of weather for an individual, the human-element that is experienced in a television forecast is removed. Given what was mentioned previously about parasocial relationship's effect on trust, removal of the weathercaster may result in the consumer having an overall lower trust in the information simply because it is no longer associated with a "friend".

3.2.5 Trust in the Forecast: Maintaining Trust

When it comes to maintaining trust, this deals largely with accuracy and consistency. Accuracy is how "right" the forecast was or, in this project, how "right the forecast was perceived by the user". Forecast consistency has been defined in many differing ways. It has been referred to as the alignment between the forecast and what the forecaster actually thinks is going to happen (Murphy, 1993; Voulgaris, 2019). It has also been defined as the similarity of a message between two different sources or the uniformity of colors, symbols, and presentation between two different sources (Weyrich et al. 2019; Williams & Eosco, 2021). In this paper, consistency is the similarity of the forecast from one forecast issue to the next (Lashley et al. 2008; Burgeno & Joslyn, 2020). Lashley et al. (2008) proposed that consistency is equally as significant as accuracy in keeping trust. While inconsistency does result in lower trust, inaccuracy was found to be far more detrimental to the forecast user's trust (Nix-Crawford, 2017; Burgeno & Joslyn, 2020).

Interestingly, failure to provide constant accuracy did not result in complete breach of trust (Keeling, 2011; Savelli & Joslyn, 2012). Many users still came back for another forecast even after an inaccuracy (Demuth et al. 2011). This may be because users expect for there to be some error and uncertainty associated with forecasting (Savelli & Joslyn, 2012).

Therefore, once trust is established, accuracy becomes the main driver in keeping it (Nix-Crawford, 2017). This makes inaccuracy worthy of study since it has the potential to drastically impact trust. When compared to television, weather apps have unique attributes that can lead to a greater chance of perceived inaccuracy. This is a result of the change in communication styles between a television forecast and a forecast found in a weather app.

3.2.6 Causes of Perceived Inaccuracy

Inaccuracy, or the perception thereof, can be found in all forecasts including those found on television. However, when the forecast is taken off of the television, the storytelling and context that accompany the forecast are removed. This can enhance the perception of inaccuracy.

The consequences of this can be seen in the weather app in two ways—misinterpretation and forecasting beyond what is known.

The first is misinterpretation. The forecast user may not interpret the forecast in the same way it was intended (Joslyn et al. 2009; Zabini et al. 2015; Losee & Joslyn, 2018). The weather app has brought about widespread transfer of forecast interpretation from the broadcast meteorologist to the forecast user. A broadcast meteorologist—having at least some form of meteorological training—can interpret the forecast and then explain it to the viewer (Morrow, 2008). For weather app users, the burden falls on them to interpret what the forecast is. With this comes a higher likelihood of misinterpretation (Zabini et al. 2015). A misinterpretation of the forecast can lead to false expectations that can lead to perceptions of inaccuracy when those false expectations do not verify.

A common source of misinterpretation is found in the communication of uncertainty. The debate of how to include uncertainty in a forecast reaches all sectors of meteorology, and the weather app is no exception. Uncertainty has a striking ability to create perceptions of inaccuracy in any forecast, no matter what medium it is taken from (Wall et al. 2017). However, because the app shifts the interpretation of that uncertainty onto the forecast user, the forecaster does not have the ability to explain the intricacies of that uncertainty (Morrow, 2008).

The app provides a way for misinterpretation to combine with the problem of forecasting beyond what is known or considered reasonably accurate. On television, the amount of uncertainty can affect what is communicated and whether specific information is left in or out of the forecast (Hunt, 2013). In a weather app, the uncertainty does not get to influence what is left in or out of the forecast (Zabini, 2016). The amount of information an app outputs is constant. When little to no uncertainty exists in the forecast, providing a lot of specific information may not be a problem. But, when forecasts of high uncertainty arise, the app does not decrease or increase the amount of information it gives due to the formatting and layout of the app. In some rainfall events, providing a reasonably accurate forecast of rainfall totals is not possible three days out. If a weather app typically provides forecasted rainfall totals, and the three-day forecast involves a high chance of rain, the app will have to show a forecast rainfall total regardless of how certain or uncertain that total is. Essentially, this is forecasting beyond what can be reliably forecasted and can be misinterpreted as having more certainty in the forecast than exists.

Misinterpretation is also found heavily in the way uncertainty is presented. For example, should one use probability of precipitation (PoPs), text-based uncertainty quantifiers, or neither? All of these forms could be used in a weather app, but the problem again involves limited communication. People assume that uncertainty exists in a forecast, thus it makes sense to quantify that uncertainty in some form (Zabini et al. 2015). Though which form is used will affect the way the forecast is interpreted and then used (Nadav-Greenberg et al. 2008). Most weather apps use PoPs to quantify uncertainty (Zabini, 2016). Prior study has shown that forecast users prefer this (Morss et al. 2008), and that the use of PoPs was associated with higher trust (Grounds, 2016). However, this does not mean that the percentage chance of rain given is being interpreted the way it was intended. In fact, research suggests that individuals tend to interpret the chance of rain in their own way (Morss et al. 2008). Though users may not grasp the concept of a seventy percent chance of rain, they can grasp the number seventy on a scale of one to one hundred. Percentages can serve as a sort of "code" or scale to define uncertainty (Zabini et al. 2015). They may understand that this is a "high" chance of rain, but they may also mistake it as meaning a long rain event or even one that will drop a lot of rain (Zabini et al. 2015; Joslyn et al. 2009). The wide array of interpretations alone can lead to false expectations and consequent perception of inaccuracy. However, Wall et al. (2017) point out another danger that comes with offering PoPs. If individuals consult a forecast for decision making purposes, they are looking to make a deterministic decision—yes or no. For example, can we have this wedding outdoors? A PoP weather forecast does not offer a yes or no, rain or no rain answer. A seventy percent chance of rain may be enough to move the wedding indoors, but there is still a chance that it will not rain, potentially leaving the decision maker disappointed. This attempt to mesh probabilistic information with deterministic decision-making leads to another chance of perceived inaccuracy (Wall et al. 2017). This problem can exist in all weather forecasts, but the lack of explanation in the app and the forcing of the user to interpret the uncertainty makes the problem worse.

Weather apps also have the tendency to forecast beyond reasonable accuracy. They introduced the idea of hyperlocal forecasting—a forecast that is given for a specific town or maybe even a specific GPS location. The app can provide a forecast for “your house”, while television tends to give a forecast for a metropolitan area or region (Zabini, 2016). This feature does not account for the fact that weather is variable regionally. The hyperlocal forecast is less about the weather in one’s area and more about the weather out their window. With weather apps being based on weather model simulations, the model resolution must be taken into account. While the resolution is good, it is not high enough to provide a forecast for every specific GPS point (Zabini, 2016; Du et al. 2018). This means that even high-resolution models technically are a conglomerate of numerous small scale regional forecasts for each square unit of the model. However, in the app, these are being advertised as point specific forecasts. The regional variability is not being accounted for. Scattered rain in an area may make for a correct forecast, but if it did not rain on the forecast user, they may feel the forecast was wrong. Regional variability is needed to appropriately address uncertainty (Zabini, 2016).

Finally, weather apps also tend to forecast too far into the future. In some cases, hourly forecasts are available for five to ten days ahead (Zabini, 2016; Du et al. 2018). Research does not support the idea that people are making decisions based on a forecast that far out (Myers, 2019). Without a need for them, these highly specific forecasts run the risk of sending the message that the forecast for three o'clock in the morning ten days in the future is known and does not account for the fact that that forecast may be questionable (Zabini, 2016; Du et al. 2018). The reason behind overpredicting is pinned on the commercialization of the weather forecast (Morrow, 2008). A weather forecast has become focused on offering more than the competition as opposed to providing a quality weather forecast (Morrow, 2008).

While it is unclear how much each of these factors influence the perceptions of inaccuracy, the public does notice and dislike inaccuracy in weather apps (Fu et al. 2013). Any perceptions of inaccuracy that arise from the weather app, can be expected to have a negative impact on the trust in the app (Burgeno & Joslyn, 2020). However, does this perception of inaccuracy extend to affect the trust in a meteorologist or news organization that is connected to the app? Does it even affect the trust in the field of meteorology as a whole? If the trust in the app was formed due to a prior relationship or para-social relationship with a meteorologist or news company, the trust is expected to remain intact and not be affected by inaccuracy as long as the relationship with that person or company is maintained in ways external to the app. If, however, the trust is built strictly on accuracy of the app, inaccuracy is expected to decrease trust in anything connected to the app.

3.3 Methodology

This project used a survey in conjunction with the first project to achieve its goals as has been done by other similar studies (Bryant et al. 2017; Zabini et al. 2015; Phan et al. 2018; Nix-

Crawford, 2017). In addition to asking demographic and weather app usage questions, there were questions inquiring about participants' trust and perceived accuracy of their app. This was used to check for any relation between the two. Questions about perceptions of uncertainty and regional variability, forecast inconsistency, and participants' thoughts of meteorologists, news organizations, and the field of meteorology were also included.

Understanding the public's perceived accuracy of their weather app involved calculating the mean of the interval data from the response choices. Respondents were asked about their trust in weather apps in general as well as their specific weather app. A Wilcoxon Signed Rank test was used to compare the means between the two. The relationship between perceived accuracy and trust and perceived consistency and trust was analyzed with Spearman correlation. Research question 11 used survey questions asking about confidence in the forecast between days 1, 3, 5, 7 and 10, and a Freidman test was used to compare the mean confidence rating between the different days. Spearman correlation was again used to understand the relationship between perceived accuracy of the app and trust in the app, meteorologists, news stations, and the field of meteorology. Table 3.1 shows the statistical tests used in this chapter.

Table 3.1 Statistical analyses used for chapter three

Research Question or Hypothesis	Statistical Test
Research Question 7 What is the public's perceived accuracy of a weather app?	Wilcoxon Signed Rank Test
Hypothesis 5 The higher the perceived accuracy, the greater the trust in the app.	Spearman Correlation
Research Question 9 What is the public's perceived consistency of a weather app?	Calculating Data Distribution
Hypothesis 6 The lower the perceived inconsistency, the greater the trust in the app.	Spearman Correlation

Table 3.1 (continued)

Research Question or Hypothesis	Statistical Test
Research Question 11 How does the public interpret the quantification of uncertainty from their weather app?	Freidman Test
Research Question 12 Does the public consider regional variability when getting a forecast from their weather app?	Calculating Data Distribution
Research Question 13 Are there any relationships between perceived accuracy and the trust put in weather apps, meteorologists, news stations, and the field of meteorology?	Wilcoxon Signed Rank Test

3.4 Results

3.4.1 Perceived Accuracy of Weather Apps

RQ7: What is the public's perceived accuracy of a weather app?

Question 26 asked respondents how they would rate the accuracy of their weather app they use most frequently. The question was Likert style and was recoded into 1-5 interval data. A similar process was performed for question 27 where respondents were asked to rate the accuracy of weather apps in general. The goal of these questions was to not only understand how accurate these individuals perceived their app to be, but also to understand how they thought their app compared to others.

Slightly more than half of respondents rated their weather app as having "high" accuracy, and that went up to 70% of the sample when combined with those who answered "very high". The mean for perceived accuracy of the specific weather app the participant used (3.81, N = 563) was greater than the perceived accuracy of weather apps in general (3.70, N = 561), though not by much. The Wilcoxon Signed Rank test led to rejection of the null hypothesis indicating that respondents thought the app they use most frequently was more accurate than weather apps in general ($Z = -5.40$, $p < 0.001$).

3.4.2 Perceived Accuracy and Trust

RQ8: How does the perceived accuracy of a weather app affect the trust in the weather app?

This research question used the responses to question 26 to get a rating for perceived weather app accuracy, and the responses from question 28 were used to get a rating of the trust participants had in their weather app. Both variables were Likert style questions and were recoded into 1-5 interval data. A Spearman correlation was then conducted to check for association between the two variables.

Hypothesis 5: The higher the perceived accuracy, the greater the trust in the app.

The one-tailed Spearman correlation was significant and the correlation was high ($r_s(557) = 0.766$, $p < 0.001$). Thus, the greater the perceived accuracy of a weather app, the greater the trust a person puts in the app.

3.4.3 Perceived Inconsistency of Weather Apps

RQ9: What is the public's perceived consistency of a weather app?

Question 30 asked how often their weather app tends to make big jumps in the forecast. An ordinal scale was used ranging from "almost always" to "never", and 82.5% fell in the "sometimes" or "seldom" categories. However, 15.5% said that their app "often" or "almost always" made big jumps in the forecast.

3.4.4 Perceived Inconsistency and Trust

RQ10: How does the perceived inconsistency of a weather app affect the trust in the weather app?

This research question used the consistency results from question 30 and the trust results from question 28. Each was recoded into 1-5 interval data, and a one-tailed Spearman correlation was again used.

Hypothesis 6: The lower the perceived inconsistency, the greater the trust in the app.

The results of the Spearman correlation revealed a weak negative association between perceived inconsistency and trust ($r_s(557) = -0.215$, $p < 0.001$).This echoes the findings of previous research that perceptions of accuracy may be the stronger predictors of trust over perceptions of consistency (Nix-Crawford, 2017; Burgeno & Joslyn, 2020).

3.4.5 Public Interpretation of Uncertainty in Weather Apps

RQ11: How does the public interpret the quantification of uncertainty from their weather app?

Questions 5-9 all asked about respondents' confidence levels in the forecast at different time intervals—one day, three days, five days, seven days, and ten days. Each participant was only asked three of the possible five questions in a random order. They were asked to rate their confidence on a Likert scale of "very low" to "very high". The data was then recoded as 1-5 interval data.

The mean rating for each question was calculated and compared using a Freidman test. The means decreased as time went on (Day 1 = 4.07, N = 374; Day 3 = 3.54, N = 358; Day 5 = 3.09, N = 350; Day 7 = 2.83, N = 359; Day 10 = 2.54, N = 359). The Freidman test led to the rejection of the null hypothesis, indicating that there was significant difference between at least some of the means ($\chi^2 = 497.39$, $p < 0.001$). A Wilcoxon Signed Rank test was then run post-hoc on each of the consecutive relationships (i.e. Day 1 vs. Day 3, Day 3 vs. Day 5, etc.). A Bonferroni adjustment was used to account for the repeated comparisons made using the

Wilcoxon Sign test. Since four comparisons were being made, the p-value required for significance fell to 0.0125. The mean confidence rating of day 1 compared to day 3 was significantly higher ($Z = -8.138$, $p < 0.001$). The same trend was observed for the other comparisons made (Day 3 vs. Day 5: $Z = -6.663$, $p < 0.001$; Day 5 vs. Day 7: $Z = -4.155$, $p < 0.001$; Day 7 vs. Day 10: $Z = -4.119$, $p < 0.001$). Thus, the public's confidence in a forecast decreases as time goes out. This could indicate that the public understands there to be more uncertainty in the forecast with time.

Questions 34 and 35 told participants that their weather app has forecasted a 70 percent and 30 percent chance of rain respectively. Participants were asked to check all responses that they expected to occur in each situation. The possible responses represented the areal coverage of rain, rain at a specific location, the rainfall totals, the duration of rain, and the intensity of the rain falling. For question 34 (Table 3.2) which asked about a 70 percent chance of rain, 66.4% of people said that most locations in the area would get rain and 29.1% of people expected rain at their house. This indicates that nearly two-thirds of people were under the correct interpretation of the forecast—that most locations would get rain. The percentage of people who chose responses related to rain totals, duration, or intensity was less than 7% for each.

Question 35 (Table 3.3) yielded different results. This question asked about a 30% chance of rain. Less than 2% of the people thought that most locations in the area would get rain, and 94.8% thought that "some locations" would get rain. Only 3.5% of the sample thought it would rain at their house. Interestingly, the frequency with which responses relating to rain totals, duration, and intensity increased rather dramatically ranging from 22% to 26.9% of the sample.

Table 3.2 Survey Question 34

Q34. If your weather app forecasts a 70% chance of rain for tomorrow, what would you expect to occur? (Check all that apply.)
N = 600

	Frequency	Percentage
Most locations in my area will get rain	374	62.3%
Some locations in my area will get rain	164	27.3%
It will rain at my house	199	33.2%
It will rain for a long duration of time	27	4.5%
There will be high rainfall totals	39	6.5%
There will be heavy downpours	13	2.2%
None of the above	9	1.5%

Table 3.3 Survey Question 35

Q35. If your weather app forecasts a 30% chance of rain for tomorrow, what would you expect to occur? (Check all that apply.)
N = 600

	Frequency	Percentage
Most locations in my area will get rain	9	1.5%
Some locations in my area will get rain	534	94.8%
It will rain at my house	20	3.3%
It will rain for a short duration of time	124	20.7%
There will be low rainfall totals	126	21.0%
There will be light rain	152	25.3%
None of the above	40	6.7%

3.4.6 Public Perception of Regional Variability in Weather Apps

RQ12: Does the public consider regional variability when getting a forecast from their weather app?

Question 32 asked participants to remember the last time that their weather app forecasted rain, but it did not rain at their location. It asked whether it rained nearby. This question worked together with question 33 to understand participants' consideration of regional variability. Question 33 then asked if the respondent thought the forecast was accurate, inaccurate, or neither for that day.

Three hundred and thirty-four people said that it had rained nearby. Of those people, 71.3% said the forecast was accurate for that day, and another 19.2% said that it was neither accurate nor inaccurate. Thus, even though it did not rain at their house, 90.5% of the people would not say that the forecast was inaccurate.

Now for those who did not get rain and there was no nearby rain, 26.8% still said the forecast was accurate while 68.3% said it was inaccurate. Of those who were unsure if it rained nearby, 48.4% said the forecast was neither accurate nor inaccurate and 29.3% said it was accurate. Overall, even when a person did not get rain at their house--regardless of whether it rained nearby or not—53.9% still said the weather forecast was accurate. Based on these results, the public does seem to be considering at least some regional variability when considering a forecast and its accuracy and validation.

Questions 36 and 37 were used to understand how the consideration of regional variability has changed with the switch in predominate weather forecast sources. Participants were asked what area they thought a forecast was for when it came from a weather app and television respectively. The choices consisted of a range that grew in spatial coverage including "your specific location", "your town", "your county", and "your county and the neighboring counties". Many apps have the capability to give a forecast for your specific location, yet only 22.3% of people thought that the forecast was for that. A majority (51.5%) thought the forecast was for their town.

In contrast, when asking about the geospatial extent of a television weather forecast, 44.7% said it was for their county and the neighboring counties. However, 24% still said it was for their town. This seems to indicate that some of the public understands that a forecast on television is for a broader ranging locale, even if the extended forecast near the end is typically for the main city where the news station is located. They also seem to understand that weather app forecasts tend to be more location-specific than television. Thus, with the weather app becoming the dominant method for getting a weather forecast, the regional variability that is being considered in a forecast may have decreased from a time when the television was the main source for a weather forecast.

3.4.7 Perceived Accuracy of App and the Field of Meteorology

RQ13: Are there any relationships between perceived accuracy and the trust put in weather apps, meteorologists, news stations, and the field of meteorology?

