THE ROLE OF SOCIAL-MEDIATED DISASTER INFORMATION SOURCES AND CONTENT ON AUDIENCE BEHAVIORS AND PERCEPTIONS

by

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(Under the Direction of Itai Himelboim)

ABSTRACT

The topics discussed and developed in this dissertation strive to propose a conceptual model describing how information sources and content characteristics affect social-mediated disaster communication outcomes in the form of communication strategies, as well as audience perceptions and behavioral engagement. The model proposes that the role that information sources play in social media content creation before, during and after disasters is shaped by broader routines, societal and systemic factors. It also contends that content characteristics affect the way in which audiences engage with messages on social media. The major tenets of the model were tested through a content analysis of disaster-related tweets posted before, during and after Hurricane Matthew, and a 2 (Post Modality: Image- vs. GIF-based Social Media Disaster Preparedness Posts) x 3 (Visual Focus: Reactive- vs. Proactive- vs. Hero-themes Social Media Post Visuals), also including an additional text-based condition, between-subjects online experiment. Content analysis results found that social media users were more likely to retweet, like and reply to image-based posts rather than text-based posts. The same was true for users engaging with video-based posts rather than image-based posts.

In turn, the online experiment results found that affective risk perception plays a mediation role in the relationship between previous hurricane experience and three target communication outcomes: crisis information sharing intentions, crisis information seeking intentions, and guidance adoption intention. The practical and theoretical implications of these findings are discussed.

INDEX WORDS: disaster communication, social media, engagement

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# INTRODUCTION

According to a recent report by the Centre for Research on the Epidemiology of Disasters (CRED) (2019), in 2018, the world faced over three hundred disaster events resulting in more than ten thousand deaths, over sixty-eight million people affected, and more than $131 billion in losses. The current global pandemic caused by COVID-19 further underscores the fact that humanity continues to face threats to health and safety posed by viruses and natural disasters alike.

In light of and in response to these threats, human ingenuity continually strives to identify and develop the means to prepare for and respond to these events. Key to that enterprise is communication. The ability for emergency managers to reach at-risk publics in these contexts is currently challenged by an increasing fragmented media landscape. Further, this difficulty is only exacerbated by the perils that the news industry weathers as its viewership and readership dwindle (Barthel, 2019) – since news media have traditionally worked as one of the primary ways in which emergency managers were able to reach their publics.

Parallel to this situation, technology sophistication and widespread adoption of these tools hold promise for addressing these challenges. Research has shown that during disasters people turn to social media platforms to check in on family and friends, fundraise, and lead crowdfunding efforts to help those affected (Fraustino et al., 2012; Gao et al., 2011). These dynamics have encouraged emergency managers to leverage social media platforms before, during and after disasters (Fugate, 2011). In turn, research in this area has identified key insights that inform best practices and communication principles in hopes of helping emergency managers achieve their target communication outcomes (J. Sutton, Ben Gibson, et al., 2015a).

Despite this progress, there are critical understudied areas they may help better inform these communication guidelines and principles. This dissertation draws from three areas of research – (1) studies focused on emergency management and disaster sociology, (2) work involving the Social-Mediated Crisis Communication (SMCC) model, and (3) the Social Amplification of Risk Framework (SARF) to propose a new conceptual model.

The Social-Mediated Disaster Information Amplification (SMDIA) model is an attempt to bridge these areas of study and complement gaps with insight from empirical studies. It upholds the idea that public-facing disaster-related content on social media can span different types of messages and a variety of modalities – and that these choices can be indicative of the functions that each actor embodies in the milieu of disaster messages. Further, it contends that audiences engage with disaster-related content in a myriad of ways. Through its articulation and first empirical testing, the SMDIA model proposes the following:

**RQ1: Are news media more likely to feature illustrative (i.e., photos) disaster visual content in their social-mediated messages rather than graphical (i.e., charts and graphs) visual content?**

**RQ2: Are government organizations more likely to feature graphical visual content in their social-mediated messages rather than illustrative visual content?**

**RQ3: Are ordinary users more likely to feature illustrative disaster visual content in their social-mediated messages rather than graphical visual content?**

**RQ4: Are organizations more likely to feature disaster visual content with an informational focus rather than a human-interest or destruction focus?**

**RQ5: Are news media more likely to feature disaster visual content with a human-interest focus rather than an information or destruction focus?**

**RQ6: Are ordinary users more likely to feature disaster visual content with a destruction focus rather than an informational and human-interest focus?**

**H1: Audiences are more likely to engage with, that is, to like (H1a), retweet (H1b) and reply (H1c) to disaster image-based social media content rather than text-based content.**

**H2: Audiences are more likely to engage with, that is, to like (H2a), retweet (H2b) and reply (H2c) to disaster video-based social media content rather than image- and text-based content.**

In addition to these hypotheses, the studies in this dissertation also seek to answer the following research questions:

**RQ7: How, if such an effect exists, do Twitter post modality (e.g., text-, image- or GIF-based) and visual focus (e.g., reactive, proactive and hero) influence affective and cognitive risk perception?**

**RQ8: How, if such an effect exists, do Twitter post modality (e.g., text-, image- or GIF-based) and visual focus (e.g., reactive, proactive and hero) influence crisis information seeking and sharing intentions among FEMA Region IV residents?**

**RQ9: How, if such an effect exists, do Twitter post modality (e.g., text-, image- or GIF-based) and visual focus (e.g., reactive, proactive and hero) influence guidance adoption intentions?**

**RQ10: Do affective and cognitive risk perceptions sequentially mediate the relationship between previous hurricane experience and crisis information seeking intentions?**

**RQ11: Do affective and cognitive risk perceptions sequentially mediate the relationship between previous hurricane experience and crisis information sharing intentions?**

**RQ12: Do affective and cognitive risk perceptions sequentially mediate the relationship between previous hurricane experience and guidance adoptions intentions?**

**RQ13: Do source credibility perceptions moderate the relationship between message credibility and guidance adoption intentions?**

Chapter 1 presents a concept explication of disaster communication. First, certain key and related terms are defined. That is followed by a description of traditional disaster communication and the disaster life cycle that has come to shape how emergency managers structure critical communication between themselves and the publics that they serve. Then, an overview of social media and how these platforms have caused a more participatory form of disaster communication is presented. The chapter ends with the proposed definition of disaster communication.

Chapter 2 draws on key ideas from disaster sociology and emergency management research, the SMCC model, and the SARF to define the first component of the proposed SMDIA model: information sources. First, a review of how information sources have been addressed in each of the conceptual frameworks is presented. That is followed by a discussion focused on the current gaps in our understanding of the role that potential information sources play in social-mediated disaster communication. The chapter then concludes with the introduction and definition of information sources in the SMDIA model context.

Similarly, Chapter 3 also draws on empirical evidence from disaster and emergency management research, studies testing the SMCC model, and SARF-related work to define the second component of the proposed SMDIA model: content. First, a review of how disaster information content characteristics have been addressed in each of the conceptual frameworks is summarized. In turn, a discussion focused on the current gaps in our understanding of the potential role of content features in social-mediated disaster communication is presented. Then, the chapter ends with the introduction and definition of key content characteristics in the SMDIA model context.

Chapter 4 then draws on key ideas from disaster sociology and emergency management research, the SMCC model, and the SARF to define the third component of the proposed SMDIA model: audience engagement. First, a review of how audience engagement has been addressed in each of the conceptual frameworks is presented. That is followed by a discussion on how audience behavioral engagement with social-mediated content has been broached in contemporary research in the area. The chapter then concludes with the introduction and definition of audience engagement in the SMDIA model context.

Following the conceptualization of the three major concepts of this dissertation – information sources, content and audience engagement, Chapter 5 then presents the research questions and hypotheses. The first main purpose of this chapter is to describe the fundamental assumptions underlying the relationships between information sources, content and audience engagement in a social-mediated disaster context. This description builds on three theories, the hierarchy of media influences, visual framing, and dual coding. The second objective of this chapter is to outline the relationships between the dissertation concepts through the articulation of research questions and the proposal of hypotheses. The third goal of this chapter is to visualize these relationships through the Social-Mediated Disaster Information Amplification (SMDIA) conceptual model.

Chapter 6 describes all the aspects related to the content analysis research design. First, a disaster event overview of Hurricane Matthew is presented. That is followed by a description of the data collection approach, wherein how the social media posts for the content analysis were gathered and collected. In turn, the corpus of Hurricane Matthew-related posts is characterized, and the sampling approach implemented is outlined. Then, the main units of analysis and tweet aspects are presented. That is followed by a description of the coding scheme, protocol development, coding team. The chapter concludes with an overview of Pilot Study 1, Pilot Study 2 and their results.

In turn, the content analysis study results are presented in Chapter 7. The descriptive statistics are addressed first. In turn, that is followed by the results of a binomial logistic regression set on exploring the relationship between information source type and image type. That is followed by the results of a multinomial logistic regression which explores the relationship between information source type and image focus is addressed. Finally, the results of three negative binomial regressions, one for each target audience engagement metric are presented.

Chapter 8 outlines the research design, the pilot thematic analysis conducted to identify prevalent visual themes in online disaster preparedness campaign materials, the sampling protocol, the experimental procedure, the items used to measure the dependent variables, and the results of the online experiment pilot study.

The online experiment study results are presented in Chapter 9. The descriptive statistics of demographic variables are described first. Their comparison to other population estimates, such as the American Community Survey (ACS) 1-year estimates is presented. In turn, that is followed with the descriptive statistics of all major variables in the study. Then, the chapter ends with the research question section, which lists the statistical results of a series of two-way MANOVAs, and mediation as well as moderation effects with serial linear regressions.

The dissertation concludes with Chapter 10, which presents the overall dissertation discussion. First, an introductory description of the study context is provided. Then, the key findings of the dissertation are listed and summarized. In turn, the theoretical implications of the findings are discussed. That is followed by a section that organizes the dissertation's findings according to the SMDIA model's concepts as well as the research goals that were articulated in the preceding chapters. Then, the study's practical implications are proposed. The discussion ends with the limitations and future research sections.

# CHAPTER 1

## DISASTER COMMUNICATION

This chapter presents a concept explication of disaster communication. First, certain key and related terms are defined. That is followed by a description of traditional disaster communication and the disaster life cycle that has come to shape how emergency managers structure critical communication between themselves and the publics that they serve. Then, an overview of social media and how these platforms have caused a more participatory form of disaster communication is presented. The chapter ends with the proposed definition of disaster communication.

Disasters have plagued mankind since the beginning of its existence. Research has shown that 205 million people were affected by natural disasters on average per year between 1995 and 2015 (Centre for Research on the Epidemiology of Disasters CRED, 2015). More concerning is the possibility that people will continue to face these events, perhaps even more so as time goes on. International researchers point to climate change, population growth and patterns of economic advancement – such as development in high-risk areas that are prone to floods and other environmental hazards, as major factors in increasing disaster likelihood (Centre for Research on the Epidemiology of Disasters CRED, 2015).

Both the inevitable and unpredictable nature of disasters implies that the strategies and mechanisms to prevent casualties and infrastructural damage must always evolve and adapt to face new challenges. This predicament also applies to communication procedures – which have recently been highlighted as a critical function of emergency management before, during and after disasters (Haddow & Haddow, 2009a). The aftermath of Hurricane Katrina stands as a timely reminder that preparing completely for a disaster is a difficult undertaking. For example, Vanderford, Nastoff, Telfe and Bonzo (2007) note that the Centers for Disease Control and Prevention's (CDC) health communication specialists faced a series of challenges reaching target audiences for the rapid dissemination of health messages – despite the fact that the agency's communication response was largely based on the dynamics of previous disasters.

Considering recent technological developments like the Internet in general and social media in particular, emergency communication managers must now adapt to a changing media landscape. In response to this, there is now a burgeoning academic and practical interest in how these technologies can be harnessed to facilitate emergency management functions. So far, researchers have explored how disaster information forms, sources and types can affect desired public outcomes (B. F. Liu et al., 2015a), but most of the research in this area so far has been descriptive with little predictive validity. There are still many understudied questions about the process by which people respond to socially transmitted disaster information. The first question this chapter aims to answer is what disaster communication entails, specifically considering the emergence of social media.

## Disaster Communication

Even though communication is a critical function of emergency and disaster management (Haddow & Haddow, 2009a), there is not an established definition of disaster communication across the literature. And while this topic has been of interest to researchers across fields and disciplines, they too have struggled in narrowing a formal conceptualization of the construct. It seems that the main issue is that research in this area suggests that disaster communication is defined by virtue of its context. In other words, if a disaster-related communication takes place before, during or after disasters, it is disaster communication. While this assumption is a good starting place, it does not contribute much in terms of establishing the bounds of the concept, nor does it lend itself to theoretical advancement. This chapter explores the different attributes that should be taken into consideration as definitional aspects of disaster communication. However, in service of clarity, a few key concepts are defined beforehand: hazard, risk and crisis.

**Hazard**

According to Hohenemser, Kates and Slovic (2000), hazards are “threats to humans and what they value” (p.169). Paton (2006) similarly argues, “hazards impact on people, they affect communities, and they disrupt the community and societal mechanisms that serve to organize and sustain community capacities and functions” (p.6). Other studies point out that “there is a broad range of natural hazards processes, but most natural hazards originate from either meteorological or geological events; a few hazards are grouped as hydrological and extraterrestrial events” (Gregg & Houghton, 2006, p. 22). The Federal Emergency Management Agency (FEMA) identifies three types of hazards: natural hazards, technological and accidental hazards, as well as terrorist hazards (Federal Emergency Management Agency, 2020). The first is associated with climatological phenomena such as floods or hurricanes; the second involves events like nuclear power plant failures and hazardous materials incidents; the third one concerns terrorist threats the range from cyberattacks to nuclear fallouts.

**Risk**

Risks are often conceptualized as the technical assessment of a hazard, and people's perception of that hazard. Walaski (2011) defines risk as "a hazard that might of might not occur, along with an understanding of the severity of the hazard and the probability of its occurrence" (p.7). Across the literature the predominant understanding of risk follows the Sandman (2000) conceptualization of risk as the function of hazard and outrage. In this context, hazard is the technical side of risk that "focuses on the magnitude and probability of undesirable outcomes;" whereas outrage concerns the perceptions and attitudes associated with the situation itself (Sandman 2000, pp.4-5). Other scholars have defined risk as "quantitative measures of hazard consequences that can be expressed as conditional probabilities of experiencing harm" (Hohenemser et al., 2000, p. 169). Similarly, Kasperson and colleagues (2000) note that risks involve "the probability of events and the magnitude of specific consequences" (p.232).

**Crisis**

According to Pearson and Clair (1998), a crisis is a "low probability, high-impact situation that is perceived by stakeholders to threaten the viability of the organization and that is subjectively experienced by these individuals as personally and socially threatening" (p.66). Coombs (2007) explains that a crisis consists of a "sudden and unexpected event that threatens to disrupt an organization's operations and poses both a financial and a reputational threat" (p.164). According to the author, these events can threaten the physical, emotional and economic wellbeing of stakeholders and they can also damage the organization's standing with the public. Researchers have also described organizational crises as "specific, unexpected and non-routine event or series of events that create high levels of uncertainty and threaten or are perceived to threaten an organization's high-priority goals" (Seeger et al., 1998, p. 233).

**Disaster**

Disasters are defined as "singular (or interactive) events that have a profound impact on local people or places in terms of injuries, deaths, property damages of environmental impacts" (Cutter, 2005, p. 105). Other scholars have defined disasters more broadly as phenomena endowed with meaning (David E Alexander, 2005), a form of collective stress situations (Barton, 2005); a "social situation characterized by non-routine, life-threatening physical destruction attributed to the forces of nature, regardless of what other causal factors may seem to be involved" (Stallings, 2005, p. 263); or as a "breakdown of established social order and the ordinarily expected coping strategies within a community of society" (Egner et al., 2012, p. 249).

Conversely, another dominant approach towards defining disaster involves determining when local authorities need external assistance in order to handle response and relief efforts. Some examples of these types of definitions include: "human, material, or environmental losses, that exceeds the local capacity to respond, and calls for external assistance" (Centers for Disease Control and Prevention, 2016, p. 1); and "emergency of such severity and magnitude that the combination of deaths, injuries, illness, and property damage cannot be effectively managed with routine procedure or resources" (Landesman, 2011, p. 1). Other definitions present disaster as "a potentially traumatic event that is collectively experienced, has an acute onset, and is time-delimited" (McFarlane & Norris, 2006, p. 4). For the purpose of this dissertation, the following definition of disaster is proposed:

*Disasters are social events related to the negative outcomes of a natural or manmade hazard of acute and sudden onset.*

The literature surrounding disaster communication poses an interesting challenge for identifying much less proposing a definition of the construct. First, the concept is used interchangeably with risk communication and crisis communication – related yet different areas of research. The first distinction addresses the practical differences between a risk, a crisis and a disaster; as such, the communication process, objectives and effects vary accordingly. The second difference is more academic in nature and corresponds to the variety of subfields within mass communication that focus on each area. For instance, Reynolds and Seeger (2005) argue, "health professionals … often frame their messages regarding the possibility of serious public health harm as risk communication. In organizational settings, including corporate contexts and disaster management, however, these perspectives more often have been framed as crisis communication" (p.43). However, both crisis communication and risk communication are relevant to disaster communication (Houston et al., 2015).

Technological innovation over the last decades has precipitated a significant shift in the dynamics of disaster communication. However, a comprehensive definition of disaster communication must take into consideration both the concepts associated with "traditional" disaster communication as well as the emerging concepts involved in the recent "participatory" disaster communication processes. The remaining sections of this chapter will address each type of disaster communication as well as the technology that has helped transform the way organizations and publics anticipate and respond to disasters.

## Traditional Disaster Communication

This section opens with a brief introduction describing the different types of communication that fall under a general category of disaster communication. That is followed by a narrower focus on the centralized, one-way, top-down communication model between organizations tasked with disaster management and the general public. Then basic emergency management concepts are presented. These concepts - such as the disaster life cycle, disaster phases communication functions, disaster information sources, and disaster information are paramount for establishing a disaster communication definition.

A predominant part of the more dated disaster communication literature pertains to the emergency management field. This area of research contributes many foundational elements that inform the major components of the communication processes in this context. As it stands, emergency management determines when an event is considered a disaster (for the mandated breakdown see the Robert T. Stafford Disaster Relief and Emergency Assistance Act); which entity is tasked with disaster response efforts; who creates disaster information messages; the content of these messages; the channels through which these messages are disseminated; as well as the communication strategies and tactics employed to achieve desirable outcomes. To complicate matters further, the literature highlights different types of communication as part of overall disaster communication.

According to the emergency management literature, disaster communication spans intra-organizational communication, communication between organizations, communication from organizations to the general public, and communication to the media (Auf Der Heide, 1989; Quarantelli, 1988). Intra-organizational – or internal organizational communication refers to communication within a particular organization. Inter-organizational – or external organizational communication refers to communication between two or more organizations. In the broadest sense, the main point of organization-to-public communication is to provide the public with timely and accurate information before, during and after a disaster (Haddow & Haddow, 2009a).

The fourth type of communication, between organizations and news media, is key because previous research has shown the role journalists and news play in keeping the public informed during disasters (Lowrey et al., 2007). Specifically, studies illustrate that news media help educate the public about how to prepare for a disaster; prompt donations for relief efforts; draw attention to hazards and develop public support to engage in actions that prevent or mitigate damage; minimize the onslaught of questions from concerned people anxious about the whereabouts of loved ones; and finally good publicity that could possibly result in increased funding (Auf Der Heide, 1989, pp. 135–136). While all four types of communication are part of a broader understanding of disaster communication, the remainder of this section focuses on concepts that apply mainly to the information exchange between organizations and the general public.

**Traditional Disaster Communication Model**

According to Muralidharan, Dillistone and Shin (2011), in the past people have relied on traditional forms of mass communication (i.e., radio, newspapers and broadcast television) to disseminate information needed to cope with a disaster. In part, this reliance has helped shape our understanding of disaster communication as a top-down, one-way communication model where organizations communicate with the general public, often through news coverage of these events or emergency announcements.

**The Disaster Life Cycle**

According to FEMA, emergency management is characterized by three components. First, it involves dealing with all types of hazards (i.e., of natural or man-made origins). Second, it calls for an inclusive approach towards emergency management partnership between all levels of government, the private sector as well as disaster victims themselves. Finally, emergency management is structured along the emergency life cycle. The emergency (or disaster) life cycle is an integral part of comprehensive emergency management as it embraces the four main phases of disaster activity: mitigation, preparedness, response and recovery. As Thorvaldsdóttir and Sigbjörnsson (2014) note, the development of the disaster life cycle was instrumental for the field and it has been widely used by practitioners as well as researchers alike. The cycle has helped researchers structure emergency management activities and functions along a logical, although often non-linear, series of phases.

***Mitigation***

Broadly speaking, the first phase of disaster management involves measures that aim to reduce the impact of a disaster. Specifically, mitigation "includes any activities that prevent an emergency, reduce the likelihood of occurrence, or reduce the damaging effects of unavoidable hazards" (Federal Emergency Management Agency, n.d., p. A-3-5). While mitigation measures should be considered well before a disaster occurs (Gregg & Houghton, 2006), many of the activities associated with this stage can also take place during other phases of the disaster life cycle (Maskrey, 1989). Specific examples of mitigation activities include strengthening buildings and infrastructures by virtue of building codes and innovative engineering practices (Schneider, 2006), in addition to other preventative measures such as insurance, strategic land-use management, risk mapping, safety codes and tax incentives (Hy & Waugh, 1990, p. 19). As these examples perhaps illustrate, many of the activities associated with mitigation measures tend to be long-term preventions and of slow onset.

***Preparedness***

The second phase of disaster management focuses on both developing and enacting plans to minimize disaster damage. Hy and Waugh (1990) explain that preparedness focuses on the "development of operational capabilities for responding to an emergency" (p.19). Some examples mentioned by these authors include emergency operations plans, warning systems, emergency operation centers, emergency communication networks, emergency public information, as well as resource management plans. From a non-organizational standpoint, preparedness can also involve activities such as "developing an emergency plan for the household, storing food and water, making sure there is a battery-powered radio on hand, and taking other steps to anticipate whatever problems a disaster might create" (Perry et al., 2001, p. 5).

***Response***

The third phase of disaster management takes place immediately before, during and after disaster impact in response to the urgent needs of those affected by a disaster. Usually, response activities center on providing emergency assistance for casualties – examples include "search and rescue, emergency shelter, medical care, and mass feeding" (National Governors' Association, 1979, p. 13). Perry and colleagues (2001) note additional examples such as “detecting threats, disseminating warnings, evacuating threatened populations, searching for and rescuing trapped disaster victims, providing emergency medical care, taking action to contain ongoing threats, and providing emergency food and shelter” (p.5).

### *Recovery*

The final phase of emergency management follows the disaster impact stage and can last as long as it takes for all systems to return to normal. The Governors Association (1979) highlights two different types of recovery activities, short-term and long-term. The former focuses on returning “vital life-support systems to minimum operating standards (for example cleanup, temporary housing),” whereas the latter centers on returning “life to normal or improved levels (for example, redevelopment loans, legal assistance, and community planning)” (National Governors’ Association, 1979, p. 13). This dichotomy is also present in Hy and Waugh’s (1990) definition of the recovery phase: “activities that restore vital life-support systems to minimum operating standards and long-term activities that return life to normal” (p.19). In addition to physical and infrastructural repairs, recovery functions also aim to reverse the negative effects a disaster might have had on the “quality of life in an affected community and on the psychosocial wellbeing of victims” (Perry et al. 2001, p.6).

## Communication Functions for Every Disaster Stage

As the previous section illustrates, each phase of the disaster life cycle strives to accomplish different objectives. It stands to reason then that the communication that takes place during each of these stages differs as much as the emergency management goals. For instance, Haddow and Haddow (2009a) present different communication strategies that correspond to each stage of the disaster life cycle. Similarly, Brandon (2002) notes that each operational function of disaster management warrants its own unique type of communication. However, in the context of that study the disaster life cycle included different elements such as prediction, detection, warning, location and response/mitigation.

**Disaster Information Source**

During a disaster people communicate with each other – often through different means in order to accomplish a wide variety of objectives. Virtually anyone can be a source of disaster information. For instance, a neighbor relaying information she saw from the news or heard from someone else can be a source just as much as the journalist or reporter providing news updates about the ongoing event. However, if we focus specifically on the traditional disaster communication perspective, the main source of information during a disaster comes from the organizations tasked with disaster management. The entities and agencies that continually update everyone on what is going on, whether an area needs to be evacuated and what protective measures each family should take to ensure their safety.

Within these entities, interactions with the general public and the media are handled by Public Information Officers (PIOs). Operating as part of the Incident Command System (ICS), the PIOs main role is "communication with the public, media, and/or coordinating with other agencies, as necessary, with incident related information requirements" (Federal Emergency Management Agency (FEMA), 2007a, p. 2). According to a 2007 report by FEMA, PIOs should gather information from response agencies, media, the general public as we all elected officials, technical specialists, in addition to emergency response guidebooks.

### *Why Disaster Information Source Matters*

Broadly speaking, the main point of disaster communication is to precipitate protective behavior (Lindell & Perry, 2012). In line with this goal, research in this area has strived to identify how different elements of communication influence decision-making and behavioral intentions. Findings show that information source attributes can play a critical role in behavioral intentions (Hu & Shyam Sundar, 2010), as well as behavioral responses to disaster communication (Lindell & Perry, 2012). Specifically, researchers point to information source hazard knowledge, trustworthiness and responsibility for taking action as underlying factors that motivate people to adopt hazard adjustments or follow protective action recommendations (Arlikatti et al., 2007). In their guide for effective message development for emergency communication, the CDC (2018) suggests that people evaluate an information source's expertise (i.e., competence and knowledge) by his or her education, position, title, organizational role and mission.

## Disaster Information

From a traditional disaster communication perspective, disaster information refers to messages and content created by disaster information sources (i.e., governmental and organizational entities tasked with disaster management) intended for the general public. In this context, this type of content includes disaster warnings, mobilizing information and protective action recommendations. According to FEMA (2007b), initial information should cover actions the public should take; impact of the incident; actions the response agencies are taking; actions businesses and industries should take; summary of the incident; and overall steps to be taken by the government and by citizens to return to normal after the incident (pp.11-12).

The literature in this area suggests that effective disaster warnings include “the nature, location, guidance, time, and source of the hazard or risk” (Sorensen, 2000, p. 121). On the other hand, mobilizing information pertains to “information that provides cues to action on how to prepare and behave in response to a disaster” (Tanner et al., 2009, p. 742). In turn, protective action recommendations (PARs) “refer to actual warnings, which are given by local authorities and derived through a protective action selection process of threat assessment, hazard mitigation, and protective response” (T. H. Kim et al., 2006, p. 2). According to the authors, usually PARs involve instructions to shelter-in-place or for evacuation. Traditional disaster communication is therefore defined here as the transmission of disaster-relevant information from emergency management officials to their target publics.

### *Why Disaster Information Matters*

In a disaster context, messages and official information disseminated by the authorities handling the situation can mean the difference between life and death. Research based on people’s responses to hazards and disasters suggest that message attributes that can affect information processing as well as the perceptions that ultimately influence behavioral responses to disaster information and warnings (Lindell & Perry, 2012). Specifically, the Protective Action Decision Model (PADM) suggests that “warning mechanisms vary in terms of their ability to attract attention and provide comprehensive messages that will change risk area residents' core perceptions of threat, protective actions and stakeholders in the desired directions" (Lindell & Perry 2012, p.628).

## Disaster Communication and Social Media

For a very long time, traditional media such as radio, television and newspapers were the primary and most trusted sources of public information during a disaster. Further, they served as the main point of contact between organization and the general public, often aided or hindered in this endeavor by journalists and news agencies (Auf Der Heide, 1989). But the arrival of new technology in the mid-1990s meant that people were able to interact, and share information in significantly different ways with the help of Internet-based applications that were non-existent up to that point in time (Lindsay, 2011). This section addresses the main definitional components of these technologies.

### Web 2.0.

In part, the aforementioned change in the way people communicate during disasters involved the shift in the technological, structural and sociological aspects of the Web. Specifically, this refers to the purpose and layout of websites that encouraged increased interactions between users (Cormode & Krishnamurthy, 2008). These developments mark the differences between what has been called Web 1.0 and Web 2.0. The latter is used to describe platforms in which "the content and applications are no longer created and published by individuals, but instead are continuously modified by all users in a participatory and collaborative fashion" (Kaplan & Haenlein, 2010, pp. 60–61).

### User Generated Content (UGC)

During the early 2000s, the growing accessibility of broadband as well as platforms that facilitate participatory and collaborative use by users resulted in a significant increase of content creation and dissemination (Amanda Lenhart, 2006). In turn, this type of media content created or produced by the general public became known as user-generated content (USG) (Daugherty et al., 2008). Based on the criteria proposed by the Organization for Economic Co-operation and Development in 2007, Balasubramaniam (2009) suggests the following requirements for determining if content falls under a user-generated category: "content which is made publicly available, through the Internet; boasting a certain level of creativity (…); created outside of professional practices" (p.28).

**Social media**

According to Kaplan and Haenlein (2010), both Web 2.0 and UGC are essential to our understanding of social media. Researchers have defined social media in many ways; ultimately the concept is generally understood as web-based platforms and services that "allow individuals to create public or semi-public profiles within a bounded system" (Boyd & Ellison, 2007, p. 211); "enable interactive communications and content exchange between users who move back and forth easily between roles as content creators and consumers" (Haddow & Haddow, 2009a, p. 25); "offer users the opportunity to publish content, to connect with other people, and to engage in conversation" (Houston et al., 2015, p. 4); and "enable the content creation, collaboration and exchange by participants and members of the public" (Vijaykumar et al., 2015, p. 654).

As can be appreciated by the variety of definitions summarized, social media is a broad concept that refers to websites and platforms that emerged with the onset of Web

2.0. The ability to create and disseminate UGC is also of importance when considering the definitional attributes of social media. As such, social media is defined as “a group of Internet-based application that build on the ideological and technological foundations of Web 2.0 and that allow the creation and exchange of User Generated Content” (Kaplan & Haenlein, 2010, p. 61). Based on these conditions, there are many different types of websites that can be considered social media. Hansen, Shneiderman and Smith (2011) observe that social media offer many services including “email, discussion forums, blogs, microblogs, texting, chat, social networking sites, wikis, photo and video sharing sites, review sites, and multiplayer gaming communities” (p.12).

**Participatory Disaster Communication**

The development and adoption of social media fundamentally changed the dynamics of disaster communication. So far, disaster communication has been presented as a one-way, top-down process where organizations tasked with emergency management generate disaster-related information and disseminate these messages through traditional mass media to reach a largely passive audience. However, these technological developments and the changes they have precipitated warrant a reexamination of how disaster communication should be conceptualized. Researchers have begun to take this into consideration. For instance, the following description of disaster communication by Fraustino, Liu and Jin (2012) reflects these concerns:

> Disaster communication deals with (1) disaster information disseminated to the public by governments, emergency management organizations, and disaster responders often via traditional and social media; as well as (2) disaster

> information created and shared by journalists and affected members of the public often through word-of-mouth communication and social media (pp.6-7).

This section begins by exploring the new participatory role the general public has come to play in this process. That is followed by a reflection of how organizations tasked with emergency management have employed social media as part of their disaster response strategies. Then the functions of social media use during disasters are described. Finally, disaster information is presented and explained. Taking into consideration the elements of traditional and participatory disaster communication, a definition of the construct is proposed as the chapter concludes with a brief discussion concerning the areas of research opportunities this project aims to address.

**Disaster Information Source**

In contrast with traditional disaster communication, information sources in participatory disaster communication are harder to identify. With the help of mobile technology and social media, the general public now creates and disseminates content to a wide audience. During the 2007 Southern California wildfires, Palen (2008) notes how people used these tools to engage in "backchannel communication," that is, "peer-to-peer communications that are not part of the official discourse of the event" (p.77). In turn, news media organizations rely on UGC that stems from this type of communication to supplement their coverage of events, in addition to leveraging social media as legitimate means of information dissemination (J. Sutton et al., 2008a).

Indeed, citizen-generated eyewitness accounts of disasters have come to play an important role in the news coverage of these events – especially considering both the need for content as well as the economic and personnel limitations that increasingly burden news media organizations. In fact, Pew Research reports that when it comes to disaster footage

> Almost 40% of the most watched videos in the 15 months from January 2011 through March 2012 came directly from citizens. Even some of the videos bearing the logo of a news organization were originally shot by citizen onlookers, a sign of today's new kind of professional/amateur news partnership (Jurkowitz & Hitlin, 2013, p. 7).

By including UGC into their coverage of an event, journalists recognize the legitimacy of audience's role as disaster information sources. Further, studies that explore news coverage of crisis and emergency events, such as the Tucson 2011 shootings, highlight that reporters are more likely to use non-official sources as well as UGC than content created by official news sources (Wigley & Fontenot, 2011). These findings help shape our current understanding of disaster communication as a collaborative process heightened by the symbiotic relationship between news organizations and a more active public.

### *Why Disaster Information Source Matters*

Recent studies have shown that disaster information sources play an important role in desirable public behavioral outcomes. For instance, an experiment conducted by Liu and colleagues (2015a) found that participants that were exposed to content generated by local information sources were more likely to engage in information-seeking behaviors. While this study specifically focused on sources that could be considered official (i.e., disaster management organizations and news media), previous research suggests that unofficial information sources can be perceived just as credible, if not more, than their official counterparts. Fessenden-Raden, Fitchen and Heath (1987) conducted a case study that explores risk communication in communities that had been affected by toxic chemical contamination. In their study they found that both official messengers and unofficial messengers provided risk information. Further, they suggest that while unofficial messengers provide accurate and inaccurate information, the public regards them as more credible than official messengers.

**Organizational Communication**

The literature about social media use during disasters is still limited and most of it, like the technology that begets it, is fairly recent (D. E. Alexander, 2014). While there are case studies that document how organizations have employed social media to communicate internally (Yates & Paquette, 2011) and externally (Simon et al., 2014) during disasters, most of the research in this area focus on how organizations can leverage these tools to communicate with target publics. For instance, Alexander (2014) notes seven different ways in which social media can be applied in disaster response by organizations: (1) to serve a listening function, where responders can gauge public emotional states; (2) to monitor an ongoing situation; (3) to facilitate emergency planning as well as crisis management; (4) to promote crowdsourcing efforts as well as collaborative development; (5) to create social cohesion and promote therapeutic initiatives; (6) to contribute to the furtherance of causes; (7) and to enhance research.

**Communication Functions**

Studies in this area highlight how social media facilitates the realization of a rich variety of communication objectives, both from the organizational perspective as well as that of the general public. According to Fraustino, Liu and Jin (2012), people employ social media during disaster because of convenience, social norms, personal recommendations, as well as humor and levity. Further, the authors explain that individuals use these platforms for information seeking, timely information, unique information, unfiltered information, determining disaster magnitude, checking in with family and friends, self-mobilization, maintaining a sense of community, and seeking emotional support and healing. Other studies have identified additional functions of social media use during disasters by part of multiple users in service of a wide range of objectives (see Houston et al., 2015).

## Disaster Information

From a participatory disaster communication perspective, the general public also contributes to the production and dissemination of disaster information. However, since most of this process largely depends on social media, disaster information generated by people unaffiliated with disaster management organizations or news media often comes in the form of UGC. Examples of this type of content identified throughout the literature include status updates, first-hand accounts, personal observations, photos and videos that showcase human and material losses, commentary, humor, safety reassurances, expressions of solidarity, synthesis of preexisting information from additional sources as well as retransmission of extant social media content via retweets or similar mechanisms (Al-Saggaf & Simmons, 2015; Starbird et al., 2010).

### *Why Disaster Information Matters*

In line with previous research findings that suggest that message content and style play an important role in desirable behavioral outcomes during disasters – namely the decision to follow protective action recommendations as well as seek and share information, a study conducted by Sutton and colleagues (J. N. Sutton et al., 2014a) identifies social media message elements that affect its retransmission by social media users. Specifically, they found that users were more likely to retweet messages that relay information about hazard impact than messages that focus on protective action guidance. Other notable study findings suggest that "officials utilized Twitter to relay information that is broadly applicable to the entire local public rather than using Twitter to post timely, focused, warning guidance for populations under imminent threat" (Sutton et al., 2014, p.783).

## Defining Disaster Communication

As this chapter has summarized, there are many things to take into consideration when establishing a disaster communication definition. First, there is the contextual bounds of the process, namely when it takes place. The literature suggests that it happens before, during and after a disaster – and it is characterized in the same way a disaster unfolds (i.e., mitigation, preparation, response and recovery). Before the onset of social media, disaster communication was a one-way, top-down information exchange between emergency management agencies and a largely passive audience. Broadly, messages were intended to keep people informed of the unfolding event, and suggest protective action recommendations. Research findings highlight that effective disaster communication and desirable public behavioral outcomes depend on perceived information source credibility as well as strategic message design. After the creation and widespread adoption of social media, disaster communication became a collaborative process where audiences came to play a more active role in user-generated disaster content creation and dissemination. However, perceived source credibility and message design are still important in this context, especially when considering additional desired public behavioral outcomes such as information seeking and information sharing. Taking all of these elements into consideration, the following definition is proposed:

> *Disaster communication is a collaborative process in which emergency management organizations, news media and the general public create and disseminate information about social events related to the negative outcomes of a natural or manmade hazard before, during and after their onset through traditional and social media channels.*

The present chapter explicated disaster communication. Through that process, the burgeoning literature focused on social media use during disasters was examined. The majority of this research consists of case studies that have adequately described a relatively recent phenomenon, but raise more questions than they answer. In light of the capabilities that social media platforms afford, emergency management professionals must critically examine the inclusion of additional desirable public behavioral outcomes. For instance, information seeking, information vetting and information sharing become increasingly relevant for three main reasons.

First, additional information seeking helps people find more information that provide detailed and more complete instructions than can be conveyed in certain social media platforms such as Twitter – which restricts message length to 280 characters. Second, with the amount of people creating and disseminating official and unofficial information, organizations should promote information vetting as part of disaster preparedness literacy as to deter people from believing and following the instructions of content that might be inaccurate or false. Third, with the array of available media channels and an increasingly fragmented audience, disaster management organizations may have to rely on online social networks to reach at-risk populations that will not receive critical disaster information otherwise. As such, people should be encouraged to share official messages that can help other people in their immediate network be informed of the ongoing event as well as the steps they can take to ensure their safety.

# CHAPTER 2

# INFORMATION SOURCES

This chapter draws on key ideas from disaster sociology and emergency management research, the SMCC model, and the SARF to define the first component of the proposed SMDIA model: information sources. First, a review of how information sources have been addressed in each of the conceptual frameworks is presented. That is followed by a discussion focused on the current gaps in our understanding of the role that potential information sources play in social-mediated disaster communication. The chapter then concludes with the introduction and definition of information sources in the SMDIA model context.

## Information Sources in a Disaster and Emergency Management Context

Research on the preparation for, experience of, and response to disaster tends to fall on one of two camps. The first camp focuses on emergency management, which in the U.S. is a government policy-mandated function. In contrast, the second camp often employs a sociological lens to explore how people experience disasters, and its effects on society. This section summarizes how information sources are defined and contested in each of the two main camps of disaster and emergency management research.

### Traditional Disaster Communication Tenets

The traditional disaster communication perspective places information sources at the center of a top-down, one-to-many information dissemination structure. This positioning has implications for who can be an information source and why. A recent

U.S. Army Corps of Engineers (2019) guide to public alerts and warnings describes the different groups that are involved with providing public emergency information:

> emergency management officials, members of emergency management agencies, public affairs personnel (i.e., public information officers, public affairs officers), emergency first responders, incident commanders, police and fire personnel, (…) radio and television broadcasters, public elected officials, and other people or organizations involved with or interest in local emergency management (p. 7).

This example illustrates that even within the hierarchical structure of traditional disaster communication, there are still a variety of people that can potentially engage in information source functions. The conceptual tenet that stems from this point is that the information source role can be characterized by the *occupation* of an individual – whether they are government employees, media personnel, elected officials, or employed by an organization.

**The Sociological Perspective**

The sociological perspective broadens the scope of our understanding of information sources outside of the one-way, top-down structure described earlier – but some of the work builds on the major assumptions from that perspective. One example of the prevalence of the traditional understanding of disaster communication is assigning hierarchical values to information sources and defining them in relation to their position on that binary or spectrum. This can be appreciated, for example, in a study that focused on exploring the potential differences between men and women in responding to earthquake aftershock warnings (O'Brien & Atchison, 1998). In that study, disaster information sources were referred to as either 'official formal' or 'non-official informal;'

the researchers called into question the accuracy of the latter while describing the former as authoritative. The conceptual tenet that can be gleaned from this point is that there are more than one information source types outside of the occupation-related information sources described earlier.

Even some of the more recent research involving social-mediated disaster communication contexts also entail a similar approach of characterizing information sources. For example, a recent study focusing on disaster-related discussions on Twitter proposed the development of user taxonomies based on the professional cues included in their profiles (Silver & Andrey, 2019). Twitter users in that study were categorized as weather experts, weather enthusiasts, first responders, (news) media, and citizens. In this example, information sources can be occupation-related (i.e., first responders), and related to topic matter expertise (i.e., weather experts and weather enthusiast). Other studies working from a social-mediated disaster context have also undertaken the task of developing different Twitter user taxonomies – like Mirbabaie and colleagues (2019), who based their Twitter user classification on disaster convergence behavior archetypes. Taken together, these studies suggest that social media afford more than one approach for the potential categorization of its users that play an information source role in a disaster context, namely, based on profile cues and posting behavior.

## Information Sources in the SMCC Model

The Social-Mediated Crisis Communication (SMCC) model defines information sources as “where the crisis information originates from” (Austin et al., 2012a, p. 193). The model proponents present a high-level distinction between (crisis) information sources as those related to an organization and information sources external to the organization (Jin & Liu, 2010). Another distinction is made within the external information sources focusing instead on the type of social media activity that a user displays. Jin, Liu and Austin (2010) differentiate between what they call influential social media creators, social media followers, and social media 'inactives.'

Influential social media creators are "either individuals or other organizations, who create crisis information for others to consume" (B. F. Liu et al., 2011, p. 346). In turn, social media followers are defined as publics "who consume the influential social media creators' crisis information" (B. F. Liu et al., 2011, p. 346). Finally, social media inactives are defined as the users "who may consume influential social media creators' crisis information indirectly through offline word-of-mouth communication with social media followers and/or traditional media who follow influential social media creators and/or social media followers, either individuals or other organizations" (B. F. Liu et al., 2011, p. 346).

Empirical testing of the SMCC model has involved the following operationalizations of crisis information sources: third-party (including friends, roommates, and journalists) and organization (i.e., the University experiencing the crisis) (Austin et al., 2012a); third-party and organization (i.e., the University experiencing the crisis) (Jin et al., 2014; B. F. Liu et al., 2011); third-party (journalists and friends) and organization (i.e., the University experiencing the crisis) (B. f. Liu et al., 2013a); federal government, local government, local media and national media (B. F. Liu et al., 2015b); and influential bloggers (i.e., media affiliation, volunteers and donors)(B. F. Liu et al., 2012).

Work involving the SMCC model and its empirical testing offer several information source conceptual tenets. First, social media enable ordinary users to become influential sources of information during crises. Second, higher-level information source binaries (i.e., third-party vs. internal) are also prevalent in a social-mediated crises context. Third, social media information sources can play different roles in disaster-related information dissemination – some users drive opinion leadership and create content, while other users share it with other users in their networks, and a third type of users is exposed to the information.

## Information Sources in the SARF

The Social Amplification of Risk Framework (SARF) conceptualizes information sources in a different way than the disaster sociology body of work and the SMCC literature. The proponents of the SARF contend that sources of information include personal experience, as well as direct and indirect communication (Kasperson et al., 1988). In a sense, then, the source of information in this context refers not to an individual or an entity, but the situation or experience from where information originates. However, the SARF concepts of amplification stations and social stations of amplification somewhat implicitly get at the concept of information source as it has been described so far.

### Risk Amplification Stations

According to Renn and colleagues (1992a), in the process of risk amplification, individuals and/or groups first perceive and interpret risk information and then react to it through behavioral responses. Per the SARF metaphor, these individuals and groups function as 'amplification stations' of the risk information. According to Kasperson and colleagues (1988), information transmitters become new information sources as the original risk information transforms itself in the process of perception and decoding. Specifically, researchers note, "a transmitter, it should be noted, is also a new information source – one that transcribes the original message from the source into a new message and sends it on to the receiver, according to institutional rules, role requirements, and anticipated receiver interests" (Kasperson et al., 1988, p. 181). According to the SARF, this is how risk information spreads.

**Social Stations of Amplification**

The SARF conceives the transmission of risk information as a process that takes place at the individual and group levels. Amplification stations correspond to individuals, whereas the concept of "social stations of amplification" refers to the larger social units in which individuals belong (Renn et al., 1992a). One of the main underlying arguments of the SARF is that individual and group factors shape the way in which risk is perceived and communicated throughout society. The broader level of social stations captures the influence of social and group norms on that risk perception and amplification process. Specifically, Renn and colleagues (1992a) explain the following:

> Individuals in their roles as members or employees of social groups or institutions do not simply follow their personal values and interpretative patterns, but they also perceive risk information according to the rules of their home organization or group. These rules are derived from professional standards and rules (characteristic for scientific communities, interest groups, media editors, political institutions, etc.,); institutional interests, functions, and foci; rules and role

> expectations pertaining to the specific position of the receiver; and interpretation of those role expectations by the holder of the position (p.141).

The original SARF description of the amplification and attenuation of risk perception provides its own information source conceptual tenets. One of the main points is that information sources can act as receivers and transmitters of information. This understanding of risk amplification concedes more nuance to the information diffusion process, which is sometimes described as a one-time, one-way occurrence. Another contribution this framework presents to our current understanding of risk amplification is that it recognizes that a behavioral response to risk information is shaped both by individual and group-level factors.

## Information Sources Research Gaps and Opportunities

The main research gap that this project seeks to address is a better understanding of how accounting for different information source types may support or challenge our current understanding of what drives audience engagement with social-mediated disaster content. While there has been a lot of research conducted to learn which social media content features may be related to a greater likelihood of information amplification across online networks, the bulk of that work can only speak to the dynamics involving just one type of information source.

For example, research has focused on how social media message content and style features can lead to greater information retransmission during different events like the 2012 Waldo Canyon Fire (J. N. Sutton et al., 2014a), the 2013 Boston Marathon Bombing (J. Sutton, Ben Gibson, et al., 2015a; J. Sutton et al., 2014a), and the 2013 Colorado Boulder Floods (J. Sutton, League, et al., 2015a). Researchers have also studied whether any critical differences between these message features and audience engagement emerge across a variety of hazard events like terrorist attacks, wildfires, blizzards, hurricanes and floods (J. Sutton, Gibson, et al., 2015c). These studies have even gone as far as to explore information retransmission behavior from different types of audience segments like the general public (J. Sutton, Ben Gibson, et al., 2015a; J. Sutton, Gibson, et al., 2015c; J. Sutton, League, et al., 2015a; J. N. Sutton et al., 2014a), and public officials specifically (J. Sutton et al., 2014a).

However, all of these terse message amplification studies focus exclusively on the disaster-related tweets authored by what the researchers describe as official response agencies, official/formal accounts, as well as official organizations at the local, state and federal level that play a public information role and/or who were served in a public safety capacity. While organizations from the private sector and non-profits were included in the 2013 Colorado Boulder Floods study – other critical information sources like news media were not taken into consideration.

This gap from the disaster and emergency management literature is partially addressed by the body of work that has been conducted to empirically test the SMCC model. To date, crisis communication researchers testing the SMCC model have explored the role of different types of information sources on publics' acceptance of organizational crisis response strategies (Jin et al., 2014; B. F. Liu et al., 2011), crisis information seeking intentions (Austin et al., 2012a; B. f. Liu et al., 2013a), and behavioral intentions related to both disaster information seeking and sharing (B. F. Liu et al., 2015b).

While these studies present a broader perspective on information sources than the terse message amplification studies, there are some factors to consider. First, the findings from those studies correspond to experimental work leveraging fictitious crisis scenarios and sampling exclusively from an undergraduate student population. Related to information sources specifically, the SMCC studies mostly employ a binary internal vs. third-party operationalization of the concept, often grouping friends and roommates along with news media as the same type of information source. The implication, then, is that these studies broaden the scope of what we know about the relationship between information sources and behavioral intentions – but a more nuanced approach to the operationalization of information sources, and a research context outside of student populations remain to be explored.

## Information Sources in the SMDIA Model

The Social-Mediated Disaster Information Amplification (SMDIA) model defines information sources as an individual or entity that shares disaster-related content on social media before, during and after a disaster. Drawing from the SARF, a person or entity is considered an information source even when the content that is being shared is done so through the act of ‘re-tweeting’ or ‘re-blogging’ social media content that was originally posted by another information source. The major conceptual tenets related to information sources, as understood from the SMDIA model, are illustrated in *Table 1*.

# CHAPTER 3

# CONTENT

This chapter draws on empirical evidence from disaster and emergency management research, studies testing the SMCC model, and SARF-related work to define the second component of the proposed SMDIA model: content. First, a review of how disaster information content characteristics have been addressed in each of the conceptual frameworks is summarized. In turn, a discussion focused on the current gaps in our understanding of the potential role of content features in social-mediated disaster communication is presented. Then, the chapter ends with the introduction and definition of key content characteristics in the SMDIA model context.

## Content Characteristics Overview

At its most basic level in this context, content refers to disaster-related information. The disaster information discussion back in Chapter 1 illustrates that there are many ways in which disaster-related information taxonomies can be determined. In turn, the effectiveness and suitability of these information taxonomies are contingent both on context and point of view. For example, an emergency management praxis understands disaster-related information intended for the public as watches, warnings, guidance, mobilizing information, protective action recommendations, etc. In contrast, when considered from a journalism perspective, public-facing disaster-related information can also involve news coverage. The following sections identify and describe the many ways in which disaster-related content has been addressed in each of the frameworks that inform this dissertation.

## Disaster and Emergency Management Perspective

In the last chapter, it was stated that even though most of our current understanding of social-mediated information diffusion dynamics stem from the study of just one information source type, there has been a lot of research conducted to learn which social media content features may be related to a greater likelihood of information amplification across online networks. This body of work focused on terse message amplification builds on prescribed risk communication guidelines while addressing some of the social media feature affordances. The terse message amplification studies specifically contribute insight about disaster-related social media (1) thematic content categories, (2) message style characteristics, and (3) conversational microstructures.

### Thematic Content Categories

The known content categories of disaster-related social media posts from emergency management entities are derived from risk communication principles and an event-specific deductive coding approach. For example, the content categories applied by Sutton and colleagues (2014b) to code Boston Marathon Bombing tweets were based on improvised explosive device (IED) risk communication guidelines (Covello et al., 2010), which involve "(1) warning themed messages (which conformed to guidance and advisory messages); (2) instructional messages (advisory and information themed messages); (3) requests for assistance (information themed messages); and (4) resiliency enhancing messages (prayers and thanks, hazard impact, and emotive content)" (J. Sutton et al., 2014b, p. 615).

In contrast, another terse messaging study employed a deductive coding approach to identify public health emerging themes in social media content related to the floods in Boulder, Colorado (J. Sutton, League, et al., 2015b). That study identified the following health communication themes: floodwater exposure, drinking water, resources/information, cleaning/sanitizing, handwashing/hygiene, and sewage/wastewater. The conceptual tenet from this point is that disaster-related social media content categories – even the ones that are theory-based and stem from the same information source – are still varied, complex and highly context-dependent.

**Message Style Characteristics**

Like thematic content, documented message style characteristics from disaster-related social media posts are also anchored in dominant risk communication principles. Recent public alerts and warning guidance recommends that communicators incorporate certain message style characteristics such as specificity and clarity (U.S. Army Corps of Engineers, 2019). According to the guidance, specificity means "being precise" when describing the core content elements that specialists recommend including in public alerts and warnings (i.e., source, threat, location, guidance/time and expiration time) (U.S. Army Corps of Engineers, 2019, p. 22).

In turn, experts define clarity as "using words that are free of jargon and clearly understood by the people who will receive the message" (U.S. Army Corps of Engineers, 2019, p. 22). The message style characteristics involving specificity and clarity are addressed in all terse messaging studies (J. Sutton, Ben Gibson, et al., 2015b; J. Sutton et al., 2014b; J. Sutton, Gibson, et al., 2015d; J. Sutton, League, et al., 2015b; J. N. Sutton et al., 2014b). In this line of research, specificity and clarity were operationalized by evaluating the sentence style (i.e., declarative, imperative, interrogative, and exclamatory) and capitalization practices that serve to emphasize a point (i.e., UPDATE).

### Conversational Microstructures

The third message content feature broached in the terse message studies are conversational microstructures. Defined as an “element of the message content that have specific social meaning such as mentioning others, including links to external resources, and signals of reported content (retweets)”(J. N. Sutton et al., 2014b, p. 767), conversational microstructure can also be considered a novel social media affordance.

In the context of terse message amplification research, conversational microstructure elements within the social media post have been operationalized by way of noting directed tweets, user mentions, the use of hashtags and the inclusion of hyperlinked content (J. Sutton, Ben Gibson, et al., 2015b).

## SMCC Perspective

The first version of the Social-Mediated Crisis Communication (SMCC) model is informed by literature focused on influential blogs and blog-mediated opinion leadership (Jin & Liu, 2010). In that nascent SMCC context, content was understood as crisis-related information that stemmed from either official organization blogs and/or influential blogs. Further, the model proponents incorporated other concepts from online-social mediated communication to describe crisis-related information: “in contrast to official organizational blogs, which are organization-generated content, external blogs represent forms of user-generated content (UGC) or public-generated content (PGC)” (Jin & Liu, 2010, p. 435).

As explained in Chapter 1, UGC is defined as "content which is made publicly available, through the Internet; boasting a certain level of creativity (…); created outside of professional practices" (Balasubramamiam, 2009, p. 28). This notion of content created outside of professional practices is also addressed by Jin and Liu (2010) when outlining the relationship between UGC and crisis news coverage:

> "There is no doubt that bloggers do not cover crises identically as do journalists. For example, bloggers are not required to follow journalistic standards such as fact checking, seeking out alternative views, comprehensively covering the news, maintaining independence from those they cover, and attempting impartiality (…) Nevertheless, bloggers provide crisis-related information that can be useful for journalists working for traditional media" (p.439).

The conceptual tenet from this point is that content in general and UGC in particular are shaped in critical ways based on the context from which they originate. The rest of the SMCC literature broaches the concept of content by way of what the model proponents call crisis information form, defined as "how the message is conveyed (e.g., via a Tweet, press release, etc.)" (Jin et al., 2014, p. 80). While at first glance crisis information form may resemble the concept of information channel, one of the SMCC studies does delve into more detail about what information form entails.

**Disaster Information Form**

In the study conducted by Liu, Fraustino and Jin (2015a), SMCC components were tested in the context of disasters. The experimental stimuli used in the study were based on real-world examples. According to Liu and colleagues (2015),

> “stimuli were modeled from government press releases, government social media posts, and news media coverage of past similar disasters. We also reviewed government and news media websites and social media accounts when copywriting to best reflect the content, language, and tone of such information releases” (p.49).

This rich description of experimental stimuli development allows us to draw a clearer conclusion about what is meant by disaster information form. First, all this content is public-facing information. Second, there is the dimension of news; on one hand from a public relations/media relations slant (i.e., press releases), and on the other hand from a journalistic perspective (i.e., news coverage).

**SARF Perspective**

Empirical research employing the Social Amplification of Risk Framework (SARF) provides the most variety and nuance regarding content. For example, risk amplification and attenuation has been studied in the context of press releases (Bakir, 2005; Raupp, 2014), news clippings (Burns et al., 1993), newspapers (Lewis & Tyshenko, 2009), news media coverage (Hill, 2001; Raupp, 2014), public comments in online news articles and message boards (Chung, 2011), discussion and casual conversations (Binder et al., 2011; Moussaïd et al., 2015), one-on-one interactions (Brenkert - Smith et al., 2013), public consultations (Masuda & Garvin, 2006), tweets (Fellenor et al., 2018a; Strekalova & Krieger, 2017; Wirz et al., 2018), and Facebook posts (Strekalova & Krieger, 2017; Wirz et al., 2018).

Risk-related information, then, encompasses many options and configurations across digital, print, verbal, written and visual modalities. Content spans discussions, information, news coverage, and more. These varieties are critical to the conceptualization of content in a rich media environment. The early theory laden SARF work also contributes an additional critical dimension to the understanding of the different dimensions of content outside of channel and modality features; namely, through the concept of risk signal.

**Risk Signal**

The signal amplification metaphor used in the SARF describes the process by which

> An information source sends out a cluster of signals (which form a message) to a transmitter, or directly to the receiver. The signals are decoded by the transmitter or receiver so that the message can be understood. Each transmitter alters the original message by intensifying or attenuating some incoming signals, adding or deleting others, and sending a new cluster of signals on to the next transmitter or the final receiver where the next stage of decoding occurs (Kasperson et al., 1988, p. 180).

Later work on the SARF elaborates further on the interwoven concepts of signals, messages, and symbols. According to Renn (1991a), messages can come in a variety of formats (i.e., written or oral) – but the content matter of a message is also characterized by other sources of information, like non-verbal communication, preconceived notions, signals or other symbols. In the SARF context, symbols are defined as “substitutes for chains of associations that evoke images about a relationship between different objects or an object or an attribute. They reduce randomness and complexity of communication within a cultural or subcultural context” (Renn, 1991a, p. 301). The conceptual tenet that stems from risk signals is that content is characterized not only by the textual and visual information included in the message, but also by the symbolic associations embedded in its context.

### Content Characteristics Research Gaps and Opportunities

Terse message amplification research has contributed significantly to our current understanding of which message features drive social media information diffusion. In the context of the Boston Marathon Bombing, tweets by emergency management entities were more likely to be retweeted if they were about hazard impact, public safety advisories and emotional encouragement – but tweets that included links were less likely to be retweeted (J. Sutton, Ben Gibson, et al., 2015b). Links were also less likely to lead to retweets in another terse message study that explored message amplification across different hazard types (J. Sutton, Gibson, et al., 2015d). That study did find, however, that certain user network and microstructure features, like number of followers and the use of hashtags, respectively, increased the likelihood of official messages being retweeted by others. Another terse message amplification study focused on the Boston Marathon Bombing did find that the kind of tweets (i.e., topic-wise) that got retweeted at the local level differed than those more likely to be retweeted by users outside of the geographical area affected by the hazard (J. Sutton et al., 2014b).

Collectively, the terse message amplification studies underscore the importance of certain message content and style features, in addition to the broader user and network-level metrices, in driving which social media posts end up retweeted by other users. But, the insight that can be gleaned from these studies – even those focused on content typologies and stylistic elements – only really speak to that which has been put in practice by emergency management entities at the local, state and federal level. The content prioritized by other actors in the social-mediated landscape is not addressed in this line of research. In addition to the issue related to narrow information source scope, there are additional post characteristics outside of the prescribed content matter guidelines peddled by prevalent risk communication principles.

From a SMCC perspective, we now know that if a person first learns about a disaster from social media channels, they are more likely to engage in information seeking behaviors and follow protective action recommendations (B. F. Liu et al., 2015a). The series of studies that have empirically tested the SMCC model have also explored how emergency management organizations engage with prominent social media users (Austin et al., 2012b), and the effects of crisis information source and form on audience perceptions and behavior (Jin et al., 2014).

Compared to the terse messaging studies, the SMCC model research affords a more nuanced understanding of the different actors that converge in a social-mediated crisis context, and, by extension, the kind of content audiences engage with too. Furthermore, the SMCC concedes that audiences encounter more content than the warning messaging posted by emergency management entities – they also see news coverage about a crisis, as well as what their friends, family, and influential social media users have to say about the matter too. In this research stream, less is known, however, about the potential effects of different types of content posted on social media.

The role of news media organizations in the amplification of disaster-related information is also explored in studies employing the SARF. In that context, research has shown that news media coverage of an on-going environmental disaster can sway public support by amplifying one competing narrative over another (Bakir, 2005). The crisis surrounding the 1995 deep-sea disposal of the Brent Spar oil rig illustrates how several actors can converge in one same controversy while producing competing risk signals. According to Bakir (2005), the amplification of one group's take over the other on behalf of the news media was accomplished in part by savvy narrative construction. The press releases distributed by the environmental interest group leveraged rich symbolism that lent itself for more compelling news storytelling than the jargon laden press releases sent by the organization at the helm of the crisis. This example serves to illustrate that images and symbols within risk-related messages can make it possible for third-party amplification stations (i.e., the media) to further amplify risk signals through its coverage.

Media attention (i.e., amount of coverage) as a proxy for risk information amplification can be found in many SARF-related studies (Bakir, 2005; Fellenor et al., 2018a; Hill, 2001; Lewis & Tyshenko, 2009; Raupp, 2014). The SARF perspective has been criticized by many, however, for conflating news coverage of issues with public concern (Fellenor et al., 2018b). Like the terse messaging studies, SARF work that stems exclusively from the study of press coverage is telling just one side of the story. However, there is plenty of SARF-related research that explores public attention to and subsequent amplification of risk-related information outside of media attention. In fact, a study conducted by Chung (2011) is located at the intersection between news media coverage and public attention to environmental crises, through the study of online public comments to news articles and message board discussions. The Internet affords researchers the unique opportunity to explore how different information actors produce, engage with, and amplify disaster-related content.

All three theoretical frameworks from which this dissertation draws from have begun to explore how social media message features affect audience engagement with content. However, there are still understudied aspects of how message characteristics may drive audience engagement with content, modality being one of them. One study conducted by Strekalova and Krieger (2017) did explore the effect of social media content modality on audience engagement with posts. In that study, the researchers did not find that post modality affected the extent to which Facebook users engaged with content posted by the National Cancer Institute (NCI) page. Specifically, “comparing the modality of risk-related messages, videos, contrary to the prediction, were not more effective in attracting audience engagement than images” (Strekalova & Krieger, 2017, p. 849). It remains to be seen whether this finding will be consistent across different social media platforms and contexts.

## Content in the SMDIA Model

The Social-Mediated Disaster Information Amplification (SMDIA) model defines content as public-facing disaster-related information shared through social media platforms before, during and after a disaster. Public-facing here is mentioned as a way to distinguish between the many types of information that can be shared though social media platforms; some of which, like primate and/or direct messages, are different in nature and purpose to the content that is meant to be visible in some capacity to other users within an online network. The major conceptual tenets related to content, as understood from the SMDIA model, are illustrated in *Table 2.*

# CHAPTER 4

# AUDIENCE ENGAGEMENT

This chapter draws on key ideas from disaster sociology and emergency management research, the SMCC model, and the SARF to define the third component of the proposed SMDIA model: audience engagement. First, a review of how audience engagement has been addressed in each of the conceptual frameworks is presented. That is followed by a discussion on how audience behavioral engagement with social-mediated content has been broached in contemporary research in the area. The chapter then concludes with the introduction and definition of audience engagement in the SMDIA model context.

One of the main objectives of this chapter is to propose a conceptualization of audience engagement. In order to do that, several streams of research are examined. The review of this work is focused on the observed or intended communication outcomes. The first half of this chapter, then, summarizes audience perceptions or behavior as explored through each of the frameworks that inform this dissertation. That is followed by the proposed dimensions of audience engagement, as conceptualized in the SMDIA model context.

## Audience Engagement in a Disaster and Emergency Management Context

Many of the emergency and risk communication principles that shape communication strategies are geared towards ensuring that at-risk publics follow protective action recommendations. At present, emergency managers design emergency communication plans focused on reducing public action delay and maximizing compliance (U.S. Army Corps of Engineers, 2019). The empirical research insight that informs these communication principles stem from work on “social influence, persuasion, behavioral decision making, attitude-behavior relationships, protective action, and innovation processes in identifying useful guidance on ways in which risk communication can influence immediate disaster response and long-term hazard adjustments” (Lindell & Perry, 2012, p. 616). At the core of this kind of work is audience behavioral response. Prevalent disaster and emergency frameworks – like Lindell and Perry’s (2012) Protective Action Decision Model (PADM) – characterize behavioral response as that which involves information searching, protective responses, and emotion-focused coping.

Outside of following protective action recommendations, there are other target communication outcomes that stem from an emergency management perspective. The terse amplification studies, for example, focus exclusively in identifying the factors that drive public retransmission of social media posts authored by emergency management entities at the local, state and federal level. Sutton and colleagues (2014b) explain that

> Serial transmission – the passing on of received information from one party to another – is a phenomenon of central interest in the study of informal communication in emergency settings. When a formal message (i.e., one constructed and delivered by official response organization) is introduced to a population, who then chooses to retransmit that message to others is of great importance: all other things being equal, retransmitted messages are likely to be seen by a larger number of persons, are likely to have been seen a larger number

> of times by any given person, and are more likely to have been received from a personally known and trusted source than messages that are not transmitted (p.766).

Based on this explanation, then, it could be said that getting the public to retransmit messages posted by emergency managers is one way to follow several risk communication principles like reaching a wide audience (Haddow & Haddow, 2009a), making statements easier to believe as they are repeated more often (i.e., illusory truth effect – see work by Hasher, Goldstein and Toppino (1977), and getting trusted and familiar sources to reinforce official messaging.