A Spearman correlation was used to compare questions in the survey relating to accuracy and trust (Table 3.4). Interestingly, all ten correlations came back as either moderately or highly positive. Not only are weather app accuracy and trust in weather apps, meteorologists, and the science of meteorology correlated, but trust in a weather app also correlates with trust in meteorologists. Thus, how weather apps perform, how accurate they are, and whether the public likes them are important issues to consider due to their potential impact on other areas in the field.

Table 3.4 Spearman correlation results

Variable 1	Variable 2	r_s	p-values
Q26. Accuracy of App	Q28. Trust in App	0.766	<.001
Q26. Accuracy of App	Q10. Trust in Meteorologists	0.444	<.001
Q26. Accuracy of App	Q11. Trust in Meteorology	0.401	<.001
Q26. Accuracy of App	Q45. Trust in News Station that makes App	0.514	0.004
Q28. Trust in App	Q10. Trust in Meteorologists	0.442	<.001
Q28. Trust in App	Q11. Trust in Meteorology	0.440	<.001
Q28. Trust in App	Q45. Trust in News Station that makes App	0.451	0.014
Q10. Trust in Meteorologists	Q11. Trust in Meteorology	0.731	<.001
Q10. Trust in Meteorologists	Q45. Trust in News Station that makes App	0.603	<.001
Q11. Trust in Meteorology	Q45. Trust in News Station that makes App	0.526	0.003

3.5 Discussion

As shown in chapter two, the weather app has become a dominant source for weather information, and thus it serves as a representative of the weather forecasting community. While chapter two's results failed to determine if a person's connection to a news station or one of its personalities influenced the choice to use a particular weather app, this chapter found that a weather app's accuracy and trust were at least moderately correlated with trust in the field of meteorology, meteorologists, and in a news station. For many, the weather app has become the face of meteorology, and it should be treated with this seriousness.

Fortunately, most participants in this study considered their weather app to be highly accurate similar to Bryant et al.'s (2017) study. This is very important and encouraging since the value a forecast holds is largely based on its accuracy (Demuth et al. 2011; Kay et al. 2015; Bryant et al. 2017). This is also helpful in maintaining trust in weather forecasting, as this study found that trust in the app was highly correlated with the perceived accuracy of the app.

Perceived consistency of the app also was shown to influence the consumer's trust put in the app. Inconsistency was sometimes noticed by survey participants and it was found to negatively impact their trust. Thus, creating weather apps that have both high accuracy and high consistency is important to the future of weather forecasting.

However, many features and messaging techniques that weather apps use can be confusing and potentially even create unrealistic expectations and subsequent perceptions of inaccuracy when those expectations fail to transpire. This study found that the public's confidence in a forecast wanes the further out the forecast extends. When analyzing the Likert data, a forecast for ten days out received a mean confidence rating between low and moderate. This implied questionable confidence in the whole forecast for that day, much less any high-resolution details that that forecast may contain. Zabini (2016) found that over 50% of the weather apps they analyzed had forecasts that extended between 10 and 15 days out. Due to a weather app's inability to change its degree of detail of a forecast should varying levels of uncertainty deem it necessary, the weather apps present a confident forecast for very far into the future without even considering the actual confidence that can be had. Even the public—showing at best moderate confidence—knows better than this. This offers support for Myers' finding that people do not make decisions based on forecasts this far out (2019). If decisions are not being made, yet a forecast's value is rooted in its ability to enhance decision making (Millner, 2008; Voulgaris, 2019), the need of 10 to 15 day forecasts is drawn into question. The weather forecasting community must re-evaluate whether these forecasts are necessary and wise and if so, whether their motivation is rooted in science or in commercialism.

In an age of hyperlocal and highly personalized content where a smartphone's location-based services are incorporated into every app and every search, the weather app industry seemed to have no other option but to join the trend. Weather apps can now provide a forecast for you based on your location. This creates a problem from a forecasting perspective though as weather is regionally variable and may differ between locations that are even short distances apart. In the most common example, rain chances may be issued for two towns, but only one may receive rain while the other stays dry. This does not mean the forecast was inaccurate. Anyone considering the area as a whole will observe that rain fell, verifying the forecast. But without that consideration, would the public still assume the forecast was accurate?

With the migration from television to apps for weather forecasts, this study found that the public has perceived a shrinking in the locale that the forecast is issued for. Unlike television, a weather app implies the forecast presented to the consumer is for one specific location or town and largely negates what is happening in the surrounding area. While concerning, the results also supported the idea that the public does consider regional variability to some extent when determining if a forecast verified. Further research will be necessary to determine how far that extent goes.

As with any forecasting, a weather app forecast must include a quantification of uncertainty. The most obvious example of this is probability of precipitation (PoPs), which is found in most weather apps (Zabini, 2016). The results of this study showed that interpretation of a percentage varied between two examples—30% and 70%. Simply changing the number changed the expectations for what it meant. When respondents were asked about their interpretation of a 70 percent chance of rain, most thought it had something to do with what area and locations would get rain (e.g. most locations would get rain, some locations would get rain, or it would rain at their house). While this finding still held true when respondents were asked about a 30 percent chance of rain, significantly more people made assumptions about the expected rainfall duration, totals, and intensity for 30 percent. This excellently illustrates the findings of Morss et al. (2008) that forecast users interpret probability of precipitation (PoP) in their own way. It also lends credence to Zabini et al. (2015) and Joslyn et al. (2009) that rainfall totals and duration may be perceived simply based on the PoP value. This finding does little more than to call for additional research, but it can be concluded that an objective measure like PoPs can be subjectively interpreted. As with previous points in this section, understanding interpretation by the public is vital to having appropriate messaging that avoids communicating inaccurate expectations. This should be a priority considering the ubiquity of PoPs especially in weather apps.

3.6 Conclusion

As weather apps have become a normal and popular way to get a weather forecast, attention needs to be given to their accuracy and consistency as well as their communication of the forecast. Accuracy and consistency are related to the trust put in weather apps, and accuracy and trust showed correlation with the trust put in the wider field of meteorology. Furthermore, the weather app has created new potential for forecast information to be misinterpreted and misperceived. If the public's view of weather forecasting now rests heavily on the shoulders of a computer interface, it is vital the research continue to ensure that these apps are helping to advance forecasting and that they are being held to a scientific standard.

CHAPTER IV

UNDERSTANDING PERFORMANCE OF NEWS MEDIA TWITTER ACCOUNTS DURING HURRICANE IRMA

4.1 Introduction

With the introduction of social media came a new outlet by which to communicate during a disaster. This has been a focus of research aiming to better understand human decision making, information consumption, risk perception, and behavioral response to threats (Pourebrahim et al. 2019; Demuth et al. 2018; Stokes & Senkbeil, 2017; Sherman-Morris et al. 2020a; Martín et al. 2020). This project adds to these efforts by examining how Twitter was used and how it performed in Hurricane Irma of 2017. This project will use a Twitter dataset to look at how different types of Twitter accounts, types of tweet content, and television market size influence the engagement of tweets. This project uses the following research questions and hypotheses to accomplish its purpose:

- RQ14: What are the differences in engagement levels for tweets with different types of content?
    - Hypothesis 7: Hurricane related tweets from news station accounts will receive higher engagement scores than non-hurricane related tweets.
    - Hypothesis 8: Hurricane related tweets from news stations' weather accounts will receive higher engagement scores than non-hurricane related tweets.

- RQ16: What are the differences in engagement temporally throughout the duration of the storm?
    - Hypothesis 9: Engagement levels will increase through the peak of the storm in each location.
- RQ17: What are the differences in engagement between the two time periods (May vs. Irma)?
- RQ18: Are their relationships between type of tweet content, market size, weather or news account, and engagement?
- RQ19: Do accounts of people who have more personalized posts in have more engagement in Irma?
    - Hypothesis 10: Accounts with more personalized posts will receive higher engagement scores on hurricane related tweets.

4.2 Literature Review

4.2.1 Twitter's Effects on Disaster Communication

Traditionally, as severe weather situations and hurricanes have occurred, television has been the main source for information (Sherman-Morris, 2010; Morss & Hayden, 2010; Zhang et al. 2007; Sherman-Morris, 2013). But the advent of social media has brought about a new way of communicating information in all situations, including disasters and hazardous events. Among the changes it has brought, are enhanced speed and efficiency in the delivery of information (Houston et al. 2015). It has also made the flow of information, even in a crisis, more informal. "Disaster communication used to be very top-down, hierarchical, and linear where public officials and experts were the ones who pushed the information out" (Sutton, 2008, para. 11). However, it is no longer just officials that have a voice. Ordinary citizens are now active participants in the journalism process (Hermida et al. 2012; Hermida, 2010). They are now the first ones on the scene and provide initial reports and media for a news story (Silver & Andrey, 2019). Furthermore, social media has caused news stories to lose much of their cohesive, unified structure, leaving the information scattered in fragments (Hermida, 2010). This requires the news consumer to put together the story themselves based off of the fragments of information they consume (Hermida, 2010). The speed, informality, and lack of structure of news on Twitter can often lead to it being very chaotic (Hermida, 2010; Houston et al. 2015). Thus, research is needed to understand the best practices that can be used in order to capitalize on the strengths of this new medium while minimizing its weaknesses.

While social media can be very chaotic, it can also create more order and structure in information gathering. For example, Twitter puts news of all different opinions and viewpoints in one place in order for users to sort through the excess of information faster and easier, taking away what they want and leaving what they do not (Bell, 2014). Social media also has the ability to expose a news consumer to more news than they might otherwise get by receiving shared posts from other people (Lee & Ma, 2012). Because of this, social media are actually able to both narrow and widen a consumer's news spread at the same time.

Social media gives users the ability to share a post with their followers, which can have an unusual effect on the post. For example, on Twitter, a "retweet" could take a tweet from being promoted by only a news station and allows it to be promoted by retweet from a celebrity, public figure, friend, or family member. Some individuals may be willing to listen to something that is promoted by a celebrity or family member, even though they would not ordinarily listen to it if it came directly from a news station (Hermida et al. 2012; Schmierbach & Oeldorf-Hirsch, 2012; Skågeby, 2010; Mills et al. 2009). Research has shown that many people rely on family members and friends for information in a disaster which underscores the power of retweeting (Sherman-Morris et al. 2020a; Hermida, 2012).

4.2.2 Benefits of Twitter in Disaster Communication

The many changes that social media have brought to the media can work beneficially in disasters. Speed is an obvious benefit (Houston et al. 2015). The faster the public is made aware of a dangerous situation, the more time they will have to be prepared. Traditional media take longer to gather information and put together a news story that can be aired on television. Studies have found that it can take up to twenty-four hours for the quality of information on television to match that of social media, simply because it is playing catch up (O'Brien, 2008; Mills et al. 2009).

By making crisis communication more informal, social media allows for the public to play a greater role in managing a crisis. Not only can citizens take part in the journalism process, but they can also take part in the disaster response (Stephenson, 2011). This is often underestimated. For example, during the September 11th terrorist attacks, Hurricane Katrina, and Hurricane Harvey many evacuations and rescues took place not by effort coordinated from above, but by improvisation of citizens helping their fellow neighbors (Henry, 2019; CBS News, 2015; Wax-Thibodeaux, 2017). Instead of formal information being distributed by officials and large media organizations, Twitter gives a voice to the people at the scene allowing them to ask for help from fellow citizens without having to use the government or media as the intermediary.

Twitter uses hashtags that serve as keywords in a tweet that can be searched in the Twitter search engine. These hashtags, when used properly, enable social media to increase organization of information and can reduce the searching that has to go in to finding specific information (Freberg et al. 2013; Silver & Andrey, 2019).

Social media also offers benefits over television when the power goes out—as is often the case in disasters. During the power outages from Hurricane Sandy, residents relied on cell signal which gave them access to Twitter and other digital means of staying alert and prepared in the disaster (Stewart & Wilson, 2016). As long as power remains out, a smartphone's battery will eventually die. Thus, social media access on a cellphone does not provide a long-term solution for information access in a disaster, but it does outlast television in that situation (Lindsay, 2011).

Not only does Twitter provide many benefits over traditional media in a disaster, but it actually fits many of the qualifications of a good disaster communication platform. It is web-based, low-cost, easy-to-use, mobile, reliable, fast, and has the ability to reach many people with a variety of information sources (Mills et al. 2009). Some of this value has been noticed and capitalized on by news stations, with many journalists now using social media as a part of their everyday job (Greer & Ferguson, 2011; Smith et al. 2007).

4.2.3 News Media on Twitter during Disasters

When it comes to disaster coverage, news media are the commonly thought of source for information. In the digital era, news media continue to play a highly prominent role in covering a disaster and diffusing information on social media (Yang et al. 2019). Amongst a variety of official voices during disaster communication, news media have been found to have the greatest ability to distribute information on social media (Wang & Zhuang, 2017). News and weather agencies were observed to be dominant sources of information during Tropical Storm Cindy in 2017 (Kim et al. 2018). During Hurricane Sandy, news media tweeted more frequently and had higher median audience levels than governmental sources (Wang & Zhuang, 2017). Though governmental sources were more likely to get retweeted during this storm (Wang & Zhuang, 2017). That being said, many of the top retweeted tweets during Hurricane Irma were produced by news media (Lachlan et al. 2019). These findings support further study of news media as a prominent source for information during natural disasters.

Some differences in Twitter use and online presence have emerged in previous literature regarding television news market size. Chan-Olmsted and Kim (2001) found that lesser watched and smaller markets were more likely to have higher amounts of digital content. But Chan-Olmsted and Park (2000) found that larger markets have more digital content. While these contradict one another, the studies were conducted long before online and digital news was mainstream and thus may be less applicable. Another study points out that journalists at different market sizes may use social media differently depending on how established their voice is on television or in the information marketplace as a whole (Lasorsa et al. 2012). During a flooding event in South Carolina, Mortenson, Hull, and Boling (2017) theorized that smaller media markets may be less equipped and skilled to cover events. Market size has also been shown to influence the level of preparedness to cover a disaster event (Spence et al. 2009). Therefore, more research is needed to better understand how news market size effects both the use of social media in a disaster and the overall coverage of a disaster as well.

4.2.4 Research of Twitter during Hurricanes

With Twitter being considered a tool for disaster communication by both the public and officials, researching of the platform has blossomed in recent years. Twitter usage and performance during tropical cyclones has been studied form a variety of angles including to better understand communication and information diffusion (Pourebrahim et al. 2019; Demuth et al. 2018), rescue and response (Mihunov et al. 2020), and evacuation compliance (Martín et al. 2020).

Observations have been made regarding the evolution of Twitter usage during hurricanes. In Hurricane Sandy, Twitter usage increased when the power went out as that meant other sources for information were no longer available (Pourebrahim et al. 2019). Tweet frequency was found to peak during the main impact stage of that storm as well as in Hurricane Irene (Pourebrahim et al. 2019; Wang & Zhuang. 2017; Mandel et al. 2012). The frequency of tweets also peaked during the landfall of Hurricane Ike but was also preceded by a lesser peak as the storm hit Cuba (Hughes & Palen, 2009). During Hurricane Harvey, the tweet maximum occurred after landfall, likely due to the subsequent flooding disaster that took place (Yang et al. 2019). In contrast, tweet frequency maxed out before landfall for Hurricane Matthew (Martín et al. 2017; Yuan et al. 2020).

The content and theme of tweets has also been noted to change during the duration of tropical cyclones (Yang et al. 2019; Huang & Xiao, 2015). During Sandy, themes progressed from planning, preparation, and information to concern for safety to response and rescue after impact (Pourebrahim et al. 2019). Interestingly, researchers found that tweets containing useful information decreased as a storm approached in favor of tweets expressing emotion (Spence et al. 2015). Events surrounding the storm can also influence the frequency of tweets, as was observed in Hurricane Matthew when an evacuation order announcement fueled a sudden spike in the number of tweets (Martín et al. 2017).

The concept of "retweeting"—sharing content from another Twitter account to your own account—has been an important focus of some of the hurricane related literature on this topic. In fact, retweeted content made up a majority of the tweets in a study from Hurricane Irma, indicating that a small number of original tweets were responsible for most of the Twitter content during this time (Lachlan et al. 2019). This makes retweeting a pivotal tool for sharing information but can also be an indication of a person agreeing with or validating a tweet, a sign or act of friendship, or a way to boost the number of followers for an account (Boyd et al. 2010). Retweeting can also be a sign of shared conversational context—maybe not a direct conversation between two users, but a sign that they are both partaking in a shared conversation (Boyd et al. 2010). Breaking news as well as tweets containing links or hashtags have both been shown to be retweeted more often (Boyd et al. 2010; Suh et al. 2010).

Retweeting notably increased amongst the population at risk from Hurricane Sandy (Kogan et al. 2015). Engagement with tweets during Tropical Storm Cindy of 2017 peaked after the storm made landfall (Kim et al. 2018). Though this storm initiated closer to land with less time for preparation and coverage of the storm to build. As more information is posted on Twitter and the overall frequency of tweets increases, there are more messages competing to be retweeted which may result in a lessening of information diffusion (Yoo et al. 2016). More research is needed to understand engagement patterns on Twitter during hurricanes and other natural disasters. It is also unclear how engagement varies amongst tweets that are related versus unrelated to the disaster, as most studies look at tweets strictly in relation to the disaster under study.

4.2.5 Broadcaster Personae's Effect on Retweeting

In addition to content and events influencing retweet activity, is it possible that the personae of the person or entity tweeting out the information could influence whether their tweet gets retweeted? According to literature on the topic, it may be possible. For example, frequent exposure to a news personality, the appearance of shared value and interest with the news person, and the overall liking of a person's personality can result in the concept of "liking", which can increase trust in that person simply because they like them (Nicholson et al. 2001;

Sherman-Morris, 2005). News personalities can build authenticity and transparency by showing their job, posting things about their personal lives, and interacting with viewers (Lasorsa et al. 2012). Being identifiable and showing a common humanness can also help people listen to what is being said (Renn & Levine, 1991).

This confluence of increased trust, liking, authenticity, transparency, and identifiability in the context of a media figure has been studied in the realm of para-social interaction (PSI) (Auter, & Palmgreen, 2000; Sherman-Morris, 2005; Rosaen & Dibble, 2008; Tsay-Vogel & Schwartz, 2014). Para-social interaction was originally studied by Horton and Wohl (1956) as a one-sided relationship or friendship between a viewer and a member of the media. As mentioned previously, retweeting could be a behavior produced by friendship (Boyd et al. 2010). Retweeting of a celebrity's post has also been shown to make a person feel as though the celebrity is more a part of their life (Kim & Song, 2016). A person's following of a celebrity on social media is an indication of a greater emotional attachment to them (Kowalczyk & Pounders, 2016). This would seem to indicate that a person may choose to retweet a tweet based on a relationship with a media member (likely unknown to the media member). While some literature has explored this thought (Bond, 2016), it is unclear as to how this relationship could impact the engagement between the public and a media member on social media during a disaster. Sherman-Morris et al. (2020) found that para-social relationship (PSR) was not related to risk perception or protective action taken during Hurricane Irma. But the study called for future research between PSR and social media. Thus, this study will contribute to this research effort by investigating the relationship between the tweeting of personal life events or details by a media member and the number of retweets they received during Hurricane Irma.

4.2.6 Retweeting to Measure Information Dissemination

It can be difficult to decide whether a message on Twitter or any other medium is actually effective at making the public take action without performing an in-depth study on a person's behavior. Just because someone is informed with what decision making is the best does not mean they will take that action. However, focusing on action taking after information reception is outside the scope of this paper. This study is primarily focused on the dissemination of information.