## Audience Engagement in the SMCC Model

The Social-Crisis Communication (SMCC) model was initially developed to help organizations choose the appropriate crisis response strategy when engaging with influential bloggers (Jin & Liu, 2010). In that context of prioritizing stakeholder reputation, audience acceptance of an organization's crisis response strategy is paramount. Several of the studies based on the SMCC model explore which facets of social-mediated crisis communication lead to that specific desirable communication outcome. For example, the study conducted by Jin and colleagues (2014) found that, in a social-mediated context, public acceptance of crisis message strategies were a function of crisis origin (i.e., the entity perceived at fault for the crisis taking place). In addition to public acceptance of organizational crisis response strategies, the SMCC studies also studied information seeking and sharing behaviors as communication outcomes.

### *Information Seeking*

According to the Blog-Mediated Crisis Communication (BMCC) model proponents, one of the three motivations for people to use influential blogs during crises is for information seeking: “blog followers search for additional information that is not available from other public channels such as news media” (Jin & Liu, 2010, p. 439). This proposed motivation aligns well with findings from earlier research documenting the underlying reasons for why at-risk publics turn to social media during emergencies. In their study of the 2007 Southern California Wildfires, Sutton and colleagues (2008a) found that “social media supports “backchannel” communications, allowing for wide-scale interaction that can be collectively resourceful, self-policing, and generative of information that is otherwise hard to obtain” (p.1). In that case study, at-risk populations turned to social media to find specific and detailed information germane to their own situation within the broader wildfire context – since news media coverage of the event was not as granular as they needed it to be to inform critical and time-sensitive decision-making.

The social media use rationale documented by Sutton and colleagues (2008) also corresponds to other SMCC-related findings. For example, one SMCC study found that, during crises, people use social media for ‘insider information’ and to check in on family and friends (Austin et al., 2012b). Public information needs during a disaster go beyond evacuation orders, protective action recommendations or organizational responses – people also leverage social media platforms to check in on family and friends.

### *Information Sharing*

Another communication outcome highlighted across the SMCC literature is information sharing behaviors. Along with information seeking and taking protective action, research in this area suggests that information sharing is also a well-documented coping behavior in times of crisis (Jin et al., 2016). A series of in-depth interviews conducted by Liu and colleagues (2013b) revealed that, during crises, some social media users may be hesitant to share information online because of social norms. Despite this reticence, study participants revealed that they often engage in crisis-related discussions offline too – this finding further supports the SMCC model's assertion that in addition to online discussions, publics engage in offline crisis-related word-of-mouth communication.

## Audience Engagement in the SARF

In the Social Amplification of Risk Framework (SARF) research, risk perception is one of the main communication outcomes of interest. SARF studies have shown that different communication aspects – such as the frequency and the valence of conversations, for example – can impact the extent to which at-risk populations evaluate environmental risks and/or benefits (Binder et al., 2011). Other risk perception-related SARF work has instead focused on the impact of information source and interaction type on at-risk publics' perceptions of hazard probability and hazard consequences, specifically within a wildfire context (Brenkert - Smith et al., 2013).

As discussed in Chapter 3, media attention to and public concern towards risk are other communication outcomes that have been studied in this line of work. Media attention to risk has been approached in these studies as the extent to which these issues receive news coverage. According to Raupp (2014), "the potential public attention to a risk event can be assessed in terms of the volume of news reporting and publication activities of that event" (p.569). This line of thinking can be appreciated in the series of studies that empirically assess the amplification of risk through the quantification of media coverage (Bakir, 2005; Hill, 2001; Wirz et al., 2018). Some SARF research conflates public concern with media coverage – like, for example, a study conducted by Lewis and Tyshenko (2009), which claimed that “a measure of public concern over environment and health issues can be garnered from news media coverage” (p.720). However, more recent work has underscored the need to differentiate between one and the other (see Fellenor et al., 2018).

Another communication outcome studied through the SARF is behavior. In the past, the public’s potential response to a hazard event has been assessed using behavioral intention proxies such as political involvement and risk-reducing action (Burns et al., 1993, p. 1892). Other examples of studied behavioral responses within the SARF include public engagement with social media posts. For example, Strekalova and Krieger (2017) focused on Facebook users’ engagement with messages posted on behalf of the National Cancer Institute. Similarly, Wirz and colleagues (2018) also studied Facebook user comments on major news organizations’ Zika related posts.

**Audience Engagement as Desirable Communication Outcome**

As a concept, audience engagement lends itself to many interpretations. For instance, some researchers conceptualize audience engagement as an opportunity for dialogic communication between an organization and its stakeholders (Young, Tully & Dalrymple, 2008). As explained by Taylor and Kent (1998), dialogic communication is “any negotiated exchange of ideas and opinions” (325). It tends to suggest that in this view audience engagement is understood as an opportunity for an organization to negotiate the exchange of ideas and opinions with its stakeholders. The main issue with this perspective is that the audience is the fixed receiver of engagement or information exchange. While valid, the operationalization that follows this approach typically situates the audience as an object to be engaged *with.*

Alternatively, researchers have also conceptualized engagement as a multidimensional construct. For instance, Fredricks, Blumenfeld and Paris (2004) advance the conceptualization of engagement as a multidimensional construct that begets "examining antecedents and consequences of behavior, emotion and cognition simultaneously and dynamically, to test for additive or interactive effects" (pp.60-61). This suggests three distinct facets of engagement: behavioral, emotional and cognitive.

**Audience Behavioral Engagement**

Behavioral engagement encompasses the outcomes of participation or involvement. For instance, behavioral engagement with media content can be understood as the text read, the show watched, the web link clicked, the social media post liked or commented on. According to van Doorn and colleagues (2010), engagement behaviors "go beyond transactions, and may be specifically defined as a customer's behavioral manifestations that have a brand or firm focus, beyond purchase, resulting from motivational drivers" (p.254). Indeed, although behavioral engagement may be measured by tangible outcomes, it is intrinsically related to other factors like motivational drivers. In fact, researchers like Calder & Malthouse (2008) argue against likening engagement to its outcomes or consequences, instead advocating for a perspective that is cognizant of the "sum of motivational experience consumers have with the media product" (p.5).

Social media platforms afford their users many distinct ways to create, share and interact with content. Research in this area has advanced a 3-tier typology that encompasses most social-mediated behaviors. It includes consuming, contributing and creating (Kim & Yang, 2017; Muntinga, Moorman, & Smit, 2011). As explained by Kim and Yang (2017), these behavior types vary in regard to the necessary level of participation and cognitive effort expended by the user, from least to most, respectively. In other words, viewing, reading and watching content is on the passive end of the continuum while writing, uploading and posting content is at the far end of the active side of interaction.

Less clear is the distinction between what may constitute one type behavior or another, seeing as reviewing, reacting, liking and sharing an existing post may be but one mere ‘click’ away, but reading, thinking, writing and posting a comment on an existing post involves more cognitive effort and may be indicative of a richer type of audience engagement. The issue becomes more complicated as researchers and practitioners strive to find appropriate indicators of passive social-mediated content consumption outside of self-reported measures, click-through rates, time spent on page as well as physiological measures difficult to ascertain outside of a laboratory setting.

At present, all the ways in which social media users can interact with existing content can be grouped into three main areas: social-endorsement, dialogue, and information dissemination.

**Social Endorsement**

Social media platforms afford users the opportunity to visibly endorse content created by other users in the network (Li, Lin & Shan, 2011). Essentially, this feature allows users to gauge the popularity of a post, image or comment in the form of “likes” in the case of Facebook and Twitter. As defined by Facebook, liking a post “is an easy way to let people know that you enjoy it without leaving a comment. Just like a comment, the fact that you liked the post is visible below it" (Facebook Help Center, 2018). In addition to Facebook, other social media platforms provide similar content interaction functionalities. For instance, in 2015, Twitter switched its star button for a heart button and its name from "favorite" to "like," per a statement released by the organization:

> We are changing our star icon for favorites to a heart and we'll be calling them likes. We want to make Twitter easier and more rewarding to use, and we know that at times the star could be confusing, especially to newcomers. You might like a lot of things, but not everything can be your favorite. The heart, in contrast, is a universal symbol that resonates across languages, cultures, and time zones. The heart is more expressive, enabling you to convey a range of emotions and easily connect with people (Oremus, 2015).

From a theoretical standpoint, researchers have advanced the argument that the like feature is an essential form of impression management, identity construction and digital social ties maintenance (Eranti & Lonkila, 2015). Previous studies have also found that while the motivations for engaging in liking behavior is highly diverse and non-generalizable within and between different users, Twitter users also "like" tweets because they perceive the post to be informational or topically relevant (Meier et al., 2014).

**Dialogue**

Social media platforms offer users the opportunity to connect in a wide variety of ways. One of the most prevalent forms of user interaction is by way of 'comments' or 'replies' in which users can submit a response both to a post itself or a comment within the post, essentially building a discussion thread.

Studies focused on how nonprofit organizations leverage social media tools to better engage its stakeholders have shown that these platforms facilitate two-way dialogue, which in turn results in a whole host of desirable outcomes such as "providing faster service for the community, generating more media coverage, and receiving positive and negative feedback from stakeholders to improve the organization" (Briones, Kuch, Liu & Jin 2011, p.41).

The exchange of information that takes place in social-mediated platforms can take many shapes. For instance, Glowacki and colleagues (2016) argue that organizations can organize Twitter chats – "a public Twitter conversation around one unique hashtag" (Smarty, 2012) – to better understand public health concerns and disseminate timely information. During crises, the opportunity for dialogue affords publics the chance to use social media to reach out to organizations and other people in order to vent (Muralidharan, Dillistone & Shin, 2011).

Comments also hold significant implications for news media organizations and journalists. According to Hille and Bakker (2014), although journalists dislike the comments section and generally abstain from participating in that particular exchange, users enjoy interacting with one another by responding to each other's comments – ultimately resulting in a good opportunity for conversation and debate (p.570).

**Information dissemination**

The third indicator of social-mediated audience behavioral engagement is information dissemination, which is conceptually distinct than content/information creation. In the context of social-mediated communication, information dissemination is the act of re-posting content by means of the respective feature available in the social media platform. For instance, in the case of Facebook, users disseminate information by "sharing" an existing post with other users in their networks. Alternatively, in Twitter, users disseminate information by "retweeting," whereas in other platforms like Tumblr, users "re-blog" content.

As discussed at length in previous chapters, information dissemination before, during and after disasters is a phenomenon that has been taking place long before the arrival of social media. However, there are several key considerations that conceptually distinguish information dissemination from the routine information exchange that takes place within and between organizations, the news media and the general public during disasters.

The first consideration worth addressing is the fact that social-mediated information dissemination essentially takes place in a social-mediated landscape, which in turn shapes the way in which the information is disseminated across different networks. Put bluntly, information dissemination comes in the forms of 'shares' and 'retweets' and 'reblogs.' The second consideration involves accessibility. Generally, social media content is more accessible to the general public than information that is circumscribed to emergency management officials and news media organizations that have privileged access to locations and sources, social media privacy settings notwithstanding.

There are, of course, many implications worth considering as well – like the wider audience scope or the veracity of the content being shared, in addition to the fantastic opportunities for individuals to play a more active role in disaster management functions that often necessitate grassroots and volunteer efforts in order to work.

## Audience Engagement in the SMDIA Model

The Social-Mediated Disaster Information Amplification (SMDIA) model defines audience engagement as the cognitive, emotional and behavioral responses to disaster-related content shared by information sources through social media before, during and after a disaster. Drawing from all three of the theoretical frameworks previously discussed in this chapter, the cognitive dimension of engagement involves the change in perceptions and beliefs as a result of social-mediated disaster communication. Related to the target communication outcomes described earlier, cognitive engagement can be addressed by risk perception, acceptance of an organization's crisis response strategy as well as message/source credibility perceptions. Similarly, emotional engagement encompasses the emotional response to social-mediated disaster communication. In turn, behavioral engagement involves information dissemination, dialogue and social endorsement. The major conceptual tenets related to audience engagement, as understood from the SMDIA model, are illustrated in *Table 3*.

# CHAPTER 5

# A CONCEPTUAL MODEL:

# HYPOTHESES AND RESEARCH QUESTIONS

The previous chapters have proposed a conceptualization of the three major concepts of this dissertation – information sources, content and audience engagement. The first main purpose of this chapter is to describe the fundamental assumptions underlying the relationships between information sources, content and audience engagement in a social-mediated disaster context. This description builds on three theories, the hierarchy of media influences, visual framing, and dual coding. The second objective of this chapter is to outline the relationships between the dissertation concepts through the articulation of research questions and the proposal of hypotheses. The third goal of this chapter is to visualize these relationships through the Social-Mediated Disaster Information Amplification (SMDIA) conceptual model.

## Information Sources and Communication Strategies Overview

Based on the discussion on Chapter 2, it was proposed that in a SMDIA-context, information sources are defined as individuals or entities that use social media to share disaster-related content. Building on the frameworks from which this conceptualization is based, it is understood that information sources can reflect the complexity of all the actors that converge in a social mediated space to share and engage with information related to a disaster. Certain streams of work employ an information source binary defined by its relationship between entities tasked with emergency management functions and the publics that they serve (i.e., official vs. unofficial, formal vs. informal, etc.). Other approaches advance work in which an information source is characterizes by the nature of the social media content that it shares or engages with (i.e., user archetypes based on content themes and/or behaviors).

In turn, the SMDIA model understands that information sources can be characterized by both the functions of the role that an entity plays regarding a disaster as well as the dynamics that it displays within its social media network. In very broad terms, the main theoretical argument proposed in this dissertation regarding social-mediated information sources is that certain types of information sources are more likely than others to share certain types of disaster-related content.

This predilection is based on communication strategies, which in turn are characterized by the overt or inadvertent role that an information source finds itself playing in a social-mediated disaster context. Broadly, these influences are broached by the Social Amplification of Risk Framework (SARF), which advances the idea that communication behavior is shaped by individual, group and societal factors (Kasperson, 1992; Renn, 1991b; Renn et al., 1992b). In turn, the hierarchy of media influences model can complement this understanding by providing a strong perspective on how *content* can also be shaped by a myriad of complex factors.

**The Hierarchy of Media Influences**

The hierarchy of media influences model presents a holistic understanding of the sociology of news by

> considering factors at five levels of analysis that shape media content, suggesting ways in which variables can be defined and reshaped. These include, from the

> micro to the macro: individual characteristics of specific newsworkers, their routines of work, organizational-level concerns, institutional issues, and larger social systems (Reese & Shoemaker, 2016, p. 396).

This model, then, focuses on how different factors at the micro-, macro- and meso-levels affect the way in which news – specifically – is made. Germane to this dissertation is the routines level, which "is concerned with those patterns of behavior that form the immediate structures of media work" (Reese & Shoemaker, 2016, p. 399). The hierarchy of media influences model proposes that routine-level factors, which are based on newsroom practices, shape the way in news is made.

The decision-making process in newsrooms that ultimately results in a finished product of published, broadcast or posted news is shaped by many factors. According to Lowrey (1999), "news organizations and journalists create routines in order to efficiently and profitably manage the world's unexpected events. Routines largely determine the content of the news product and therefore the way the world is made known through the news" (p.10). A routine-level approach based on the hierarchy of media influences model could contend that a social media post created by a news media organization can be indicative of newsroom routines.

In turn, these newsroom routines are reflective of the overall news industry. The current news media landscape presents a series of challenges that editors and journalists must grapple with in order to remain operational. For example, a recent Pew Research Center report suggests that the print news media "industry's financial fortunes and subscriber base have been in decline since the mid-2000s, and website audience traffic, after some years of growth, has leveled off" (Pew Research Center 2019, ¶1). Moreover, other reports underscore the importance of social media as a critical pathway to news websites (Anderson & Caumont, 2014). It is plausible to suggest then that to survive increasing audience fragmentation and the challenges of going digital, editors and journalists must adapt and incorporate social media best practices shown to draw engagement from users.

Related to the pursuit of audience engagement is that of ‘engaged journalism.’ According to Green-Barber (2018), engaged journalism is

> an inclusive practice that prioritizes the information needs and wants of the community members it serves, created collaborative space for the audience in all aspects of the journalistic process, and is dedicated to building and preserving trusting relationships between journalists and the public (¶8).

The use of social media, among other tools, can help journalists participate in a more engaged form of journalism practice – a dynamic that has been recognized as both an economic and moral imperative by journalists (Brown, 2019). Emergency managers tasked with public outreach should also strive for a more participatory engagement with the publics that they serve, particularly because reports have shown that at-risk publics expect organizations to be responsive on social media during an emergency (Fraustino et al., 2012), while other studies have documented that social media engagement during the recovery stage of a disaster can help affected communities recover (Calder et al., 2020).

The use of visuals in new stories are a documented fixture in newsroom routines (Lowrey, 1999). As explained in Chapter 3, there are many types of visuals – including the illustrative (i.e., photos and images) and graphic (i.e., charts, maps, graphs) modalities. While studies have shown that ‘quantitative forms’ of news, like data journalism and its visualizations, have become prevalent in mainstream journalistic practice (Coddington, 2015), there are some reasons why illustrative visuals may be more ubiquitous in certain contexts than in others.

First, data visualizations require more time and technical effort to produce. This was the case more than two decades ago – for example, Lowrey (1999) explained that "because creating infographics from scratch is time consuming, news artists commonly create and file away templates for maps and charts for future use" (p.13). Despite the technological advancement that may make the production of graphical visual elements easier, not all journalists have the technical capabilities to create interactive visual materials. Also, disasters are often characterized as ongoing and rapidly unfolding events that do not leave editors or journalists with that much time to spend on the development of a single visual.

Another reason why news editors may opt to include illustrative visuals instead of graphical ones is because that selection more closely aligns with news values. Fahmy, Kelly and Kim (2016) explain:

> Washington Post Assistant Managing Editor for Photography Joe Elbert has a described a hierarchy that classifies editorial photographs into four categories: informational, graphically appealing, emotionally appealing, and intimate. The more that news photographs manifest emotional and intimate human elements, the higher they are located in this hierarchy. He argues that photo editors should select photographs from the upper end of the hierarchy as often as possible (p.549).

Following this line of thought and anchored in the routines-level of journalistic practice, it is reasonable then to suggest that when faced with an array of different visuals, journalists and editors will choose the more compelling visuals, i.e., illustrative images.

Research centered on the journalistic routines and practices that characterize image selection for digital platforms and a social media context also echo that argument. For example, Schwalbe, Silcock and Candello (2015) interviewed and surveyed key visual decision-makers in newsrooms across the United States and Europe. Through those interviews and surveys, they found that many of these journalists and editors believe that both the transition to a "24-7 news cycle" and the popularity of social media have both contributed to the growing prominence of images. Specifically, one of their respondents, Christopher Dickey – "foreign editor of *The Daily Beast* and former *Newsweek* Paris bureau chief and Middle East reginal editor" – stated the following:

> Images make news unforgettable. As the news stream is reduced to 140-character tweets- essentially headlines and captions – the power of photos grows exponentially. They show so much so fast. In a  twitterized worlds, where headlines go viral but the texts do not, a picture is worth, well, 50 tweets (Schwalbe et al., 2015, p. 474).

These trends, coupled with the increasing practice of journalists incorporating citizen eyewitness accounts or other forms of user-generated content (UGC) into disaster news coverage (Jurkowitz & Hitlin, 2013) make it plausible to suggest that journalists and editors are more likely to feature illustrative visuals, given that choice. As such, the following research question is posed:

**RQ1: Are news media more likely to feature illustrative disaster visual content in their social-mediated messages rather than graphical visual content?**

The literature suggests that the selection of images that accompany a news story run parallel to its topic. According to Seelig (2006), visual content "was strictly visual representations of factual news occurrences that were deemed newsworthy by the social structure at [the newspaper]" (p.21). In line with this way of thinking, Seelig (2006) adds that hard news photos are of factual news occurrences, whereas other types of news – such as feature stories – endowed photo editors with more leeway to consider alternative ways of illustrating the news, may that be with graphics or illustrations (i.e., paintings and drawings). Since disasters are typically considered hard news, it is likely that the predominant visual content choice will be illustrative rather than graphical.

The theoretical underpinning of the hierarchy of media influences argument could easily apply to other contexts in which content is created. For instance, routines in an emergency management context can ultimately determine the way in which entities at the local, state and federal level develop content. Chapter 3 summarized that many aspects of emergency risk and disaster communication are informed by prevalent risk communication guidelines and principles. One of such popular communication guidelines encourages the use of visuals and infographics to convey facts and figures. According to Yavar and colleagues (2012),

> infographics are a mean and a method for presenting information through visualization. This mean is used in conditions where simplicity and quick conveying of meaning related to data or where transferring large amount of

> information, news or even scientific and technical context to the addressee is necessary (p.1).

According to Gallicano, Ekachai and Freberg (2014), graphical visual content, such as infographics, constitute a “form of strategic storytelling, a practice that occurs when an employee shares an organization’s story to advance an organization’s goals with one or more key audiences” (p.3). By sharing information-rich visual content, organizations tasked with emergency management can ensure that publics are informed and better able to engage in the protective action recommendations suggested.

Additional research has also found that the use of graphic visuals can hep at-risk publics better understand their risk, thus better positioning them to take protective action. For instance, Liu and colleagues (2017) conducted an experiment to assess how people responded to Wireless Emergency Alerts (WEAs) with or without maps. The main underlying point of that study was that maps could help increase the risk comprehension of at-risk publics. According to Liu and colleagues (2017):

> Specifically, maps that contained more information increase participants’ message comprehension (albeit with an extremely small effect size). However, message comprehension was a key component in creating message and compliance and, to a lesser extent, information sharing behavior in the tested incidents. Thus, if maps can be developed to further enhance message comprehension, they may prove to be even more influential in helping at-risk publics understand and respond to WEAs (pp.502-503).

Indeed, earlier studies have also found that the use of graphics and maps helps increase the risk comprehension and perception of at-risk publics. In an experiment conducted by

Sattler and Marshall (2002), participants exposed to enhanced hurricane graphics (essentially, the ones including estimated time of landfall) displayed a “better understanding of the advisories, the precautionary actions they should take, and would perceive the hurricane threat more seriously compared to those viewing the currently used graphics” (p.46). In addition, if emergency management organizations are led by the main goal of providing timely and factual information to the at-risk publics they serve before, during and after a disaster (Haddow & Haddow, 2009b), it is plausible to propose that organizations are more likely to feature graphical visual content rather than illustrative content on their social media messages. As such, the following research question is posed:

**RQ2: Are government organizations more likely to feature graphical visual content in their social-mediated messages rather than illustrative visual content?**

One of the major goals of the SMDIA model is to explore the communication dynamic of ordinary social media users vis-à-vis other information sources in a disaster context. While a routine approach for this information source type is outside of the scope of this work, research anchored in disaster sociology has found that people use social media during disasters as a coping (Fraustino et al., 2012) and sense-making mechanism (Heverin & Zach, 2012).

Studies that focus on social media use before, during and after disasters have found that the process of taking and sharing disaster-related images can be a strong component of post-disaster resiliency. For instance, in their case study of social media use during the Cyclone Winston, Finau and colleagues (2018) note that the most prevalent trend observed were “individual personal account and documentation of destruction. These included a wide variety of images and videos of people’s homes, property and some of their livestock being caught in the devastation” (p.131). The study concludes that social media played a complimentary role to mainstream media by “allowing Pacific voices to tell their stories and share their experience with the cyclone” (p.134). The main point related to this dissertation is that capturing and sharing disaster-related images can be an important component of individual storytelling and coping following a disaster. Other studies have also noted that people use social media to share images and videos of their lived experiences during a disaster, as documented by Slick’s (2019) phenomenological case study of YouTube videos uploaded by the people who bore witness to the 2016 Fort McMurray wildfire.

As mentioned previously, ordinary social media users have the means to create user-generated content before, during and after disasters – and both researchers and journalists have documented the extensive content creation activity of ordinary users in a disaster or crisis context. However, even within the realm of content creation possibilities and opportunities, it is easier for the average user to take a photo (illustrative content type) than it is to create a graph, chart or infographic (graphical content type). Due to the convenience of the former and the onerous process of the other – especially in mobile devices, where most people access social media to view and share content, the following research question is posed:

**RQ3: Are ordinary users more likely to feature illustrative disaster visual content in their social-mediated messages rather than graphical visual content?**

One of the major goals of this project is to explore in greater the detail the kind of visual content shared by different information sources during a disaster. So far, visual content types along the illustrative and graphic binary has been discussed – however, there are other features of visual content that warrant further study. One of such features is the content matter of images, in other words, what the pictures are about. Apart from driving certain aspects of communication strategies, routines also shape the way in which visuals depict content matter. Research employing a framing approach to the study of visuals helps describe how routines come to characterize the way in which individuals, groups, entities or events are portrayed in visual mediums.

***Visual Framing***

According to Rodriguez and Dimitrova (2011), "the idea of framing first appeared in Goffman's seminal work in 1974, which postulated that the context and organization of messages affect audiences' subsequent thoughts and actions about those messages" (p.49). Since then, framing theory has been applied to a rich variety of research contexts – visual communication being one of them. Visual modalities involve features that make its framing seem less overt than the one involving text – as explained by Messaris and Abraham (2001),

> As far as viewers' responses to framing are concerned, the analogical quality of images has the following consequence. Precisely because it can make images appear more natural, more closely linked to reality than words are, it can also inveigle viewers into overlooking the fact that all images are human-made, artificial constructions. This is one sense, then, in which visual framing may be less obtrusive, more easily taken-for-granted than verbal framing. Evidence of the

> potential unobtrusiveness of visual framing has existed for some time in studies on viewers' reactions to the formal conventions of visual communications (close-ups vs. long shots, editing and so forth) (p.216).

This point is closely related to many of the qualities that make disaster-related user-generated content and eye-witness accounts compelling. Extant research has documented the way in which certain news media organizations visually frame their coverage of natural disasters. For example, Borah (2009) found that U.S. newspaper coverage of Hurricane Katrina and the 2004 Indian Tsunami included visual frame categories of loss vs. gain, pragmatic, human-interest, political and other. Collectively, these frames captured images that depicted the physical scope of destruction, human grief, death and suffering – but also images of politicians visiting disaster sites.

Like how information sources in the SMDIA context can be conceptualized in more than one way – so can the many ways in which visual illustrative content can depict disaster-related themes. Chapter 3 presented three main themes of disaster-related visual frames – informational focus, human-interest focus and destruction focus. While the previous discussion argued that organizations were more likely than other sources to opt for graphical visual content in their social-mediated disaster communication strategy, it does not imply that this particular source refrains from sharing illustrative visual content as well. It is plausible to suggest, however, that within the particular type of illustrative visual content, organizations are more likely than other sources to prioritize an informational focus rather than other focuses which may bring attention to negative outcomes of a disaster – such as human suffering, tragedy and widespread physical infrastructure damage – none of which are positive topics or aspects of a situation that an organization would strategically want to align itself with. As such, the following research question is posed:

**RQ4: Are organizations more likely to feature disaster visual content with an informational focus rather than a human-interest or destruction focus?**

In turn, concerning news media organizations and the way in which they frame their illustrative social media content, when faced with the opportunity to opt for a vivid, emotionally captivating human-interest angle rather than an informative or destruction focus, photo editors will choose the former. This point is brought up by Fahmy and colleagues (2016) when discussing the role that news values play in swaying visual editorial decisions in newsrooms. Specifically, they contend that "informational photos, such as photos of news conferences can be important for readers, but editors prefer emotional images and, especially, shots of tragedy" (Fahmy et al., 2016, p. 549). In fact, their visual analysis of Hurricane Katrina coverage by newspapers and wire services found that "the images as presented depict a U.S. news coverage routine where the story of a huge, impersonal event is told in large part through the accounts of individuals personally experiencing pain and loss, especially people of color" (p.554).

Other studies expand on the media representations of disaster, some of which do focus on the plight and suffering of others. As explained by Greenberg and Scanlon (2016),

> Media portrayals of disaster have long been associated with notions of solidarity and the impetus to help strangers and ameliorate their suffering. During natural disasters and other complex emergencies, the motivation of humanitarian relief agencies on the ground and those watching safely from home is often to witness

> humanity in action, and provide some type of support, be it a financial donation, a signature on a petition, or other acts of fundraising and social awareness training (p.10).

Greenberg and Scanlon (2016) explain that, in times of disaster, journalists and nonprofit organizations collaborate with one another. Nonprofits, typically at the scene of the event itself, provide journalists with compelling human-interest visuals for their coverage of the event. In turn, these relief organizations profit from this exchange when the images that they provided are shared by journalists, thereby increasing public attention to and concern for the devastated. In light of these dynamics and the aforementioned predilection of news editors to opt for the more emotionally compelling images of disasters, the following research question posed:

**RQ5: Are news media are more likely to feature disaster visual content with a human-interest focus rather than an information or destruction focus?**

So far, it has been explained that each information source type is influenced by broader forces that ultimately shape the type and focus of the visual content they create and share through social media channels. While ordinary users may be influenced by coping mechanism motivations, their content creation is bound to certain realities that can determine the type of focus that will be more predominant. First and foremost, ordinary users generally do not have privileged or direct access to key emergency management officials, leaders or sources like journalists do – nor are they bound by emergency management functions and all that this responsibility entails. This point suggests that it would be generally unlikely for ordinary users to prioritize and informational focus over any of the other types of focus.

Apart from these limitations, ordinary users also enjoy opportunities that journalists and emergency management officials may not: they occupy the space wherein the disaster takes place. News media organization's growing reliance on user-generated content is illustrative of the fact that there are only so many photojournalists available at a specific time and place. The geospatial scope of a disaster allows ordinary people to bear witness to its destruction. This reality and the opportunity that technology presents allow ordinary people to document and share the effects of a disaster with others.

Research in this area has noted that people who experience these events tend to capture images and videos that document the scope of destruction witnessed first-hand. Through their in-depth interviews with government officials, journalists and ordinary citizens, Tandoc and Takahashi (2017) found that many affected residents had captured photos and videos of how the Typhoon Haiyan had affected them. For example,

> During the interviews, other participants showed photos and videos they had captured during and in the immediate aftermath of the storm. A telephone company technician showed videos on his mobile phone he had taken after nearly drowning when raging flood waters swept his office. "I took it for documentary purposes so that when I get a signal, I can post them [on Facebook]," he said. "Also document it for myself, because it is important, because I have experienced it" (p.11).

In light of these documented practices both in reports, news articles and research, the following research question is posed:

> **RQ6: Are ordinary users more likely to feature disaster visual content with a destruction focus rather than an informational and human-interest focus?**

## Content Features and Audience Engagement Overview

Based on the discussion on Chapter 3, it was proposed that in a SMDIA-context, content is defined as disaster-related information shared through social media by information sources. Like the case of information sources, building on the frameworks from which this conceptualization is based, it is understood that content can encompass a rich variety of messages and information that is shared in a social mediated space. Certain streams of work understand disaster-related information to involve public-facing content including disaster warning, watches, advisories and protective action recommendations.

Other frameworks recognize that, in a disaster context, key actors bring with them different types of content – like how news media organizations provide disaster-related coverage, which is distinct in its nature from public-facing emergency management updates and instructions. Finally, a growing body of work brings attention to the content that lay audiences create and interact with before, during and after a disaster – a phenomenon that did exist prior to social media, but now benefits from easier modes of production and dissemination.

The SMDIA model upholds the idea that public-facing disaster-related content on social media can span different types of messages and a variety of modalities – and that these choices can be indicative of the functions that each actor embodies in the milieu of disaster messages. In very broad terms, one of the four main theoretical arguments proposed in this dissertation regarding social-mediated content is that certain types of content modality are more likely than others to drive audience engagement with messages. Similarly, the second proposed theoretical argument contends that certain types of content modality are more likely than others to affect audience perceptions of risk as well as source and message credibility. Third, certain types of illustrative content foci are more likely than others to drive audience engagement with messages. The fourth proposed theoretical argument maintains that certain types of illustrative content foci are more likely than others to affect audience perceptions of risk as well as source and message credibility.

## Modality and Audience Behavioral Engagement

The first factor associated with increased social-mediated audience behavioral engagement is content modality. According to Kiousis and Dimitrova (2006), content modality is defined as "the use of text, graphics, sound, and video on a single communication platform" (p.350). Indeed, content modality can be understood as the general format of content. In a computer-mediated context in general and a social media one in particular, current features support the following content modalities: text-based content, image-based content, audio-based content, and video-based content.