Previous studies have turned to social media engagement as a measure of successful and influential messaging (Mirbabaie et al. 2020; Lee et al. 2017; Riquelme & González-Cantergiani, 2016; Mirbabaie et al. 2014). Jiang et al. (2016) suggested that a social media message is most effective when the audience is highly engaged. Views, retweets, likes, comments, and replies are all ways of being engaged with a message. Engagement on social media has actually been considered a behavior instead of just an affective state (Jiang et al. 2016).

Considering information dissemination, retweeting is the best engagement measure to show the reach of a post (Cha et al. 2010; Kwak et al. 2010, Silver & Andrey, 2019). However, total number of followers is important to at least consider because it shows the initial "possible" audience for a message, and thus shows the initial scope of possible engagement (Meyer & Tang, 2015). The overall number of tweets put out by an account is not a good measure for success, since it leaves out how much reach those tweets are getting (Mirbabaie et al. 2014). However, it has been found that the more a newsroom tweets, the lower engagement they tend to receive. This is blamed on the overload of information discouraging attention from the audience (Meyer & Tang, 2015). Retweeting also helps identify who the influencers are in the information marketplace (Oh et al. 2015; Mirbabaie et al. 2020; Lee et al. 2017; Riquelme & González-

Cantergiani, 2016; Mirbabaie et al. 2014). Using engagement as a means of investigating social media during a disaster has been recommended by previous research (Jiang et al. 2016; Silver & Andrey, 2019). Thus, this study makes use of retweet metrics as a way to understand what information was penetrating furthest into the social network.

4.3 Storm Synopsis

Hurricane Irma formed on August 30th, 2017, near the Cabo Verde Islands (Figure 4.1). The storm made the long track across the central tropical Atlantic before impacting the Northern Lesser Antilles on September 5th at which point it was already apparent that Florida would experience direct impacts. During this time, Irma had already achieved category 5 status and was receiving ample media attention. In the following days, Irma tracked along the northern rim of the Greater Antilles. On September 9th, the storm was located between Cuba and the Florida Keys. It then turned northward and made landfall on September 10th. From there, it took an inland track along the western edge of the Florida peninsula. The storm was declared a remnant low over the southeastern U.S. on September 12th. The initial Floridian landfall occurred in the Florida Keys when the storm was category 4 strength. The storm made a second landfall in Florida as a category 3 storm. Before hitting Florida, Irma caused extensive power outages in Puerto Rico (National Hurricane Center, 2018). The storm was responsible for directly killing 47 people across its lifetime and caused an estimated 50 billion dollars in damage in the U.S. alone (National Hurricane Center, 2018). In respect to this study, Irma was unique in that it affected every single television market in the state. This made it ideal for studying the influence of market size on communication in a disaster. It also provided a plethora of news station and meteorologist Twitter accounts that were being used for disaster communication.

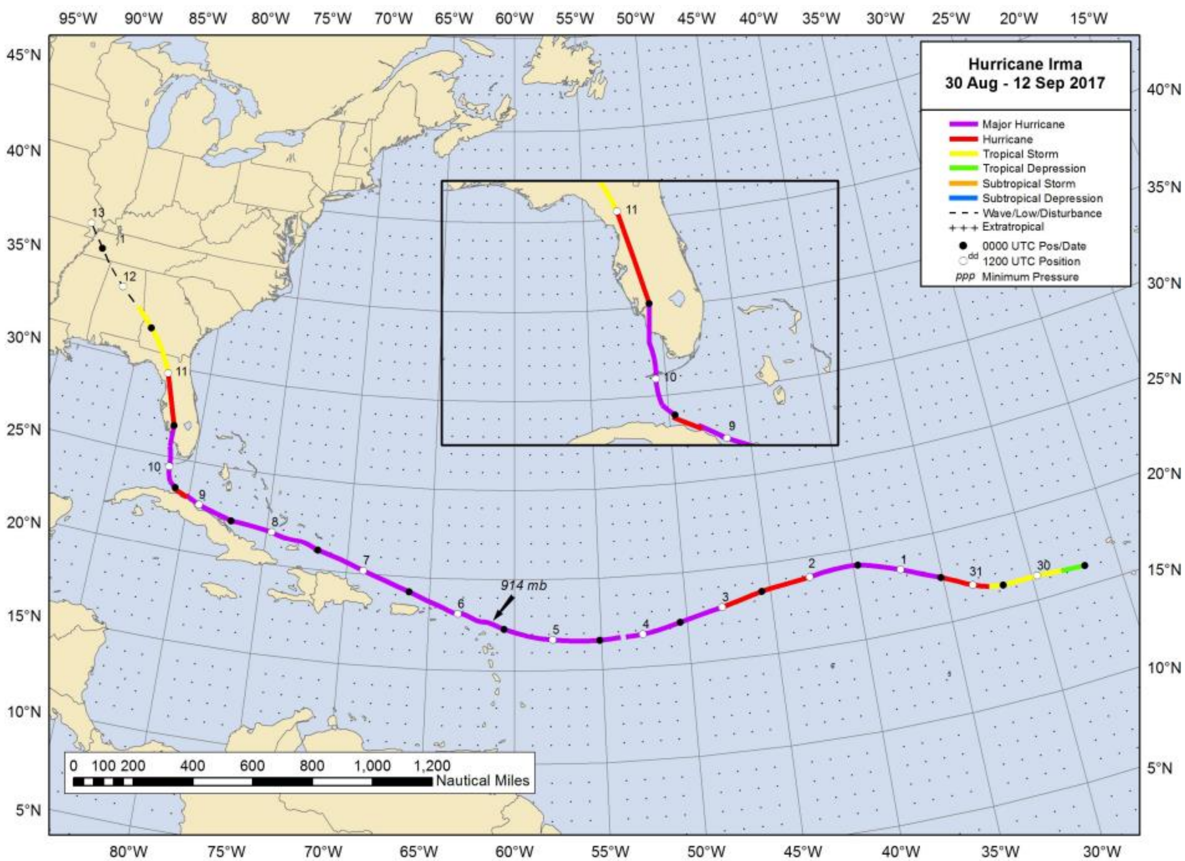

Figure 4.1 Hurricane Irma track (National Hurricane Center, 2018).

Hurricane Irma originated as a tropical depression near the Cabo Verde Islands. The storm moved westward and quickly intensified into a major hurricane. It remained a powerful hurricane and reached its peak intensity near the northern Lesser Antilles. The storm stayed just north of the Greater Antilles before turning northward into southern Florida. Irma then tracked along the west coast of Florida before weakening to a tropical storm in the panhandle.

4.4 Methodology

Tweets were collected from two time periods using the Social Media Tracking and Analysis System (SMTAS) that has the ability to harvest tweets. The first time period of focus begins at 12:00 a.m. eastern daylight time (EDT) on May 9th, 2017 and ends May 16th, 2017 at 7:00 p.m. EDT. The second time period for which data was gathered was 12:00 a.m. EDT on September 5th, 2017. The cut off time for the tweets was 7:00 p.m. EDT on September 12th, 2017. The raw September dataset include 643,632 replies, retweets, and tweets. The May dataset included 73,832. After removing retweets and replies, the September dataset contained 29,803 original tweets, and the May dataset contained 13,877. Tweet metadata included: time and date, actor (who the account was for), actor follower count, tweet body, and number of retweets. Other data that was calculated and then recorded includes: account type (news, weather, or broadcast meteorologist), television market name and size, engagement index, relation of the tweet to Irma, as well as the type of content each tweet contained.

There were 166 different twitter accounts (actors) analyzed. Thirty-two of these were news channel accounts, 9 of them were news channel accounts strictly related to weather, and 125 were personal accounts for broadcast meteorologists. These accounts were found in all television markets within the state of Florida.

Tweet content was defined by whether a tweet was hurricane related or not. A dictionary of words that were hurricane related was created (Appendix B) and the Linguistic Inquiry and Word Count (LIWC) software was used to examine whether tweets had words contained in the dictionary (Lachlan et al. 2019). A tweet that contained at least one word from the dictionary was considered hurricane related. The dictionary included several sub-dictionaries that divided the hurricane related words into different categories associated with different aspects of the storm

(Table 4.1). These sub-dictionaries were used later in the analysis of tweet content (Yuan et al. 2020). The categories include: meteorology/science, naming, meteorological impacts, warning, forecast, damage and negative impacts, and preparation and response. A few examples of each category can be found in the table below. The process of using keywords to formulate a dataset is consistent with other studies (Pourebrahim et al. 2019; Yang et al. 2019; Hughes & Palen, 2009).

Table 4.1 Sub-dictionaries from the hurricane-related dictionary

Dictionary Category	Examples of some words used
Meteorology/Science	eye wall, outer band, wind shear
Naming	Irma, hurricane, #irma
Meteorological Impacts	wind, tornado, rain, surge, gust
Warning	warning, watch, advisory
Forecast	strengthening, GFS, track shift, forecast
Damage & Negative Impacts	impact, power outage, shelter, cancel, damage
Preparation & Response	evacuation, preparation, rescue

An engagement index was computed for each tweet to standardize the engagement. To calculate this, the number of retweets a tweet had garnered was divided by the number of followers that the tweeting account had at the time of the tweet. The resulting number was then multiplied by one thousand in order to make the values slightly larger and easier to work with. The values ranged from 0 for tweets with no retweets to a maximum of 3,000 for a tweet that had 3 retweets, but the originating account only had one follower at the time of the tweet. The need for index resulted from the follower counts of each actor fluctuating throughout the duration of the storm. With the audience size fluctuating, even if just slightly, it makes raw engagement values incomparable as a larger audience may yield higher engagement and vice versa.

A random subset of 259,644 retweets from September was used to calculate how quickly a tweet received most of its engagement. Between half and two-thirds of retweets occurred during the first two to three hours after the tweet was published, with approximately 85-90% of the retweets occurring within 24 hours of the tweet. Thus, some statistical analysis refrains from including September 12 tweets as they may not have had enough time to receive their full engagement thus truncating their engagement values and adding bias to the dataset.

An additional area of concern revolved around the viral or high performing tweets in the dataset. It was common for an actor to have a few tweets that received hundreds if not thousands more retweets than was considered typical for the actor. These viral tweets had the possibility to affect the mean engagement and therefore introduce bias into any statistical tests being performed. Thus, all statistical tests involving engagement were performed twice—once where all tweets were included and again where the top 1% of tweets in each account were removed from the dataset. Thus, if these two statistical analyses differed, it could be assumed that the viral tweets were asserting too heavy of an influence on the statistics.

All statistical tests used were non-parametric as tweet engagement data was highly skewed due to most tweets receiving near zero retweets. For hypotheses 7 and 8, the tweets from each account were divided between those that were hurricane related and those that were not. A Mann Whitney U test was then used to check for significant difference between the two groups within each account. For hypothesis 9, the duration of the storm was divided into four parts—pre-impact, pre-impact in cone, impact, and post-impact. This varied for each market examined as the markets further north entered into the subsequent stages at roughly one day behind their southern-most counterparts (Figure 4.2). The chart below shows when each market entered into each stage. Pre-impact was before any impacts arrived in the market and before the market entered the cone of uncertainty. Pre-impact in cone meant no tropical storm force winds had arrived and the market was within the cone of uncertainty. The impact stage signaled the arrival of tropical storm force winds as measured by the National Hurricane Center's Surface Wind Field graphic. The post-impact stage meant that tropical storm force winds had ceased.

A Kruskal Wallis test was then used to compare engagement levels at each stage of the storm within each market. No cross-market comparisons were made. For research question 16, the sub-dictionaries mentioned above were used to calculate the relation of each tweet to the different aspects of the storm. Each tweet was analyzed by LIWC and was assigned a value between 0 and 100 to showcase its relation to one of the specific categories with 100 indicating that all words were related to the category. Scatterplots were created for each category to show the number of tweets related to each category, the extent of the relation (0-100), and how these two variables evolved over the duration of the storm.

Table 4.2 Statistical analyses for chapter four

Research Question or Hypothesis	Statistical Test
Hypothesis 7 Hurricane related tweets from news station accounts will receive higher engagement indices than non-hurricane related tweets.	Mann Whitney U Test
Hypothesis 8 Hurricane related tweets from news stations' weather accounts will receive higher engagement indices than non-hurricane related tweets.	Mann Whitney U Test
Research Question 15 What are the differences in engagement temporally throughout the duration of the storm?	Scatterplot Comparisons
Hypothesis 9 Engagement levels will increase through the peak of the storm in each location.	Kruskal Wallis Test
Research Question 16 What are the differences in engagement between the two time periods (May vs. Irma)?	Mann Whitney U Test
Research Question 17 Is there a relationship between market size and location and tweet quantity and content?	Bootstrapped Confidence Interval Comparison of Frequencies
Research Question 18 Do people who have more personalized posts in May have more engagement in Irma?	Spearman Correlation

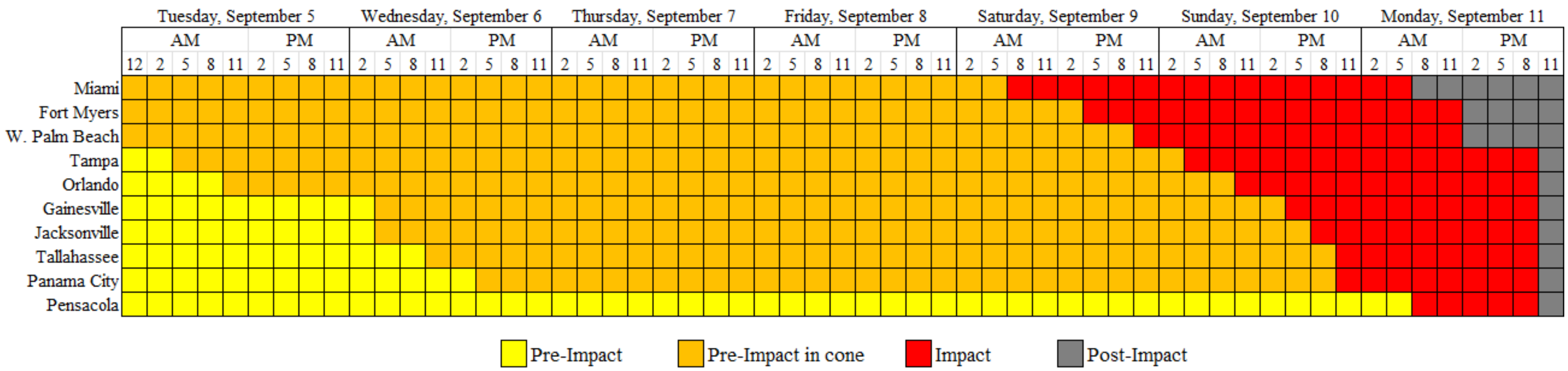

Figure 4.2 Progression of impact stages by television market

The South Florida markets were already in the “pre-impact in cone” stage at the beginning of the dataset. These markets began entering the “impact” stage on Saturday, September 9th as tropical storm force winds entered the area. The northernmost markets ran roughly 24 to 36 hours behind the southern markets. On September 11th, all markets entered into the “post-impact” stage as the storm was downgraded to a tropical depression and tropical storm force winds were no longer present in the markets.

Research question 17 took the mean engagement of each account in both May and September and then used a Mann Whitney U test to check for significant difference in engagement between the two time periods. For research question 18, tweet frequency and the percentage of hurricane related tweets per market was calculated. Comparisons were then made to see if any markets varied in the number of tweets in general or the amount that were related to the hurricane. For research question 19, the researcher went through each tweet in the May dataset originating from a broadcast meteorologist account and coded them according to whether or not they were "personal posts". Personalized posts were tweets that were considered to be about the broadcaster or an expression of a personal part of their life—a post that builds or expresses their personality. Examples of these tweets included pictures of the broadcaster on the job or behind the scenes, a happy Mother's Day wish, or a photo of an event in their personal life. After coding, the broadcast meteorologist accounts were then divided according to the mean number of followers each account had during Irma. A Spearman correlation was then performed on each group of accounts to check for relation between the number of personalized posts observed in May versus the broadcast meteorologist's mean engagement value from during Irma. Having divided up the accounts into sub-groups based on follower count, the correlation could then be compared based on number of followers (account size). Below is a table of the statistical methods used to evaluate each research question and hypothesis (Table 4.2).

4.5 Results

While weather accounts and broadcast meteorologist accounts contributed to the results of this study, news accounts were most often identified as the primary drivers behind the significance of the results. Of the top 10 actors who tweeted the most in the September dataset, seven of the actors were news accounts, one actor was a weather account, and two were broadcast meteorologists (BM) (Table 4.3). The accounts with the most followers were also news accounts.

Table 4.3 Top 10 Twitter Accounts by tweet frequency and follower count from September dataset (N=29,803)

Top 10 Most Frequent Tweeters			Top 10 Highest Follower Counts	
Actor	# of Tweets	% of Dataset	Actor	Mean Follower Count
@WPBF25News	1294	4.3	@wsvn	315,938
@WFTV	1033	3.5	@nbc6	266,682
@JohnMoralesNBC6	959	3.2	@FOX13News	257,605
@CBSMiami	922	3.1	@Fox35News	200,800
@CBS12	909	3.1	@WFTV	177,415
@actionnewsjax	816	2.7	@wesh	175,584
@WCTVPinPointWX	789	2.6	@WPLGLocal10	155,764
@wxgarrett	748	2.5	@WJXT4	145,653
@FCN2go	688	2.3	@abcactionnews	145,491
@wesh	648	2.2	@WPTV	136,362

Below are the results for the research questions and hypotheses for this chapter.

4.5.1 Tweet Content Related to Retweeting

RQ14: What are the differences in retweet levels for tweets with different types of content?

Hypothesis 7: Hurricane related tweets from news station accounts will receive higher engagement indices than non-hurricane related tweets.

Hypothesis 8: Hurricane related tweets from news stations' weather accounts will receive higher engagement indices than non-hurricane related tweets.

The engagement indices of tweets considered hurricane related were compared with those considered non-hurricane related. A Mann Whitney U test was used to compare the mean ranks of engagement indices from both types of tweets in both news and weather accounts. For news accounts, 19 of the 32 actors had significantly greater engagement for hurricane related tweets compared to non-hurricane related (Table 4.4). Interestingly, 7 actors had a lower mean engagement for hurricane related tweets, 2 of which were significant. When removing the top 1% of tweets, the two actors with significantly less engagement for hurricane related tweets flipped to having significantly more engagement. There were likely some high performing tweets that were non-hurricane related influencing the means. Thus, 21 of 32 news accounts had significantly more engagement for tweets that related to Irma when the viral tweets were left out. Three of the four weather accounts tested had significantly greater engagement for hurricane related tweets. This did not change when removing the top 1% tweets.

Based on the table above, the news accounts dataset excluding the top 1% showed Tampa had 3 accounts with significantly more engagement for hurricane related tweets, Jacksonville also had 3, West Palm Beach had 3, Miami had 4, Orlando had 3, Ft. Myers had 1, Tallahassee had 1, and Pensacola had 3. This showcases fairly even distribution between most of the markets. However, Gainesville or Panama City have no significant results. This provides some evidence that the significant rise in engagement for hurricane related tweets appeared in larger to mid-size markets. These two smaller markets also had a lower number of tweets overall, which could make achieving significance harder. Additionally, they have fewer news stations in these markets to even have a chance at showing significance.