### *Text-based*

While the earlier forms of computer-mediated communication relied predominantly on text-based interactions like email and instant messaging (Kimbrough et al., 2013), the design of major contemporary social media platforms prioritizes image- and video-based content. According to Wang and colleagues (2010):

> Visual cues which are more dominant than verbal cues are absent in traditionally text-based CMC. Contemporary Internet-based communication tools like SNSs, however, were designed specifically to accommodate visual cues including images and videos. These mediated environments facilitate synchronous display

> of both visual and textual cues; this contrasts sharply with early text-based CMC as visual cues now serve as prominent elements during impression formation (p.228).

Despite the design preference for more visual and vivid content, the pervasiveness of computer-mediated text-based interactions have largely shaped how people socialize and interact with one another in online environments. In fact, the findings of the 5-year Stanford Study of Writing underscore (1) that the current generation of young adults writes more than any generation before, and (2) that this is likely due to the fact that most newer forms of social interaction occur online, which in turn “almost always involve text” (Thompson, 2009, p. 4).

***Image-based***

Research that focuses on identifying which disaster communication aspects drive successful outcomes (i.e., message retransmission, wider audience reach, etc.) has identified photos as a prevalent type of content shared through social media platforms. According to Genes and colleagues (2014), the most retweeted posts during two New York snowstorms included general tips or photos, as opposed to actionable information. Other studies have also found photos to be a prevalent modality in content that is shared by other users in social media platforms during other contexts, like elections and the ensuing civic unrest. Specifically, Zhou and colleagues (2010) found that posts that were retweeted the most during the 2009 elections in Iran included photos and videos.

Outside of the context of crises and disasters, there is a significant body of research that points to the role of modality – especially photos – in message retransmission likelihoods on social media platforms. In first place, recent study findings suggest that the primacy of visual content may span across different types of social media, regardless of whether the platform is primarily image- or video-based.

For instance, a study conducted by Hessel Lee and Mimno (2017) found evidence to support the claim that there are online communities in which visual content might serve to predict popularity, even more so than social features. This particular study focused on Reddit, “a social news website where users vote to determine which stories will be featured in high-visibility locations” (Mills, 2011, p. 1) – more importantly, Reddit is primarily a text- and link-based platform, although it also has image- and video-based threads or “sub-reddits.”

Another crucial point to consider is whether social media users are drawn to visual content, more so than text-based forms. So far, research in this area has shown that social media posts that feature pictures that include a person’s face are more likely to receive likes and comments than those that don’t (Bakhshi et al., 2014).

Regarding what makes images popular on these types of platforms, Khosla, Das Sarma and Hamid (2014) claim that, ultimately, it is an interplay between image content and user-level dimensions. Specifically, Khosla and colleagues (2014) found that popular images tend to have certain core characteristics in common, namely “color, gradients, deep learning features and the set of object present” (p.1). The most popular pictures in their dataset included images that had striking colors and included objects such as miniskirts, bikinis, brassieres, perfumes and revolvers – however, user-level cues were paramount to an image’s success in the social media platform.

Images also play a crucial role in online social-mediated disaster communication. According to Liu and colleagues (2008), in times of disaster, people take photographs to make sense of the events that are taking place. Indeed, the authors explain that this activity can all at once provide information about what is going on, be newsworthy or of interest to journalists that are covering the unfolding events, or even be therapeutic, as taking pictures during a disaster be understood as a form of emotion-based coping. Other researchers (Qu et al., 2011) that have documented social media use during disasters, attest to people using social media platforms to express how they feel about what is transpiring.

Image-based social media content has been shown to attract engagement – in the forms of likes and comments (Hessel et al., 2017). Some scholars (Bakhshi et al., 2014) suggest that this may be because images feature certain aspects like faces, which have been shown to be strong drivers of interpersonal communication. In turn, other scholars suggest that image-based content popularity can be attributed to enticing colors and vivid content (Khosla et al., 2014). Coupled with the fact that people routinely capture and share photos during disasters as part of their sense-making processes (S. B. Liu et al., 2008) and emotion-focused coping mechanisms (Qu et al., 2011), it is plausible to suggest that image-based social media content could be a strong predictor of social-mediated audience behavioral engagement. As such, the following hypothesis is proposed:

**H1: Audiences are more likely to engage with disaster image-based social media content rather than text-based content.**

Based on the conceptualization of audience engagement in the SMDIA context advanced in Chapter 3, the following hypothesis regarding social endorsement is proposed:

**H1a: Audiences are more likely to like disaster image-based social media content rather than text-based content.**

In turn, audience engagement also considers a dimension of information dissemination as part of one of the major components of the SMDIA model. As such, the following hypothesis is proposed:

**H1b: Audiences are more likely to retweet disaster image-based social media content rather than text-based content.**

Audience engagement also entails a third and final dimension, which consists of dialogue. In the SMDIA model context, that concept is operationalized as the extent to which publics reply to social media posts. Finally, the following hypothesis is proposed:

**H1c: Audiences are more likely to reply to disaster image-based social media content rather than text-based content.**

The primacy of image-based content over text-based content regarding audience reception and engagement has been documented across the literature. Less clear perhaps is the underlying connection between image-based content and the behavioral engagement it purportedly precipitates. Outlining the relationship between visual content, the emotional and physiological states it evokes, and the behavior that follows is then crucial to its conceptualization.

According to Lang and colleagues (1998), “pictures evoke a spectrum of measurable emotional reactions” (p.199). Earlier studies suggest that these emotional reactions may stem from the fact that “pictorial information can match the stimulus properties of real object or event referents, activating cognitive representations associated with strong emotional responses” (Lang et al., 1993, p. 262). To complicate matters further, researchers typically distinguish between two key dimensions of emotion: valence and arousal (Lane et al., 1999). The former "refers to the direction of behavioral activation associated with emotion, either toward or away from a stimulus," while the latter "refers to the intensity of the emotional activation, ranging from excited to calm" (Lane et al., 1999, p. 990). In turn, the literature suggests that emotions can shape behavioral responses (Loewenstein et al., 2001). To the extent that the influence is direct or indirect is still the topic of debate among researchers (Baumeister et al., 2007).

***Video-based***

Several social media platforms count with the capabilities necessary for their users to create, watch, share and engage with richer types of multimedia content, such as videos. In fact, Facebook's latest feature, Facebook Live, allows users to use their phones to broadcast audio-visual content in real time (Bernazzani, 2019). This tool boasts higher rates of engagement than previous iterations of audio-visual content sharing mechanisms in the social network: According to Connolly and Beteille (2017), "people comment more than 10 times more on Facebook Live videos than on regular videos" (¶7).

While Facebook Live indeed has potential to support emergency and crisis management – reports have noted how news media organizations have implemented the tool for streaming press conferences in real time and facilitating question-and-answers sessions (Mullin, 2016), it can also be used for nefarious purposes such as streaming violent content like "shootings, rapes, murders, child abuse, torture, suicides and attempted suicides" (Kantrowitz, n.d., p. 1). Regardless of this unfortunate development, current studies focused on social-mediated disaster communication underscore the need for further research on the effects of image- and video-based modalities have on emergency communication (B. F. Liu et al., 2015b), as its implications for information source perceptions and subsequent audience behaviors remain largely understudied.

As previously discussed in Chapter One, social media is a blanket term for a wide variety of websites and applications. Kaplan and Haenlein (2010) propose six main types of social media: blogs, collaborative projects (e.g., Wikipedia), social networking sites (e.g., Facebook), content communities (e.g., Youtube), virtual social worlds (e.g., Second Life), virtual game worlds (e.g., World of Warcraft).

The focus of this section is on two of these categories, social networking sites and content communities. Kaplan and Haenlein (2010) define the former as "applications that enable users to connect by creating personal information profiles inviting friends and colleagues to have access to those profiles, and sending e-mails and instant messages between each other" (p.63). In regard to the latter, the authors explain, "the main objective of content communities is the sharing of media content between users" (Kaplan & Haenlein 2010, p.63). The authors suggest that this particular type of social media spans different "media types" like text, photos, videos and PowerPoint presentations.

Even though different social media categories might blur as social networking site users share different types of content, the distinction matters when considering widespread video dissemination causes, structure (i.e., propagation patterns) and outcomes. Specifically, it matters for three main reasons.

The first reason why the distinction between both types of social media sites matters is because online social networking sites convey much more information about a video than the information used in early video popularity prediction studies (Li et al., 2013). Research in this area suggests that a considerable amount of studies have only considered data from content community sites like YouTube, essentially basing prediction models on video age and number of views. Furthermore, as Li and colleagues (2013) argue, social networking sites afford other dimensions that warrant future study, such as which users in the network have shared the video, number of comments, number of likes, among others.

The second reason why the distinction matters is because social networking sites play a significant role in video content popularity (Ma et al., 2014). Even though major social networking sites like Facebook and Twitter both have their own video platforms, users still share embedded videos hosted in content communities such as YouTube. The third reason underlying the importance of the distinction concerns the social dynamics that result in content dissemination and popularity. According to Vallet and colleagues (2015), this is largely due in part to the structure of social networking sites and the phenomena it begets. Specifically, online social networks "make use of the crowd to generate traffic toward the videos, as users leverage their social circles to share video links with friends and followers" (Vallet et al. 2015, p.1591). In other words, social networking sites provide the necessary backdrop for people to post, watch or share videos, activities that are grounded in social dynamics.

Social networking sites and content communities participate jointly in a symbiotic relationship that results in the dissemination of multimedia content. Indeed, as Honigman (2015) explains,

> Youtube might have made uploading videos easy, but when it came to actually helping you find things you might enjoy it was often inadequate, other than the videos they chose to feature on their homepage. It was the massive social engines

> like Facebook and the organic process of sharing and social momentum that enabled videos to burst out of obscurity and onto the radar of a huge audience (¶16).

One crucial aspect of this relationship is the role of social influence. When exploring video-viewing and sharing patterns of RenRen and Youku users – the Chinese counterparts of Facebook and YouTube, respectively – Ma and colleagues (2014) found that social media users that are part of a same network are likely to share interests as well, which makes posts including a video similar to a relevant recommendation.

Regardless of the fact that sharing behaviors and viewing patterns on social media are shaped by the social relationships that enable them (Ma et al., 2014), scholars in this area have noted that what motivates users to share video content remains largely understudied (Vallet et al., 2015). In addition, there is also a considerable lack in the literature regarding whether or not the modality of the content has any bearing on its popularity. Since the advent of social media, some platforms only came along to stagnate and disappear altogether after some time, whereas others have continually adapted and evolved over the years

Research in computer-mediated communication in general and social media in particular have explored many fascinating and transcendental phenomena. However, innovation comes hand in hand with new opportunities to explore behaviors and patterns that were not possible before. While research regarding content modality effects in social-mediated communication remains a relatively recent and understudied area, there is a robust literature about content modality effects that might inform some of the unanswered questions regarding the relationship between content modality and information dissemination in a disaster social-mediated communication context.

For over a century, the plurality of mass media channels such as newspapers, radio and television has inspired research in the social and behavioral sciences geared towards identifying crucial differences between the platforms and their implications (DeFleur et al., 1992). Content modality studies have explored the effect of messages presented in text, audio or audio-visual format concerning health-related information (Byrne & Curtis, 2000; Corston & Colman, 1997), law cases (Chaiken & Eagly, 1976; Fishfader et al., 1996), education (Clark & Paivio, 1991; Mayer et al., 2001), news (DeFleur et al., 1992; Furnham et al., 2002; Ravaja et al., 2006), stories (Koehler et al., 2005), marketing (Sparks et al., 1998), as well as non-fiction recollections (Glasford, 2013; Yadav et al., 2011).

The body of research centered on content modality has contributed insight regarding the role of information format in several aspects of communication effectiveness, such as recall (Byrne & Curtis, 2000; Corston & Colman, 1997; DeFleur et al., 1992; Furnham et al., 2002; Mayer et al., 2001; Yadav et al., 2011), persuasion (Chaiken & Eagly, 1976), audience attitudes about the speaker or information source (Sparks et al., 1998), message comprehensibility (Chaiken & Eagly, 1976), education (Clark & Paivio, 1991), juror decisions (Fishfader et al., 1996), as well as emotional state and engagement (Fishfader et al., 1996; Glasford, 2013; Koehler et al., 2005; Ravaja et al., 2006).

From a broader perspective, the content modality literature generally supports two main assumptions regarding the adequacy of one type of modality over another. The first consensus suggests that text is the best modality when presenting complex information, as assessed primarily by tests of recall. For example, Chaiken and Eagly (1976) found that text modality leads to higher persuasion effects when the material is more complex or harder to understand. Moreover, studies justify this and similar findings with a number of explanations.

For instance, Corston and Colman (1997) argue that the adequacy of text over video modality may be due to participants' ability to reread text to further enhance their comprehension, an affordance not yet available to participants in the video condition – an explanation largely based on self-pacing theory. Other scholars have gone as far as to suggest that video modality's inadequacy for conveying complex information is largely due to the fact that videos may be too distracting (Byrne & Curtis, 2000). An additional explanation contends that text modality's effectiveness rests in the increased cognitive effort involved in reading, which leads to increased learning or information retention (Furnham et al., 2002).

The second consensus supported by the content modality body of research insists that information presented in a video modality is more engaging and emotionally arousing; in turn, this has many implications on audience perceptions and behavior. For instance, Fishfader and colleagues (1996) found that video scene recreations affect juror decisions regarding perceptions of levels of defendant liability, namely due to emotional reactions to the content. In another study, participants in the video condition reported greater intentions to take political action compared to participants in the text condition, a difference partly explained by increased anger in the former condition (Glasford, 2013).

In line with previous information complexity studies, messages presented in a video format can actually enhance learning, provided the content is simple rather than complex (Furnham et al., 2002). In regard to persuasion, when information is presented in an audiovisual modality, information source characteristics gain more salience (Sparks et al., 1998). More recent studies have also found that audiovisual versions of a story elicit higher levels of engagement, sympathy and recall of certain information than their text-based counterparts (Yadav et al., 2011).

From a theoretical point of view, the differences between modalities have largely been attributed to the nuances inherent in the cognitive processing of imagery and linguistic information. Notable among these theories is Clark and Paivio's (1991) dual coding theory (DCT), which is an "empirically well-founded characterization of the mental processes that underlie human behavior and experience. DCT explains psychological phenomena by the collective action of nonverbal and verbal mental systems that are specialized for the processing of imagery and linguistic information, respectively" (p.150). The theory broadly suggests that people process different types of content in a unique way. Further, text- or image-based modalities have significant implications for emotion, cognition, motor skills and other psychological domains.

Key to the process of cognitive information processing is the fact that each modality involves distinct mechanisms for conveying meaning. In contrast to text-based content, videos can be understood as more information-rich data objects (Li et al., 2013), since they inadvertently or not include more details. Scholars explain that videos, television and other audiovisual channels are characterized by both linguistic and iconic symbol systems (Furnham et al., 2002; Salomon, 1979) (Furnham et al., 2002; Salomon, 1979). Indeed, audiovisual content has the capacity to both 'show' and 'tell' information (Corston & Colman, 1997).

Research in this area has found that the additional information afforded by audiovisual modality – the images and sounds that might accompany a narration or on-screen text, for instance, may point to higher levels of audience engagement (Koehler et al., 2005). Moreover, in addition to the fact that pictures and videos can convey meaning more easily and quickly in contrast to text-based content (Furnham et al., 2002), researchers have also documented that audiences find audiovisual content to be a more compelling medium since it brings stories to life and can provide more realistic renderings of the information or message being communicated (Yadav et al., 2011).

One of the more striking differences between content modalities is that non-verbal representations generate higher emotional reactions to stimuli than their text-based counterparts – moreover, empirical research in DCT also underscores the relationship between emotions and successful education outcomes (Clark & Paivio, 1991). This finding may have significant implications for social-mediated content dissemination as well, seeing as research regarding social transmission of information has found that emotion plays a determinant role in that process as well (Berger & Milkman, 2013).

Specifically, there is a consensus in the body of literature centered on the role of emotion on content dissemination that emotionally arousing content – regardless of valence, is the underlying motivation that drives people to share content with others (Berger, 2011; Berger & Milkman, 2013). Studies have also found a relationship between emotionally charged content and information dissemination behavior in a social-mediated context (Stieglitz & Dang-Xuan, 2013). According to Ravaja and colleagues (2006), “most theorists endorse the view that emotions are constituted by three aspects or components: subjective feelings, expressive behavior, and physiological arousal” (p.240). The latter “indicates the level of activation associated with the emotional experience and ranges from very excited or energized at one extreme to very calm or sleepy at the other” (Ravaja et al. 2006, p.240).

During times of disasters or crises, social media users can come across a wide variety of content in their homefeeds and newsfeeds. Since these platforms have the capabilities to support multimedia content, the types of disaster-related posts created and shared during those times can be primarily text-, image- and video-based or a combination of each modality. When considering which structural, social and thematic elements are helpful for predicting video content popularity across social media networks, studies have shown that widespread audiovisual content dissemination depends on factors such as the intrinsic attractiveness of the video (Li et al., 2013), post- and user-level features (Vallet et al., 2015), as well as the connections between users in a given online social network (Ma et al., 2014).

Less is known, however, about what drives users to share videos through social media – especially in contrast with other types of content modality such as text- or image-based posts. Nevertheless, earlier research in content modality effects underscores considerable differences between modalities that may ultimately explain why social media users are more likely to share one type of content over another. First, studies in this area broadly boast a consensus that audiovisual content is more emotionally engaging than other types of content (Clark & Paivio, 1991; Fishfader et al., 1996; Glasford, 2013; Koehler et al., 2005; Ravaja et al., 2006; Yadav et al., 2011). In addition to being more emotionally engaging, videos have also been found to be more physiologically arousing in contrast to other content modalities (Detenber et al., 1998). In turn, recent research findings strongly suggest that arousal plays a crucial role in social sharing of online content (Berger, 2011; Berger & Milkman, 2012). As such, the following hypothesis is proposed:

**H2: Audiences are more likely to engage with disaster video-based social media content rather than image- and text-based content.**

Based on the conceptualization of audience engagement in the SMDIA context advanced in Chapter 3, the following hypothesis regarding social endorsement is proposed:

**H2a: Audiences are more likely to like disaster video-based social media content rather than image- and text-based content.**

In turn, audience engagement also considers a dimension of information dissemination as part of one of the major components of the SMDIA model. As such, the following hypothesis is proposed:

**H2b: Audiences are more likely to retweet disaster video-based social media content rather than image- and text-based content.**

Audience engagement also entails a third and final dimension, which consists of dialogue. Finally, the following hypothesis is proposed:

**H2c: Audiences are more likely to reply to disaster video-based social media content rather than image and text-based content.**

### Modality, Audience Perceptions & Behavioral Intentions

The SMDIA model contends that the proposed relationship between information sources, content characteristics and audience engagement may be characterized by emotions, attitudes and perceptions. Drawing first from the SARF, the SMDIA model recognizes that risk perception – in all its complexity – is at the core of all audience behavioral responses to disaster-related content. As such, and in relation to disaster-related content modality, the following research question is posed:

> **RQ7 How, if such an effect exists, do Twitter post modality (e.g., text-, image- or GIF-based) and visual focus (e.g., reactive, proactive and hero) influence affective and cognitive risk perception?**

Risk perception in this context follows the conceptualization and operationalization presented by Trumbo and colleagues (2016), which distinguished between two risk dimensions that they call cognitive and affective. In that context of hurricane risk perception, Trumbo and colleagues (2016) describe this two-dimensional approach to risk perception as that which includes

> cognitive elements such as the degree to which the individual perceives personal control over hurricane risk, thinks the risk of hurricanes is increasing, or believes scientists understand hurricane risk; and affective elements such as the degree to which individuals dread the possibility of a hurricane and how anxious or angry the idea of a hurricane makes the individual (p.2236).

In addition to social media content modality, RQ1 also ponders the role of different visual foci on audience cognitive and affective risk perceptions. This portion of the dissertation corresponds to the experimental approach that allows this project to explore how audience perceptions may affect in one capacity or another the outcome variables. As part of the study design, a choice was made between a fictitious disaster scenario – similar to the ones employed by most of the empirical work involving the SMCC model –

or a disaster-related study based on the preparedness phase of a disaster. Recall from Chapter 1 that disasters are conceptualized along four different stages: mitigation, preparedness, response and recovery.

According to Tierney and colleagues (2001), disaster preparedness often entails activities that help prepare at-risk publics for an eventual hazard event, like a hurricane. In light of the research design choice of focusing on a hurricane preparedness scenario, the visual focus types were revisited to closely reflect the current visual themes prioritized by emergency management entities. Three major visual foci were identified and selected: reactive, proactive and hero. Visual elements that illustrate a reactive visual focus depict the negative consequences of a hurricane or flood (i.e., destruction, empty grocery store shelves, etc.). In turn, visual elements that illustrate a proactive visual focus depict people proactively engaging in the recommended guidance (i.e., making an evacuation plan, buying food and water, etc.). Visual elements exhibiting the hero visual focus depict organizations "saving the day" or "helping" people in need (i.e., government distributing water and supplies, emergency responders evacuation at-risk families, etc.).

Specifically involving content modality and illustrative visual content focus type, the other research questions posed as part of this work explore their potential effect on crisis information seeking and sharing intentions:

> **RQ8 How, if such an effect exists, do Twitter post modality (e.g., text-, image- or GIF-based) and visual focus (e.g., reactive, proactive and hero) influence crisis information seeking and sharing intentions among FEMA Region IV residents?**

In addition to cognitive and affective risk perceptions, and disaster information seeking and sharing intentions, this project also explores whether content modality and illustrative visual content focus in a hurricane preparedness context is also related to audience behavioral intentions associated with guidance adoption. As such, the following research question is posed:

> **RQ9 How, if such an effect exists, do Twitter post modality (e.g., text-, image- or GIF-based) and visual focus (e.g., reactive, proactive and hero) influence guidance adoption intentions?**

The SMDIA model also takes into consideration other factors that have been shown to affect certain communication outcomes, such as previous disaster experience and disaster information seeking and sharing intentions along with risk perception:

> **RQ10 Do affective and cognitive risk perceptions sequentially mediate the relationship between previous hurricane experience and crisis information seeking intentions?**

And:

> **RQ11 Do affective and cognitive risk perceptions sequentially mediate the relationship between previous hurricane experience and crisis information sharing intentions?**

Other research questions proposed to better understand how different factors shape the social-mediated disaster information amplification process include:

> **RQ12 Do affective and cognitive risk perceptions sequentially mediate the relationship between previous hurricane experience and guidance adoptions intentions?**

And:

**RQ13 Do source credibility perceptions moderate the relationship between message credibility and guidance adoption intentions?**

## The SMDIA Model Visualization

To recapitulate, throughout the first chapters of this dissertation, the major concepts and guiding principles of the Social-Mediated Disaster Information Amplification (SMDIA) were presented. The model draws from research in emergency management and disaster communication, the Social-Mediated Crisis Communication (SMCC) model, and the Social Amplification of Risk Framework (SARF) to broaden our current understanding of disaster-related communication dynamics that take place in a social-mediated context.

In Chapter 2, the concept of information sources was defined as an individual or entity that shares disaster-related content on social media before, during and after a disaster. That was followed by the definition of content presented in Chapter 3, which suggests that content is defined as public-facing disaster-related information shared through social media platforms before, during and after a disaster. In turn, Chapter 4 focused on defining audience engagement, understood as the cognitive, emotional and behavioral responses to disaster-related content shared by information sources through social media before, during and after a disaster.

The present chapter has alluded to several of the SMDIA model guiding principles related to each of the three major concepts and the factors that shape their interactions. Using the hierarchy of media influences model, the tenets of visual framing, and dual-coding theory, the potential relationships between the concepts has been articulated by proposing hypotheses and posing research questions. *Figure 1* illustrates these concepts and their relationship in visual form. Social-mediated content is at the center of the process. In this context, it is understood that disaster-related content is shaped by systemic, institutional, organizational, practices and individual-level factors. This tenet stems from the work related to the hierarchy of media influences model as well as the SARF. In turn, the social-mediated content is seen as the starting point of audience engagement – visualized through its three main dimensions, emotion, perception and behavior.

The SMDIA model depicts five levels of influence, similar to Reese and Shoemaker's (2016) Hierarchy of Media Influences model. Based on their conceptualization of each of these levels and their adaptation to better fit the context of a social-mediated disaster communication environment, the following definitions are proposed. Going outward from the center, the first level is that of individual influence. The level of analysis at that level is based on individual characteristics, perceptions, attitudes, and behavior that shape the way in which a person interacts with content. The second level is that of 'practices' – more closely related to Reese and Shoemaker's (2016) "routines" level, which is understood "as a social practice, routines are the ways of working that constitute that practice, including those unstated rules and ritualized enactments that are not always made explicit" (p.399). As such, in the SMDIA context, 'practices' can be defined as those patterns of behavior that structure the use of social media before, during and after a disaster.

In turn, the ‘organizations’ level of influence refers to both the implicit and explicit rules that characterize the way in which an organizational entity approaches social-mediated engagement. For example, this could apply to a company’s policy on livestreaming press conferences on Facebook. Another example is the social media handbook rules of use and engagement that communication officers, interns or others tasked with monitoring and using these platforms have to follow. The fourth level of influence in the SMDIA model corresponds to institutions, which can be understood as a broader level of organizational. For example, *BuzzFeed News* may have particular ways in which they approach sharing content on their social media accounts, but larger patterns can be observed across different organizations – like promoting stories through social media by including text, an image and a link to the website. The final influence level is ‘systems,’ it corresponds to the highest level of influence, like policy, infrastructure and political systems. As is the case with certain countries that block social media, the process of social-mediated content creation and engagement requires some fundamentals, like access to the infrastructure that supports the Internet, not necessarily a given in some countries and even more so after a disaster has destroyed the infrastructure needed for this.

CHAPTER 6

STUDY 1 CONTENT ANALYSIS METHOD

This chapter describes all the aspects related to the content analysis research design. First, a disaster event overview of Hurricane Matthew is presented. That is followed by a description of the data collection approach, wherein how the social media posts for the content analysis were gathered and collected. In turn, the corpus of Hurricane Matthew-related posts is characterized, and the sampling approach implemented is outlined. Then, the main units of analysis and tweet aspects are presented. That is followed by a description of the coding scheme, protocol development, coding team. The chapter concludes with an overview of Pilot Study 1, Pilot Study 2 and their results.

## Disaster Event Overview

Hurricane Matthew began as a tropical wave off the west coast of Africa on September 23, 2016. After a five-day trajectory through the Atlantic, the tropical wave had gathered enough strength to be categorized as a tropical storm. Days later, it reached hurricane status as it made its way through the Caribbean. By October 1, 2016, it had reached its peak as a Category 5 hurricane near Colombia. At the time, Hurricane Matthew's was the most intense hurricane that the Atlantic basin had experienced since Hurricane Ivan in 2004 (Stewart, 2017).

Hurricane Matthew made landfall in Haiti as a Category 4 on October 2, 2016. Reuters reports that the death toll following Matthew's wake in Haiti was approximately

900 casualties. The situation worsened as island's infrastructure damage led to the cholera outbreaks that claimed some of the lives that had been spared by the storm (Brice & Guyler Delva, 2016). Matthew also made landfall in Cuba as a Category 4 hurricane on October 5, 2016. According to Stewart (2017), although there were no casualties reported in Cuba, media reports declared that damages were estimated at around $2.58 billion USD. A few days later, Matthew made landfall in Grand Bahama Island on October 7, 2016 - despite the storm's extensive damage to infrastructure, no casualties were reported in the Bahamas.

Matthew then headed towards the United States on October 7, 2016. By then, a weakened Category 3 Matthew scourged the coast of Florida and Georgia. As an even weaker Category 1 hurricane, it made landfall in South Carolina on October 8, 2016. From there, it coasted through the North Carolina shore the next day. Hurricane Matthew finally dissipated on October 10, 2016, off the coast of Nova Scotia. Official reports indicate that Hurricane Matthew left thirty-four direct deaths in its wake through the United States – two in Florida, two in Georgia, four in South Carolina, twenty-five in North Carolina and 1 in Virginia (Stewart, 2017).

## Data Collection Approach

As discussed in Chapter 1, there are currently many types and varieties of social media platforms. However, to study the relationships between the different SMDIA concepts proposed so far (i.e., information sources, content characteristics and audience engagement) this dissertation focused on disaster-related posts from one social media platform only, Twitter. Exploring the potential differences that may arise in the social-mediated disaster information amplification process when considering multiple platforms was outside the scope of this work.

Twitter was chosen as the social-mediated context primarily because, at the time of data collection, its application-programming interface (API) allowed certain service providers to access in some capacity all tweets that were posted publicly (Hitlin, 2015). This was considered a critical advantage over other types of social media platforms, like Facebook or Instagram, which had restrictions on large-scale systematic data collection approaches (Bastos & Walker, 2018). To collect the tweets for the study, Crimson Hexagon was used.

**Crimson Hexagon**

Crimson Hexagon is a social media analytics platform that (1) provides access to all publicly available tweets through Twitter's firehose[1], and (2) features an automated nonparametric content analysis algorithm (Hitlin, 2015). In addition to the twitter post itself, Crimson Hexagon automatically collects other tweet properties such as the post date and time; its URL; the post author's twitter handle; and, when available, the country, state/region, city/urban area. The software has been tested and validated by leading nonpartisan fact tanks such as the Pew Research Center. According to Hitlin (2015), the Crimson Hexagon software meets the Pew Research Center's "high standards for accuracy and repeatability" (¶17).

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[1] According to Giglietto and Selva (2014), the Twitter database can be accessed in one of three ways though its API: (1) by the search/rest API, (2) the streaming API, and (3) firehose. The latter, exclusively for Twitter partners, is the only way in which 100% of all publicly available tweets can be collected because the former restrict the collection of tweets.

**Data Collection Timeframe**

The tweets collected for this study were posted between September 23, 2016, and October 24, 2016. The timeframe was selected because it spans the entirety of the Hurricane Matthew event – from when it was first detected as a storm in late September up until two weeks after it dissipated. Tweets posted in that two-week window allowed the project to include disaster-related content shared during the recovery phase of the event.

Although Crimson Hexagon grants access to all publicly-available tweets that match the search criteria for the selected time period – there are certain restrictions and limitations concerning data export. First, since the total number of posts for the selected date range was higher than 10,000, Crimson Hexagon automatically selects a random sample from those posts into a file that contains no more than 10,000 posts. Second, attempting to bulk export data a second time for the same date range yields the same sample of posts as the first export, although there are more than 10,000 posts selected. Third, Crimson Hexagon only allows the export of up to 50,000 posts a day – if different timeframes for each bulk export were selected, that amounts to five individual exports.

These limitations resulted in a somewhat complicated data collection process. For the first few days of the sample timeframe, when Hurricane Matthew had not yet become a prominent topic in Twitter, the census of all tweets posted across several days could be and were exported in their entirety. As more than 10,000 Hurricane Matthew-related tweets were posted in a single day, Crimson Hexagon then randomly selected 10,000 of those posts for export. This means that for the days in which Hurricane Matthew was a prominent topic in Twitter, a fixed random sample of 10,000 tweets represents the posts that were available in this timeframe for this study. Ultimately, the tweets for the content analysis were collected during a five-day span in June 2018.

**Boolean Search Query**

Tweets posted within the sample timeframe were collected by querying Crimson Hexagon for posts that contained at least one of the following query operators: “Tropical” AND “Storm” AND “Matthew;” “Hurricane” AND “Matthew;” “Tormenta” AND “Tropical” AND “Matthew;” “Huracán” AND “Matthew;” “Tempête” AND “Tropicale” AND “Matthew;” “Ouragan” AND “Matthew;” and “L’ouragan” AND “Matthew.” The queries are in three different languages because the areas directly affected by Hurricane Matthew include countries where English, Spanish or French is the official language.

## Tweet Census and Sampling Approach

Using Crimson Hexagon, a census of all publicly available Twitter tweets concerning Hurricane Matthew posted between September 23, 2016, and October 24, 2016, were located. The keyword query through Crimson Hexagon yielded 5,663,069 posts. From that total and due to the data export limitations discussed earlier, 249,084 of those posts – representing approximately 4.39% of the total number of tweets – were collected. Due to time constraints and financial limitations, stratified random sampling was employed to winnow the census of tweets down to a feasible number for individual human coding.

However, sampling social media content often presents its own unique considerations to address. The first, as explained by Giglietto and Selva (2014), is that Twitter observations rarely fit a normal distribution. In the case of retweets, research has shown that only a few posts are retweeted many times, and that most tweets posted are only retweeted a few times if at all (Van Grove, 2010). This has significant implications for the dataset. A highly retweeted tweet will appear as many times as it was retweeted, essentially saturating the sample. However, by deleting all the retweets there is then a risk of under-sampling highly retweeted posts that were the most predominant tweets in the social-mediated conversation surrounding a topic.

To avoid saturating the sample with retweeted posts and potentially under-sampling highly retweeted posts, a sampling strategy based on number of retweets was developed. First, tweets in the dataset were organized by frequency, this facilitated identifying how many times a post was retweeted. Then, a histogram of retweet frequency values was created in order to identify natural thresholds to separate and allocate posts into one of four distinct categories: (1) no retweet, (2) low retweet rate, (3) moderate retweet rate, and (4) high retweet rate. Since highly retweeted posts tend to be significantly fewer than those that either hardly get retweeted or do not get retweeted, the number of high retweet rate posts were selected as the baseline for the rest of the sampling strata.

This strategy was applied to each of the five weeks in the sampling timeframe. This choice was informed by the fact that the threshold for moderate and high retweet rates vary depending on if the topic on Twitter had yet to reach traction, was at its peak or had waned over time. *Table 4* through *Table 8* (see Appendix A) illustrate the retweet rate categories, their range, the total posts, the total original posts and the sampled posts for each of the five weeks.

To select the posts for each of the remaining sampling strata for analysis, Random.org Random Integer Generator was used to randomly select numbers for the no retweet category, the low retweet rate category, the moderate retweet rate category, which corresponded to the number of remaining available posts for analysis in each category. In the end, $N$ = 2,060 tweets were selected for the content analysis.

## Units of Analysis

The main unit of observation in this study are tweets. *Tweets* are defined as any post created by a Twitter user; it may include an image, video, link and up to 140 characters of text (Sreenivasan et al., 2011). Five main aspects of tweets are examined in this content analysis: audience behavioral engagement, content modality, visual content type, visual content focus, and information source type.

**Audience behavioral engagement** is defined as the outcome of participation or involvement. Specifically, it pertains to the many ways in which social media users interact with content. As discussed in Chapter 4, there are three main ways in which social media users interact with content: (a) social endorsement, (b) dialogue, (c) information dissemination (C. Kim & Yang, 2017).

Social endorsement is a visible cue that illustrates the extent to which a social media post has been positively received in its network. In the case of Twitter, social endorsement comes in the form of a “like” (Oremus, 2015). It is measured as the number of times in which a tweet has been “liked” by Twitter users. Dialogue is the replies to or comments toward a specific social media post. In the case of Twitter, dialogue comes in the form of replies to Tweets, essentially forming a thread. It is measured as the number of replies a Tweet has from users. Information dissemination is the act of re-posting content by means of the respective features available in the social media platform. In the case of Twitter, information dissemination occurs via re-tweets. It is measured by the number of times a Tweet has been retweeted by other users in the network.

**Content modality** can be understood as the general format of content. Twitter currently supports the following content modalities: text-based content, image-based content, GIF-based content, and video-based content. Text-based content is a social media post that only includes text. In the context of this study, text-based content is a tweet that does not include an embedded image or video. Image-based content is a social media post that may include text as well as images, or just an embedded image. Image-based content in Twitter is a tweet that may include text characters, images and/or a link that includes an image. GIF-based content is a social media post that may include text as well a GIF, or just a GIF. GIF-based content in Twitter is a tweet that may include text characters and a GIF, or just a GIF. Video-based content is a social media post that may include text as well as a video, or just an embedded video. Video-based content in Twitter is a tweet that may include text characters, videos and/or a link that includes a video.

**Visual content type** refers to the different categories of images a social media post may include. According to King (2015), visual messaging research highlights two different types of visual content image studied: (1) graphical, and (2) illustrative. Graphical visual content involves “data-driven representations” of information – for example, ratios, probabilities, frequencies, etc. (King, 2015, p. 194). In Twitter, graphical visual content includes images that depict graphs, charts, infographics and other forms of data visualization. Illustrative visual content is social media posts that include pictures that capture the physical, material and emotional effects of an event. In Twitter, illustrative visual content includes photographs and pictures that are non-numeric and have indexical qualities (King 2015, p.194).

**Visual content focus** is the thematic element that the images included in a social media post illustrate or prioritize. There are three main foci that pertain to social-mediated disaster communication: informational focus, human-interest and destruction. Visual content with an informational focus is that which centers on illustrating the practical. An informational focus may include photographs of government officials during a press conference, as well as photographs of objects. Visual content with a human-interest focus involves images that feature people outside of press conferences. A human-interest focus will involve photographs of victims or heroes within the context of a disaster. This type of visual content focus predominantly concentrates on conveying the extreme or intense emotional states of the people experiencing the disaster. The focus of destruction is social media posts that include images that depict the environment, scenery and climatological phenomena – especially when it stands to provide clear situational awareness regarding "the state of things." Depictions of collapsed infrastructure and the decimation of the environment following a natural disaster are fine examples of this type of visual content focus.

**Information source type** is defined as the individual or entity associated with the Twitter account that posted the tweet. There are four main types of social-mediated disaster communication information sources: celebrities, news media organizations, government organizations, and "ordinary users." Organizations are defined as public entities at the local, state and federal level participating in emergency management functions, this includes fire departments, law enforcement agencies, emergency management agencies, emergency medical services and the military (Coppola, 2015). This type of information source also includes non-governmental relief organizations that are defined as “nonprofit, civilian-based and staffed organizations that depend on outside sources of funding and materials (…) to carry out a humanitarian-based mission and associated goals in a target population” (Coppola 2015, p.523).

News media organizations are defined as commercial organizations or individuals committed to the daily delivery of news in text, audio or visual format. This applies to (1) the digital counterpart of legacy news media organizations (e.g., The New York Times, CNN, etc.); (2) news media organizations endemic to the Internet and without an offline equivalent (e.g., the Huffington Post); (3) and individual journalists affiliated with a news media organization. Celebrities are defined as individuals who accrue considerable media attention and enjoy public recognition due to their social status or career affiliation such as actors and actresses, as well as distinguished athletes, artists or military personnel (Hellmueller & Aeschbacher, 2010; McCracken, 1990). The fourth main social-mediated disaster communication information source type, “ordinary users,” is defined as any social media user that is not a celebrity, journalist, public official, non-governmental relief organization representative, or automated twitter bot.

In addition to these main information source types, there are other information sources that are common in a social-mediated disaster communication context. These other sources include Twitter bots or automated users; politicians; CEO’s; and information dissemination entities, which are users that are not automated bots nor news media organizations, but that focus on aggregating and sharing content with similar thematic content.

## Coding Scheme

Coders rated each tweet on 18 items (Please see Appendix B for coding protocol). Additional post items included basic information provided by Crimson Hexagon such as tweet post date, URL, contents, author, name, country, state/region, city/urban area, category (valence), klout score, gender, number of posts, number of followers and number of friends. The items coded also included the main aspects previously mentioned.

Coders first identified themselves as either Coder 1 or Coder 2. Then, they checked whether the tweet was still publicly available by using the post URL. While Crimson Hexagon provides certain information about tweets that were publicly shared during the specified date range, all posts were not necessarily available at the time of analysis. This is due to many reasons including but not limited to Twitter eliminating the account, as the platform has been known to do with accounts associated with bots and trolls (Timberg & Dwoskin, 2018). Another reason as to why certain posts were unavailable at the time of coding was due to users changing their privacy settings since the tweet was originally publicly posted in 2016. Research has documented that social media users tend to change their privacy settings for several different reasons (Rainie, 2018).

After checking whether a tweet was still live, coders noted whether the Twitter user that posted the tweet was a verified account. Key engagement metrics were assessed by noting the number of likes, retweets and replies that the post had at the moment of data coding. Coders examined each tweet's author and determined the best fitting information source type, choosing between (1) celebrities, (2) news media organizations, (3) relief organizations, (5) private/corporate organizations, (6) "ordinary users," (7) Twitter bots, (8) politicians, (9) CEO's, and (10) information dissemination entities. Twitter bots are accounts that typically do not have a profile picture, have many posts, only seem to share links to other websites or news articles, and hardly have any followers. In turn, information dissemination entities are users that, based on Twitter activity and profile cues, do not seem to be either Twitter bots or news media organizations, but actual users that aggregate and share content typically related with a specific industry or topic area.

In addition, coders determined the tweet type for each of the posts. The majority of these categories were adapted from Sutton and colleagues' (2015a) terse message retransmission studies – when needed, supplemental categories were incorporated into the coding protocol following Pilot Study 1 and Pilot Study 2. Coder categorized each tweet as either (1) hazard information, (2) hazard impact: deaths/destruction, (3) closures/openings, (4) protective action recommendation, (5) information, (6) help/directed information, (7) thank you/appreciation, (8) volunteer/donate/help, (9) emotion/judgment/evaluation, (10) humor, (11) prayer, (12) miscellaneous, (13) unsure or not on topic, or (14) alert.

Coders also noted whether tweets included links to external webpages or embedded content. Further, they categorized this linked content into one of eight options: (1) news organization website, (2) government organization website, (3) relief organization website, (4) private/corporate organization website, (5) crowdfunding platform, (6) link not found, (7) another user's social media post, or (8) other.

Regarding some of the specific content features presented in Chapter 3 and discussed in Chapter 5, coders determined each post's modality, choosing between (1) text-based, (2) image-based, (3) GIF-based, and (4) video-based. Image-based posts were further categorized as the coders determined whether the visual content was either illustrative or graphic. Further, within image-based illustrative posts, coders noted the visual foci including (1) humor, (2) not related to Hurricane Matthew, (3) Features people, (4) Features animals, and (5) features nature and destruction. The original image-based illustrative foci discussed in Chapter 5 and alluded to earlier in this Chapter – informational, human-interest and destruction – were modified and adapted following Pilot Study 1 to address the variability of content that may have fit in both of these categories.

Other additional content categories that were added or modified following Pilot Study 1 and Pilot Study 2 include the more granular categories of ‘people focus’ illustrative images (i.e., hero focus, human-interest focus, ‘talking head’ focus, and other), and video types (i.e., user-generated video, news coverage, support or relief effort video, graphic/informative, and other).

## Coders and Reliability

Coders were one doctoral candidate and one full professor, the former in mass communication and the latter in marketing. Both coders were female and Hispanic. The protocol include manifest as well as latent variables. According to Riffe, Lacy and Fico (2014), the latter may constitute a threat to within-study and external validity in content analyses. In order to assess reliability, coders independently rated several randomly selected tweets on all items, 15% of the overall final study sample after cleaning the data and removing retweets from the sample. The reliability coefficient for each variable was assessed using Scott's pi, which corrects for chance agreement (Riffe, Lacy & Fico, 2014).

## Pilot Study 1 and Pilot Study 2

Two pilot studies were conducted in order to test and evaluate the coding protocol and coding process. For each pilot study, the Boolean search query was used in Crimson Hexagon to again access the census of all publicly available Hurricane Matthew-related tweets posted within September 23, 2016, and October 24, 2016. For the purpose of the pilot studies, a simpler data export strategy was employed than the one previously described and used for the main content analysis. One randomly sampled export of 10,000 tweets were used for the pilot studies. However, similar to the main content analysis stratified sampling strategy, frequencies were also used to divide the dataset into four categories that reflect the extent to which posts were shared by other users in the network: no retweet rate posts, low retweet rate posts, moderate retweet rate posts, and high retweet rate posts. At that point, the duplicates were removed, and n = 216 posts were selected for analysis, the number of posts that represent 10% of the study sample – the minimum threshold for conducting the inter-coder reliability assessment (Riffe et al., 2014).

For Pilot Study 1, both coders coded all items for the 216 posts. However, the results of the first pilot study did not yield acceptable intercoder reliability for most of the items. As such, coder 1 and coder 2 met to discuss critical discrepancies in coding and issues with the original coding protocol. Following those discussions and edits to the coding protocol, a second pilot study was conducted. For Pilot Study 2, a different set of 216 posts were selected from the same post sample used for Pilot Study 1. *Table 9* illustrates Krippendorff's alpha for all major variables from Pilot Study 2. However, Krippendorff's alpha was not calculated for the audience engagement metrics (i.e., number likes, favorites and retweets) because the number associated with these metrices were still increasing during the data coding stage. For example, if coder 1 coded posts earlier than coder 2, the numbers for these items were found to shift slightly. Following the coding discrepancies identified in Pilot Study 1, referring to a particular post's URL to verify which coder had made the mistake, it was found that the numbers had continue to increase even then.

# CHAPTER 7

# STUDY 1 CONTENT ANALYSIS RESULTS

This chapter presents the content analysis study results. The descriptive statistics are first presented. In turn, that is followed by the results of a binomial logistic regression set on exploring the relationship between information source type and image type. That is followed by the results of a multinomial logistic regression which explores the relationship between information source type and image focus is addressed. Finally, the results of three negative binomial regressions, one for each target audience engagement metric are presented.

## Descriptive Statistics

As it was explained in the previous chapter, the posts that were selected for analysis following Crimson Hexagon's exporting limitations and the stratified sampling strategy employed were $N$ = 2,060. About 81.4% ($N$ = 1,677) of those tweets were available for analysis at the time the posts were coded between December 2018 and March 2019. The remaining 18% ($N$ = 383) of the posts were unavailable.

Despite the fact that the phrases, keywords and hashtags included in the Boolean search query used to gather tweets through Crimson Hexagon were in English, Spanish and French exclusively, a few of the posts in the datasets were, for the most part, written in another language. This mainly happened because users tended to use hashtags in English while writing a post in another language such as German or Portuguese. Of the tweets that were available for analysis, 70.3% ($N$ = 1179) of them were written in

English, 27.1% (*N* = 455) of them were written in Spanish, and 1.8% (*N* = 37) of them were written in French – and six posts were written in another language.

Of the tweets available for analysis, 51.2% (*N* = 859) were posted by Twitter accounts which did not have a verified badge. The remaining 48.8% (*N* = 818) of the tweets were posted by "verified" Twitter users. A 2016 report (Navarra, 2016) showed a considerable increase of accounts being granted a "verified" status on behalf of Twitter. Around that time, there were only about 150,000 verified users, which in contrast with the 300 million active users that the platform boasted at the time, represent a very exclusive category (Kamps, 2015). Further, as Kamps (2015) explains, the verified users were for the most part journalists and sports figures. The public submission process for acquiring a verified status has been put on hold since February 2018. Twitter claims it is working on a new authentication and verification program (Twitter FAQ, 2018).

In addition to verified vs. unverified users, coders also distinguished between the different types of users by determining which of the ten information source categories best described the user responsible for posting the tweet being coded. The most prominent information source type identified were news media organizations. The users that were coded as this particular information source type were responsible for posting 35.5% (N = 595) of the tweets analyzed. This was followed by ordinary users (18%, N = 317), government organizations (11.4%, N = 192), relief or nonprofit organizations (10%, N = 168), information dissemination entities (9.4%, N = 157), private organizations (3.8%, N = 63), celebrities (3.5%, N = 59), bots (3.3%, N = 56), politicians (2.7%, N = 45), and CEOs (1.5%, N = 25). *Table 10* illustrates the prevalence of the fourteen different tweet types that the coders examined.

In the case where a tweet included more than one type of information, for coding purposes, the more prevalent aspect of the message was used to categorize the post according to the different information type categories in the codebook. Prevalence was determined by focusing on the implied purpose or point of the message itself. Prevalence as also assessed by gauging the extent to which the posts focused more on one aspect more than the other(s), in terms of topic, length, syntax, capitalization and exclamation points.

In regard to modality, most of the tweets available for analysis – 49% (N = 822) – were image-based posts. Text-based posts comprised 36.1% (N = 606) of the tweets in the dataset, while the rest of the posts, about 11.7% (N = 197) and 3.1% (N = 52) were video- and GIF-based posts, respectively. Within the image-based posts category, 58.3% (N = 479) of the images were illustrative, while the remaining 41.7% (N = 343) were graphic image type. As for links, 53.8% (N = 902) of the posts included a link while 46.2% (N = 775) of the posts did not. *Table 11* illustrates the frequencies of the different websites types that each link redirected to.

Coders also examined five different illustrative image visual focus types. Of the posts available at the time of analysis that were image-based and included an illustrative image, 45.1% (*N* = 216) featured people, 30.3% (*N* = 145) featured nature and destruction, 9% (*N* = 43) featured other categories, 7.7% (*N* = 37) was not related to Hurricane Matthew, 5.2% (*N* = 25) featured animals, and 2.7% (*N* = 13) featured humor. Within the image-based illustrative-type posts that featured people, 49.1% (*N* = 106) included a hero focus, 38% (*N* = 82) included a human-interest focus, 11.1% (*N* = 24) included a "talking head" focus, and 1.9% (*N* = 4) included another focus. In turn, of the posts available at the time of analysis that were video-based, 30.5% (*N* = 60) of them were coded as user-generated videos, 30.5% (*N* = 60) of them were coded as support or relief effort videos, whereas 21.8% (*N* = 43) of the videos were coded as news coverage, 12.2% (*N* = 24) were coded as graphic or informative, and 5.1% (*N* = 10) were coded as other.

Concerning audience engagement metrics, of the tweets available for analysis, 14.1% (*N* = 236) of posts were not retweeted at all. The post that was retweeted the most was shared 62,224 times. The number of retweets coded displayed a Mdn of 31 (*M* = 531.57, *SD* = 3323.84). Of the tweets available for analysis, 45.9% (*N* = 770) of posts were not replied to at all. The post that was commented on the most had 6,100 replies. The number of replies coded displayed a Mdn of 1 (*M* = 19.55, *SD* = 164.35). Of the tweets available for analysis, 18.5% (*N* = 310) of posts were not favorited at all. The post that was favorited the most was liked 137,009 times. The number of likes coded displayed a Mdn of 17 (*M* = 959.77, *SD* = 7474.05). *Table 12* illustrates the frequencies of each different type of post modality and engagement metrics:

In order to further explore the relationships between the target independent variables and dependent variables, the free software environment for statistical computing, R, version 3.5.3 was used. Since the main dependent variables, number of retweets, number of likes, and number of replies are count data, defined as “statistical information obtained by counting the number of occurrences of categorical data rather than by measuring variables on a number scale” (Vogt & Johnson, 2011, p. 81), only certain types of statistical tests are appropriate. Within these types of statistical tests, negative binomial regression stands as a suitable approach for modelling count data

(Gardner et al., 1995), specifically because of over-dispersion (i.e., when the variance exceeds the mean) which may be due to the presence of zeroes and outliers in the dataset (Payne et al., 2018). Since indeed the variance exceeds the mean of the number of retweets (M = 531.57, Var = 11047961.6), number of replies (M = 19.55 , Var =27013.747), and number of likes (M = 959.77, Var = 55861431.3), negative binomial regression is the more suitable choice than a Poisson regression.

Negative binomial regression models were run to determine if the six main predictor variables – tweet language, the presence of a verification badge, tweet modality, tweet type, information source type and the inclusion of a link – played a role in predicting retweet, reply and liking rates. Using the glmulti package in R, best subset negative binomial regression was conducted. Essentially, best subset approach seeks to identify the "best fit model from all possible subset models" based on specific goodness-of-fit criteria (Zhang et al., 2016, p. 2), where the number of models equals $2^p$, where p equals the number of predictor variables considered. In the case of this study, $2^{11} = 2048$ models were developed and compared based on the Akaike information criterion (AIC), defined as a goodness-of-fit measure used to select among statistical models (…) it adjusts for the number of parameters; the greater the number, the bigger the "penalty" (…) the better the fit, the lower the value of the AIC (Vogt & Johnson 2011, p.7*). Tables 13, 14* and *15* illustrate the negative binomial regression results for the best fit models seeking to predict retweet, liking and reply rates.

In the case of retweets, the best fitting model according to the lowest AIC metric among all subset regression models includes (1) tweet language, (2) tweet type, (3) source type, and (4) modality as its predictor variables. The odds ratio is a "measure of association" (Vogt & Johnson 2011, p.267), which basically illustrates the predicted change on the outcome variables based on one unit change in the predictor.

The full model shows that the effect of tweets written in Spanish, French and other languages other than English make retweeting less likely. Results show that there are certain tweet types that are conducive to higher retweet rates in contrast with tweets that focus on hazard information. These tweets include closures/openings, protective action recommendations, emotion, humor, prayer, and miscellaneous. However, regarding tweet type specifically, there were certain types of tweets that made retweet rates less likely. These include tweets that were not on topic, those that provided general information, and hazard impact. Tweets authored by news media organizations, government organizations, relief organizations, private organizations, ordinary users, bots, CEOs and information dissemination entities were less likely to be retweeted than tweets authored by celebrities. In regard to post modality, tweets that were image-based, GIF-based and Video-based were more likely to be retweeted than text-based posts.

In the case of replies, the best fitting model according to the lowest AIC metric among all subset regression models includes (1) the presence of a verification badge, (2) tweet type, (3) source type, and (4) modality as its predictor variables. Similar to the retweet model, posts authored by unverified users in Spanish, French or other languages were less likely to be replied to in contrast with verified users whose tweets were in English. Tweets authored by news media organizations, government organizations, relief organizations, private organizations, ordinary users, bots, CEOs and information dissemination entities were less likely to be replied to than tweets authored by celebrities. However, tweets authored by politicians were more likely to be replied to than tweets authored by celebrities, although this result was not statistically significant. Tweets that were image-based, GIF-based and video-based were more likely to be replied to than text-based posts. Differing from the retweet model, all tweet type categories that were statistically significant were associated with higher likelihoods of being replied to. These tweet types include closures/openings, protective action recommendations, volunteer, emotion, humor, prayer, miscellaneous, and not on topic.

In the case of likes, the best fitting model according to the lowest AIC metric among all subset regression models includes (1) the presence of a verification badge, (2) tweet type, (3) source type, and (4) modality as its predictor variables. Similar to the replies model, posts authored by unverified users were less likely to be liked in contrast with the tweets posted by verified users. Like the reply model and yet different to the retweet model, all tweet type categories that were statistically significant were associated with higher likelihoods of being liked. These include closures/openings, protective action recommendations, volunteer, emotion, humor, prayer, and miscellaneous. Similar to the previous two models, tweets authored by news media organizations, government organizations, relief organizations, private organizations, ordinary users, bots, CEOs and information dissemination entities were less likely to be liked than tweets authored by celebrities. And again, image-, GIF- and video-based modalities made tweets more likely to be liked than text-based posts.

A binomial logistic regression was run to determine if the type of information source can predict the likelihood of choosing a particular type of visual content between illustrative and graphic categories. In order to meet one of the basic assumption for this statistical test, specifically concerning the number of cases per cell, information source was recoded to include only four categories. Relief organizations, private organizations, bots and information dissemination entities were recoded as “other sources,” whereas politicians and CEOs were added to the celebrity information source category. The following *Table 16* illustrates the results of the binomial logistic regression analysis of information sources’ visual content type.

The results suggest that both news media organizations ($p < .05$) and government organizations ($p < .001$) are more likely to feature graphic images in their image-based tweets rather than illustrative images.

A multinomial logistic regression was run in order to determine if specific types of information sources are more likely to feature one type of illustrative image focus rather than others. In order to meet one of the basic assumption for this statistical test, specifically concerning the number of cases per cell, the illustrative image focus type was recoded to only include three types. Specifically, humor, not related to Hurricane Matthew, features animals were included in the “other” category. The following Table 17 illustrates the results of this multinomial logistic regression:

The results of the multinomial logistic regression suggest that news media organizations ($p < .01$) and ordinary users ($p < .001$) are less likely to include illustrative images that feature people rather than other types of image focus.

## Hypothesis and Research Question Testing

The first set of research questions focused on the relationship between information source type and the predilection for posting tweets with one type of visual content over another. Binomial logistic regression analysis was used to test if information source significantly predicted predilection for one type of visual content over another.

The results of the regression show a highly significant overall effect (*Wald*=29.025, *df*=4, *p*<.000). RQ1, which asked whether news media are more likely to feature illustrative disaster visual content in their social-mediated messages rather than graphical visual content, was not supported (β = 0.619, *df*=1, *p* <.05). In fact, results show that, like government organizations, news media organizations are statistically significantly more likely to feature graphical visual content rather than illustrative content in their social-mediated messages. RQ2, which asked whether government organizations are more likely to feature graphical disaster visual content in the social-mediated messages rather than illustrative visual content, was supported (β = 1.069, *df*=1, *p* <.001). Finally, RQ3, which asked whether ordinary users are more likely to feature illustrative disaster visual content in their social-mediated messages rather than graphical visual content, was not supported (β = 0.2319, *df*=1, *p* =.504).

The second series of research questions focus on the relationship between information source type and illustrative image focus. Based on the results of a multinomial logistic regression, RQ4, which asked whether government organizations are more likely to feature disaster visual content with a people focus rather than other types of focus, was not supported (β = 0.051, *df*=1, *p* =.903). RQ5, which asked whether news media are more likely to feature disaster visual content with a people focus rather than other types of focus, was not supported, although the results were statistically significant (β = -0.732, *df*=1, *p* <.05). In fact, news media organizations were less likely to feature disaster visual content with a people focus rather than other types of focus. RQ6, which asked whether ordinary users are more likely to feature disaster visual content with a destruction focus rather than other types of focus, was not supported (β = -0.398 , *df*=1, *p*

= .322). However, ordinary users were found to be less likely to feature content with a people focus ($\beta$ = -1.243, *df*=1, *p* = .001), than the "other" criteria used as the constant for the model.

The next series of hypotheses explore the relationship between content modality and audience engagement. To accomplish that, negative binomial regression analysis was used to test if content modality significantly predicted retweet rates, like rates and reply rates. The results of a negative binomial regression on retweets shows that for a one unit change in image-based tweets, the difference in the logs of expected counts of the number of retweets is expected to change by 0.700 (0.464-0.934, p <.000), given that the other predictor variables in the model are held constant. As such, H1a, which states that audiences are more likely to share disaster image-based social media content rather than text-based content, is supported.

The results of a negative binomial regression on likes shows that for a one unit change in image-based tweets, the difference in the logs of expected counts of the number of likes is expected to change by 0.635 (0.363-0.905, p <.000), given that the other predictor variables in the model are held constant. As such, H1b, which states that audiences are more likely to favor disaster image-based social media content rather than text-based content, is supported.

In turn, the results of a negative binomial regression on replies shows that for a one unit change in image-based tweets, the difference in the logs of expected counts of the number of replies is expected to change by 0.682 (0.419-0.943, p <.000), given that the other predictor variables in the model are held constant. As such, H1c, which states that audiences are more likely to reply to disaster image-based social media content rather than text-based content, is supported too. Taken together, H1a, H1b and H1c support H1, which states that audiences are more likely to engage with disaster image-based social media content rather than text-based content.

The following series of hypotheses also considered the effect of modality on audience engagement, specifically focusing the increased likelihood of engagement of video-based content rather than image- and text-based content. The results of a negative binomial regression on retweets shows that for a one unit change in video-based tweets, the difference in the logs of expected counts of the number of retweets is expected to change by 2.605 (2.273-2.948, $p < .000$), given that the other predictor variables in the model are held constant. As such, H2a, which states that audiences are more likely to share disaster video-based social media content rather than image- and text-based content, is supported.

The results of a negative binomial regression on likes shows that for a one unit change in video-based tweets, the difference in the logs of expected counts of the number of likes is expected to change by 2.716 (2.380-3.155, $p <.000$), given that the other predictor variables in the model are held constant. As such, H2b, which states that audiences are more likely to favor disaster video-based social media content rather than image- and text-based content, is also supported.

In turn, the results of a negative binomial regression on replies shows that for a one unit change in video-based tweets, the difference in the logs of expected counts of the number of replies is expected to change by 2.604 (2.243-2.977, $p <.000$), given that the other predictor variables in the model are held constant. As such, H2c, which states that audiences are more likely to reply to disaster video-based social media content rather than image- and text-based content, is supported too. Taken together, H2a, H2b and H2c support H2, which states that audiences are more likely to engage with disaster video-based social media content rather than image- and text-based content.

# CHAPTER 8

# STUDY 2 ONLINE EXPERIMENT METHOD

This chapter outlines the research design, the pilot thematic analysis conducted to identify prevalent visual themes in online disaster preparedness campaign materials, the sampling protocol, the experimental procedure, the items used to measure the dependent variables, and the results of the online experiment pilot study.

## Research Design Overview

This study involves a 2 (Post Modality: Image- vs. GIF-based Social Media Posts) x 3 (Visual Focus: Reactive- vs. Proactive- vs. Hero-themed Social Media Post Visuals), including an additional text-based condition, between-subjects experiment design. An online self-report questionnaire was used to measure past hurricane experiences, crisis information seeking and sharing intentions, risk perceptions, hurricane preparedness adoption intentions, source credibility perceptions, message credibility perceptions, manipulation check items, and demographic items. Prior to the online experiment, two pilot studies were conducted in order to (a) identify prevalent themes in online hurricane preparedness social media campaign materials, (c) use the visual thematic analysis findings to inform the development of the stimulus materials for the online pilot experiment, and (b) pretest the main online experiment setup.

### Disaster Preparedness Message Development

The disaster preparedness copy used for the online experiment was based on real national public service campaign materials. The U.S. Federal Emergency Management

Agency (FEMA) regularly partners and shares materials from the national public service campaign, “Ready,” which aims to educate and motivate Americans to proactively prepare for and respond to a variety of natural and man-made disasters (*About the Ready Campaign | Ready.Gov*, n.d.). The Ready campaign also features a Hurricane Seasonal Preparedness Digital Toolkit that provides preparedness-related copy for social media posts, and links to FEMA’s vast online multimedia library (*Hurricane Seasonal Preparedness Digital Toolkit | Ready.Gov*, n.d.).

The copy used for the online experiment posts was specifically adapted from Ready’s 2019 Hurricane Preparedness Week Daily Themes materials. The disaster preparedness posts developed for the online experiment focused on five areas shown in *Table 18.* In addition to the text-based information of the disaster preparedness social media posts, accompanying videos and images were needed as well. To identify the prevalent themes in online hurricane preparedness campaign visual materials, a pilot study was conducted.

**Pilot Study 1: Disaster Preparedness Visual Themes Analysis**

A textual analysis of FEMA’s online multimedia gallery was conducted to identify prevalent themes to inform the development of stimulus materials. The primary criteria used to collect the visuals for analysis was whether they could be used alongside one of the five hurricane preparedness themes listed earlier. Visuals collection ceased when the saturation criterion was met (Saunders et al., 2018). To analyze these FEMA visuals, a qualitative data analysis technique involving data reduction, data display, and conclusion drawing/verification the was employed (Fisher Liu, 2009; Miles & Huberman, 1994). Potential visual themes were first identified, coded and listed. Then, redundancies were eliminated by grouping similar themes.

Three main visual themes emerged from the analysis: reactive, proactive and hero visual themes. The "reactive" visual theme groups all the videos and images that illustrate the destructive outcomes associated with strong winds, storm surge or floods (i.e., collapsed physical structures, flooded houses, etc.) and/or negative outcomes that are common in disaster scenarios (i.e., gridlock traffic in last-minute evacuations, empty food store shelves, etc.). In turn, the "proactive" visual theme groups all the videos and images that show individuals proactively engaging in commonly recommended protective actions (i.e., buying supplies, creating a kit, preparing to evacuate). Finally, the "hero" visual theme includes all the videos and images that show emergency management stakeholders (i.e., police, firemen, Coast Guard, etc.) "taking care of," rescuing or helping disaster-stricken populations.

Since these depictions often incorporate the same visual elements across themes, visuals were coded based on the most prevalent theme. In other words, there were materials that displayed events that could fit more than one of the main thematic areas identified through the analysis. The final determination was based on which was the most dominating/prevalent depiction. In this context, thematic prominence was determined by camera angle and focus, as well as the temporal dimension or how long an instance took place.

## Stimulus Materials Development

The online experiment involved showing participants one out of seven versions of a mock Twitter profile belonging to a supposed federal disaster and weather hazard mitigation agency.

**The National Flood and Hurricane Mitigation Center (NFHMC).** A fictitious U.S. federal disaster mitigation agency was created for the online experiment. The NFHMC is based on FEMA, the National Oceanic Atmospheric Administration (NOAA) agency, the National Weather Service (NWS) and the National Hurricane Center (NHC). A logo, similar in nature to that of the NWS, was created.

**The NFHMC Twitter Profile.** FEMA's Region IV Twitter profile was used to create the NFHMC profile. Certain elements, namely the Twitter profile picture, the Twitter banner profile picture, the Twitter account name, the Twitter account handle, the Twitter bio, and the website link were all edited to reflect the NFHMC-specific elements. In turn, the verified badge, the location of the Twitter account, the date of the account creation, the number of photos of videos, the six-image preview of the photos and videos uploaded, and the number of tweets, following, followers, likes and lists from FEMA's Region IV profile were kept the same. The Twitter profile was created using Adobe Photoshop graphic design software. *Figure 3* illustrates a blank version of the NFHMC Twitter profile.