These findings do indicate that a majority of markets saw an increase in tweet engagement amongst their respective accounts when hurricane related words were mentioned in the tweet body. However, this was not the case universally. Other factors are likely influencing these results.

Table 4.4 P-value of Mann Whitney U test and change in mean engagement between content types

Actor	Full Dataset P-value	Increase or decrease in mean engagement for hurricane related tweets	Dataset (Minus Top 1%) P Value	Increase or decrease in mean engagement for hurricane related tweets
@abc27	0.039	↑	0.035	↑
@ABC7SWFL	0.026	↓	0.043	↓
@abcactionnews	<0.001*	↑	<0.001*	↑
@actionnewsjax	<0.001*	↑	<0.001*	↑
@CBS12	<0.001*	↑	<0.001*	↑
@CBSMiami	<0.001*	↑	<0.001*	↑
@FCN2go	<0.001*	↑	<0.001*	↑
@Fox10News	0.006*	↑	0.010*	↑
@FOX13News	<0.001*	↓	<0.001*	↑
@FOX29WFLX	0.270	↑	0.270	↑
@Fox35News	<0.001*	↑	<0.001*	↑
@Fox4Now	0.216	↑	0.253	↑
@mycbs4	0.484	↓	0.484	↓
@mysuncoast	0.157	↑	0.194	↑
@NBC2	0.003*	↑	0.001*	↑
@nbc6	<0.001*	↑	<0.001*	↑
@news6wkmg	<0.001*	↑	<0.001*	↑
@WCJB20	0.279	↓	0.279	↓
@WCTV	0.018*	↑	.024*	↑
@weartv	0.004*	↑	0.004*	↑
@wesh	<0.001*	↑	<0.001*	↑
@WFLA	0.014*	↑	0.009*	↑
@WFTV	0.085	↑	0.055	↑
@winknews	0.821	↑	0.773	↑
@WJHG_TV	0.942	↓	0.905	↑
@WJXT4	<0.001*	↑	<0.001*	↑
@WKRG	<0.001*	↓	<0.001*	↑
@WMBBTV	0.043	↓	0.043	↓
@WPBF25News	<0.001*	↑	<0.001*	↑
@WPLGLocal10	<0.001*	↑	<0.001*	↑
@WPTV	<0.001*	↑	<0.001*	↑
@wsvn	<0.001*	↑	<0.001*	↑
Weather accounts				
@7Weather	<0.001*	↑	<0.001*	↑
@StormTeam8WFLA	0.007*	↑	0.007*	↑
@WCTVPinPointWX	<0.001*	↑	<0.001*	↑
@WFTVWeather	0.441	↓	0.464	↓

(*) Indicates significance ($\alpha = 0.05$)

4.5.2 Retweet Frequency Through Storm Duration

RQ15: What are the differences in engagement temporally throughout the duration of the storm?

The storm duration was divided into four time periods: Pre-impact, Pre-impact in cone, Impact, and Post-impact. Some markets were not able to compare all four stages. For example, the Pensacola/Mobile market never entered the cone of uncertainty and Miami, Ft. Myers, and West Palm Beach were already in the cone at the start of the dataset. Furthermore, despite the potential engagement bias that could occur on September 12th, it was included in these tests due to the need for more post-impact tweets.

Hypothesis 9: Engagement levels will increase through the peak of the storm in each location.

A Kruskal Wallis test was run to compare the mean engagement in each market at each stage of the storm. The table below shows that the pre-impact in cone and post-impact periods had significantly different levels of engagement in every market that was tested (Table 4.5). The most significant results showed up when the post-impact period was a part of the test. The fewer significant results earlier in the timeline of the storm could indicate that the storm was already a big news headline and that the preparation was grabbing attention in the same way that the storm did when it made landfall. In the chart below, the mean engagement index was plotted for each market at each stage to show the direction of the statistical significance (Figure 4.3).

Table 4.5 Kruskal Wallis results comparing engagement between impact stages

Impact Stage	Miami	Ft. Myers	West Palm Beach	Tampa	Orlando	Jacksonville	Tallahassee	Panama City	Pensacola/ Mobile
Pre-Impact → Pre-Impact in cone	-	-	-	1	0.002*	0.295	1	1	-
Pre-Impact → Impact	-	-	-	1	<0.001*	1	1	0.155	0.035*.
Pre-Impact → Post-Impact	-	-	-	0.24	<0.001*	1	0.001*	0.014*	<0.001*
Pre-Impact in cone → Impact	0.001*	0.884	1	1	0.011*	1	1	0.093	-
Pre-Impact in cone → Post-Impact	<0.001*	0.021*	<0.001*	<0.001*	<0.001*	0.031*	<0.001*	0.008*	-
Impact → Post-Impact	<0.001*	0.004*	<0.001*	0.001*	<0.001*	0.141	0.003*	1	0.785

(*) Indicates significance ($\alpha = 0.05$)

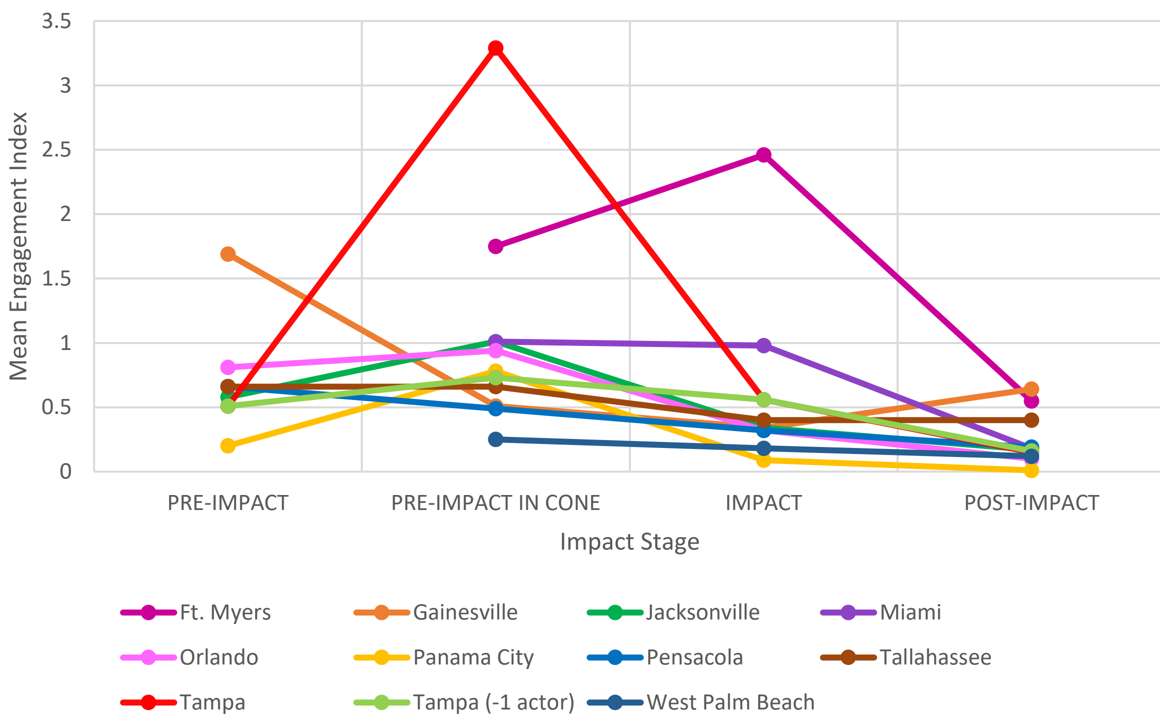

Figure 4.3 Change in mean engagement index between storm impact stages by market (full dataset)

The mean engagement for most markets slightly rose between "pre-impact" stage and "pre-impact in cone" stage and then decreased during the "impact stage". The decrease continued into the "post-impact stage, though it was less noticeable. This figure is based on the entire dataset instead of having removed the top 1% of tweets.

For most markets, there was a slight increase in engagement from pre-impact to pre-impact in cone stage. Gainesville was an exception to this. Pensacola's value for the pre-impact in cone stage is interpolated by splitting the difference between the mean engagement index during pre-impact stage and impact stage due to the market never entering into the cone. Tampa had one actor that had very few followers which was creating skewed data.

Upon removing that actor from the dataset, Tampa behaved similarly to the other markets. Most markets saw their mean engagement decrease or stay the same when moving from pre-impact in cone stage to impact. Finally, a downward trend occurred when transitioning from impact to post-impact. When removing the top 1% of tweets, no major changes occurred in the data, though some markets may have seen more similar means between pre-impact in cone stage and impact stage (Figure 4.4).

The table below provides the raw values (Table 4.6). Most markets experienced their greatest engagement during the pre-impact in cone stage. This does not support the hypothesis that engagement would increase through the peak of the storm. Rather, engagement seemed to increase through the time of preparation before plateauing or declining as the storm moved in.

Research was also conducted on the content of tweets over the storm's duration. The LIWC sub-dictionaries were used to place each hurricane related word into a category. The categories included: meteorology/science, naming, meteorological impacts, warning, forecast, damage and negative impacts, and preparation and response. Each tweet was also given a percentage ranging from 0 to 100 depending on how many words in the tweet were related to the category with a percentage of 100 indicating that all words were related to the category. The scatterplots showing the number of tweets in each category are included below with the y-axis indicating the extent of the tweet's relation to the category (0-100) and the x-axis being time.

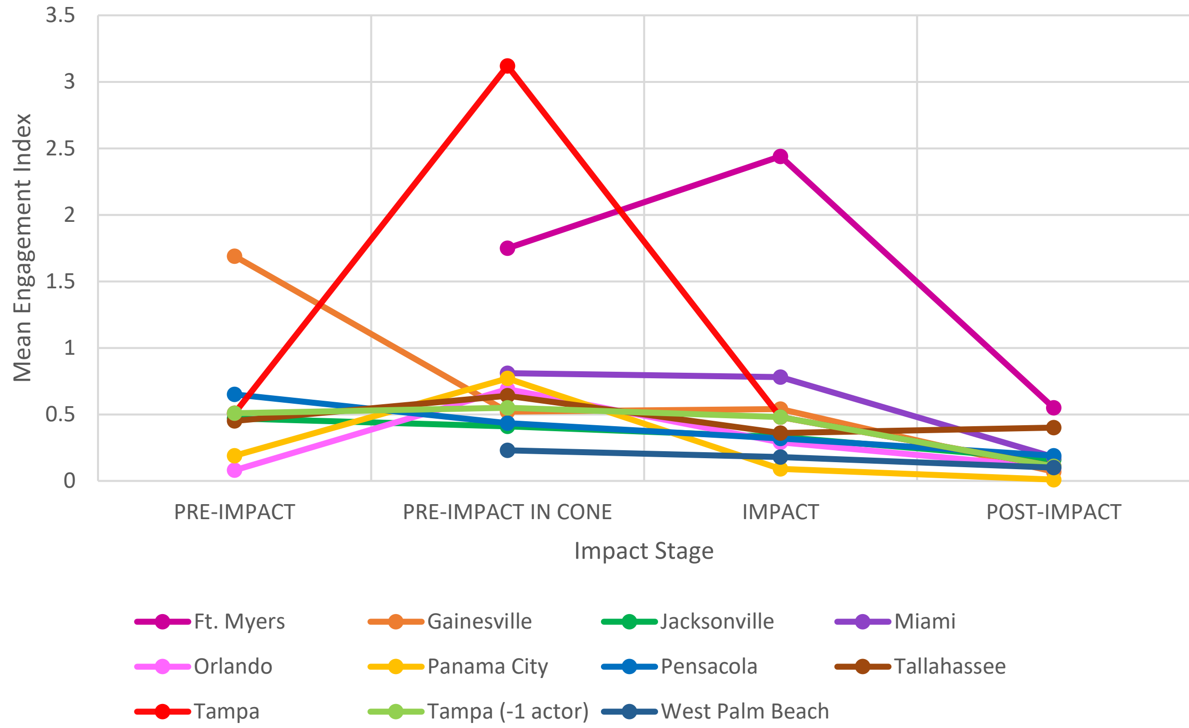

Figure 4.4 Change in mean engagement index between storm impact stages by market (dataset minus top 1%)

This figure shows nearly the same results as Figure 4.3 indicating that even when removing the top 1% of tweets, the change in mean engagement from one impact stage to another is minimal.

Table 4.6 Mean engagement index values during each impact stage of Irma

Full Dataset	Pre-Impact	Pre-Impact in cone	Impact	Post-Impact
Ft. Myers	-	1.75	2.46	0.55
Gainesville	1.69	0.51	0.34	0.64
Jacksonville	0.58	1.01	0.34	0.17
Miami	-	1.01	0.98	0.18
Orlando	0.81	0.94	0.32	0.10
Panama City	0.20	0.78	0.09	0.01
Pensacola	0.66	-	0.32	0.19
Tallahassee	0.66	0.66	0.40	0.40
Tampa	0.51	3.29	0.56	0.15
Tampa (minus 1 actor)	0.51	0.73	0.56	0.16
West Palm Beach	-	0.25	0.18	0.12

Dataset Minus Top 1%	Pre-Impact	Pre-Impact in cone	Impact	Post-Impact
Ft. Myers	-	1.75	2.44	0.55
Gainesville	1.69	0.52	0.54	0.07
Jacksonville	0.47	0.41	0.33	0.16
Miami	-	0.81	0.78	0.18
Orlando	0.08	0.69	0.29	0.10
Panama City	0.19	0.77	0.09	0.01
Pensacola	0.65	-	0.32	0.19
Tallahassee	0.45	0.64	0.36	0.40
Tampa	0.51	3.12	0.48	0.11
Tampa (minus 1 actor)	0.51	0.55	0.48	0.11
West Palm Beach	-	0.23	0.18	0.10

The top half of the table displays the results using the entire dataset of tweets. The bottom half of the table shows the results using the dataset less the top 1% of tweets.

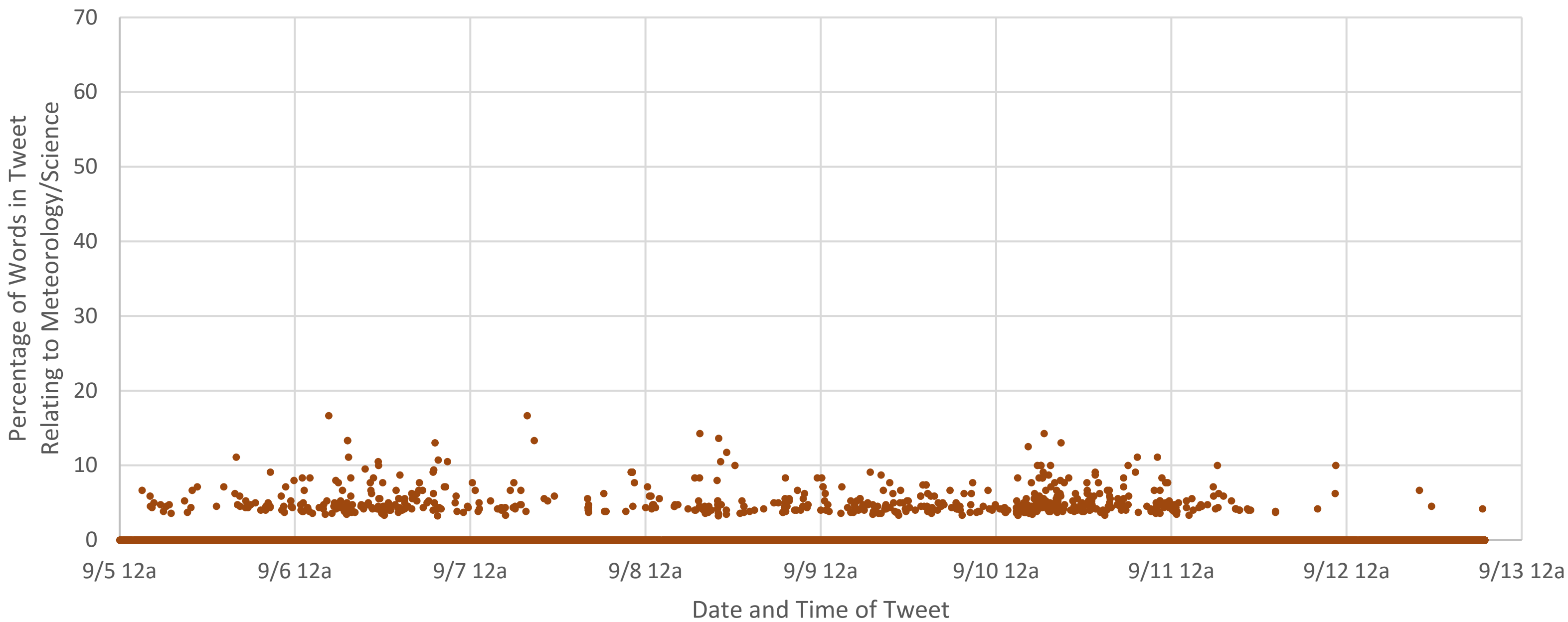

Figure 4.5 Tweets related to meteorology and science of Irma over time

One dot equals the occurrence of a tweet related to the meteorology and science of Irma. Its position on the x-axis is determined by the time and date on which the tweet was published, and its position on the y-axis is determined by what percentage of words in the tweet were related to the meteorology and science of the storm (0%-100%). Two notable clusters stand out when Irma impacted Puerto Rico and then Florida.

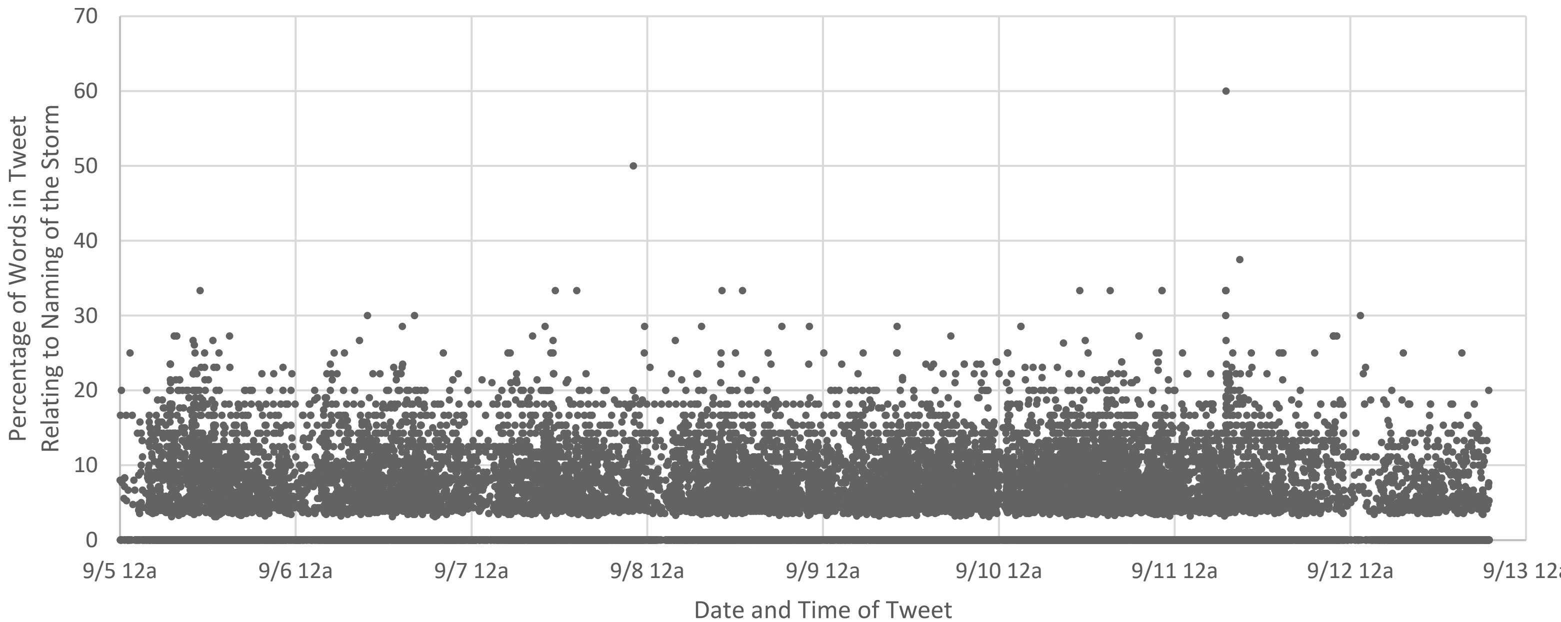

Figure 4.6 Tweets related to the naming of the storm over time

One dot equals the occurrence of a tweet related to the name or naming of Irma. Its position on the x-axis is determined by the time and date on which the tweet was published, and its position on the y-axis is determined by what percentage of words in the tweet were related to the name or naming of the storm (0%-100%). There was very little change observed over time.