**Twitter Posts Visuals.** The first step in developing the different Twitter post visuals needed for the experiment was finding videos that could potentially fit one of the five stories for any of the three different visual theme conditions. A total of fifteen videos were collected from either FEMA's online media gallery and YouTube account, the

Coast Guard's online media gallery, or several news organizations' YouTube accounts. The videos were cropped if they included a watermark, and they were cut for length as well. Then, the cropped and shortened video files were saved in GIF format. One of the GIF stills was used as each story's image condition counterpart.

**Twitter Posts.** To create the Twitter posts, certain existing elements from tweets posted on FEMA's Region IV Twitter profile were integrated, such as (1) the date in which the Tweets were posted, and (2) the specific engagement metrics (i.e., likes, retweets, replies). This ensured that the mock NFHMC Twitter profile matched FEMA Region IV's posting frequency, and audience engagement extent.

**Manipulation**

Study participants were shown one of seven conditions: (1) a text-based condition, (2) a reactive GIF condition, (3) a proactive GIF condition, (4) a hero GIF condition, (5) a reactive image condition, (6) a proactive image condition, or (7) a hero image condition. Each of the visual conditions had one type of post modality and one type of visual focus.

**Post Modality.** Each hurricane preparedness story had one of three modality versions: text-based, image-based, and GIF-based. The copy, tweet post date, and engagement metrics were held constant across the different conditions.

**Visual Focus.** Each hurricane preparedness story had one of three visual focus themes: reactive focus, proactive focus and hero focus. The visual focus themes were based on the findings of the disaster preparedness visual theme analysis. The copy, tweet post date, and engagement metrics were held constant across the different conditions

## Sample and Amazon Mechanical Turk

In broad terms, Amazon Mechanical Turk (MTurk) can be defined as a "crowdsourcing web service that coordinates the supply and the demand of tasks that require human intelligence to complete" (Buhrmester et al., 2011). Researchers and social scientists alike use MTurk for research participants recruitment. According to Buhrmester, Kwang and Gosling (2011), MTurk counts with several features that make it an ideal tool for researchers, namely its "integrated participant compensation system; a large participant pool; and a streamlined process of study design, participant recruitments, and data collection" (p.3).

Participants recruited via MTurk are part of what the web service labels "Mechanical Turk workers," individuals that willingly complete human intelligence tasks in order to receive monetary compensation. Research has shown that MTurk workers are relatively representative of the American Internet users population (Paolacci et al., 2010), some studies claiming that the former is actually more demographically diverse than the latter (Buhrmester et al., 2011). Regarding the quality of the data obtained from MTurk participants and how it compares to data obtained through other recruitment methods, research concludes that the former is at least as reliable as the latter (Buhrmester et al., 2011; Paolacci et al., 2010).

There are some differences between MTurk participants and the US general population. Paolacci et al. (2010) report that the MTurk sample (1) has a higher number of females, (2) is slightly younger than the general population, (3) reports higher educational attainment, and (4) discloses lower income levels. However, despite these disparities, the MTurk population is closer to a representative U.S. sample than the population of the average American undergraduate student typically sampled for most research (Buhrmester et al., 2011; Paolacci et al., 2010).

The participants for the online experiment were recruited using Amazon MTurk so long as they met the two study requirements. The first requirement is that the participants must currently reside in one of the eight states served by FEMA Region IV: Alabama, Kentucky, Mississippi, North Carolina, Southern Carolina, Florida, Georgia, and Tennessee. These specific states were selected because they tend to encounter hurricanes with more frequency than midwestern or west coast states. The second qualification that participants had to meet was to complete the experiment HIT through either a laptop or desktop. The stimulus materials and the Qualtrics survey are not optimized for mobile. In addition, exploring the potential effects of device type – although an interesting aspect worth researching – is outside of the current scope of this project. Qualtrics embedded data and branch features were used to ensure that MTurk users accessing the study through a mobile device (i.e., smartphone or tablet) would be immediately redirected to the end of the survey.

## Dependent Measures

A total of six dependent variables were measured to assess the effect of social-mediated disaster preparedness post modality and visual focus on audience perceptions and behavioral intentions. The dependent variables related to audience perceptions include (1) risk perceptions, (2) source credibility perceptions, and (3) message credibility perceptions. In turn, the dependent variables related to audience behavioral intentions include (1) crisis information seeking and sharing intentions, and (2) adoptions intentions. Additional dependent measures include information recall. Past hurricane experience was assessed as well to explore its potential moderating effect on audience perceptions and behavioral intentions.

**Past Hurricane Experiences.** To measure the potential moderating effect of past hurricane experience on audience perceptions and behavioral intentions, past hurricane experiences were assessed with two questions developed by Demuth et al. (2016). The first question includes five items describing typical hurricane-related experiences, participants had to respond whether they or someone in their household experienced those events, answers were either "yes" or "no." The second question asks participants to rate the severity of their own hurricane experiences impact, with the Likert scale measuring 7 points from "not at all severe" to "extremely severe."

**Crisis Information Seeking and Sharing.** Crisis information seeking intentions were measured using a seven-item question developed by Lee and Jin (2019). Participants were asked to indicate the extent that they agreed with a series of statements describing information seeking behaviors through different means, with the Likert scale measuring 7 points from "strongly disagree" to "strongly agree."

**Risk Perception.** Risk perception was measured by assessing both the affective and cognitive risk perception using a scale developed by Trumbo et al. (2016). Affective risk perception was assessed by asking participants to rate the extent that they agree with a series of statements regarding how the possibility of a major hurricane makes them feel, with the Likert scale measuring 5 points from "strongly disagree" to "strongly agree." In turn, cognitive risk perception was assessed by asking participants to rate the extent that they agree with a series of statements regarding different ways to understand the risks of hurricanes, with the Likert scale measuring 5 points from “strongly disagree” to “strongly agree.”

**Adoptions Intentions.** The extent to which participants agreed to engage in the protective action recommendations promoted in the experiment’s preparedness stories was assessed using a modified version of Terpstra and Lindell's (2012) adoptions scale. Participants were asked if they intended to do any of the five recommended actions promoted in the NHFMC’s posts, with the Likert scale measuring 5 points from “certainly not” to “certainly.”

**Source Credibility.** The extent to which participants perceived the NFHMC as a credible source was assessed using McCroskey and Teven's (1999) source credibility scale. Participants were asked to rate the NFHMC on eighteen different qualities using semantic differential pairs.

**Message Credibility.** Participants’ message credibility perceptions were measured individually for each of the five posts. Participants were shown the individual story post and were asked to rate the extent that they found the information to be believable, accurate, trustworthy, biased and complete, with the Likert scale measuring 7 points from “strongly disagree” to “strongly agree.” The message credibility scale was adapted from the one developed by Flanagin and Metzger (2000).

In addition to the previous hurricane experiences question and the six dependent variables, the questionnaire also included two manipulation check questions, an open-ended text-entry attention check question, and a series of demographic questions including age, sex, race, marriage status, education level, income, and political affiliation.

A final open-ended question at the end of the survey asks participants for feedback on the study.

## Pilot Study Results

A pilot study was conducted to assess the viability of the experiment setup. An Amazon MTurk HIT was created to recruit participants to participate in the experiment. The location qualifier was set (only the eight states from FEMA Region IV), and the mobile device disqualifier was added to the Qualtrics survey. The first time the study was launched, the Amazon MTurk “masters” qualification was selected, and the number of study completions stalled after only a few responses. The study was launched a second time removing the “masters” qualification, but again it stalled after about 12 completions. An assessment of the open-ended questions revealed that most participants felt that the .50 cent compensation for the average 20-minute task completion time was too low. The study was then re-launched offering $1.00 for completing the MTurk HIT. Participants that had already participated in the experiment were given a retroactive bonus to ensure that the compensation was fair and consistent. Further, participants that had completed the experiment through the earlier launches were given a qualifier to bar them for participating in the study a second time.

# CHAPTER 9

# STUDY 2 ONLINE EXPERIMENT RESULTS

This chapter presents the online experiment study results. The descriptive statistics of demographic variables are presented first. Their comparison to other population estimates, such as the American Community Survey (ACS) 1-year estimates is described. In turn, that is followed with the descriptive statistics of all major variables in the study. Then, the chapter ends with the research question section, which lists the statistical results of a series of two-way MANOVAs, and mediation as well as moderation effects with serial linear regressions.

## Descriptive Statistics of Demographic Variables

The demographic variables in this dataset were compared with those of 2018 American Community Survey (ACS) 1-year estimates (U.S. Census Bureau, 2018). Two estimates were obtained from the ACS. The first estimate corresponds to the aggregate demographics from Alabama, Florida, Georgia, Kentucky, Mississippi, North Carolina, South Carolina, and Tennessee. These eight states comprise the areas served by FEMA Region IV, as well as the states from which the experiment participants were sampled from. In turn, the second estimate corresponds to the general U.S. population. The comparison of the study demographic variables vis-à-vis these two estimates allows for a more nuanced contrast of the similarities and differences between them (see *Table 19*, *Table 20*, and *Table 21* in Appendix A).

Some of the demographic variables in the study were measured in a different way than how the ACS presents its data. Certain study variables, like educational attainment and income, were re-coded to facilitate comparison between the different estimates. However, other demographic variables reflect the estimates for age groups outside of the scope of the present study. For example, the ACS marriage status estimates correspond to the total population over 15 years of age and older – which makes sense considering that, under certain conditions, many states in the U.S. allow the marriage of two individuals under the age of eighteen (Stritof, 2019). Also, the Hispanic or Latino and race estimates from the ACS dataset are based on the "all ages" estimates, which include children and minors – a population that is not available or accessible through Amazon MTurk. These population discrepancies, then, mean that both the FEMA Region IV and the general U.S. population estimates for the Hispanic or Latino, race and marriage status variables could be different because they include a wider range of the general population.

Regarding the present study, age was a continuous variable ($M$ = 39.49, $SD$ = 12.60), the participants age ranged from 18 to 73. Gender was a nominal variable with male coded as '1, 'female as '2' (Male = 34.7%, Female = 65.3%). Hispanic or Latino ethnicity was a dichotomous variable with yes coded as '1' and no coded as '2;' the participants who indicated being of Hispanic or Latino descent were 9.8% of the study sample. Race was a nominal variable with its categories coded as '1' (white), '2' (black), '3' (Asian), '4' (other), and '5' (refuse to answer). Most participants identify as 'white' (75.9%), followed by 'black' (15.1%), then 'Asian' (4.5%), and finally, the respondents that 'didn't know or refused to answer' (4.5%). Marriage status was a nominal variable with married coded as '1,' widowed coded as '2,' divorced coded as '3,' separated coded as ‘4,’ and never married coded as ‘5.’ Married participants account for most of the sample (50.6%), followed by never married (35.9%), divorced (10.6%), widowed (2.0%), and separated (.8%).

Educational attainment was an ordinal variable with seven categories ranging from ‘high school incomplete’ to ‘post-graduate degree,’ coded from 1 to 7, accordingly. Participants reported obtaining a four-year college or bachelor’s degree (33.1%), some college (18.8%), an associates degree (17.1%), a postgraduate degree (14.7%), high school complete (11%), some postgraduate or professional school (4.1%), and high school incomplete (1.2%). The sample median for education was ‘6,’ indicating four-year college or bachelor’s degree (*SD* = 1.54). Income was also an ordinal variable with twelve categories ranging from ‘less than 10k’ to ‘150k or more,’ coded from 1 to 12, accordingly. For income, participants reported $50,000 to just under $75,000 (23.3%), $30,000 to just under $40,000 (13.9%), $75,000 to just under $100,000 (13.5%), $40,000 to just under $50,000 (13.1%), $20,000 to just under $30,000 (10.2%), $10,000 to under $20,000 (9.8%), $100,000 to just under $150,000 (8.2%), less than $10,000 (3.7%), refuse to answer (2.0%), $150,000 or more (1.6%), and don’t know (.8%). The sample median for income was ‘5,’ indicating the $40,000 to just under $50,000 range (*SD* = 2.16).

State was measured as a categorical variable (Alabama coded as ‘1,’ Florida ‘2,’ Georgia ‘3,’ Kentucky ‘4,’ Mississippi ‘5,’ North Carolina ‘6,’ South Carolina ‘7,’ Tennessee ‘8,’ and other ‘9’). Most participants reported residing in Florida (34.7%), followed by Georgia and North Carolina (18.0%), then Tennessee (8.2%), followed by

Alabama and Kentucky (6.5%), South Carolina (5.3%), Mississippi (2.4%), and other (.4%).

In comparison with the general U.S. population, the ACS estimates illustrate that the FEMA Region IV states population tends to be the most similar regarding age and the male/female ratio. Slight differences can be observed for marriage status, educational attainment and income. There are less married and never married people; there are more separated, divorced and widowed people. While there are less people that report having a bachelor's degree or higher, there are more people that report having incomplete high school, complete high school, as well as some college and/or associate degrees. Regarding income, FEMA Region IV states report more people with incomes ranging from less than 10k to slightly less than 75k, and less people reporting incomes that are 75k a year or higher. The sharper contrasts between the sample states and the general U.S. population, according to the ACS estimates, involve ethnicity and race. There are less people of Hispanic and/or Latino ethnicity than in the general U.S. population. Concerning race, there are less white and Asian people, but more black people.

Compared to the ACS estimates of the FEMA Region IV states, the present MTurk sample is similar in age, but heavily skewed towards females. There are less people that report a Hispanic or Latino ethnicity. Regarding race, the sample includes more white people and Asian people, but less black people. At least in that regard, the MTurk sample more closely mirrors the general U.S. population than it does the FEMA Region IV states estimates. The share of participants that were either married or never married where higher than the sample states; but there were less participants that reported being widowed, divorced or separated.

Previous research shows that the MTurk population is more representative of national samples than other types of convenience sampling (Berinsky et al., 2012; Huff & Tingley, 2015; Hunt & Scheetz, 2018). However, the present study design may have had unforeseen implications on the sample demographics. First, there was restricting MTurk workers from any location outside of the FEMA Region IV states – although 3 participants reported 'other' as their current state of residence, the HIT settings on Amazon MTurk ensure that the HIT was not visible to workers outside the study sample states. Considering recent incidents involving automated responses (i.e., bots) and MTurk workers with little to no English language proficiency that infiltrate studies (Simone, 2019), a simple screening test was used to recruit participants. Only MTurk workers that answered the screening test correctly were given the system qualification to participate in the online experiment. Further, the online experiment was only available to MTurk workers that accessed the study from either a laptop or desktop, since the survey on Qualtrics was designed to boot any prospective participants from accessing the study from a mobile device.

## Descriptive Statistics of Major Variables

### Previous Hurricane Experience and Risk Perception

In addition to the demographic variables mentioned above, previous hurricane experience was assessed to be included as a control in the analyses. Previous hurricane experience was measured by using six different items asking respondents to indicate whether they had experienced a series of hurricane-related aspects including evacuation ($M$ = .612, $SD$ = .488), property damage ($M$ = .551, $SD$ = .498), financial losses ($M$ = .338, $SD$ = .474), injury ($M$ = .032, $SD$ = .178), and distress ($M$ = .538, $SD$ = .499). The sixth previous hurricane experience item asked respondents to indicate their impact severity appraisal (*M* = 3.24, *SD* = 1.60). *Table 22* illustrates the mean, standard deviation and alpha of all six of the previous hurricane experience items. The first five items were combined in the analyses and the mean as well as alpha value of this measure is shown (*M* = 2.07, *SD* = 1.44, α = .657) in *Table 23.*

Affective risk perception was measured using four different items asking respondents to indicate the extent that they felt fearful (*M* = 5.16, *SD* = 1.61), worried (*M* = 5.49, *SD* = 1.43), dread (*M* = 4.66, *SD* = 1.75), and depressed (*M* = 3.75, *SD* = 1.71) due to hurricanes. *Table 22* illustrates the mean, standard deviation and alpha of all four of the affective risk perception items. The four items were combined in the analyses and the mean as well as alpha value of this measure is shown (*M* = 4.77, *SD* = 1.40, α = .884) in *Table 23.*

In turn, cognitive risk perception was measured using four different items asking respondents to indicate the extent that they believed that hurricanes cause catastrophic destruction (*M* = 6.39, *SD* = .795), cause widespread death (*M* = 5.47, *SD* = 1.30), pose great financial threat (*M* = 6.26, *SD* = .950), and pose a threat to future generations (*M* = 5.33, *SD* = 1.47). *Table 22* illustrates the mean, standard deviation and alpha of all four of the affective risk perception items. The four items were combined in the analyses and the mean as well as alpha value of this measure is shown (*M* = 5.86, *SD* = .899, α = .775) in *Table 23.*

**Crisis Information Seeking and Sharing Intentions**

Crisis information seeking intentions was measured by using seven different items asking respondents to indicate how likely they were to search for more hurricane-related information by looking on Twitter (*M* = 4.47, *SD* = 2.14), looking on Instagram (*M* = 3.08, *SD* = 1.95), looking on Pinterest (*M* = 2.35, *SD* = 1.66), looking on Snapchat (*M* = 2.29, *SD* = 1.69), talking to people (*M* = 5.49, *SD* = 1.54), emailing people (*M* = 3.53, *SD* = 1.92), and texting people (*M* = 5.17, *SD* = 1.83). *Table 24* illustrates the mean, standard deviation and alpha of all seven of the crisis information seeking intentions items. These seven items were combined in the analyses and the mean as well as the alpha value of this measure is shown (*M* = 3.77, *SD* = 1.14, α = .739) in *Table 23.*

Due to the survey design, participants could answer "Not Applicable" (N/A) if they believed that a crisis information seeking item did not apply to them. The result, then, was that each individual crisis information seeking intention item had a different number of "N/A" cases. About 6.9% of respondents answered that information seeking intentions involving Pinterest and Snapchat were not applicable to them. That was followed, from most to least, by Twitter (4.9%), Instagram (4.5%), texting (2.0%), and both face-to-face/phone conversations as well as emailing people (1.6%) to seek more hurricane preparedness information. For data analysis purposes, the "N/A" responses were re-coded as "Strongly Disagree" (1). The means and standard deviations stated earlier are based on the recoded crisis information seeking items.

In turn, crisis information sharing intentions was measured by using seventeen different items asking respondents to indicate how likely they were to share hurricane-related information by emailing people (*M* = 3.83, *SD* = 1.98), calling people (*M* = 5.26, *SD* = 1.74), texting people (*M* = 5.46, *SD* = 1.58), "liking" a Facebook post (*M* = 4.93, *SD* = 1.98), "share" a Facebook post (*M* = 4.80, *SD* = 2.07), "comment" on a Facebook page (*M* = 3.80, *SD* = 1.96), "retweet" a tweet (*M* = 4.17, *SD* = 2.20), tweet (*M* = 3.74, *SD* = 2.12), post a blog post (*M* = 2.48, *SD* = 1.73), upload pictures to Instagram (*M* = 3.07, *SD* = 1.98), upload pictures to Pinterest (*M* = 2.41, *SD* = 1.78), “like” an Instagram post (*M* = 4.25, *SD* = 2.19), “share” an Instagram post (*M* = 3.66, *SD* = 2.22), “comment” on an Instagram post (*M* = 3.27, *SD* = 1.99), “like” a Pinterest post (*M* = 3.28, *SD* = 2.22), “re-pin” a Pinterest post (*M* = 2.66, *SD* = 1.89), and “comment” on a Pinterest profile (*M* = 2.59, *SD* = 1.84). *Table 24* illustrates the mean, standard deviation and alpha of all seventeen of the crisis information sharing intentions items. These seventeen items were combined in the analyses and the mean as well as the alpha value of this measure is shown (*M* = 3.74, *SD* = 1.34, α = .927) in *Table 23*.

Like the case of crisis information seeking intentions, participants could also answer “Not Applicable” (N/A) if they believed that a crisis information sharing item did not apply to them. The result, then, was that each individual crisis information sharing intention item had a different number of “N/A” cases. About 14.3% of respondents answered that information sharing intentions involving posting a blog post were not applicable to them. That was followed, from most to least, by “re-pinning” a Pinterest post (11.8 %), commenting on a Pinterest profile (11.0%), “liking” a Pinterest pin (10.2%), uploading a picture to Pinterest (9.4%), retweeting (7.3%), tweeting (7.3%), sharing an Instagram post (6.1%), “liking” an Instagram post (5.7%), sharing a Facebook post (5.3%), uploading a picture on Instagram (5.3%), commenting on an Instagram page (4.9%), commenting on a Facebook page (4.1%), “liking” a Facebook post (3.7%), texting (1.2%), and emailing people (.8%) to share hurricane preparedness-related information. Calling people to share hurricane preparedness-related information was the only crisis information sharing intentions item that did not have an “N/A” response. For data analysis purposes, the "N/A" responses were coded as missing values. The means and standard deviations stated earlier are based on the recoded crisis information sharing items.

**Source Credibility Perception**

Source credibility perception was measuring using eighteen different items asking respondents to indicate the extent that they perceive the National Flood & Hurricane Mitigation Center to be intelligent (*M* = 6.14, *SD* =1.17), be trained (*M* = 6.29, *SD* =.938), be expert (*M* = 6.22, *SD* = 1.10), be informed (*M* = 6.32, *SD* = 1.01), be competent (*M* = 6.17, *SD* =1.10), be bright (*M* = 6.00, *SD* = 1.15), care about them (*M* = 5.64, *SD* = 1.33), have their interest at heart (*M* = 5.66, *SD* = 1.35), not be self-centered (*M* = 5.74, *SD* = 1.52), be concerned with them (*M* = 5.74, *SD* = 1.26), be sensitive (*M* = 5.56, *SD* = 1.21), be understanding (*M* = 5.76, *SD* = 1.17), be honest (*M* = 5.92, *SD* = 1.30), be trustworthy (*M* = 6.17, *SD* = 1.14), be honorable (*M* = 5.95, *SD* = 1.22), be moral (*M* = 5.95, *SD* = 1.23), be ethical (*M* = 6.13, *SD* = 1.08), be genuine (*M* = 6.17, *SD* = 1.05). Several items were re-coded, including intelligent, informed, bright, "cares about me," "has my interest at heart," "concerned with me," honest, honorable and moral. *Table 25* illustrates the mean, standard deviation and alpha of all eighteen of the perceived source credibility items. These eighteen items were combined in the analyses and the mean as well as the alpha value of this measure is shown (*M* = 5.97, *SD* = .924, α = .960) in *Table 23.*

**Message Credibility Perception**

Message credibility perception was measured using five different items asking respondents to indicate the extent that they perceived each hurricane preparedness post as believable, accurate, trustworthy, unbiased and complete. For Post 1, respondents indicated the extent that they perceived the hurricane preparedness post as believable (*M* = 6.33, *SD* = 1.01), accurate (*M* = 6.28, *SD* = .979), trustworthy (*M* = 6.28, *SD* = .941), unbiased (*M* = 5.32, *SD* = 1.72), and complete (*M* = 5.44, *SD* = 1.34). The unbiased item was recoded. *Table 26* illustrates the mean, standard deviation and alpha of all five of the Post 1 message credibility items. These five message credibility items corresponding to Post 1 were combined in the analyses and the mean as well as the alpha value of this measure is shown (*M* = 5.93, *SD* = .895, $\alpha$ = .773) in *Table 23*.

For Post 2, respondents indicated the extent that they perceived the hurricane preparedness post as believable (*M* = 6.35, *SD* = .949), accurate (*M* = 6.33, *SD* = .929), trustworthy (*M* = 6.30, *SD* = .918), unbiased (*M* = 5.47, *SD* = 1.64), and complete (*M* = 5.74, *SD* = 1.26). The unbiased item was recoded. *Table 26* illustrates the mean, standard deviation and alpha of all five of the Post 2 message credibility items. These five message credibility items corresponding to Post 2 were combined in the analyses and the mean as well as the alpha value of this measure is shown (*M* = 6.04, *SD* = .904, $\alpha$ = .829) in *Table 23*.

For Post 3, respondents indicated the extent that they perceived the hurricane preparedness post as believable (*M* = 6.07, *SD* = 1.05), accurate (*M* = 5.95, *SD* = 1.13), trustworthy (*M* = 5.95, *SD* = 1.13), unbiased (*M* = 4.99, *SD* = 1.80), and complete (*M* = 5.30, *SD* = 1.42). The unbiased item was recoded. *Table 26* illustrates the mean, standard deviation and alpha of all five of the Post 3 message credibility items. These five message credibility items corresponding to Post 3 were combined in the analyses and the mean as well as the alpha value of this measure is shown (*M* = 5.65, *SD* = 1.03, α = .834) in *Table 23.*

For Post 4, respondents indicated the extent that they perceived the hurricane preparedness post as believable (*M* = 6.45, *SD* = .884), accurate (*M* = 6.37, *SD* = .977), trustworthy (*M* = 6.37, *SD* = .953), unbiased (*M* = 5.42, *SD* = 1.73), and complete (*M* = 5.78, *SD* = 1.27). The unbiased item was recoded. *Table 26* illustrates the mean, standard deviation and alpha of all five of the Post 4 message credibility items. These five message credibility items corresponding to Post 4 were combined in the analyses and the mean as well as the alpha value of this measure is shown (*M* = 6.08, *SD* = .904, α = .806) in *Table 23.*

For Post 5, respondents indicated the extent that they perceived the hurricane preparedness post as believable (*M* = 6.21, *SD* = 1.01), accurate (*M* = 6.11, *SD* = 1.08), trustworthy (*M* = 6.06, *SD* = 1.13), unbiased (*M* = 4.88, *SD* = 1.98), and complete (*M* = 5.53, *SD* = 1.47). The unbiased item was recoded. *Table 26* illustrates the mean, standard deviation and alpha of all five of the Post 5 message credibility items. These five message credibility items corresponding to Post 5 were combined in the analyses and the mean as well as the alpha value of this measure is shown (*M* = 5.76, *SD* = 1.05, α = .817) in *Table 23.* The mean credibility perception score for each of the five posts was averaged into one message credibility measure (*M* = 5.89, *SD* = .847).

**Guidance Adoption Intention**

Guidance adoption intention was measured using five different items asking respondents the extent that they would gather information about risks (*M* = 5.19, *SD* = 1.92), gather information about shelters and evacuation routes (*M* = 5.24, *SD* = 1.95), purchase flood insurance (*M* = 4.36, *SD* = 2.27), assemble an emergency supplies kit (*M* = 5.88, *SD* = 1.64), and download the FEMA mobile application (*M* = 4.26, *SD* = 2.08). *Table 22* illustrates the mean, standard deviation and alpha of all five of the guidance adoption intention items. The five items were combined in the analyses and the mean as well as alpha value of this measure is shown (*M* = 4.99, *SD* = 1.47, α = .798) in *Table 23.*

Due to the survey design, participants could answer "Not Applicable" (N/A) if they believed that a guidance adoption intentions item did not apply to them. The result, then, was that each individual guidance adoption intentions item had a different number of "N/A" cases. About 9.8% of respondents answered that guidance adoption intentions involving acquiring flood damage insurance was not applicable to them. That was followed, from most to least, by downloading the FEMA application (5.3%), gathering information about hazard risks (3.3%), gathering information about evacuation routes and shelters (3.3%), and assembling an emergency kit (2.4%). For data analysis purposes, the "N/A" responses were recoded as one, "strongly disagree" – and "already done" was recoded as seven, "strongly agree." The means and standard deviations stated earlier are based on the recoded guidance adoption intentions items.

Also, participants could answer "Already Done" if they had already completed the guidance recommendation within the last year. The result, then, was that each individual guidance adoption intentions item had a different number of "Already Done" cases. About 37.6% of respondents answered that they had already assembled an emergency kit. That was followed, from most to least, by gathering information about hazard risks (28.6%), gathering information about evacuation routes and shelters (26.1%), acquiring flood damage insurance (22.4%), downloading the FEMA application (5.3%). For data analysis purposes, the “Already Done” responses were coded as zero. The means and standard deviations stated earlier are based on the recoded guidance adoption intentions items.

## Research Questions

RQ7 sought to explore how, if such an effect exists, do Twitter post modality (e.g., text-, image- or GIF-based) and visual focus (e.g., reactive, proactive and hero) influence affective and cognitive risk perceptions among FEMA Region IV residents. A two-way MANOVA was run. No significant results were found. RQ8 sought to explore how, if such an effect exists, do Twitter post modality (e.g., text-, image- or GIF-based) and visual focus (e.g., reactive, proactive and hero) influence crisis information seeking and sharing intentions among FEMA Region IV residents. A two-way MANOVA was run. No significant results were found. RQ9 sought to explore how, if such an effect exists, do Twitter post modality (e.g., text-, image- or GIF-based) and visual focus (e.g., reactive, proactive and hero) influence guidance adoption intentions among FEMA Region IV residents. A two-way ANOVA was conducted. No significant results were found.

RQ10 sought to examine whether affective and cognitive risk perceptions sequentially mediate the relationship between previous hurricane experience and crisis information seeking intentions. PROCESS macro model 6 (Hayes, 2018) was used to explore mediation effects with serial linear regression. Results show that previous hurricane experience was a statistically significant predictor of affective risk perception [$\beta = .18$, $t(245) = 2.98$, 95% CI [.06, .30], $\rho \leq .003$], and that affective risk perception was a significant predictor of crisis information seeking intentions [$\beta = .11$, $t(245) = 2.18$, 95% CI [.01, .22], $\rho \leq .029$]. These findings support the mediation role of affective risk perception in the relationship between previous hurricane experience and crisis information seeking intentions. Approximately, 8% of the variance in crisis information seeking intentions was accounted for by the predictors ($R^2 = .083$). Affective risk perception was a significant predictor of cognitive risk perception [$\beta = .20$, $t(245) = 5.26$, 95% CI [.13, .28], $\rho \leq .000$], however cognitive risk perception was not a significant predictor of crisis information seeking intentions. Nor was previous hurricane experience a significant predictor of cognitive risk perception. See *Figure 4*.

RQ11 sought to examine whether affective and cognitive risk perceptions sequentially mediate the relationship between previous hurricane experience and crisis information sharing intentions. PROCESS macro model 6 (Hayes, 2018) was used to explore mediation effects with serial linear regression. Results show that previous hurricane experience was a statistically significant predictor of affective risk perception [$\beta = .18$, $t(245) = 2.98$, 95% CI [.06, .30], $\rho \leq .003$], and that affective risk perception was a significant predictor of crisis information sharing intentions [$\beta = .21$, $t(245) = 3.50$, 95% CI [.09, .33], $\rho \leq .000$]. These findings support the mediation role of affective risk perception in the relationship between previous hurricane experience and crisis information sharing intentions. Approximately, 14% of the variance in crisis information sharing intentions was accounted for by the predictors ($R^2 = .140$). Affective risk perception was a significant predictor of cognitive risk perception [$\beta = .20$, $t(245) = 5.26$, 95% CI [.13, .28], $\rho \leq .000$], however cognitive risk perception was not a significant predictor of crisis information sharing intentions. Nor was previous hurricane experience a significant predictor of cognitive risk perception. See *Figure 5*.

RQ12 sought to examine whether affective and cognitive risk perceptions sequentially mediate the relationship between previous hurricane experience and guidance adoption intentions. PROCESS macro model 6 (Hayes, 2018) was used to explore mediation effects with serial linear regression. Results show that previous hurricane experience was a statistically significant predictor of affective risk perception [$\beta$ = .18, $t$(245) = 2.98, 95% CI [.06, .30], $\rho \leq$ .003], and that affective risk perception was a significant predictor of guidance adoption intentions [$\beta$ = .26, $t$(245) = 4.43, 95% CI [.14, .38], $\rho \leq$ .000]. These findings support the mediation role of affective risk perception in the relationship between previous hurricane experience and guidance adoption intentions. While previous hurricane experience was not found to be a significant predictor of cognitive risk perception, affective risk perception was [$\beta$ = .20, $t$(245) = 5.26, 95% CI [.13, .28], $\rho \leq$ .000]. In turn, cognitive risk perception was also a significant predictor of guidance adoption intentions [$\beta$ = .18, $t$(245) = 1.97, 95% CI [.00, .36], $\rho \leq$ .049]. Approximately, 31% of the variance in guidance adoption intentions was accounted for by the predictors ($R^2$ = .317). See *Figure 6.*

RQ13 sought to explore the moderating effect of source credibility perceptions on the relationship between message credibility and guidance adoption intentions. PROCESS macro model 1 (Hayes, 2018) was used to explore moderation effects with serial linear regression. No significant results were found.

# CHAPTER 10

# DISCUSSION

This chapter presents the overall dissertation discussion. First, an introductory description of the study context is provided. Then, the key findings of the dissertation are listed and summarized. In turn, the theoretical implications of the findings are discussed. That is followed by a section that organizes the dissertation's findings according to the SMDIA model's concepts as well as the research goals that were articulated in the preceding chapters. Then, the study's practical implications are proposed. The discussion ends with the limitations and future research sections.