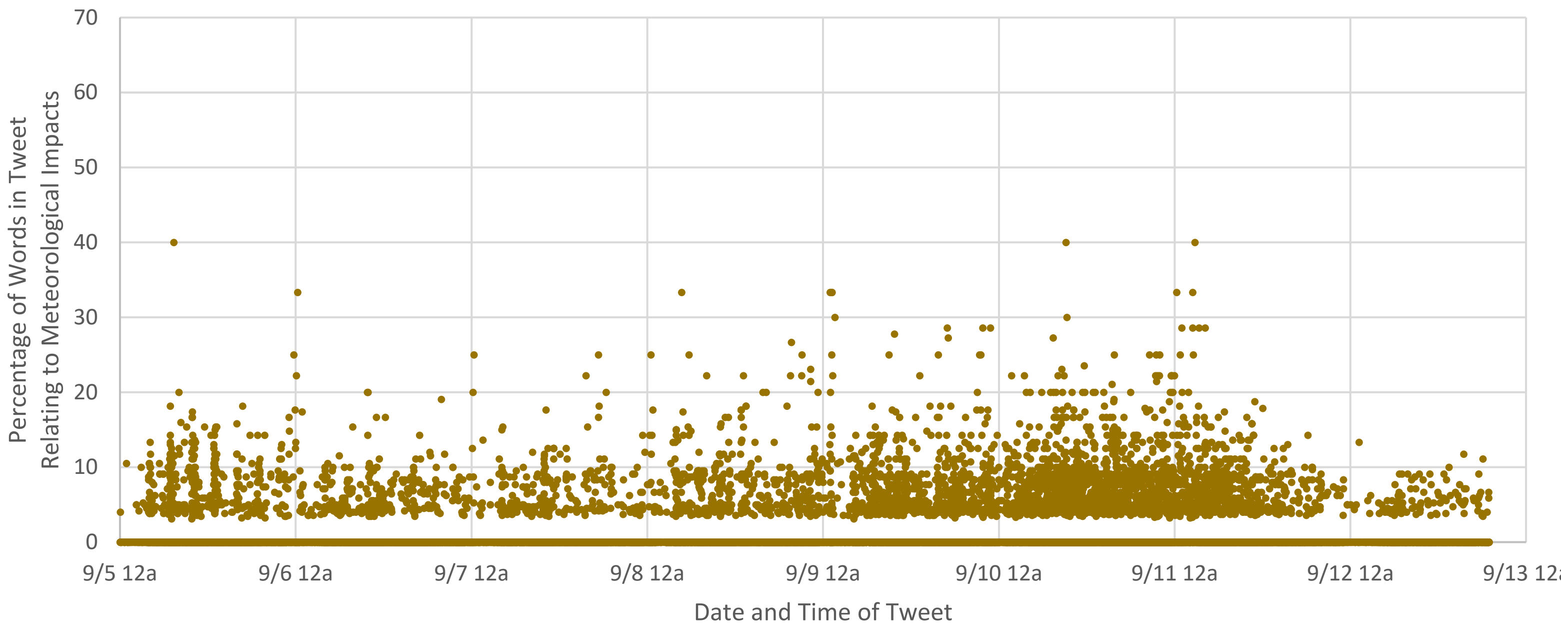

Figure 4.7 Tweets related the meteorological impacts of Irma over time

One dot equals the occurrence of a tweet related to the meteorological impacts of Irma. Its position on the x-axis is determined by the time and date on which the tweet was published, and its position on the y-axis is determined by what percentage of words in the tweet were related to the meteorological impacts of the storm (0%-100%). The greatest cluster occurred on the day of landfall in Florida, as well as the day before and after.

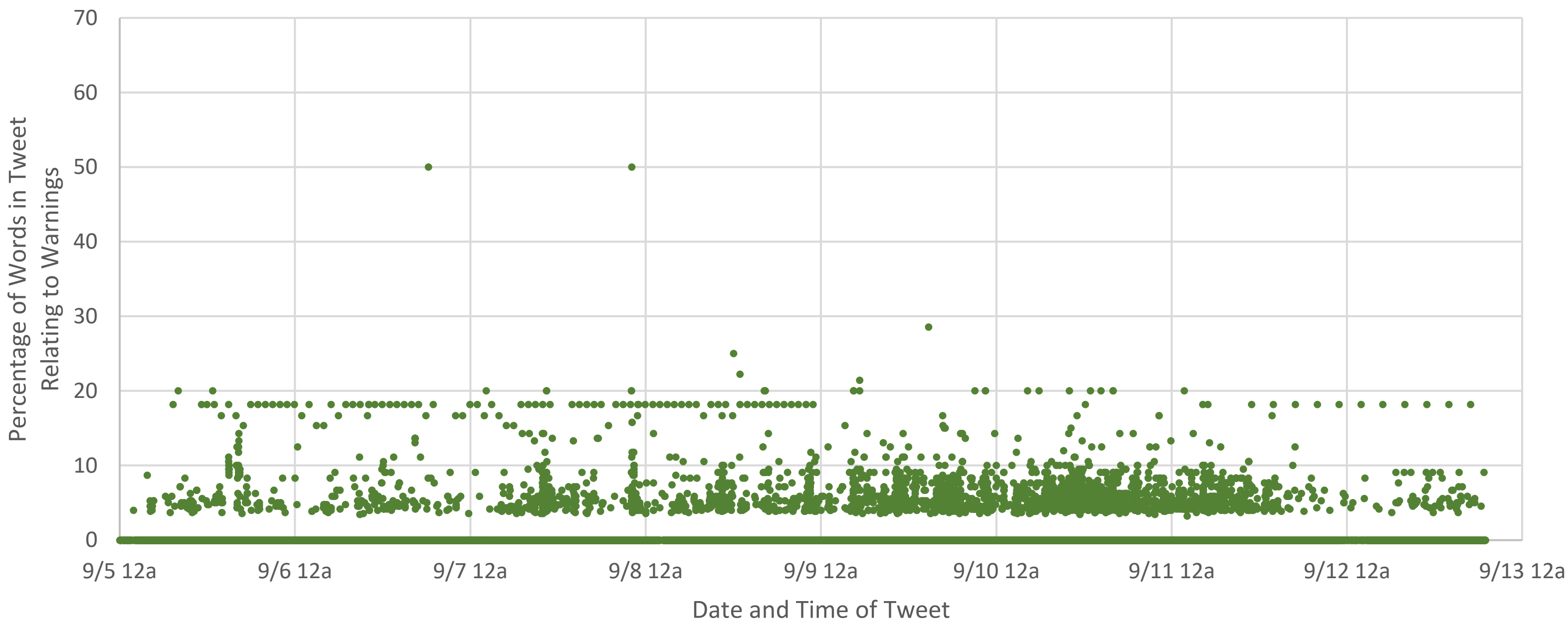

Figure 4.8 Tweets related to warnings issued for Irma over time

One dot equals the occurrence of a tweet related to the warnings issued for Irma. Its position on the x-axis is determined by the time and date on which the tweet was published, and its position on the y-axis is determined by what percentage of words in the tweet were related to the warnings issued for the storm (0%-100%). The greatest cluster was found the day of and the before landfall. Several either solid or regularly dotted horizontal lines appear in the graph. These are occurrences of “bot” tweets which are regularly posted by a computer to keep followers up to date either every hour or every time an update is posted, etc.

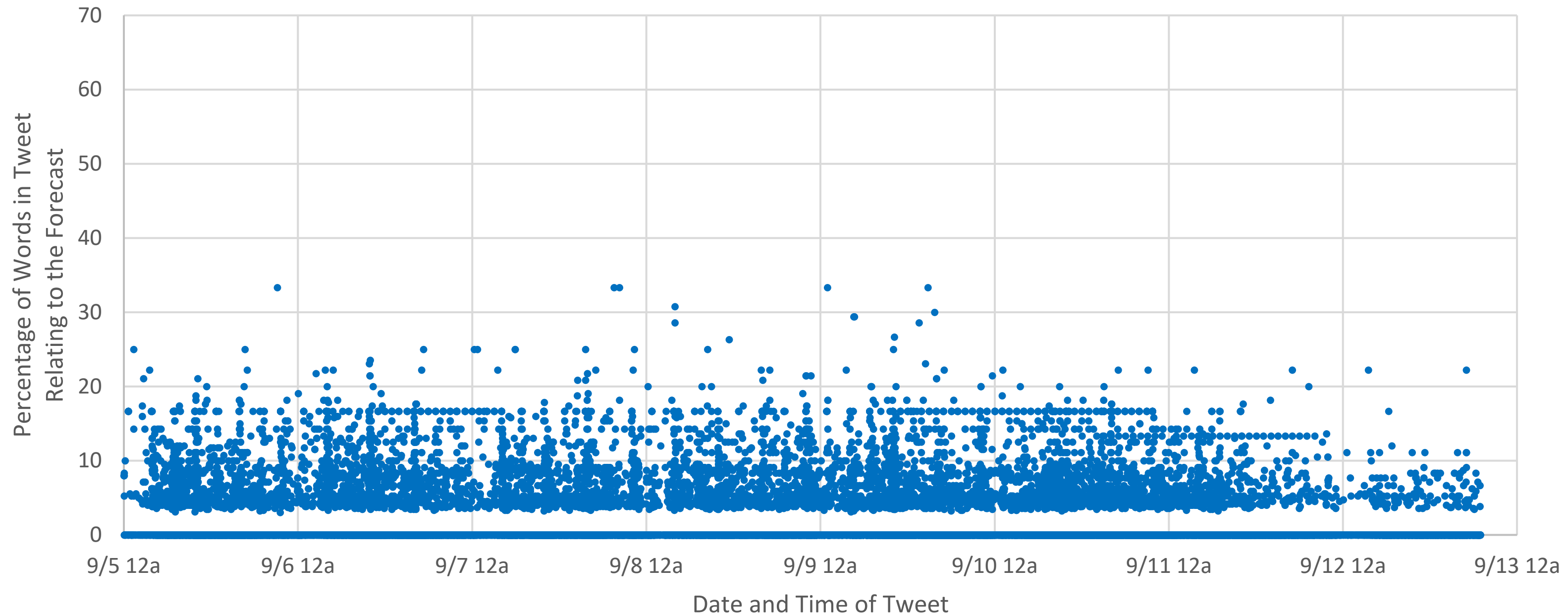

Figure 4.9 Tweets related to the forecast for Irma over time

One dot equals the occurrence of a tweet related to the forecast for Irma. Its position on the x-axis is determined by the time and date on which the tweet was published, and its position on the y-axis is determined by what percentage of words in the tweet were related to the forecast for the storm (0%-100%). There is no readily apparent variation until the final day of the dataset, after the storm had made landfall when this category of tweets decreases. More bot tweets are observed in this graph.

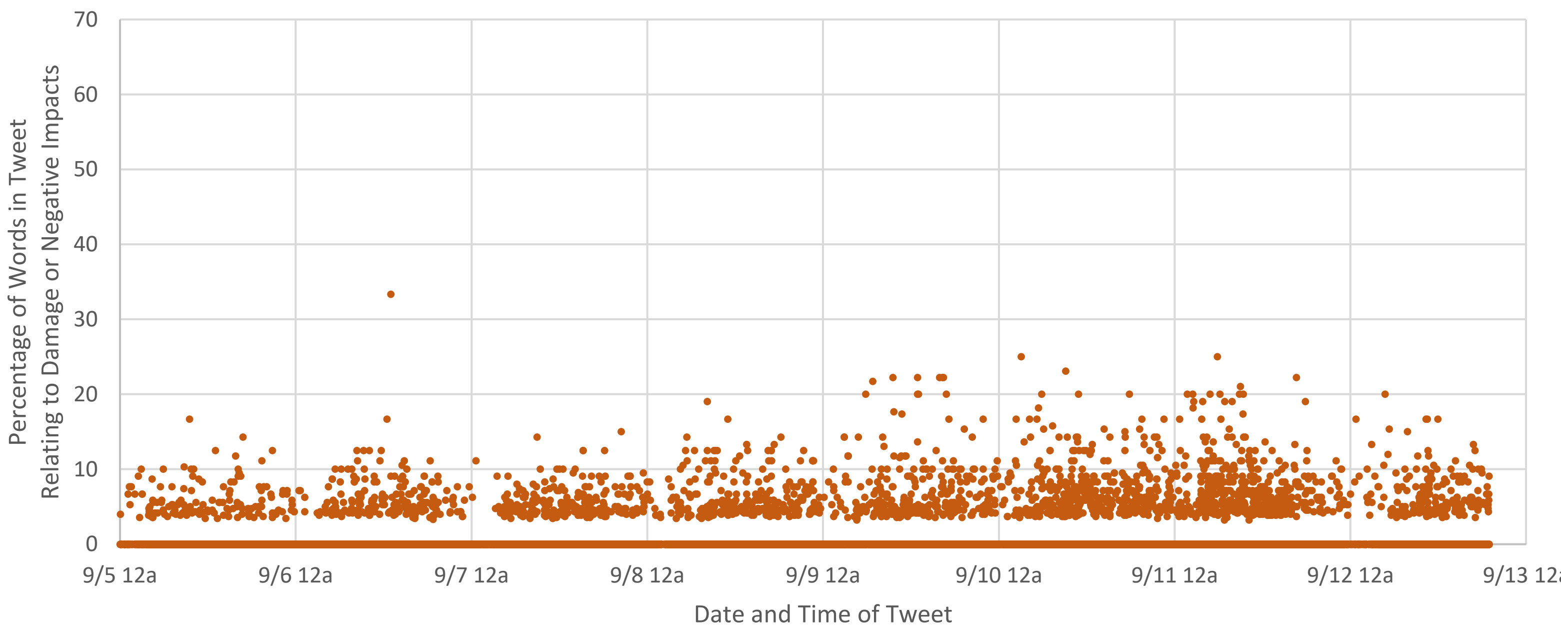

Figure 4.10 Tweets related to damage or negative impacts over time

One dot equals the occurrence of a tweet related to the damage or negative impacts of Irma. Its position on the x-axis is determined by the time and date on which the tweet was published, and its position on the y-axis is determined by what percentage of words in the tweet were related to the damage or negative impacts of the storm (0%-100%). This category follows a noticeable diurnal pattern in the days leading up to Irma's landfall, with the tweets dropping off during the overnight. As the storm makes landfall in Florida, that pattern disappears.

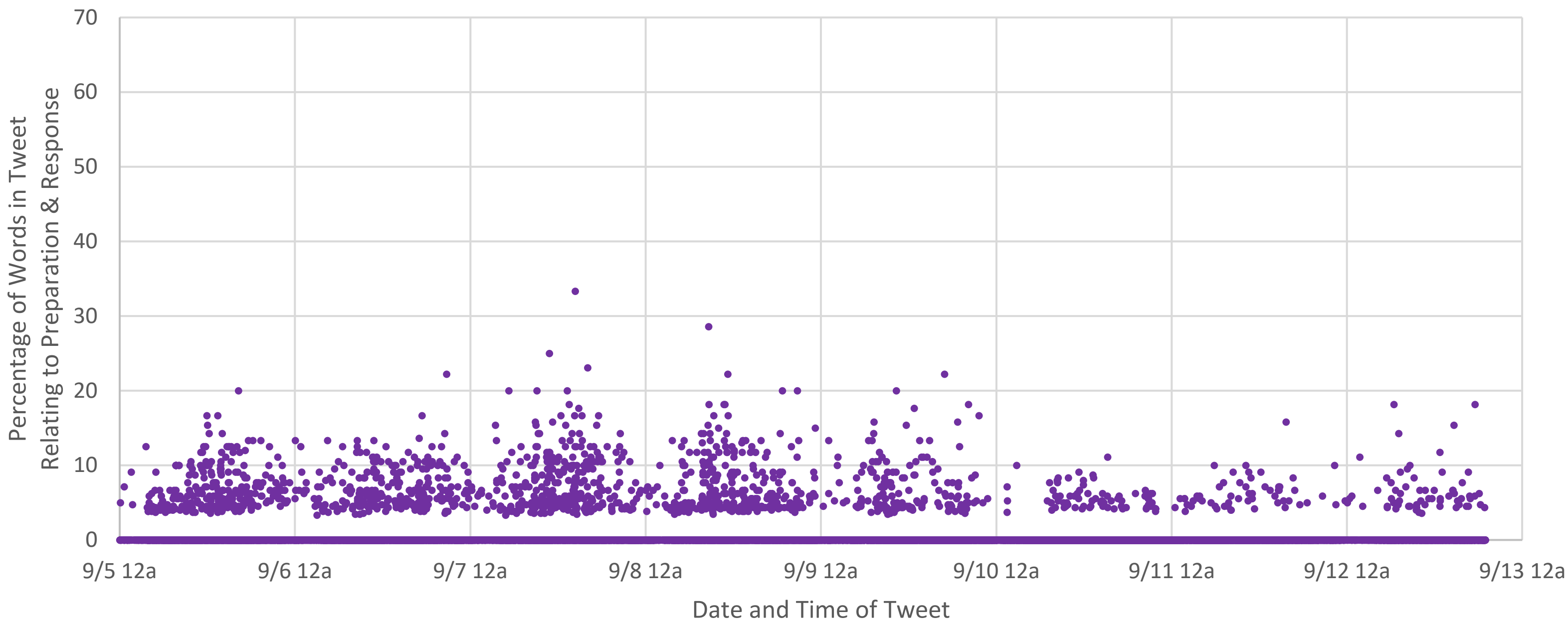

Figure 4.11 Tweets related to preparation for and response to Irma over time

One dot equals the occurrence of a tweet related to the preparation for and response to Irma. Its position on the x-axis is determined by the time and date on which the tweet was published, and its position on the y-axis is determined by what percentage of words in the tweet were related to the preparation for and response to the storm (0%-100%). This category also follows a diurnal pattern with a decrease in tweet occurrence overnight and tweets most heavily related occurring during the middle of the day.

Meteorology/science terms--referring to the scientific anatomy and structure of the hurricane--were mentioned frequently on September 6th as Irma passed through the northern Lesser Antilles and Puerto Rico (Figure 4.5). The frequency then increased again on the 9th as Irma approached Florida and then on the 10th as the storm made landfall. These terms became nearly non-existent in tweets during the “post-impact” stage.

Words associated with the meteorological impacts of the storm occurred regularly throughout the dataset with a frequency maximum occurring during the “impact” stage and the preceding 24 hours (Figure 4.7). Tweets with content about the forecast for the storm were found to be common throughout the dataset with a noticeable decrease occurring after the storm had passed (Figure 4.9).

Words and phrases indicating damage and negative impacts of the storm occurred daily as the storm had a destructive path throughout the entire dataset (Figure 4.10). However, tweets with these words became more frequent during the latter half of the dataset as the storm was hitting Florida and had left destruction in its wake. Finally, words related to preparation for and response to the storm were found more heavily in the first half of the dataset and less frequently after the storm began impacting the state (Figure 4.11).

Some of the content categories showed very clear diurnal cycles, whereas other did not. Preparation and response related tweets very clearly dropped off during the overnight hours each night. Tweets with content focused on damage and negative impacts followed a similar pattern, though the pattern became slightly less distinct during the impact stage. Tweets relating to the storm’s forecast were observed at all hours of the day, though some days showed enhanced clustering on the scatterplots in the morning hours. This could indicate a focus on providing a forecast update after most of the public slept and was unaware during the overnight. Tweets related to warning information exhibited diurnal patterns when the storm was still more than two days away (Figure 4.8). But as the storm approached, the diurnal patterns disappeared. The categories of “meteorology/science”, “naming” (Figure 4.6), and “meteorological impacts” did not show clear diurnal patterns as tweets with this type of content are relevant at all times and may be more time-sensitive in their need to be posted as a specific event is occurring instead of when it is convenient.

The researcher noticed solid horizontal lines and lines with regularly occurring dots showing up in each scatterplot. Upon reviewing the tweets responsible for the dots, these were identified as bot tweets—tweets that are published via an automated bot without human involvement. These were most frequently seen in the content categories of “forecast” and “warning”. Many meteorologists will set up their Twitter account to automatically send out a standardly worded tweet as each new advisory for a storm is released. Thus, this makes sense that most of the bot tweets were showing up in the forecast and warning related graphs.

4.5.3 Retweet Frequency on Normal Week Versus During Irma

RQ16: What are the differences in engagement between the two time periods (May vs. Irma)?

A Mann Whitney U test was run to compare the mean engagement indices for each market and actor between the two time periods. When analyzing the data at the market level, all markets except Pensacola had significantly more engagement during Irma than they did during the week in May (Table 4.7). Pensacola was on the periphery of the cone of uncertainty and also was the furthest from the storm’s impacts. Despite a lack of significance, the market still had higher mean engagement during the September time period.

When comparing the engagement during the two time periods at the account level, the results were far less straightforward (Table 4.8). Seventy-two percent of all news accounts saw a significant increase in engagement during Irma, but only 50% of weather accounts showed a significant increase in engagement. For broadcast meteorologist (BM) accounts, only 39% showed a significant increase in engagement. This indicates a clear trend of which account types were most responsible for the significant difference in engagement per market. While most of the significant differences between the time periods indicated a higher mean during Irma, there were nine accounts (7 BM and 2 news) that had significantly lower engagement during Irma than during May.

Table 4.7 P-values from Mann Whitney U test for difference between engagement in May and during Irma by market

Market Name	Full dataset p-value	Dataset Minus Top 1% p-value
Ft. Myers	<0.001*	<0.001*
Gainesville	<0.001*	<0.001*
Jacksonville	<0.001*	<0.001*
Miami	<0.001*	<0.001*
Orlando	<0.001*	<0.001*
Panama City	<0.001*	<0.001*
Pensacola/Mobile	0.430	0.504
Tallahassee	0.017*	0.034*
Tampa	<0.001*	<0.001*
West Palm Beach	<0.001*	<0.001*

(*) Indicates significance ($\alpha = 0.05$)

Table 4.8 P-values from Mann Whitney U test for difference between engagement in May and during Irma by individual account

Market	Actor	P-value (full dataset)	P-value (dataset -top 1%)	Change in mean engagement from May to September (full dataset)	Change in mean engagement from May to September (Dataset - top 1%)
Ft. Myers	@ABC7SWFL	0.005*	0.004*	↓	↑
	@CodyMurphyWx	0.63	0.63	↑	↑
	@danibeckstrom	0.062	0.062	↑	↑
	@DerekBeasleyWX	0.122	0.122	↑	↑
	@Fox4Now	<0.001*	<0.001*	↑	↑
	@JasonDunning	0.024*	0.024*	↑	↑
	@JimTFarrell	0.08	0.08	↑	↑
	@jpweather	0.013*	0.012*	↑	↑
	@KristenWeather	0.155	0.155	↑	↑
	@MattDevittWINK	0.024*	0.024*	↓	↓
	@mattgraysky	0.014*	0.014*	↑	↑
	@NBC2	<0.001*	<0.001*	↑	↑
	@RobDunsTV	0.862	0.862	↑	↑
	@ScottZWINK	0.015*	0.015*	↑	↑
	@TonySadiku	0.947	0.947	↑	↑
	@winknews	<0.001*	<0.001*	↑	↑
	@WxDickey	0.031*	0.031*	↑	↑
	@ZachMalochWX	0.32	0.32	↑	↑
Gainesville	@AlexCalamiaWx	0.216	0.216	↑	↑
	@mycbs4	0.096	0.096	↑	↑
	@WCJB20	<0.001*	<0.001*	↑	↑
	@wcjbweather	0.393	0.393	↑	↑
Jacksonville	@_WeatherStove	0.12	0.12	↑	↑
	@actionnewsjax	0.846	0.781	↑	↑
	@collinsweather	0.4	0.4	↑	↑
	@ErinFirstAlert	0.001*	0.001*	↑	↑
	@FCN2go	<0.001*	<0.001*	↑	↑
	@FCNLindsey	0.931	0.931	↑	↑
	@fcnmike	<0.001*	<0.001*	↑	↑
	@fcntim	<0.001*	<0.001*	↑	↑
	@GaughanSurfing	<0.001*	<0.001*	↑	↑
	@mikefirstalert	0.002*	0.002*	↑	↑
	@NixonFirstAlert	0.001*	0.001*	↓	↓
	@RichardNunn1	0.364	0.364	↑	↑

Table 4.8 (continued)

Market	Actor	P-value (full dataset)	P-value (dataset -top 1%)	Change in mean engagement from May to September (full dataset)	Change in mean engagement from May to September (Dataset - top 1%)
Jacksonville cont.	@WeatherLauren	0.082	0.059	↑	↑
	@WJXT_Rebecca	<0.001*	0.001*	↑	↑
	@WJXT4	<0.001*	<0.001*	↑	↑
	@wxgarrett	<0.001*	<0.001*	↑	↑
Miami	@7Weather	<0.001*	<0.001*	↑	↑
	@AdamBergNBC6	0.063	0.079	↑	↑
	@AngieNBC6	0.354	0.408	↑	↑
	@bcameron7	0.385	0.346	↑	↑
	@CBSMiami	<0.001*	<0.001*	↑	↑
	@CraigSetzer	0.229	0.24	↑	↑
	@DaveWarrenCBS4	0.003*	0.004*	↑	↑
	@JenniferLocal10	0.002*	0.002*	↑	↑
	@JohnMoralesNBC6	<0.001*	<0.001*	↑	↑
	@JulieDurda	0.056	0.066	↑	↑
	@karlenechavis	<0.001*	<0.001*	↓	↓
	@LissetteCBS4	<0.001*	<0.001*	↑	↑
	@LizHortonTV	0.375	0.385	↑	↑
	@nbc6	<0.001*	<0.001*	↑	↑
	@PhilFerro7	<0.001*	<0.001*	↑	↑
	@RyanNBC6	<0.001*	<0.001*	↑	↑
	@SteveMacNBC6	0.028*	0.028*	↑	↑
	@thebettydavis	0.33	0.33	↑	↑
	@VivianGonzalez7	<0.001*	<0.001*	↑	↑
	@WPLGLocal10	<0.001*	<0.001*	↑	↑
	@wsvn	<0.001*	<0.001*	↑	↑
Orlando	@amysweezey	0.013*	0.016*	↑	↑
	@BShieldsWFTV	<0.001*	<0.001*	↑	↑
	@DaveCocchiarell	0.159	0.181	↑	↑
	@ebonideonwftv	0.477	0.429	↑	↑
	@EricBurrisWESH	<0.001*	<0.001*	↑	↑
	@fox35brooks	0.809	0.809	↑	↑
	@FOX35Glenn	0.006*	0.006*	↑	↑
	@Fox35News	<0.001*	<0.001*	↑	↑
	@GWaldenWFTV	0.006*	0.005*	↑	↓
	@jaymekingfox35	0.132	0.132	↑	↑

Table 4.8 (continued)

Market	Actor	P-value (full dataset)	P-value (dataset -top 1%)	Change in mean engagement from May to September (full dataset)	Change in mean engagement from May to September (Dataset - top 1%)
Orlando cont.	@kristingiannas	0.143	0.164	↑	↑
	@KyleGravlin	0.481	0.397	↑	↑
	@news6wkmg	<0.001*	<0.001*	↑	↑
	@RMcCranieWFTV	0.643	0.674	↓	↓
	@TMainolfiWESH	<0.001*	<0.001*	↑	↑
	@tomsorrells	0.129	0.129	↑	↑
	@TroyNews6	0.089	0.089	↑	↑
	@TTerryWFTV	<0.001*	<0.001*	↑	↑
	@wesh	<0.001*	<0.001*	↑	↑
	@WFTV	0.06	0.068	↑	↑
	@WFTVWeather	<0.001*	<0.001*	↑	↑
Panama City	@JordanPatrickWX	0.331	0.331	↑	↑
	@PeoplesAnthony	1	1	↑	↑
	@RyanMichaelsWX	0.038*	0.038*	↓	↓
	@smithwjhg	<0.001*	<0.001*	↑	↑
	@TylerAllender	0.001*	0.001*	↑	↑
	@WJHG_TV	0.096	0.086	↑	↑
	@wmbbjustin	0.002*	0.002*	↑	↑
	@WMBBTV	<0.001*	<0.001*	↑	↑
Pensacola/Mobile	@ashleyruizwx	0.137	0.137	↑	↑
	@Fox10News	<0.001*	<0.001*	↓	↓
	@jake_wpmi	0.165	0.165	↑	↑
	@matt_barrentine	0.833	0.833	↑	↑
	@michaelwhitewx	0.778	0.778	↑	↑
	@ThomasGeboyWX	0.022*	0.022*	↑	↑
	@wearallenstrum	0.822	0.866	↑	↑
	@wearkdaniel	0.706	0.706	↓	↓
	@weartv	0.536	0.514	↑	↑
	@WKRG	0.115	0.131	↑	↑
	@WKRG_John	0.329	0.329	↓	↓
Tallahassee	@abc27	0.415	0.487	↑	↑
	@AlexCorderoWX	0.08	0.103	↑	↑
	@BrittanyBedi	0.071	0.071	↓	↓
	@CharlesRoopWCTV	0.048*	0.056	↑	↑
	@JenMeyers_wx	0.57	0.57	↑	↑

Table 4.8 (continued)

Market	Actor	P-value (full dataset)	P-value (dataset -top 1%)	Change in mean engagement from May to September (full dataset)	Change in mean engagement from May to September (Dataset - top 1%)
Tallahassee cont.	@robnucatola	0.49	0.584	↑	↑
	@WCTV	<0.001*	<0.001*	↑	↑
	@WCTVMike	0.806	0.806	↑	↑
	@WCTVPinPointWX	0.339	0.24	↑	↑
Tampa	@abcactionnews	0*	<0.001*	↑	↑
	@AshleyBatey	0.636	0.701	↑	↑
	@BobbyDWeather	0.064	0.074	↑	↑
	@DaveOFox13	0.119	0.119	↑	↑
	@DenisPhillips28	<0.001*	<0.001*	↑	↑
	@FOX13News	<0.001*	<0.001*	↑	↑
	@grant_gilmore	<0.001*	<0.001*	↑	↑
	@GregDeeWeather	<0.001*	<0.001*	↑	↑
	@mysuncoast	<0.001*	<0.001*	↑	↑
	@MySuncoastWx	0.883	0.883	↓	↓
	@PaulFox13	<0.001*	<0.001*	↑	↑
	@sjervewfla	0.122	0.129	↑	↑
	@StormTeam8WFLA	0.044*	0.044*	↑	↑
	@Suncoastweather	0.052	0.052	↑	↑
	@TampaBayWeather	<0.001*	<0.001*	↑	↑
	@weatherlindsay	0.697	0.63	↑	↑
	@WFLA	<0.001*	<0.001*	↑	↑
	@wflaEd	0.024*	0.024*	↑	↑
	@wflaian	0.078	0.078	↑	↑
	@wflaLeigh	<0.001*	<0.001*	↑	↑
West Palm Beach	@BillWalshTV	0.127	0.14	↑	↑
	@CBS12	<0.001*	<0.001*	↑	↑
	@chrisfarrellcbs	0.031*	0.031*	↑	↑
	@FOX29WFLX	0.015*	0.015*	↓	↓
	@glennglazer	0.016*	0.016*	↑	↑
	@jmatthewscbs12	0.003*	0.003*	↓	↓
	@JoeySovine	<0.001*	<0.001*	↓	↓
	@jordanlive5	0.291	0.291	↓	↓
	@katewentzelwx	0.833	0.833	↑	↑
	@loleskywx	<0.001*	<0.001*	↑	↑
	@stephaniesinewx	<0.001*	<0.001*	↓	↓

Table 4.8 (continued)

Market	Actor	P-value (full dataset)	P-value (dataset -top 1%)	Change in mean engagement from May to September (full dataset)	Change in mean engagement from May to September (Dataset - top 1%)
West Palm Beach cont.	@SteveWeagleWPTV	0.189	0.189	↑	↑
	@SurfnWeatherman	<0.001*	<0.001*	↑	↑
	@wpbf_cris	<0.001*	<0.001*	↑	↑
	@wpbf_mike	0.51	0.33	↑	↑
	@wpbf_sandra	0.333	0.333	↑	↑
	@wpbf_vanessa	0.191	0.169	↑	↑
	@WPBF25News	<0.001*	<0.001*	↑	↑
	@WPTV	<0.001*	<0.001*	↑	↑
	@WxLadyFelicia	0.066	0.076	↑	↑

(*) Indicates significance ($\alpha = 0.05$)

When looking at the relationship between account type and significant difference, news accounts most frequently showed a change in engagement from May to September and BM accounts were least likely to exhibit significant change (Table 4.9). BM accounts were also more likely than other account types to show a significant decrease in engagement during the storm. Weather accounts in the dataset were often sporadically or inconsistently used which could explain the lack of the some of the accounts seeing a significant rise in engagement during Irma. Finally, a majority of broadcast meteorologists did not see an increase in engagement during Irma and a small subset actually saw their engagement fall during the storm.

The markets with the fewest number of actors with significant differences between May and September were smaller markets—Tallahassee, Pensacola, and Gainesville (Table 4.10). The exception to this was Panama City. Most markets had 50-65% of their accounts that showed significant difference. When removing the top 1% of tweets, there was no change in the number of accounts that came back as significant except for in Tallahassee where the number of accounts that had significant differences decreased. This may have been due to a few viral tweets that affected the significance in the accounts of that market. Since most other markets did not see a

Table 4.9 Frequency of significantly different engagement between May and Irma by account type

Did the accounts have significantly different engagement between May & Sept?

Account Type		Full Dataset Frequency (Percentage)	Dataset Minus Top 1% Frequency (Percentage)
BM	No	59 (53.6%)	60 (54.5%)
	Yes	51 (46.4%)	50 (45.5%)
	Total	110 (100%)	110 (100%)
News	No	7 (21.9%)	7 (21.9%)
	Yes	25 (78.1%)	25 (78.1%)
	Total	32 (100%)	32 (100%)
Weather	No	3 (50%)	3 (50%)
	Yes	3 (50%)	3 (50%)
	Total	6 (100%)	6 (100%)

Table 4.10 Frequency of significantly different engagement between May and Irma by market

Did the accounts engagement significantly differ between May and Sept?

Market		Full Dataset Frequency (Percentages)	Dataset Minus Top 1% Frequency (Percentages)
Ft. Myers	No	8 (44.4%)	8 (44.4%)
	Yes	10 (55.6%)	10 (55.6%)
	Total	18 (100%)	18 (100%)
Gainesville	No	3 (75%)	3 (75%)
	Yes	1 (25%)	1 (25%)
	Total	4 (100%)	4 (100%)
Jacksonville	No	6 (37.5%)	6 (37.5%)
	Yes	10 (62.5%)	10 (62.5%)
	Total	16 (100%)	16 100%)

Table 4.10 (continued)

Market	Full Dataset Frequency (Percentages)	Dataset Minus Top 1% Frequency (Percentages)	Market
Miami	No	7 (33.3%)	7 (33.3%)
	Yes	14 (66.7%)	14 (66.7%)
	Total	21 (100%)	21 (100%)
Orlando	No	10 (47.6%)	10 (47.6%)
	Yes	11 (52.4%)	11 (52.4%)
	Total	21 (100%)	21 (100%)
Panama City	No	3 (37.5%)	3 (37.5%)
	Yes	5 (62.5%)	5 (62.5%)
	Total	8 (100%)	8 (100%)
Pensacola/Mobile	No	9 (81.8%)	9 (81.8%)
	Yes	2 (18.2%)	2 (18.2%)
	Total	11 (100%)	11 (100%)
Tallahassee	No	7 (77.8%)	8 (88.9%)
	Yes	2 (22.2%)	1 (11.1%)
	Total	9 (100%)	9 (100%)
Tampa	No	8 (40%)	8 (40%)
	Yes	12 (60%)	12 (60%)
	Total	20 (100%)	20 (100%)
West Palm Beach	No	8 (40%)	8 (40%)
	Yes	12 (60%)	12 (60%)
	Total	20 (100%)	20 (100%)

change, that indicates that the high performing tweets were not having an overwhelming influence on the results.

4.5.4 Relationship between TV Market and Tweet Quantity and Content

RQ17: Is there a relationship between market size and location and tweet quantity and content?

Overall, larger markets had more tweets in the September dataset than smaller markets (Table 4.11). The table below shows that Miami and Orlando had the most tweets and accounted for 21% and 17.8% respectively. The largest market in the study, Tampa, had substantially fewer tweets than the other large markets.

Tweet content remained relatively similar between markets (Table 4.11). Frequencies were used to determine how many tweets in each market were hurricane related. The data was bootstrapped with 1,000 resamples and a 95% confidence interval was conducted in addition to the frequencies.