According to the Pew Research Center (2019a), as of 2019, "around seven-in-ten Americans use social media to connect with one another, engage with news content, share information and entertain themselves" (¶1). Since the early versions of what would later be known as social media first emerged in 1997 (Boyd & Ellison, 2007), these platforms have irrevocably transformed the way in which many people connect and maintain relationships with one another. Anecdotally, some have noted that certain social media platforms like Facebook allow individuals to loosely maintain ties with acquaintances and childhood friends – a once-challenging feat now made easy thanks to online social networking sites (Beck, 2017).

People also use social media during crises and emergencies. From as early as the 2007 Southern California Wildfires (see Sutton et al., 2008), researchers have taken note that during disasters people turn to social media platforms for a myriad of reasons that run the gamut from looking for situation updates (Fraustino et al., 2012) to leading crowdsourcing efforts to match available resources with known needs (Gao et al., 2011) and more. Indeed, people's use of social media before, during and after disasters is a well-documented phenomenon (Fraustino et al., 2012). This phenomenon has drawn the interest of emergency managers that are tasked with the challenge of reaching at-risk publics before, during and after disasters (Fugate, 2011). The stakes have never been higher for emergency managers to integrate social media into their emergency risk and crisis communication – since viewership and readership of broadcast and print news, respectively, have been at a decline for quite some time (Barthel, 2019) – and it is primarily through news media that emergency managers have been able to reach target publics in the past (Haddow & Haddow, 2009b).

At this point, the conversation focusing on social media for emergency management has shifted from contemplating its integration into emergency communication efforts to identifying the strategies that will most likely result in desirable outcomes. This project proposed that in a social-mediated context, desirable communication outcomes include audience engagement with content, and compliance with recommended protective guidance. As articulated in Chapter 4, audience engagement involves social endorsement, dialogue, and information dissemination – in the case of Twitter specifically, liking, replying, and retweeting, respectively. Based on a growing body of work outlining the relationship between content modality and its relationship with a wide variety of emotional, cognitive and behavioral outcomes, it was proposed that social media content modality may play a strong role in shaping the way in which users engage with disaster-related content online. The main idea being that social media users are more likely to engage with posts that are more visual and motion oriented – think images and GIFs/videos – rather than text-based posts.

Apart from post modality, this project also explored the role of additional visual content characteristics on social media user engagement with disaster-related posts, specifically visual content type and focus. There are two types of visual content: illustrative (like photographs), and graphic (like maps and charts). While risk communicators and researchers may be keener on presenting content in a graphical and/or data-driven way (Yavar et al., 2012), research exploring image effects in news consumption have identified an audience predilection for emotion laden content (Lang et al., 1998; Lowrey, 1999). In line with this predilection, it was proposed that social media users were more likely to engage with image-based posts that were illustrative rather than image-based posts that were graphic. In turn, visual focus deals with the thematic content that illustrative image-based posts prioritize – put simply, what the photo or image is about. Exploring the prevalence and potential effects of different visual foci in social-mediated disaster content was undertaken using a two-pronged approach – one took inventory using a content analysis, another teased out potential effects through an online experiment.

In addition to social-mediated content characteristics, this project also focused on information sources, the entities responsible for sharing disaster-related content on social media. It sought to better understand the role that news media organizations, government agencies, 'ordinary users' and others play in the creation and dissemination of social-mediated content during a disaster. Specifically, the dissertation explored any potential similarities or differences in the type of visual content focus that these actors prioritize in their social media messages, particularly in a disaster context. It also sought to better understand how previous hazard experience and risk perception relate to perceptions of disaster-related content, and behavioral intentions regarding disaster information seeking and sharing.

## Key Findings

In order to accomplish the dissertation objectives outlined in the previous section, two main studies were conducted. The first main study involved a content analysis of a sample of hurricane Matthew-related tweets. Specifically, 2,060 tweets were individually coded for eighteen items. The second main study involved a between-subjects 3 (modality: text-, image- and GIF-based posts) x 3 (visual focus: reactive, proactive and hero) online experiment in which participants were shown a mock Twitter profile of a faux U.S. federal weather entity, 'The National Flood and Hurricane Mitigation Center' – the profile included five hurricane preparedness tweets. The key findings from both these studies were:

- RQ1, which asked whether news media are more likely to feature illustrative disaster visual content in their social-mediated messages rather than graphical visual content, was not supported by the results of a binomial logistic regression. However, the results were statistically significant, meaning that news media organizations were more likely to feature graphical visual content in their social-mediated messages rather than illustrative visual content.
- A binomial logistic regression supported the second research question (RQ2), which asked whether government organizations are more likely to feature

graphical disaster visual content in their social-mediated messages rather than illustrative visual content.

- The third research question (RQ3), which asked whether ordinary users are more likely to feature illustrative disaster visual content in their social-mediated messages rather than graphical visual content, was not supported by the results of a binomial logistic regression.

- In turn, the fourth research question (RQ4), which asked whether government organizations are more likely to feature disaster visual content with a people focus rather than other types of focus, was not supported by the results of a multinomial logistic regression.
- Likewise, the fifth research question (RQ5), which asked whether news media organizations are more likely to feature disaster visual content with a people focus rather than other types of foci, was not supported by the results of a multinomial logistic regression. However, the results were statistically significant, meaning that news media organization were more likely to feature disaster visual content with other foci rather than people focus.
- Similarly, the sixth research question (RQ6), which asked whether ordinary users are more likely to feature disaster visual content with a destruction focus rather than other types of focus, was not supported by the results of a multinomial logistic regression.
- A series of negative binomial regressions supported H1, which stated that social media users are more likely to engage with image-based posts than they are to engage with text-based posts. Specifically, results show that users were more

likely to retweet (H1a), like (H1b) and reply to (H1c) image-based posts rather than text-based posts.

- A series of negative binomial regressions also supported hypothesis H2, which stated that social media users are more likely to engage with video-based posts than they are to engage with either image- or text-based posts. Specifically, results show that users more likely to retweet (H2a), like (H2b) and reply to (H2c) video-based posts rather than image- and text-based posts.
- No significant results were found when exploring how, if such an effect exists, do Twitter post modality and visual focus influence affective and cognitive risk perceptions (RQ7).
- No significant results were found when exploring how, if such an effect exists, do Twitter post modality and visual focus influence crisis information seeking and sharing intentions (RQ8).
- No significant results were found when exploring how, if such an effect exists, do Twitter post modality and visual focus influence guidance adoption intentions (RQ9).
- Previous hurricane experience was a statistically significant predictor of affective risk perception, and affective risk perception was a significant predictor of crisis information sharing intentions. Taken together, these findings support the mediation role of affective risk perception in the relationship between previous hurricane experience and crisis information sharing intentions (RQ10).
- Previous hurricane experience was a statistically significant predictor of affective risk perception, and affective risk perception was a significant predictor of crisis

information seeking intentions. Taken together, these findings support the mediation role of affective risk perception in the relationship between previous hurricane experience and crisis information seeking intentions (RQ11).

- Previous hurricane experience was a statistically significant predictor of affective risk perception, and affective risk perception was a significant predictor of guidance adoption intentions. Taken together, these findings support the mediation role of affective risk perception in the relationship between previous hurricane experience and guidance adoption intentions (RQ12).
- No moderating effect of source credibility perceptions on the relationship between message credibility and guidance adoption intentions (RQ13) were found.

## Theoretical Implications

One of the major objectives of this dissertation was to better understand the role of modality as a driver for user engagement with social-mediated disaster context. Building on a body of work advancing the idea that visual content prompts higher emotional arousal (Lang et al., 1998) and engagement intentions (Baumeister et al., 2007), the results of the context analysis align well with what we have seen so far. Which is, essentially, that social media users are more likely to engage with visual content rather than text-based content.

At first glance, the findings provide emergency risk and crisis communicators with a more nuanced understanding of the social media post design elements that are more likely to elicit specific target desirable communication outcomes. This finding builds on existing knowledge and deepens our current understanding of whether and to what extent these modality outcomes also play out in a social-mediated online environment. Indeed, videos, GIFs and images are more likely to prompt higher engagement from audiences – but what can be said about the kinds of videos, GIFs and images that drive that behavior?

Before, during and after a disaster event like Hurricane Matthew, many Twitter users converged to create, share, and engage with hurricane-related posts. The content analysis took inventory not only of whether a post was text-, image-, GIF-, or visual-based, but what these visuals conveyed. The content of disaster-related images shared on and through social media channels has increasingly become the focus of research seeking to identify mechanisms by which machine learning techniques can help emergency managers glean critical insight from large datasets (Imran et al., 2013).

Some recent examples have shown that social media disaster-related images can be a source of situational awareness (Z. Wang & Ye, 2019), as well as indicators of disaster recovery across time (Shibuya & Tanaka, 2019). As far as this project goes, the careful individual coding of each of the sampled Hurricane Matthew tweets revealed interesting patterns related to visual content supplemental to the hypothesis testing. For instance, the disaster stage is critical for the kind and type of pictures that are shared – in part a homage of sorts to the classic and prevalent disaster conceptualizations focused on timeframe as a definitional praxis.

Most of the graphic Hurricane Matthew images were shared earlier rather than later in the storm's trajectory potentially because the satellite imagery was the first and only Hurricane Matthew visual for some time until the storm made landfall. Journalists, meteorologists and climate enthusiasts alike shared GIFs and links associated with news updates of the upcoming hurricane's projected path and intensity. Editors would be remiss to add illustrative visuals depicting strong winds and storm surge of previous hurricanes to a storm that had yet to take place – recent examples of such instances where the image from one event is used as part of the messaging of another event illustrate that it can be a routine that is widely criticized by some stakeholders (Smith, 2020).

Following the disaster life cycle, during the acute stages of Hurricane Matthew, the visual focus shifted from graphic visuals to illustrative ones, especially those that captured the strength, might and sheer force of the destructive capabilities of the hurricane winds and storm surge. Immediately following the impact of the storm, the visual priorities again shifted to document the scope of destruction left in Hurricane Matthew's wake – structures destroyed and families destitute. It is at this junction that the major information source actors also shift – if the beginning of the storm was heralded by journalists and meteorologists, and the baton was shared with ordinary users and storm-chasing journalists during the acute stage of the storm, the later portions of the cycle was dominated strongly by non-profit and relief organization revving gears to spearhead crowdfunding relief efforts. The visuals stop focusing on acute hurricane impact and floods and instead turn to the good Samaritans praying and working together to help those in need. The Red Cross and Samaritan's Cross emerge as if summoned to fundraise.

As research in disaster sociology and crisis communication show, there are different situations before, during and after an event that precipitate certain audience behaviors. For example, high uncertainty associated with the projected path of a hurricane may motivate at-risk publics to engage in information milling behaviors, where they search for more details about what is going on to better inform their risk response. Similarly, using social media before the onset of an event can help users gauge to what extent and how other people in their networks may be preparing for the upcoming event. For example, pictures of lines at grocery stores or empty shelves may give the unprepared person a boost to get supplies before the storm. Timing is also crucial during an event, when people turn to social media to check in with family and friends, cope with anxiety and document their own experience of what is going on (Fraustino et al., 2012). Practitioners' efforts to wield timing for favorable outcomes may be better poised for success with a more nuanced understanding of when and how to send certain information, as well as the way in which the messages are designed. For example, hosting a Q&A session several days before the onset of a hurricane can help practitioners get a better understanding of where their publics are at, it can also help instill a sense of urgency to those that have not begun to prepare. Following the storm, authorities can engage with publics by asking them to submit their own images of how the disaster affected them.

Outside of this linear progression of visual storytelling that follows a beginning, middle and end – there are other types of disaster-related images that do not quite fit the same temporal sequence as the others. They are the memes. They are the unusual hurricane-related stories that become popular due if anything to their unconventional occurrence, like the image of the Florida homeowner who parked their car inside the living room to safeguard their vehicle against damage; or, alternatively, the image of the zoo animals that were sheltered in the facility's restrooms. This type of social-mediated disaster visual communication closely relates to the well-documented phenomenon of using humor in social media to cope with the uncertainty and anxiety of a looming or unfolding disaster (Murthy & Gross, 2017).

Apart from the odd and the funny, a third type of visual that is anachronic as well is that which focuses on press conferences, press briefings or simply stock images that are used in news stories. The prevalence of these types of images in a disaster context are indicative of broader journalistic norms at play. Lowrey (1999) explained that one of the prominent TV news routines involved visual variations – as he explained, “too many shots of “talking heads” leads to visual boredom, and so will be avoided, even at the expense of the news value of these shots” (p.13).

In the Hurricane Matthew tweet content analysis, of the 479 illustrative image-based posts nearly 45.1% of these featured people. Further, “talking head” focus accounted for nearly 11.1% of all illustrative images with a people focus. However, the hero (49.1%) and human-interest foci (38%) were the most prevalent types of illustrative images that featured people. This aligns well with what Lowrey (1999) described about TV newsroom routines. At a broader level, this finding also speaks to broader routines that can be discerned in a social-mediated context – that dramatic or human-interest frames are prioritized.

## Unsupported Research Questions

In the content analysis there were several research questions that were not supported by the statistical tests. The first of these was RQ1, which asked whether news media organizations were more likely to feature illustrative disaster visual content in the social-mediated messages rather than graphical visual content. The results did not support this question, in fact, they suggest that the opposite is true: that news media organizations are more likely to feature graphical rather than illustrative visual content in their disaster-related social media posts. This finding may be due to the fact that in the days leading up to the storm, news media organizations and their affiliated meteorologists focused on sharing stories about Hurricane Matthew's predicted trajectory. These kinds of stories typically came accompanied with maps. Further, when the storm finally made landfall in some of the countries where it wreaked the most havoc, it continued along its path. While human interest is a recognized news value, so is proximity – and as the storm neared the shores of the U.S. mainland, in all likelihood the focus of the storm coverage shifted to prioritize local audiences which needed timely information about the hurricane's path and intensity.

Another research question that was not supported by the results was RQ3, which asked whether ordinary users were more likely to feature illustrative disaster visual content in their social-mediated messages rather than graphical visual content. The main underlying assumption of the question was that since mobile technology and the visual documentation of disaster are ubiquitous during these events, naturally illustrative content would be more prevalent. There are two potential reasons why this research question was not supported. The first one concerns Twitter as a social media platform and the characteristics that have come to define the way in which these users connect with one another and why. There are certain events that draw the attention of particular interest groups.

For example, other studies focusing on Twitter chatter about storms found that weather enthusiasts and aficionados – unaffiliated to government entities, meteorologists or journalists – converge to discuss and share content related to their interests (Silver &

Andrey, 2019). These converging communities of content[2] and the kind of messages that they choose to interact with could potentially explain the predilection of this study's 'ordinary users' to post or share tweets with graphic visuals.

The second reason why RQ3 was not supported may have to do with the social media platform chosen for the study. Reports have shown that in contrast with Twitter, Facebook is known to be used by a wider and more representative portion of the U.S. population (Barthel, 2019). The act of capturing, documenting and sharing vivid images of lived experiences during a disaster may be a more prevalent dynamic in a social media platform like Facebook, where the connection between users is due to them being friends or family.

Also related to the content analysis, research questions four through six, which asked whether certain information source types were more likely to feature certain visual foci over others – were also not supported by the statistical tests. Regarding news media organizations, it was expected that they would prioritize a human-interest focus; instead, descriptive statistics illustrate that news organizations tended to share visual posts with a nature and destruction focus the most. As mentioned previously, this could be due to the

[2] In this context, the concept of 'communities of content' closely resembles what Rowley (2004) calls "communities of interest." According to Rowley (2004), "communities of interest are gathered around topics of common interest and members typically have a significant higher degree of interaction than in a transaction-based community. These communities usually have chat rooms, message boards, and discussion groups to support extensive member interactions; they are characterized by a significant quantity of user-generated content" (p.37).

shifting news cycle and the refocus of attention from the despair in Haiti to the storm that then headed to the U.S. coast.

In turn, concerning government organizations, it was expected that they would post visual content with an informational focus; instead, descriptive statistics show that they featured a human-interest focus in their visual content. Delving a bit deeper into the kind of visual content shared by government organizations – they did tend to share graphical visuals (N = 65) more than illustrative ones (N = 47), which was expected. However, within the illustrative category for visuals, the label ‘human-interest’ may be a misnomer, since it essentially means that the illustrative visuals featured people. Within the ‘features people’ category, coders also selected between different depictions of people. It is here that this (non) finding makes sense – when posting illustrative visuals that featured people, government organizations prioritized “hero” depictions and “talking head” depictions over the actual “human-interest” depictions, of which they only actually included 3 posts.

Finally, it was expected that ordinary users would post visual content with a nature and destruction focus; instead, descriptive statistics show that they featured “other” visual content the most. This result may be due to the fact that many of the more prevalent categories of visual content focus (i.e., ‘features animals,’ ‘features humor,’ etc.) were grouped as ‘other’ to meet the minimum cell case number assumption for the multinomial logistic regression. Further, an additional reason goes back to the discussion about the potential differences between the kind of disaster-related posts that may be more prevalent in Facebook than in Twitter.

In the online experiment study, there were also several research questions that were not supported by statistical tests. No statistically significant effects or relationships were found for any research questions involving content modality or image focus. There are several potential explanations for this outcome. First, the experiment design – seeing all of the posts in the NFHMC's Twitter profile rather than a Twitter timeline may have impacted the experiment, since Twitter users more typically encounter other users' posts in the Twitter feed rather than a single user's profile. Further, the between-subjects design where a single participant sees five posts of the same modality and visual focus may also have implications for how the content is perceived and the potential effects that modality may have.

Another potential explanation for the results obtained may be due to the participants recruited for the online experiment. First, they are MTurkers – they are financially motivated and may go through the experiment too quickly in order to maximize their time and efforts to secure financial rewards from other HIITs. Second, focusing exclusively on MTurkers who use desktops and laptops as part of the study design may have implication for the kind of Internet users that participated in the study. Related to that, participants were not asked if they are social media users, much less if they were familiar with Twitter itself. It is then a possibility that they may not have even been cognizant of the nuance in the stimulus materials they were shown.

Together, these experiment design and participant recruitment decisions may have impacted the extent to which modality was a salient feature for the experiment. For example, being shown a screenshot of a tweet that includes the user avi and the engagement icons plus the post content itself all technically constitute an image – even if the post is text-based. Similarly, if a participant was shown a Twitter profile complete with a profile picture, banner picture, etc., text-based condition participants were then exposed to a variety of images too. This quandary underscores the complexity of defining and distinguishing the concept of modality in social media, which is quite broad. An argument could be made that modality effects can be a function of the extent to which it varies among a social media feed (i.e., a user seeing an image-based post among a stream of mostly text-based posts). However, the growing complexities of the ways in which social media affordances allow their users to share content with one another may make the study of that dynamic a futile pursuit. Instead, then, perhaps the focus should narrow not so much on modality, but what is said or depicted in social media messages.

The findings from this work, even the ones that were not statistically significant or supported, do contribute to the literature in this area. Social-mediated disaster communication research is arguably still in its infancy. The re-creation of a Twitter profile down to the last detail for the online experiment of this work and the results obtained from those efforts can help future researchers make better experimental design decisions. Decisions that are still needed, since across the disaster communication effectiveness literature, researchers have raised concerns that certain methodological approaches may be unethical. For example, contacting at-risk publics during a disaster to gauge their perceptions, attitudes and behavioral intentions may overburden them at a critical time when they need to make decisions for their health and safety (Lavin et al., 2012). Another ethical concern related to methodological approaches is contacting these affected populations shortly after the onset of a disaster, because it is a vulnerable time (Lavin et al., 2012). Online experiments present an opportunity for potential respondents to participate when and where they may feel most comfortable. This study presents one design approach, which can either be replicated or modified in future studies – especially for researchers seeking to evaluate the potential effects of actual posts used before, during and after disasters by key government officials.

## The SMDIA Model

Through the content analysis and online experiment, the Social-Mediated Disaster Information Amplification (SMDIA) model's major conceptual tenets and the relationship among them was explored. This section organizes the dissertation's findings according to the SMDIA model's concepts as well as the goals that were articulated in the preceding chapters.

### Information Sources

One of the major goals of the SMDIA model was to advance the understanding that social-mediated information sources involve much more than the official/unofficial, informal/formal, and internal/external binary conceptualizations across the major theoretical frameworks that inform the model.

Through the content analysis, Hurricane Matthew-related tweets were attributed to ten different information source types. Based on descriptive statistics alone, the top three information source types were news media organizations (35.5%), ordinary users (18.9%), and government organizations (11.4%). However, the tweets that were retweeted the most were actually posted by ordinary users and relief organizations. This descriptive observation lends support to the claim that research focused on identifying which message content and style features lead to audience retransmission (i.e., the terse message retransmission studies) could stand to gain by also exploring the content characteristics of messages posted by other information sources outside of the 'official' entities. Formal hypothesis testing in this dissertation further contributes to this research gap. Overall, the content analysis results suggest that some information source types are more likely to post certain content types more than others. By identifying these content type predilections by source type, more is now known about routines and their potential end result in social media communication strategies.

**Content**

Related to content, the SMDIA model contends that disaster-related information shared through social media can come in a variety of modalities. Through both the content analysis and the online experiment, this dissertation explored the prevalence of different types of visuals and their potential effect on audience engagement – as proposed by the SMDIA model.

Nearly half of all Hurricane Matthew tweets coded in this study were image-based posts. Within these types of tweets, 58.3% of them included an illustrative image and 41.7% included a graphic image. Formal hypothesis testing found that government organizations were in fact more likely to feature graphic visual content rather than illustrative content. It was interesting to see that news organizations were also found to be more likely to feature graphic visual content rather than illustrative content.

**Audience Engagement**

One of the main points of the SMDIA model was that content modalities drive audience engagement with social media posts. The formal hypothesis testing results involving information sharing in the content analysis align well with previous research that has found that more visual modalities draw higher levels of content popularity across online social networks. The richer contribution to this area of study was to also consider other dimensions of audience engagement with online content, in the form of likes and replies.

While the online experiment did not find a statistically significant relationship between content modality and audience engagement – it did help better understand how additional audience engagement dimensions (i.e, perceptions) and behavioral intentions relate to one another. For example, affective risk perception does play a mediation role in the relationship between previous hurricane experience and three target communication outcomes: crisis information sharing intentions, crisis information seeking intentions, and guidance adoption intention. That affective risk perception, rather than cognitive risk perception, can affect these outcomes further affirms the body of work that upholds emotions and emotional engagement as a critical piece in achieving target disaster communication outcomes.

## Practical Implications

The main practical implication of this work is that the findings can help news editors, journalists, communication specialists, public information officers and emergency managers better design strategic communication materials to achieve desired outcomes. Audience engagement with social-mediated emergency preparedness content is increasingly becoming critical in times when social media platform algorithms play a decisive role in which content becomes visible to online audiences. During an emergency, it may mean the difference between life and death. Related to this main practical implication, there are three additional implications.

The first implication is that the results of this work can help emergency managers and public information officers have a fuller understanding of the different actors that can converge in a social-mediated disaster communication context. In Chapter 2, where information sources were discussed, it was noted that most of the best practices insight comes from studies that have exclusively focused on “official sources.” Further, there is research that has documented that many government organizations interact mostly amongst themselves on social media (Lai et al., 2017; Wukich & Mergel, 2016). This myopic perspective and the approach it engenders limits emergency managers from embracing some of the more promising features of social media platforms. With the insight that stems from this work, like for example that stakeholders such as politicians and celebrities are the main drivers of audience engagement, information officers can design preemptive communication outreach strategies where relationships with these actors are established and fostered well before a disaster takes place. Then, when help is needed to amplify ‘official’ messaging, there are less obstacles in accomplishing that when partnerships have already been made.

The second implication, and it cannot be understated, is that this work provides insight into what kind of content is more closely related to audience engagement. At the highest level, modality is shown to be key. However, there are other findings that can help emergency managers design more efficient communication strategies. Regarding the likelihood that audiences will share (i.e., retweet) posts, there are certain types of information that make this behavior more likely – namely, posts that include prayers and humor. While a disaster is a serious event, the understanding that audiences are looking for reassurance and ways to cope may also be helpful in designing communication strategies. In the case of audience likes and replies to tweets, prayers and humor are also among the top tweet types that drive that type of engagement. This is not to say that FEMA should be tweeting memes at the acute stage of a disaster, but perhaps they can create other Twitter handles/accounts that incorporate key messaging into a more lighthearted format.

The third practical implication is that the results afford a deeper understanding of the relationship between audience perceptions and target behavioral outcomes. How respondents felt about a risk had a statistically significant impact on their intentions to look for more information, share information, and engage in the recommended guidance. Conversely, the same was not so for what respondents thought about hurricane and flood-related risks. This finding can be helpful as government agencies and emergency management communicators design and develop preparedness campaign materials. Specifically, more onus should be placed on emotionally compelling narratives rather than fact and figures – if the main purpose of the campaign is to promote information seeking and sharing behaviors as well as guidance compliance.

A final practical implication is that the results of this work can inform the study of social-mediated disaster communication messages that is conducted across several U.S. federal agencies – including the National Institute of Standards and Technology (NIST). According to NIST (2020), "under the National Construction Safety Team Act (NCST), signed into law October 2002, the National Institute of Standards and Technology (NIST) is authorized to investigate major building failures in the United States." In 2018, the NCST Advisory Committee, a group of experts that advises NIST on the NCST investigation and reports its progress to the U.S. Congress, recommended that the NCST

Hurricane Maria project that focuses on emergency communications should also incorporate social media into its study. Through the findings of this dissertation, the importance of the inclusion of visuals in any work exploring the communication effectiveness of social media messages cannot be understated.

## Limitations

Like any research enterprise, this study has its limitations. Beginning with the content analysis, the first set of limitations involve using Crimson Hexagon as a mechanism for the collection of social media data. In the case of Twitter, while Crimson Hexagon gives users access to all 'historical' tweets – its exporting limitations result in the researcher not having control over which tweets get 'randomly' selected for export, and why. Further, while a tweet may be captured in the .csv file exported by Crimson Hexagon, the post may not be available if and when the researcher attempts to access the once publicly available post through the post url. In the case of this study, about 18% of the tweets that were selected for analysis were no longer available.

Outside of the issues that Crimson Hexagon may present, there are other limitations inherent in the content analysis design. For instance, one would be remiss to attempt to generalize the findings of a study that focused on just one social media platform (Twitter) during just one particular disaster (Hurricane Matthew). Each disaster is unique in its geographical and temporal dimensions as well as the scope of physical and social disruption left in their wake. What may have been a fixture during one event – say, an image type that was more likely to go 'viral' than others – may not resonate in quite the same way during a different disaster. All of this is to say that what drives audience engagement during one specific event may not be the case in a different one.

Another limitation in the study is the main underlying assumption that audience engagement is driven by information source and content characteristics, whereas it has become known that social media platforms increasingly play a decisive role in determining which content is prominent and visible across networks – and that which is not.

Concerning the online experiment, there are several limitations to address as well. In first place, using Amazon Mechanical Turk as a participant recruitment approach presents many issues. These issues include the proliferation of automated responses and MTurkers with little to no English language proficiency – both of which the online experiment pilot study was rife with, unfortunately. It is cumbersome – and not very cost efficient – to incorporate the measures necessary to identify and screen bots and MTurkers that cannot understand basic study instructions. Although recent studies have shown that MTurk workers are more representative of the American general population than other traditional sources of experiment participants (i.e., undergraduate college students) they are still different than the general population.

There are other experimental design limitations worth mentioning in this section as well. While focusing on hurricane preparedness posts made sense considering the participant sampling criteria (FEMA Region IV states), that is not the case so much when it came to *when* respondents participated in the study – January, somewhat 'off-season' in regard to hurricanes. Attempting to measure risk perceptions for a hazard that was not timely at the time or even in a couple of months from when the study was launched, may have played an unexpected role in the results obtained. Another limitation was not measuring social media use. Whether or not participants are regular social media users or even have experience using Twitter may have played a role in their perceptions and behavioral intentions. By measuring social media use, at the very least, researchers can have an idea of whether or not a participant being asked to evaluate the content of a particular social media post is familiar with the platform itself. An additional limitation is that only participants that accessed the MTurk HIIT through either a laptop or desktop could participate in the study. It is unclear how many MTurk workers complete HIITs through mobile devices like smartphones or tablets.

## Future Research

There are several promising future research directions that can build on the results of this work. One line of research can focus on exploring the role that devices play in audience engagement with social-mediated disaster content. Another line of research can explore if the patterns that emerge in audience engagement with certain content types is consistent across disaster types or even across different disaster events for similar hazards. Content analysis approaches that involve individual human coding lay the groundwork for identifying emerging practices that can then be explored in machine learning efforts that allow researchers a broader scope in the study of this phenomena.

An additional promising area of research is that which focuses on audience engagement. In Chapter 4, the concept of audience engagement was addressed from the different frameworks that inform this work. Throughout the dissertation, since the discussion has focused on a social-mediated context – it is implied that engagement involves the three dimensions of social endorsement (likes), dialogue (replies), and information dissemination (retweets). However, this conceptualization and its operationalization prioritized engagement outcomes that could be easily measured through a content analysis.

The concept can be understood more broadly too. For example, in the SMCC model, offline word-of-mouth communication is considered a behavioral outcome of social-mediated communication. Further, in the context of social media, the complexities of the platform and the way in which users can engage with content elude the conceptualization proposed in this work. Case in point, a Facebook user can screenshot a post that they want to share with friends. But instead of using the platform's affordances to do so – like the ability to re-post the message by sharing it, posting it on a friend's wall or sending it through messenger – they send it through a text message instead. In this text message thread, the other friends 'react' to the post and respond to it. It is a similar engagement through a different pathway. In that sense, a social media user that may appear to be a passive social media consumer based on the extent that they do or do not directly engage with content, may actually be quite engaged with the content they come across in their online social networks. Future work can focus on better parsing out these complexities and their implications. Alternatively, other studies can incorporate physiological measurements to the operationalization of engagement, like skin conductance, eye tracking, etc.

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APPENDIX A

CONTENT ANALYSIS CODING PROTOCOL

**Coding Protocol for Content Analysis**

**Q1: Coder Identification** (*Coders should indicate who they are*).
1 = Coder 1
2 = Coder 2

**Q2: Tweet ID Number** (*Coders should indicate the case number assigned to the tweet*).
________________________________________

**Q3: Is the tweet available** (*Coders should indicate if the tweet is still publicly available*).
1 = Yes
2 = No

**Q4: Date (Format MONTHDAY)** (*Coders should indicate the date in which the tweet posted*)
________________________________________

**Q5: Tweet Language** (*Coders should indicate what language the tweet's content is written in*).
1 = English
2 = Spanish
3 = French
4 = Other (please indicate ________________________________________ )

**Q6: Is the Tweet Author a Verified Account?** (*Coders should indicate if the tweet author's Twitter user profile has a verified account badge*).
1 = Yes
2 = No

**Q7: Number of Retweets** (*Coders should indicate the number of times the tweet has been retweeted*).
________________________________________

**Q8: Number of Likes** (*Coders should indicate the number of times the tweet has been liked*).
________________________________________

**Q9: Number of Replies** (*Coders should indicate the number of times other Twitter users have replied to the author's tweet*).

________________________________________

**Q10: Information Source Type** (*Coders should indicate what category the tweet's author best fits into. Celebrities are individuals that have received a lot of media attention because of their social status or career – popular actors, actresses, athletes, artists or military personnel fall in this category. News media organizations include the digital version of offline major news media like The New York Times or Fox News, digital news media like the Huffington Post, and journalists. Government Organizations include every public office, department or representative including firemen and police departments. Relief Organizations include non-governmental relief organizations, which are nonprofit humanitarian-based groups like The Red Cross or Salvation Army. Private or Corporate Organizations are food, product or service companies like The Home Depot, Chick-fil-A or Facebook. "Ordinary Users" are tweet authors that do not fall into any of the previous categories. Twitter bots are accounts that typically do not have a profile picture, have many posts, only seem to share links to other websites or news articles, hardly have any followers. Politicians are individuals that identify themselves as such. CEO's are individuals that describe themselves as such. Information Dissemination Entities are users that do not seem to be Twitter bots or news media organizations, but actual users that aggregate and share content typically related with a specific industry or topic area*).