Table 4.11 Number of tweets and percentage of tweets considered hurricane related per market during Irma

Market #	Market Name	Total Tweets (Percentage of total tweets in dataset)	Percentage of Tweets Hurricane Related (C.I.)	
16	Miami	6268 (21%)	70.2%	(69.0-71.3%)
19	Orlando	5300 (17.8%)	70.2%	(69.0-71.5%)
47	Jacksonville	4638 (15.6%)	70.0%	(68.6-71.3%)
38	West Palm Beach	4282 (14.4%)	57.9%	(56.4-59.3%)
11	Tampa	3372 (11.3%)	70.0%	(68.5-71.4%)
108	Tallahassee	2066 (6.9%)	67.4%	(65.5-69.7%)
61	Ft. Myers	1567 (5.3%)	73.1%	(70.9-75.4%)
58	Pensacola/Mobile	1478 (5%)	57.1%	(54.6-59.6%)
154	Panama City	688 (2.3%)	66.9%	(63.0-70.5%)
162	Gainesville	144 (0.5%)	79.2%	(72.4-86.0%)
	Total	29,803 (100%)		

All but three markets had between 66.9% and 73.1% of their tweets that were hurricane related. West Palm Beach and Pensacola/Mobile only had 57%-58% of their tweets in this category, and Gainesville had 79.2%. The Pensacola/Mobile market was the furthest market from the main impact area of the storm, which could explain the lower occurrence of hurricane-related tweets. Gainesville is a small market with little Twitter activity, thus the presence of a news story as big as Irma could have resulted in more emphasis on the storm as opposed to tweets related to other stories since those tweets are found less frequently anyway. The biggest anomaly is West Palm Beach. This market deviated significantly from its surrounding markets and from other markets of similar size. It is unclear as to why this deviation occurred.

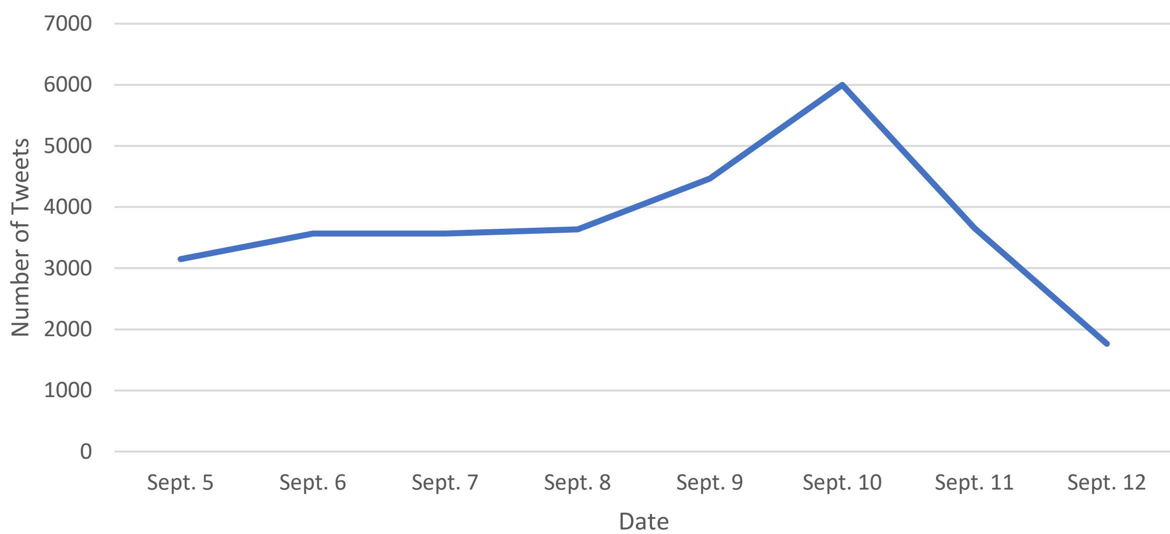

Figure 4.12 Number of tweets per day during Irma

The number of tweets per day very slightly increased up until the day before landfall when a more rapid rise occurred. That rise continued into the day of landfall before dropping significantly in the days following the storm.

When the overall number of tweets over the duration of the event was considered, a slight gradual rise occurred up until the day before landfall (Figure 4.12). From there, the number of tweets rose to a high on the 10th—landfall—before taking a steep dive on the 11th. This same trend could be observed when tweet counts were broken up by market, with the exception of the smaller or lesser affected markets (Figure 4.13).

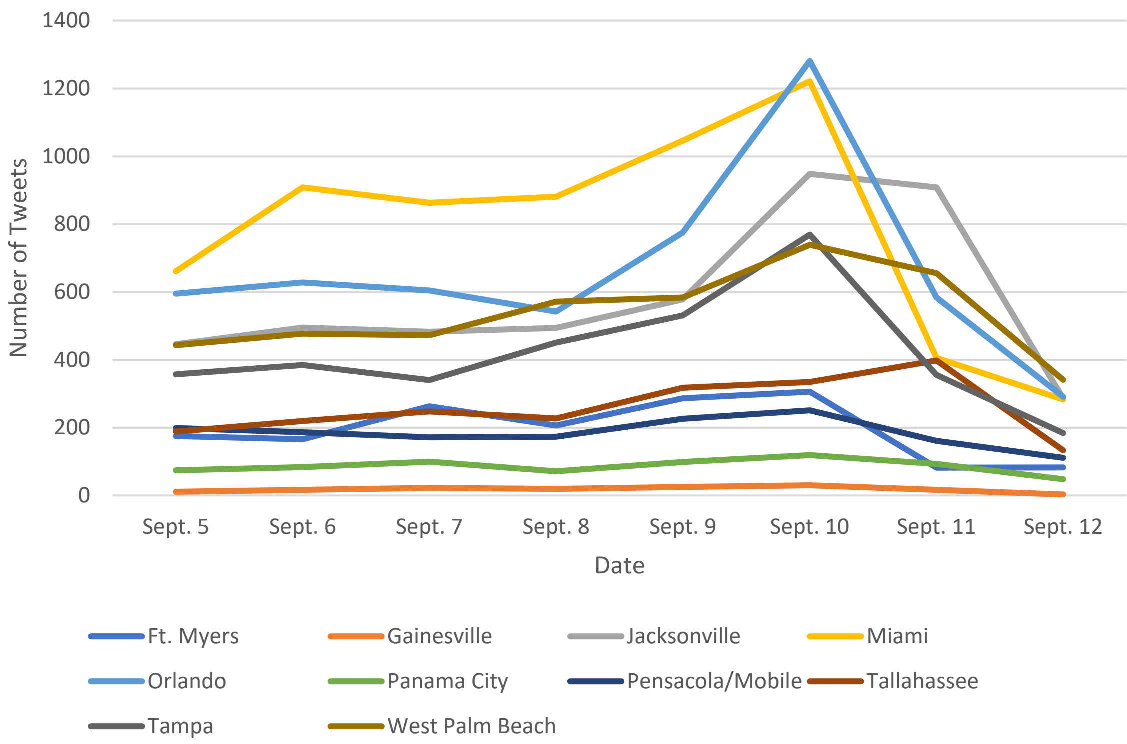

Figure 4.13 Number of tweets per day per market during Irma

Large markets had relatively little change in number of tweets published up until the day before landfall when a drastic increased was observed. The maximum number of tweets occurred on the day of landfall before a rapid decrease observed after the storm. Interestingly, smaller markets did not exhibit near as much variation as larger markets did.

These conclusions suggest that larger and mid-size markets tended to behave very similarly regarding how much of their Twitter output was related to the hurricane. Smaller markets showed more deviation (both upward and downward) in the number of tweets related to the storm. The similarity is a bit surprising given the vast differences in the overall number of tweets put out by each market. The total number of tweets gradually rose through the peak of the event, with a sharper rise and subsequent fall in the day before and day after landfall. Smaller or lesser affected markets were less likely to follow that trend.

4.5.5 Effect of Posting Personal Content on Retweet Levels during Irma

RQ18: Do people who have more personalized posts in May have more engagement during Irma?

One hundred eighty-nine tweets from the May dataset were coded as personalized posts, and they were found amongst 71 of the 111 broadcast meteorologists that tweeted during May. The total number of personalized posts were summed up for each actor and a bivariate Spearman correlation was then performed to understand whether there was a correlation between the number of personalized posts and engagement indices of each tweet during the September dataset. The Spearman correlation coefficient was 0.062 ($p < 0.001$) indicating a very weak positive correlation. When removing the top 1% of tweets, the correlation only rose to 0.065 ($p < 0.001$). A moderate positive correlation ($r_s = 0.410$, $p < 0.001$) was found between mean actor follower count and the number of personalized posts. Some limitations exist with these findings. While the engagement values have been standardized to account for the audience size of each account, they are not equally comparable. Engagement is not a perfect function of audience size (i.e. follower count). To make for a more accurate conclusion, the actors were divided into groups based on follower counts. For example, actors with a mean number of followers in September between 1000-1999 were in their own category. A Spearman correlation was then run for each group. The table below shows a breakdown of the correlation coefficients for each group (Table 4.12).

The correlations all remain very weak. Perhaps the strongest signal that there is any substantial relationship is in the 0 – 1,999 follower range where the highest correlation coefficients are found, and both are significant. Interestingly, when mean follower count tops 10,000, the correlation coefficients become negative, albeit very weak.

Table 4.12 Spearman correlation between personalized tweets and retweets garnered during Irma by mean follower count

Mean Follower Count (September)	Correlation Coefficient	p-value
0 - 999	0.079	0.018*
1,000 - 1,999	0.124	<0.001*
2,000 - 2,999	0.045	0.083
3,000 - 3,999	0.006	0.761
4,000 - 4,999	0.077	<0.001*
5,000 - 9,999	0.006	0.76
10,000 - 14,999	-0.046	0.092
15,000 +	-0.028	0.164

(*) Indicates significance (α = 0.05)

Finally, the 200 most retweeted tweets were examined. These tweets usually had videos or pictures of impressive scenes. The most retweeted tweet was of flamingoes at Busch Gardens being guided to their shelter for the storm. Often these tweets contained animals, before-and-after comparisons, and Andrew-Irma comparisons. Several of the tweets had footage of looters raiding stores as the storm arrived. Tweets that contained humor also performed very well. While using retweets to measure engagement and information diffusion is well supported by literature, there are some limitations. Retweets are only one measure of engagement. This study did not account for other engagement metrics such as likes or replies. With retweets being a primary vehicle for tweet sharing, other engagement patterns could be observed with different engagement metrics that could be more focused on showing approval or actually corresponding with the tweet's author.

4.6 Discussion

Between the three account types analyzed in this study, news station accounts had the greatest following and were most influential in causing significance in statistical tests due to their much larger follower counts as well as more pronounced fluctuations in content and engagement. Furthermore, the accounts with the largest follower counts were from larger markets.

This helps clear up the contradictory findings of Chan-Olmsted and Kim (2001) and Chan-Olmsted and Park (2000) in relation to which market size has more digital content. Based on previous literature, smaller news markets were thought to be potentially disadvantaged and less robust in their coverage of disasters (Mortenson et al. 2017). The findings of this research would seem to lend credence to this idea. Smaller markets had fewer news stations to aid in coverage and had lower tweet frequencies than their larger counterparts. They also failed to produce a significant difference in the number of retweets garnered between hurricane related and non-hurricane related tweets. The smaller markets showed mixed results on the change of engagement from one phase of the storm to the next. Further research will be needed for this however as Florida’s smaller markets are primarily in the northern part of the state and were not impacted by the storm’s most intense part until it had already weakened some. When analyzed at the market level, smaller markets garnered more engagement during Irma when compared to a more typical news week in May, even though Pensacola’s difference was not significant. This again may be more related to their overall lack of centrality to the storm’s most intense impacts. But when analyzing at the individual account level, the news, weather, and BM accounts in smaller markets were much less likely to show a significant difference in engagement between the week in May and Irma. When looking into tweet content, the Pensacola market had lower occurrence of hurricane related tweets, but as mentioned, it was further from the impacts. Smaller markets overall seemed to show slightly greater deviation from the average percentage of hurricane related tweets in larger markets. While not a lot of information can be surmised from this, the results may again be due to a lower tweet count overall in these markets. This would mean that the weight one tweet carries in the percentage calculation is greater in small markets and thus could lead to the greater chance of deviation. Smaller markets also failed to show much change in the number of tweets that were tweeted daily throughout the event. Overall, this seems to indicate that smaller markets provided less coverage with a lower likelihood of seeing differences in the amount of engagement received on social media during Irma.

In the same vein as hurricanes Sandy, Irene, and Ike, Irma's tweet frequency peaked during the mean impact of the event (Pourebrahim et al. 2019; Wang et al. 2017; Mandel et al. 2012). Consistent with findings from other storms, the content put on Twitter by news stations and their personnel changed through the duration of the event (Yang et al. 2019; Huang & Xiao, 2015; Pourebrahim et al. 2019). Tweets related to the scientific anatomy and structure of Irma were found when it was approaching land (i.e. Puerto Rico and Florida). After the storm made landfall, focus shifted away from this and more toward damage and negative impacts from the storm. The meteorological impacts and warning related tweets were found most heavily around the time of impact, whereas tweets focusing on preparation for the storm were found most heavily two to five days pre-impact.

Hypotheses 7 and 8 were supported by a majority of the findings but not universally. As a general rule, tweets related to the hurricane were more likely to get retweeted. Hypothesis 9 was not supported as retweeting most often peaked before the storm when the market was located in the cone of uncertainty. This was not the case in Tropical Storm Cindy from 2017 when engagement peaked after landfall, though this storm was weaker and formed closer to landfall. This likely resulted in lesser urgency and less time to for media coverage to build. Yoo et al. (2016) also noted that as tweet frequency increased, the more messages there were to compete for engagement. Seeing as how the engagement peaked and was followed by a significant rise in the number of tweets being published, these findings may support Yoo et al.'s thoughts. Engagement was also found to be higher during Irma than during a typical news week in May. Thus, during disasters news media should expect an uptick in engagement with their social media.

Differences in account type did affect engagement performance and tweet frequency. News accounts were far more likely than weather accounts and BM accounts respectively to see more engagement in Irma than during the typical news week in May. And BM accounts were the most likely of the three account types to see significantly lower engagement during Irma. BM accounts generally had lower tweet counts overall and were less consistent in their tweeting habits. This makes sense as an account contributed to by one meteorologist is likely to have less content than a news account contributed to by a whole newsroom. However, understanding why BM accounts performed so differently in their engagement is likely more complex. It could follow the trend seen elsewhere in this paper that accounts and markets with fewer followers are less likely to see changes in engagement. But it may be deeper than that. The public may have been looking to the news accounts to provide the news and storm related information. Whereas they may more routinely look to personal broadcast meteorologist accounts for personalized content. In short, they may be looking to the news accounts to learn about the news and to the broadcaster accounts to learn about the broadcaster. While the broadcast meteorologist is a source for weather information, they are also a social media personality which could make following them on Twitter akin to following a pseudo-celebrity. The public's decision to follow them may be a mixture of a desire for weather information and an emotional attachment to them (Kowalczyk & Pounders, 2016).

Research question 19 builds on this thought. Initially it was found that BM accounts with more personalized posts in May had a weak positive correlation to more retweets during Irma. But this did not account for dividing up the accounts by follower count. Upon investigating this, BM accounts with under 2,000 followers showed a weak positive correlation between more personalized posts in May and more retweets in Irma, and this result was statistically significant. While not a smooth transition, the correlation tended to become weaker the larger the follower count became. Eventually for accounts with over 10,000 followers, the correlation actually became weakly negative. Indicating that the more personalized posts observed in May, the fewer retweets received in Irma. While the relationship appears quite weak, there is limited evidence that follower count does impact whether posting of personalized content will result in more retweets during a disaster.

Broadcasters that have smaller follower counts may be new to a market or serve a less prominent role in the market. Building on the previously mentioned thoughts, it is possible that a broadcaster's followers do not just follow them because they are another "weather voice" in the community, but rather because they want to follow them, learning more about their personal life due to emotional attachment. When the followers are more motivated by emotional connection, engagement with tweets may be more dependent on how well that emotional connection is being fostered through personalized tweets. Thus, when the broadcaster posts content, their followers may engage with it due to an emotional connection or relationship and not specifically due to the content or context of the post (Boyd et al. 2010). However, as a broadcaster's following grows, and their reach and authority in a market expands, their following may pivot to one that is less emotionally attached. They may become just another "weather voice" for many people and thus interaction with their tweets may be more reliant on content and less on the emotional attachment between consumer and broadcaster. Some additional supporting evidence of this was observed in chapter two when most survey participants who had downloaded a news station's weather app reported rarely or never watching that news station on television. This is a possible explanation for why the correlation decreases and eventually becomes negative as follower count grows. This topic will require substantially more research that is beyond the scope of this paper.

4.7 Conclusion

Tweets that were related to the hurricane made up roughly two-thirds of all the September dataset. These generally had greater engagement in the news and weather accounts; however, this was not absolute--especially in smaller markets. A broadcaster's posting content about themselves or their life in a time period prior to Irma was only weakly correlated with any change in engagement during the storm. This change appeared to be related to follower count. Smaller follower counts showed a positive correlation, whereas larger follower counts showed a negative correlation.

Tweet content, frequency, and engagement all evolved throughout the storm and the time before and after. Content containing terms referring to the anatomy, structure, and physical evolution of the storm was most frequently found in tweets when the storm was impacting a land mass. Tweets containing content on the forecast and meteorological impacts of the storm were widely used in all timeframes except for post-storm. Words related to damage and negative impacts were found most frequently in tweets occurring as the storm was hitting and afterward. Contrastingly, words describing preparation and response to the storm were found most frequently before the storm.

Tweet frequency gradually rose until the 24 hours before the storm at which point it rose more dramatically before peaking as the storm hit. However, this trend was not observed in engagement which either increased or stayed stable as the market entered the cone of uncertainty—the time-period when most markets saw the greatest engagement. After this point, engagement plateaued or declined as the storm hit and then dropped with the storm's passing. When comparing the engagement to a more typical news week, all markets that were in the main path of the storm saw significantly greater engagement during Irma. However, this was largely driven by news accounts seeing more engagement during the storm, as only half of weather accounts and even fewer broadcaster accounts saw significant increase in engagement during the storm. Smaller markets were less likely to have accounts with significant engagement differences between the two time periods.

This study shows that market size, account type, time, and tweet content all influence the engagement a tweet receives. Further research will be necessary to better understand how market size influences Twitter performance during other hurricanes. Researchers should also continue to investigate the relationship between posting personal content on Twitter and its effect on Twitter performance in a disaster.

CHAPTER V

CONCLUSION

5.1 Conclusion

This dissertation furthered previous research in the area of digital weather communication by investigating the public's weather app usage and perception as well as the usage and performance of news media Twitter accounts during Hurricane Irma. Previous research was not able to conclusively say that the weather app had become the dominant medium for weather information and even less was known about digital media during severe weather. Likewise, past work on social media use in a hurricane had focused very little on engagement and even less on the difference Twitter usage and performance across varying television market sizes. This paper filled this gap. A survey was used to understand the public's app usage and perceptions, and a dataset of tweets from news media Twitter accounts during Irma was used to investigate content, frequency, and engagement of the tweets.

Chapter two used an online survey with 600 participants of all ages from across the U.S. The weather app was rated as the primary source for weather information. It became the second most prominent source during severe weather, preceded by websites. Television was the third most popular source of weather information during severe weather. Younger people were more likely to be app users with over 80% of people aged 18-30 using a weather app, but the weather app was still the dominant source of the majority for each age bracket tested. Gender was significantly associated with information source, as males were more likely to be website or televisions users than females and less likely to be app users than females.

Most people (80%) reported getting notifications about severe weather on their phone, indicating the value that smartphone alerts provide. However, it was unclear if these were weather app notifications or WEA alerts. Based on the survey data, it could not be concluded that a majority of app users had their app notifications turned on. A slight majority of people downloaded a weather app of their choosing as opposed to using the standard one that came on their smartphone. Furthermore, these people had a higher self-perceived weather knowledge and interest rating compared to people using the standard app.

Weather app usage frequency was found to be significantly related to smartphone brand, gender, and the time of day the app is used. Reliance on the smartphone was found to be related to gender and device brand, which was itself also related to gender.

The third chapter used a survey in conjunction with chapter two. Most weather app users believed their app to be highly accurate and sometime inconsistent. Perceived accuracy was highly correlated with trust in the app, and perceived inconsistency was negatively correlated with trust in the app. This underscores the importance of consistency in addition to accuracy to give weather apps the most value.

The public’s confidence in a forecast decreased the further out in time the forecast was for. The results also showed that the public understood the probability of precipitation to mostly indicate the extent of the area that would see rain. However, roughly a quarter of the respondents made inferences about the rainfall totals and the duration and intensity of rain when given a “percent chance of rain”. The public also perceived the weather apps forecast region to be smaller than that for a television forecast. However, they still indicated that rain nearby instead of at their home was adequate verification for a day where rain was forecasted on their app. This indicates that the public does account for some regional variability in the app's forecast, though the extent of that will need further research.

As mentioned previously, trust in the app and the app's perceived accuracy were highly correlated, but app accuracy was also moderately correlated with trust in meteorologists, the science of meteorology, and a news station that made a weather app. This indicates that inaccuracies in the app could have additional effects on the trust in other areas of meteorology.

Finally, in chapter four, tweets that were related to Hurricane Irma were more likely to get more retweets than those unrelated to the storm. The engagement index scores quantifying the number of retweets most often peaked in a location before the storm impacts began but after the location had entered into the cone. All television markets studied saw a greater engagement index score in Irma than during the more typical news week analyzed from May. Pensacola still had a higher mean engagement during Irma, though it was the only market with an insignificant difference. This was attributed to its distance from the worst impacts of the storm and its exclusion from the cone of uncertainty.

Differences emerged in how television markets of differing sizes covered and performed during the storm. Smaller markets showed very little change in the number of tweets published over the duration of the event. This was in contrast to larger markets seeing a peak in tweet frequency during the main impact stage of the storm. Accounts from smaller markets were also less likely to have significantly different engagement during Irma than during the normal week in May. The average amount of content that was hurricane related was similar between market sizes, though smaller markets depicted slightly more variability than the largest of markets.

An interesting correlation was observed between the amount of personal content tweet by meteorologists during a week in May and the number of retweets received during Irma. The correlations were all weak, but they were positive for accounts with less than 10,000 followers and negative for those with greater than 10,000 followers. The accounts with less than 2,000 followers showed a significantly positive correlation and seemed to be where the positive correlation was most concentrated. It was theorized that the followers of these smaller accounts may have been more likely to like the meteorologist and follow them due to an attachment or one-sided friendship with the meteorologist. Thus, retweeting during Irma may have been more correlated because the retweeting was based less on content and more on who published the tweet (i.e. the meteorologist). Whereas larger accounts may have been more likely to be followed by a broader audience who viewed them more as an additional weather voice in the community and were less interested in following them for their personal content. Further research will be needed in this area.

Accessing a weather forecast has clearly moved into a new, digital era that will require continued research and adaptation to new technologies. The three projects of this dissertation come together to create a broad understanding of how this digital transition has affected people. Chapter two focuses on the physical aspects of medium usage and user demographics. Chapter three focuses on the non-physical aspects of user perception, opinion, and interpretation. And chapter four focuses again on physical, yet more intentional, behavior and interaction with digital media in a specific setting. They unite to establish what people are doing and thinking in relation to digital media and weather information.

This research adds to the literature on this topic, by establishing the weather app as the predominant source for weather information. This conclusion has been speculated based on many recent studies, but a broad sample was needed before the conclusion could be confirmed. This will hopefully encourage future research into weather apps since they play such a vital role in communicating the weather forecast. Furthermore, future work can also be used to understand whether the weather app is continuing to make gains in its monopoly on the weather forecast market. The third chapter established a relationship between accuracy, inconsistency, and trust. This underscores how crucial it is for weather forecasts to be accurate and consistent, both as perceived by the public and in reality. This should cause the weather community to evaluate how weather apps can better achieve these goals. This study found that probability of precipitation and regional variability are subjective and may play a role in how the public perceives the accuracy and consistency of their weather app. These two concepts are not exclusive to weather apps however and should promote not only a debate on what method of uncertainty quantification is best but also how the public will perceive the quantification used.

So much literature has been devoted to studying Twitter usage during hurricanes. However, very little of the research focuses on engagement with tweets. While understanding the context, content, sentiment, and frequency of tweets is very important to gauge the information setting during the storm, it accomplishes very little in understanding what the public is actually paying attention to or is interested in. This study bridged this gap and will hopefully spur more research and new methods by which to measure human interaction with information on Twitter, especially research looking at other types of engagement such as likes and replies. While looking at the public's interaction with tweets, this research did not investigate public conversation of Twitter during the storm as many studies have done, but rather looked at media's conversation to learn how official sources are using their platform.

This dissertation can provide help to the field of meteorology as it seeks to communicate weather information clearly on digital media. News and weather organizations from across the world use weather apps to market their weather forecast. This research can provide app developers with better information on how to present data in a weather app and things to consider when choosing how to formulate the forecast. How far out should the forecast extend? How should uncertainty be quantified? When should the app update? How often should it update? Can averaging techniques be used to lessen the inconsistency of the forecast? This dissertation answers some of these questions, but it only scratches the surface on some of the others. Based on the conclusions of this paper, future work can pave the way forward in answering them.

News and weather organizations often use social media to provide weather stories and reports. They can learn what to expect from their Twitter audience during a hurricane which could help them make more timely posts, get more engagement, and ideally spread the information further into the social network. This can also help researchers understand the public's behavior and information needs during a hurricane. In turn, those tweeting can tailor their Twitter coverage to meet the public with the information they need as they seek to make decisions and clear up uncertainty.

This study is an important step forward for meteorology because it focuses on where the science meets the public. The public's usage of and reliance on weather forecasting is a main pillar of the value it provides. Thus, understanding their usage of it and how they think about it crucial in upholding its value. Future work will be able to continue these research processes to understand how continually and rapidly evolving technology affects forecast usage and perception by the public.

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APPENDIX A

SURVEY

Thank you for being willing to complete this survey and provide us with accurate answers! Your participation in this research is completely voluntary, and you may withdraw or quit at any time. If you choose to participate, you must answer all required questions. This survey will let researchers understand what sources the public is turning to for weather information, as well as the public's opinions and habits regarding those sources. Completion of this one-time survey will take an average of 11-13 minutes. This research project is being led by Cole Vaughn at Mississippi State University. If you have any questions or concerns regarding the survey, you may contact him at (cv441@msstate.edu). If you have any questions about your participation as a research subject, please feel free to contact the MSU Regulatory Compliance Office by phone at 662-325-3294, by e-mail at irb@research.msstate.edu, or on the web at http://orc.msstate.edu/participant/. Please check the statement below to begin the survey.

o I am at least 18 years old and agree to participate in this study.
o I am not 18, or I choose not to participate at this time

What is your Prolific ID? Please note that this response should auto-fill with the correct ID. If it does not, please provide your Prolific ID in the space below.

____

To begin, please answer a few questions about the sources you use to get weather information.

1. What would you describe as your main source for getting a weather forecast?

o Television
o Weather App or Widget
o Social Media
o Radio
o A website on the internet
o Other

2. Where in the last 24 hours have you obtained a weather forecast? (Check all that apply.)

o Television
o Weather App or Widget
o Social Media
o Radio
o A website on the internet
o Other
o None

3. Which source is typically the first source to alert you that severe weather is occurring near you?

- o Television
- o Weather App Notification
- o Mobile Phone Emergency Alert
- o Social Media
- o Radio
- o A website on the internet
- o Tornado Siren
- o NOAA Weather Radio
- o Friends or Family
- o Other

4. After you have been alerted about the severe weather by (pipe above answer), what source or sources do you typically go to next for more information? Check all that apply.

- o Television
- o Weather App or Widget
- o Social Media
- o Radio
- o A website on the internet
- o Other

Next, please answer a few questions about your confidence in weather forecasting.

5. On a scale of 1 to 10, with 1 being low confidence and 10 being high confidence, how would you rate your confidence in the forecast for 1 day from now?

- o Very High
- o High
- o Moderate
- o Low
- o Very Low

6. On a scale of 1 to 10, with 1 being low confidence and 10 being high confidence, how would you rate your confidence in the forecast for 3 days from now?

- o Very High
- o High
- o Moderate
- o Low
- o Very Low

7. On a scale of 1 to 10, with 1 being low confidence and 10 being high confidence, how would you rate your confidence in the forecast for 5 days from now?

- o Very High
- o High
- o Moderate
- o Low
- o Very Low

8. On a scale of 1 to 10, with 1 being low confidence and 10 being high confidence, how would you rate your confidence in the forecast for 7 days from now?

- o Very High
- o High
- o Moderate
- o Low
- o Very Low

9. On a scale of 1 to 10, with 1 being low confidence and 10 being high confidence, how would you rate your confidence in the forecast for 10 days from now?

- o Very High
- o High
- o Moderate
- o Low
- o Very Low

Using the questions below, please describe your trust in meteorologists and meteorology.

10. How would you rate your trust in meteorologists?

- o Very high
- o High
- o Moderate
- o Low
- o Very low

11. How would you rate your trust in the science of meteorology?

- o Very high
- o High
- o Moderate
- o Low
- o Very low

Next, there are a few questions about your smartphone and weather app usage.

12. Do you have a smartphone?

- o Yes
- o No

13. How often do you use a weather app?

- o Multiple times per day
- o Once per day
- o More than once per week, but not daily
- o Once per week
- o Less frequently than once per week
- o Never

14. How many weather apps do you have on your phone?

- o 0
- o 1
- o 2
- o 3
- o 4
- o 5+

15. What time of day do you most frequently use your weather app?

- o Early Morning (5am – 9am)
- o Late Morning (9am – Noon)
- o Lunchtime (Noon – 2pm)
- o Afternoon (2pm – 5pm)
- o Evening (5pm – 10pm)
- o Night (10pm – 5am)
- o Anytime you are bored

16. Most smartphones come with a weather app already on them. However, some people choose to download a different weather app onto their smartphone.

Have you ever downloaded a weather app?

- o Yes
- o No

17. Do you prefer to use the weather app you downloaded or the one that came on your phone?

o The weather app I downloaded
o The weather app that came on my phone

18. From the list of weather apps below, please select any of the apps that you use regularly? (Check all that apply.)

o The Weather Channel
o Accuweather
o Weather Underground
o WeatherBug
o Local News Station's Weather app
o Other

19. Which notifications do you get on your smartphone about the weather? (Check all that apply).

o Rain is close to you
o Lightning is close to you
o Severe weather
o Weather headlines
o Other
o None

20. When your phone gives you a severe weather alert notification, do you normally see severe weather?

o Yes
o No

21. What would you say are the most important features of your weather app? (Check all that apply.)

o Hourly Forecast
o Chance of Precipitation
o Current Information
o Severe Weather Alert
o 5-Day Forecast
o 10-Day Forecast
o Satellite and Radar
o Pollen Count
o Lightning Detection Alert
o Airport Delays
o UV Index

- News Headlines about Weather
- 10+ Day forecast
- Weather Videos
- Advertisements

22. How convenient do you consider your weather app to be?

- Very convenient
- Convenient
- Somewhat convenient
- Not very convenient
- Not convenient

23. How useful do you consider your weather app to be?

- Very useful
- Useful
- Somewhat useful
- Not very useful
- Not useful

24. How convenient do you consider a TV weather forecast to be?

- Very convenient
- Convenient
- Somewhat convenient
- Not very convenient
- Not convenient

25. How useful do you consider a TV weather forecast to be?

- Very useful
- Useful
- Somewhat useful
- Not very useful
- Not useful

26. How would you rate the accuracy of the weather app you use most frequently?

- Very high
- High
- Moderate
- Low
- Very low

27. How would you rate the accuracy of weather apps in general?

- o Very high
- o High
- o Moderate
- o Low
- o Very low

28. How would you rate your trust in the weather app you use most frequently?

- o Very high
- o High
- o Moderate
- o Low
- o Very low

29. How would you rate your trust in weather apps in general?

- o Very high
- o High
- o Moderate
- o Low
- o Very low

30. Sometimes there will be large changes in the forecast over time. For example, maybe you look at the forecast in the morning and it shows rain over the weekend, but then you look at the forecast in the afternoon and it shows sunshine for the weekend instead.

How often does your weather app tend to make big jumps in the forecast?

- o Almost always
- o Often
- o Sometimes
- o Seldom
- o Never

31. On average, how many days of the week do you think the weather app you use most frequently gets the forecast correct?

0 1 2 3 4 5 6 7

32. Try to remember the last time your weather app forecasted rain, but it did not rain at your location. Did it rain nearby?

o Yes
o No
o Not sure

33. How would you describe the weather app's forecast for that day?

o Accurate
o Inaccurate
o Neither accurate nor inaccurate

34. If your weather app forecasts a 70% chance of rain for tomorrow, which of the following do you think is/are likely to occur? (Check all that apply.)

o Most locations in my area will get rain.
o Some locations in my area will get rain.
o It will rain at my house.
o It will rain for a long duration of time
o There will be high rainfall totals
o There will be heavy downpours
o None of the above.

35. If your weather app forecasts a 30% chance of rain for tomorrow, which of the following do you think is/are likely to occur? (Check all that apply.)

o Most locations in my area will get rain.
o Some locations in my area will get rain.
o It will rain at my house.
o It will rain for a short duration of time
o There will be low rainfall totals
o There will be light rain
o None of the above.

36. When you look at the forecast on your weather app, what location do you think that forecast is for?

o Your specific location
o Your town
o Your county
o Your county and the neighboring counties

37. When you look at the forecast on television, what area do you think that forecast is for?

- o Your specific location
- o Your town
- o Your county
- o Your county and the neighboring counties

38. How involved do you think a meteorologist is in formulating the forecast for your weather app?

- o Very involved
- o Involved
- o Somewhat involved
- o Not very involved
- o Not involved

39. How involved do you think a computer is in formulating the forecast for your weather app?

- o Very involved
- o Involved
- o Somewhat involved
- o Not very involved
- o Not involved

40. Have you ever watched one of the meteorologists that put the forecast in your weather app deliver the forecast on TV?

- o Yes
- o No
- o Not that I know of

41. How often do you watch that meteorologist on TV?

- o Multiple times a day
- o Every day
- o A few times per week
- o A few times per month
- o Almost never

42. Do you follow that meteorologist on social media?

- o Yes
- o No

43. Think about a time when your weather app got the forecast wrong. How responsible do you think that meteorologist was for the poor forecast?

- o Fully responsible
- o Partially responsible
- o Not responsible

44. How often do you watch the TV channel or news station that makes your weather app?

- o Multiple times a day
- o Every day
- o A few times per week
- o A few times per month
- o Almost never

45. How would you rate your trust in that news station or TV channel?

- o Very high
- o High
- o Moderate
- o Low
- o Very low

We have a few final questions regarding your smartphone.

46. What brand is your smartphone?

- o Apple
- o Samsung
- o Google
- o Other

47. How long has it been since you got your very first smartphone?

- o 0 – 1 years
- o 2 – 3 years
- o 4 – 5 years
- o 6 – 8 years
- o 9 – 12 years
- o 13 years +

48. When is the first time you typically use your smartphone after waking up?

- o I use it before I even get out of bed.
- o I use it right after I get out of bed.
- o I use it after being out of bed for an hour or so.
- o It is usually a long time after waking up before I use my phone.

49. How easily could you function without your smartphone for a day?

- o Very Easily
- o Easily
- o Somewhat Easily
- o Not Easily
- o Not at all Easily

Before finishing, can you tell us a little bit about yourself using the questions below?

50. What is your age?

____

51. How would you describe your gender?

- o Female
- o Male
- o Transgender female
- o Transgender male
- o Gender variant/Non-conforming
- o Prefer not to identify

52. How would you describe your race or ethnicity? (Check all that apply.)

- o White
- o Hispanic or Latino
- o Black or African American
- o Asian
- o American Indian or Alaska Native
- o Native Hawaiian or Pacific Islander
- o Middle Eastern or North African
- o Mixed race
- o Other

53. What is your highest level of education?

o Some High School
o High School Graduate
o Some College
o Associate’s Degree
o Bachelor’s Degree
o Advanced Degree

54. What is your zip code?

____

55. How would you classify the area in which you live?

o Urban area
o Suburban area
o Rural small town
o Rural outside of town
o Not sure

56. How would you describe your knowledge about the weather?

o Very High
o High
o Moderate
o Poor
o Very Poor

57. How would you describe your interest in the weather?

o Very High
o High
o Moderate
o Low
o Very Low

Thank you for participating in this study. Please click the button below to be redirected back to Prolific and register your submission.

APPENDIX B

HURRICANE RELATED WORDS

HURRICANE RELATED WORDS

Meteorology Science	Name	Meteoro-logical Impacts	Warning	Forecast	Forecast (cont.)	Damage and Negative Impacts	Preparation and Response
eye	#irma	winds	warnings	Cuba	uncertainty	impacts	evacuations
eye wall	#HurricaneIrma	wind	warning	weakening	track	impact	evacuation
eyewall	Irma	mph	watches	weaken	forecast	power	mandatory
outer band	hurricane	tornadoes	watch	weakened	category	outages	voluntary
outer bands	hurricanes	tornado	advisories	strengthening	categories	outage	preparation
wind shear	storm	surge	advisory	strengthened	satellite	shelter	recovery
warm water	tropical	floods	severe	strengthen	projected path	disaster	rescue
rain bands	depression	flooded		GFS	landfall	school closing	rescues
rain band	major hurricane	flooding		ECMWF	advisory	school closure	supplies
shear		flood		Euro	NHC	cancellation	preparation
right front quadrant		gusts		intensity	wind	cancelled	preparations
eyewall replacement		gust		leeward islands	tropics	canceled	preparing
eye wall replacement		rain		Virgin Islands	cone	cancel	prepared
		tide		path	pressure	damage	prepare
		water level		Track shift	Models	path	sandbag
				surge	Model	pier damage	sandbags
				Hurricane hunters		death toll	sand bag
				Hurricane Hunter		beach erosion	sand bags
				Caribbean		carbon monoxide poisoning	shutter
				Gulf of Mexico			
				National hurricane center		state of emergency	
				Computer model		boil water notice	