1 = Celebrities
2 = News Media Organizations
3 = Government Organizations
4 = Relief Organizations
5 = Private/Corporate Organizations
6 = "Ordinary Users"
7 = Twitter Bots
8 = Politicians
9 = CEO's
10 = Information Dissemination Entity

**Q11: What type of tweet is it?** (*Coders should indicate the best tweet category in respect to the thematic content. The 'hazard information' category includes tweets that include including information describing all tropical cyclone watches and warnings in effect along with details concerning tropical cyclone locations, intensity and movement – including messages about landfall, category and windspeed. The 'hazard impact: deaths/destruction' category includes tweets that provide vivid details about the death or destruction caused by the hurricane or any hurricane-related hazard. The 'closures/openings' category includes tweets that include information about facilities, functions, schools, businesses and/or roads that have closed/opened. The 'protective action recommendation' category includes tweets that provide specific information about how to protect oneself and others (including animals) during a disaster, including evacuation and shelter-in-place orders. The 'information' category includes tweets that include general updates and available resources. The 'help/directed information'* *category includes tweets that explicitly involve one user responding to another user's questions and/or requests for assistance or information. The 'thank you/appreciation' category includes tweets that include statements of thanks and appreciation. The 'volunteer/donate/help' category includes tweets that include information about ways to volunteer or donate to disaster response efforts – also messages that showcase efforts by others to volunteer, donate or help. The 'emotion/judgment' category includes tweets that include emotive statements about Hurricane Matthew, the response and/or the recovery efforts. The 'humor' category includes tweets that include humorous, sarcastic and sardonic content. The 'prayer' category includes tweets that include prayers or requests for prayers. The 'miscellaneous' category includes tweets that include information about Hurricane Matthew but focus on odd and miscellaneous events out of the ordinary. The 'unsure or not on topic' category includes tweets that appear to not be related to Hurricane Matthew in any capacity whatsoever. The 'alert' category includes tweets that explicitly include an alert or notification*).

1 = Hazard Information
2 = Hazard Impact: Deaths/Destruction
3 = Closures/Openings
4 = Protective Action Recommendation
5 = Information
6 = Help/Directed Information
7 = Thank You/Appreciation
8 = Volunteer/Donate/Help
9 = Emotion/Judgment/Evaluation
10 = Humor
11 = Prayer
12 = Miscellaneous
13 = Unsure OR Not on Topic
14 = Alert

**Q12: Does the tweet include an embedded link to an external webpage?**

1 = Yes
2 = No

**Q13: If tweet includes an embedded link to an external webpage, where does the link redirect towards?**

1 = News Organization Website
2 = Government Organization Website
3 = Relief Organization Website
4 = Private/Corporate Organization Website
5 = Crowdfunding Platform
6 = Link not Found
7 = Another User's Social Media Post
8 = Other

**Q14: What is the tweet's modality**? (*Coders should indicate what kind of post is the tweet. The tweet is text-based when it only includes text. The tweet is image-based if it includes an embedded image by itself or in addition to text or as part of an embedded link. The tweet is GIF-based if it includes a GIF by itself or in addition to text. The tweet is video-based if it includes an embedded video by itself or in addition to text or as part of an embedded link*).

1 = Text-Based
2 = Image-Based
3 = GIF-Based
4 = Video-Based

**Q15: If tweet is image-based, what kind of image does the tweet include?** (*Coders should indicate is the embedded image is an illustrative display of disaster information or a graphic display of disaster information. A graphic display of disaster information is an image that portrays numbers, charts and other numerical as well as fact-based visualizations such as infographics. An illustrative display of disaster information includes photographs of people, nature, animals and structures*).

1 = Illustrative Display of Disaster Information
2 = Graphic Display of Disaster Information

**Q16: If tweet is image-based and includes an illustrative display of disaster information, what is the focus of the photo?** (*Coders should indicate whether the embedded illustrated image predominantly portrays one of the following: A 'humor' focus can be a meme or other image whose primary intent is humor. 'Not related to Hurricane Matthew' are images that are not related to Hurricane Matthew in any capacity whatsoever. A 'features people' focus is a Hurricane Matthew-related photo that predominantly features an individual or group of people. A 'features animal' focus is a Hurricane Matthew-related photo that predominantly features an insect, an animal or a group of animals. A 'features nature and destruction' focus is a Hurricane Matthew-related photo that predominantly features the effects of the disaster on things like buildings, bridges, houses and other physical structures; weather phenomena like ominous clouds, rain, lightning and pictorial portrayals of the invisible yet palpable weather phenomena such as gusts of wind. The 'other' category is for stock images that can accompany a Hurricane Matthew-related story but by itself are not distinguishable from other stock images of its kind).*

1 = Humor
2 = Not Related to Hurricane Matthew
3 = Features People
4 = Features Animals
5 = Features Nature & Destruction
6 = Other

**Q17: If the tweet is image-based and includes an illustrative display of disaster information with a "features people" focus, what is the type of people focus?**
*(Coders should indicate whether the embedded illustrative image with people focus predominantly portrays one of the following: A 'hero' focus is an image of an individual or groups of people engaging in behaviors that are of benefit to at-risk or vulnerable people. A 'human-interest' focus is an image of an individual or groups of people that predominantly features emotion, whether positive or negative. A 'talking head' focus is an image of an individual or groups of people that typically entail pictures of people speaking at a podium or press conference. The 'other' category is for images of people that do not fit any of the previous categories)*

1 = Hero Focus
2 = Human Interest Focus
3 = Talking Head Focus
4 = Other

**Q18: If tweet is video-based, what kind of video does the tweet include?** (*Coders should indicate if the embedded video best fits one of the following categories. A user-generated video is that which does not appear to have high production values or any news tickers or other industry cue. A news coverage video is that which includes a news ticker, watermark or logo and/or any video footage being shown as part of a news clip or segment. A support or relief video is a video whose primary purpose is to rally support for volunteers or donations or resources, typically professionally rendered with high production value. A graphic or informative video includes content that focuses on providing facts, figures or information – it is not part of news coverage or relief support video. Other is for videos that do not fir any of the previous four categories*).

1 = User-Generated Video
2 = News Coverage
3 = Support or Relief Effort Video
4 = Graphic/Informative
5 = Other

*Table 1.* Social-Mediated Disaster Information Amplification Model Information Sources Conceptual Schema

| | From Emergency and Disaster Communication Research | From the Social-Mediated Crisis Communication Model | From the Social Amplification of Risk Framework |
|---|---|---|---|
| Integrates | Due to their lawfully mandated function, government entities at the local, state and federal level are sources of public-facing information<br><br>A variety of information source characterizations and archetypes can be drawn from social media profile cues | Embraces a broader understanding of information sources by considering the role of news media organizations<br><br>The behavior of social media users can also be leveraged to characterize information sources (i.e., opinion leaders, inactives) | Suggests that recipients of information can become information sources as they ‘re-transmit’ the risk information signal<br><br>Information sources can operate from individual to group and social system levels |
| Challenges | Binaries that characterize information sources as either ‘official’ or ‘unofficial’<br><br>Prioritizing ‘official sources’ in a one-way, top-down communication structure | Binaries that characterize information sources as either ‘internal’ or ‘external’ to an organization facing a crisis<br><br>Grouping friends, family and news media into the same type of information source | Can conflate a variety of information sources with news media coverage of said information sources |

*Table 2.* Social-Mediated Disaster Information Amplification Model Content Conceptual Schema

| | From Emergency and Disaster Communication Research | From the Social-Mediated Crisis Communication Model | From the Social Amplification of Risk Framework |
|---|---|---|---|
| Integrates | Social-mediated content includes information about hazard updates and public guidance on protecting health and safety<br><br>Content characteristics can be based on standard communication principles related to target communication outcomes<br><br>Social media affordances (i.e., conversational microstructures) can also characterize content | Understands that during a time characterized by dearth of information, user-generated content addresses many informational and emotional needs<br><br>Considers that information form is critical for audience perceptions and behavioral responses to content | Contends that information on social media can come in a variety of modalities<br><br>Proposes the concept of 'risk signal' which involves not just the technical components of a message, but the symbols and meanings attached as well |
| Challenges | Content matter and style guidelines gleaned only from content and dynamics involving 'official' information | Conclusions about content drawn from the study of information form or channels | Most of insight on content drawn from exploring one type of information (news coverage) |

*Table 3.* Social-Mediated Disaster Information Amplification Model Audience Engagement Conceptual Schema

| | From Emergency and Disaster Communication Research | From the Social-Mediated Crisis Communication Model | From the Social Amplification of Risk Framework |
|---|---|---|---|
| Integrates | Considers public compliance with protective guidance as a target communication outcome<br><br>Understands retransmission of terse message a desirable communication outcome | Considers public acceptance of an organization’s crisis response strategy as a favorable disaster communication outcome<br><br>Recognizes public information seeking and information sharing as common audience behavior during a crisis<br><br>Proposes that audience engagement with social media content also takes place offline (i.e., texting, talking about it, etc.) | Highlights risk perception as a critical audience response to and driver of communication<br><br>Understands social media user comments on posts to be an indicator of audience engagement |
| Challenges | Leverages information dissemination as a catch-all for how audience engages with social media content is articulated | Most of what is known about audience engagement with content stems from fictitious crisis scenarios and self-report answers about behavioral intentions | Conflating media coverage of an issue with public concern |

*Table 4.* Tweet Sampling Summary for Weekly Subset 1

| Retweet Rate | Range | Total Posts | Original Posts | Sampled Posts |
|---|---|---|---|---|
| No Retweet | 1 | 9,621 | 9,621 | 104 |
| Low Retweet | 2-9 | 4,811 | 1,378 | 104 |
| Moderate Retweet | 10-20 | 2,027 | 145 | 104 |
| High Retweet | 21-220 | 5,064 | 104 | 104 |

*Note.* Total number of publicly available tweets captured by Crimson Hexagon from September 23, 2016, to September 29, 2016, was 104,809. Total number of tweets exported was 21,523. Total number of tweets sampled for weekly subset 1 was 416.

*Table 5 Tweet Sampling Summary for Weekly Subset 2*

| Retweet Rate | Range | Total Posts | Original Posts | Sampled Posts |
|---|---|---|---|---|
| No Retweet | 1 | 38,160 | 38,160 | 102 |
| Low Retweet | 2-6 | 13,295 | 4,677 | 102 |
| Moderate Retweet | 7-23 | 6,978 | 641 | 102 |
| High Retweet | 24-416 | 5,792 | 102 | 102 |

*Note.* Total number of publicly available tweets captured by Crimson Hexagon from September 30, 2016, to October 6, 2016, was 2,919,852. Total number of tweets exported was 64,225. Total number of tweets sampled for weekly subset 2 was 408.

*Table 6 Tweet Sampling Summary for Weekly Subset 3*

| Retweet Rate | Range | Total Posts | Original Posts | Sampled Posts |
|---|---|---|---|---|
| No Retweet | 1 | 34,204 | 34,204 | 103 |
| Low Retweet | 2-6 | 10,905 | 3,850 | 103 |
| Moderate Retweet | 7-27 | 8,703 | 737 | 103 |
| High Retweet | 8-2220 | 9,942 | 103 | 103 |

*Note.* Total number of publicly available tweets captured by Crimson Hexagon from October 7, 2016, to October 13, 2016, was 2,387,617. Total number of tweets exported was 63,754. Total number of tweets sampled for weekly subset 3 was 412.

*Table 7 Tweet Sampling Summary for Weekly Subset 4*

| Retweet Rate | Range | Total Posts | Original Posts | Sampled Posts |
|---|---|---|---|---|
| No Retweet | 1 | 31,880 | 31,880 | 105 |
| Low Retweet | 2-9 | 15,148 | 4,625 | 105 |
| Moderate Retweet | 10-35 | 6,840 | 415 | 105 |
| High Retweet | 36-1219 | 10,765 | 105 | 105 |

*Note.* Total number of publicly available tweets captured by Crimson Hexagon from October 14, 2016, to October 20, 2016, was 206,735. Total number of tweets exported was 64,633. Total number of tweets sampled for weekly subset 4 was 420.

*Table 8 Tweet Sampling Summary for Weekly Subset 5*

| Retweet Rate | Range | Total Posts | Original Posts | Sampled Posts |
|---|---|---|---|---|
| No Retweet | 1 | 15,022 | 15,022 | 101 |
| Low Retweet | 2-5 | 5,961 | 1,904 | 101 |
| Moderate Retweet | 6-24 | 5,860 | 582 | 101 |
| High Retweet | 25-737 | 8,106 | 101 | 101 |

*Note.* Total number of publicly available tweets captured by Crimson Hexagon from October 21, 2016, to October 24, 2016, was 44,056. Total number of tweets exported was 34,949. Total number of tweets sampled for weekly subset 5 was 404.

*Table 9. Krippendorff's Alpha for Pilot Study 2 Items*

| Item | α | 95%CI |
|---|---|---|
| Account Availability | .98 | [.93-1.00] |
| Language | .96 | [.91-1.00] |
| Account Verified | .98 | [.95-1.00] |
| Source Type | .87 | [.81-.92] |
| Tweet Type | .71 | [.64-.79] |
| Link | .96 | [.89-1.00] |
| Link Type | .82 | [.72-.92] |
| Tweet Modality | .95 | [.91-.99] |
| Image Type | .97 | [.91-1.00] |
| Image Focus | .87 | [.75-.94] |
| People Image Focus Type | .91 | [.73-1.00] |

*Note.* Intercoder reliability was assessed using Krippendorff's Alpha.

*Table 10: Tweet Type Frequency*

| Tweet Type | N | Percent |
|---|---|---|
| Hazard Information | 368 | 21.9% |
| Volunteer/Donate/Help | 328 | 19.6% |
| Information | 224 | 13.4% |
| Hazard Impact: Deaths & Destruction | 170 | 10.1% |
| Emotion/Judgment/Evaluation | 123 | 7.3% |
| Miscellaneous | 119 | 7.1% |
| Unsure or Not on Topic | 86 | 5.1% |
| Humor | 82 | 4.9% |
| Closures/Openings | 48 | 2.9% |
| Alert | 44 | 2.6% |
| Prayer | 40 | 2.4% |
| Protective Action Recommendation | 23 | 1.4% |
| Thank You/Appreciation | 18 | 1.1% |
| Help/Directed Information | 4 | .2% |
| Total | 1677 | 100% |

*Table 11. Link Type*

| Link Type | N | Percent |
|---|---|---|
| News Organization Website | 493 | 54.7% |
| Social Media Post | 105 | 11.6% |
| Government Organization Website | 102 | 11.3% |
| Relief or Nonprofit Organization Website | 101 | 11.2% |
| Private Organization Website | 38 | 4.2% |
| Link not Found | 22 | 2.4% |
| Crowdfunding Platform | 11 | 1.2% |
| Total | 902 | 100% |

*Table 12. Post Modality and Engagement Metrics Frequencies*

| Post Modality | Retweets *M* *Mdn* | Likes *M* *Mdn* | Replies *M* *Mdn* | *N = 1677* |
|---|---|---|---|---|
| Text-Based | 372.64<br>4 | 784.87<br>2 | 16.41<br>0 | 606 |
| Image-Based | 371.55<br>41.5 | 665.99<br>25 | 10.81<br>1 | 822 |
| GIF-Based | 351.27<br>135 | 265.48<br>67.5 | 9.56<br>2 | 52 |
| Video-Based | 1735.80<br>245 | 2906.87<br>229 | 68.26<br>8 | 197 |

*Table 13. Negative Binomial Regression Results for Retweets*

| Predictor | $\beta$ | *S E* $\beta$ | Wald's $\chi^2$ | *p* | $e^{\beta}$ (odds ratio) |
|---|---|---|---|---|---|
| Constant | 6.012 | 0.290 | 20.675 | *** | 4.083 |
| Language (English) | | | | | |
| Spanish | -1.009 | 0.114 | -8.857 | *** | 3.644 |
| French | -2.205 | 0.316 | -6.976 | *** | 1.101 |
| Tweet Type (Hazard Info.) | | | | | |
| Closures/Openings | 0.862 | 0.294 | 2.928 | ** | 2.369 |
| Protective Action Recommendation | 1.319 | 0.403 | 3.268 | ** | 3.740 |
| Appreciation | -0.279 | 0.457 | -0.612 | NS | 7.559 |
| Volunteer | 0.126 | 0.163 | 0.771 | NS | 1.134 |
| Emotion | 1.236 | 0.204 | 6.035 | *** | 3.442 |
| Humor | 1.936 | 0.247 | 7.835 | *** | 6.932 |
| Prayer | 2.104 | 0.329 | 6.383 | *** | 8.199 |
| Miscellaneous | 1.361 | 0.204 | 6.656 | *** | 3.901 |
| Not on Topic | -0.758 | 0.238 | -3.182 | ** | 4.681 |
| Information | -0.494 | 0.166 | -2.966 | ** | 6.102 |
| Hazard Impact | -0.352 | 0.182 | -1.930 | . | 7.029 |
| Alert | 0.348 | 0.308 | 1.130 | NS | 1.417 |
| Source Type (Celebrity) | | | | | |
| News Media | -1.545 | 0.267 | -5.768 | *** | 2.133 |
| Government | -1.299 | 0.291 | -4.457 | *** | 2.726 |
| Relief Organization | -1.330 | 0.289 | -4.594 | *** | 2.644 |
| Private Organization | -2.565 | 0.344 | -7.441 | *** | 7.685 |
| Ordinary Users | -0.821 | 0.269 | -3.049 | ** | 4.398 |
| Bots | -5.248 | 0.380 | -13.798 | *** | 5.256 |
| Politicians | 0.270 | 0.374 | 0.723 | NS | 1.311 |
| CEOs | -2.123 | 0.451 | -4.702 | *** | 1.196 |
| Information Dissemination Entity | -1.959 | 0.291 | -6.716 | *** | 1.409 |
| Modality (Text-Based) | | | | | |
| Image-Based | 0.700 | 0.108 | 6.453 | *** | 2.014 |
| GIF-Based | 1.339 | 0.278 | 4.814 | *** | 3.816 |
| Video-Based | 2.605 | 0.158 | 16.425 | *** | 1.353 |

*Table 14. Negative Binomial Regression Results for Replies*

| Predictor | $\beta$ | *S E* $\beta$ | Wald's $\chi^2$ | *p* | $e^{\beta}$ (odds ratio) |
|---|---|---|---|---|---|
| Constant | 3.234 | 0.306 | 10.541 | *** | 25.405 |
| Verified (Verified) | | | | | |
| Unverified | -1.360 | 0.130 | -10.410 | *** | 0.256 |
| Source Type (Celebrity) | | | | | |
| News Media | -2.337 | 0.282 | -8.260 | *** | 0.096 |
| Government | -2.404 | 0.310 | -7.734 | *** | 0.090 |
| Relief Organization | -2.965 | 0.308 | -9.617 | *** | 0.051 |
| Private Organization | -3.425 | 0.378 | -9.050 | *** | 0.032 |
| Ordinary Users | -1.768 | 0.299 | -5.907 | *** | 0.170 |
| Bots | -5.766 | 0.772 | -7.467 | *** | 0.003 |
| Politicians | 0.580 | 0.394 | 1.471 | NS | 1.786 |
| CEOs | -2.601 | 0.488 | -5.329 | *** | 0.074 |
| Info. Diss. Entity | -2.351 | 0.325 | -7.225 | *** | 0.095 |
| Modality (Text-Based) | | | | | |
| Image-Based | 0.682 | 0.120 | 5.641 | *** | 1.978 |
| GIF-Based | 1.641 | 0.297 | 5.513 | *** | 5.161 |
| Video-Based | 2.604 | 0.170 | 15.234 | *** | 13.518 |
| Tweet Type (Hazard Info.) | | | | | |
| Closures/Openings | 2.051 | 0.314 | 6.520 | *** | 7.781 |
| Protective Action Rec. | 1.169 | 0.432 | 2.702 | ** | 3.218 |
| Appreciation | 0.827 | 0.496 | 1.667 | . | 2.288 |
| Volunteer | 0.885 | 0.176 | 5.020 | *** | 2.423 |
| Emotion | 1.412 | 0.222 | 6.336 | *** | 4.104 |
| Humor | 2.061 | 0.262 | 7.850 | *** | 7.859 |
| Prayer | 1.291 | 0.352 | 3.665 | *** | 3.640 |
| Miscellaneous | 1.772 | 0.215 | 8.240 | *** | 5.885 |
| Not on Topic | 1.135 | 0.254 | 4.468 | *** | 3.113 |
| Information | -0.013 | 0.185 | -0.072 | NS | 0.986 |
| Hazard Impact | 0.253 | 0.198 | 1.278 | NS | 1.288 |
| Alert | 0.161 | 0.358 | 0.450 | NS | 1.175 |

*Table 15. Negative Binomial Regression Results for Likes*

| Predictor | $\beta$ | $S\,E\,\beta$ | Wald's $\chi^2$ | $p$ | $e^{\beta}$ (odds ratio) |
|---|---|---|---|---|---|
| Constant | 6.053 | 0.319 | 18.934 | *** | 4.255 |
| Verified (Verified) | | | | | |
| Unverified | -1.009 | 0.131 | -7.690 | *** | 3.642 |
| Tweet Type (Hazard Info.) | | | | | |
| Closures/Openings | 1.886 | 0.324 | 5.823 | *** | 6.596 |
| Protective Action Recommendation | 2.388 | 0.449 | 5.314 | *** | 1.089 |
| Appreciation | 1.059 | 0.506 | 2.089 | * | 2.883 |
| Volunteer | 1.137 | 0.177 | 6.405 | *** | 3.117 |
| Emotion | 2.557 | 0.226 | 11.302 | *** | 1.290 |
| Humor | 2.849 | 0.271 | 10.489 | *** | 1.727 |
| Prayer | 3.029 | 0.364 | 8.323 | *** | 2.068 |
| Miscellaneous | 3.028 | 0.219 | 13.781 | *** | 2.066 |
| Not on Topic | 0.305 | 0.259 | 1.178 | NS | 1.356 |
| Information | 0.101 | 0.182 | 0.556 | NS | 1.107 |
| Hazard Impact | 0.236 | 0.198 | 1.190 | NS | 1.266 |
| Alert | 0.679 | 0.348 | 1.950 | . | 1.973 |
| Source Type (Celebrity) | | | | | |
| News Media | -2.485 | 0.297 | -8.346 | *** | 8.326 |
| Government | -2.611 | 0.325 | -8.032 | *** | 7.346 |
| Relief Organization | -1.596 | 0.322 | -4.953 | *** | 2.026 |
| Private Organization | -2.387 | 0.385 | -6.202 | *** | 9.185 |
| Ordinary Users | -0.658 | 0.313 | -2.09 | * | 5.177 |
| Bots | -6.916 | 0.482 | -14.346 | *** | 9.917 |
| Politicians | -0.104 | 0.417 | -0.249 | NS | 9.012 |
| CEOs | -2.014 | 0.503 | -4.002 | *** | 1.334 |
| Information Dissemination Entity | -2.028 | 0.337 | -6.016 | *** | 1.315 |
| Modality (Text-Based) | | | | | |
| Image-Based | 0.635 | 0.121 | 5.250 | *** | 1.888 |
| GIF-Based | 1.505 | 0.308 | 4.883 | *** | 4.508 |
| Video-Based | 2.716 | 0.176 | 15.623 | *** | 1.582 |

*Table 16. Binomial Logistic Regression Analysis of Information Sources' Visual Content Type*

| Predictor | $\beta$ | *S E* $\beta$ | Wald's $\chi^2$ | *df* | *p* | $e^{\beta}$ (odds ratio) |
|---|---|---|---|---|---|---|
| Constant | -0.765 | 0.271 | 7.999 | 1 | .005 | 0.465 |
| Information Source | | | | | | |
| News Media Organizations | 0.619 | 0.291 | 4.534 | 1 | .033 | 1.857 |
| Government Organizations | 1.069 | 0.331 | 10.432 | 1 | .001 | 2.911 |
| Ordinary Users | 0.231 | 0.346 | 0.446 | 1 | .504 | 1.260 |
| Other Sources | -0.091 | 0.312 | 0.086 | 1 | .769 | 0.913 |

Note. The dependent variable encoding for Visual Content Type was Illustrative Image = 0, and Graphic Image = 1. The independent variable encoding for Information Source Type was Celebrity = 0, News Media Organizations = 1, Government Organizations = 2, Ordinary Users = 3, and Other Sources = 4.

*Table 17. Multinomial Logistic Regression Analysis of Information Sources' Image Focus*

| Predictor | $\beta$ | *S E* $\beta$ | Wald's $\chi^2$ | *df* | *p* | $e^{\beta}$ (odds ratio) |
|---|---|---|---|---|---|---|
| Image Focus: Features People | | | | | | |
| Constant | 0.985 | 0.221 | 19.793 | 1 | .000 | |
| Information Source | | | | | | |
| Celebrities | 0.663 | 0.536 | 1.531 | 1 | .216 | 1.941 |
| News Media Organizations | -0.732 | 0.288 | 6.437 | 1 | .011 | 0.481 |
| Government Organizations | 0.051 | 0.415 | 0.015 | 1 | .903 | 1.052 |
| Ordinary Users | -1.243 | 0.392 | 10.079 | 1 | .001 | 0.288 |
| Image Focus: Features Nature & Destruction | | | | | | |
| Constant | 0.251 | 0.252 | 0.995 | 1 | .319 | |
| Information Source | | | | | | |
| Celebrities | 0.624 | 0.589 | 1.123 | 1 | .289 | 1.867 |
| News Media Organizations | 0.074 | 0.311 | 0.057 | 1 | .812 | 1.077 |
| Government Organizations | -0.857 | 0.567 | 2.290 | 1 | .130 | 0.424 |
| Ordinary Users | -0.398 | 0.402 | 0.980 | 1 | .322 | 0.672 |

Note. The dependent variable encoding for Visual Content Focus was Features Other = 0, Features People = 1, and Features Nature & Destruction = 2. The independent variable encoding for Information Source Type was Other Information Sources = 0, Celebrities = 1, News Media Organizations = 2, Government Organizations = 3, and Ordinary Users = 4.

*Table 18. Disaster Preparedness Themes and Post Copy*

| Hurricane Preparedness Theme | Copy |
|---|---|
| Know your hurricane risk | Live in the coast? You're most at risk for extreme winds, flooding and storm surge during a hurricane. Know your risk before the storm. Click here to learn more: https://bit.ly/2D1ytuJ |
| Know your evacuation zone | Know before you go: You may have to evacuate quickly due to a hurricane. Learn your evacuation routes and identify where you will stay. Text SHELTER and your zip code to 43362 to find open shelters. |
| Check your insurance coverage | 30: The number of days it takes for flood insurance to begin. Find out if you live in a flood prone area and how flood insurance can lessen the financial impact of a flood by clicking here: https://bit.ly/1ly4gAK |
| Assemble disaster supplies | Hurricane + high winds (frequently) = power loss. Store enough supplies (e.g., food, bottled water) to last at least 3 days – if possible for a week or more. Click here for a basic supply list ready.gov/kit |
| Download the FEMA application | Disasters don't plan ahead. You can. Download the FEMA App for real-time weather alerts, safety tips, shelter & housing assistance program information: https://www.fema.gov/mobile-app #HurricanePrep |

*Table 19. Demographic Variables Comparison 1*

| Variable | Online Experiment (N = 245) | FEMA Region IV States Estimates[1] | General U.S. Population Estimates[1] |
|---|---|---|---|
| *Age (median)* | 37 (*SD* = 12.60) | 39.0 (*average median value*) | 38.2 |
| *Gender* | | | |
| Male | 34.7% | 48.0%[3] | 48.7%[3] |
| Female | 65.3% | 51.9%[3] | 51.3%[3] |
| *Hispanic or Latino* | 9.8% | 13.1%[4] | 18.2%[4] |
| *Race* | | | |
| White | 75.9% | 70.3%[4] | 72.1%[4] |
| Black | 15.1% | 21.4%[4] | 12.7%[4] |
| Asian | 4.5% | 2.5%[4] | 5.6%[4] |
| Other[2] | 4.5% | 0.5%[4] | 1.0%[4] |

*Note.* [1] Data obtained from the 2018 American Community Survey (ACS) 1-Year Estimates. [2]Includes answers to the "*refuse to answer*" option. [3]Based on the "*18 years and older*" estimates. [4]Based on "*all ages*" estimate.

*Table 20. Demographic Variables Comparison 2*

| Variable | Online Experiment (N = 245) | FEMA Region IV States Estimates[1] | General U.S. Population Estimates[1] |
|---|---|---|---|
| *Marriage Status* | | | |
| Married | 50.6% | 46.8%[2] | 47.8%[2] |
| Widowed | 2.0% | 6.4%[2] | 5.7%[2] |
| Divorced | 10.6% | 12.1%[2] | 10.9%[2] |
| Separated | .8% | 2.2%[2] | 1.9%[2] |
| Never Married | 35.9% | 32.2%[2] | 33.8%[2] |
| *Educational Attainment* | | | |
| HS Incomplete | 1.2% | 12.5%[3] | 11.7%[3] |
| HS Complete | 11.0% | 29.3%[3] | 27.4%[3] |
| Some College/Associates | 35.9% | 31.2%[3] | 30.6%[3] |
| Bachelor's or Higher | 51.8% | 27.0%[3] | 30.0%[3] |

*Note.* [1] Data obtained from the 2018 American Community Survey (ACS) 1-Year Estimates. [2]Based on the "*Total population over 15*" estimates. [3]Based on the "*population 18 to 24 years*" and "*population 25 years and over*" estimates.

*Table 21. Demographic Variables Comparison 3*

| Variable | Online Experiment (N = 245) | FEMA Region IV States Estimates[1] | General U.S. Population Estimates[1] |
|---|---|---|---|
| *Income* | | | |
| Less than 10k | 3.7% | 7.0% | 6.3% |
| 10 to under 50k | 46.9% | 38.8% | 34.6% |
| 50 to under 75k | 23.3% | 18.2% | 17.4% |
| 75 to under 100k | 13.5% | 12.3% | 12.6% |
| 100 to under 150k | 8.2% | 13.1% | 15.0% |
| 150k or more | 1.6% | 10.4% | 14.2% |
| Other[2] | 2.9% | | |
| *State* | | | |
| Alabama | 6.5% | 7.3%[3] | 1.5%[3] |
| Florida | 34.7% | 32.9%[3] | 6.7%[3] |
| Georgia | 18.0% | 15.4%[3] | 3.2%[3] |
| Kentucky | 6.5% | 6.7%[3] | 1.4%[3] |
| Mississippi | 2.4% | 4.4%[3] | .9%[3] |
| North Carolina | 18.0% | 15.6%[3] | 3.2%[3] |
| South Carolina | 5.3% | 7.7%[3] | 1.6%[3] |
| Tennessee | 8.2% | 10.1%[3] | 2.1%[3] |
| Other | .4% | | |

*Note.* [1] Data obtained from the 2018 American Community Survey (ACS) 1-Year Estimates. [2]Includes answers to the "*don't know*" and "*refuse to answer*" options. [3]Based on the "*18 years and older*" estimates.

*Table 22. Means and Alpha Coefficients for Major Variables 1*

| | *Min – Max* | *Mean* | *SD* | *α* |
|---|---|---|---|---|
| *Previous Hurricane Experience 1* | | | | |
| Had Evacuated | 0-1 | .612 | .488 | |
| Had Property Damage | 0-1 | .551 | .498 | |
| Had Financial Losses | 0-1 | .338 | .474 | |
| Had Been Injured | 0-1 | .032 | .178 | |
| Had Distress | 0-1 | .538 | .499 | .657 |
| *Previous Hurricane Experience 2* | | | | |
| Impact Severity Perception | 1-7 | 3.24 | 1.60 | |
| *Affective Risk Perception* | | | | |
| Fearful | 1-7 | 5.16 | 1.61 | |
| Worried | 1-7 | 5.49 | 1.43 | |
| Dread | 1-7 | 4.66 | 1.75 | |
| Depressed | 1-7 | 3.75 | 1.71 | .884 |
| *Cognitive Risk Perception* | | | | |
| Cause Catastrophic Destruction | 1-7 | 6.39 | .795 | |
| Cause Widespread Death | 1-7 | 5.47 | 1.30 | |
| Pose Great Financial Threat | 1-7 | 6.26 | .950 | |
| Pose Threat to Future Generations | 1-7 | 5.33 | 1.47 | .775 |
| *Guidance Adoption Intentions* | | | | |
| Gather Information Risks | 1-7[2] | 5.19 | 1.92 | |
| Gather Information Evacuation | 1-7[2] | 5.24 | 1.95 | |
| Get Flood Insurance | 1-7[2] | 4.36 | 2.27 | |
| Assemble Emergency Kit | 1-7[2] | 5.88 | 1.64 | |
| Download FEMA App | 1-7[2] | 4.26 | 2.08 | .798 |

*Note*. [2]The "*Already Done*" and "*N/A*" answers were recoded. "*Already Done*" was recoded as 7, "*Strongly Agree*," and "*N/A*" was recoded as 1, "*Strongly Disagree*."

*Table 23. Means and Alpha Coefficients for Major Variables Indexes*

| | *Min – Max* | *Mean* | *SD* | *α* |
|---|---|---|---|---|
| Previous Hurricane Experience 1 | 0-5 | 2.07 | 1.44 | .657 |
| Affective Risk Perception | 1-7 | 4.77 | 1.40 | .883 |
| Cognitive Risk Perception | 1-7 | 5.86 | .899 | .811 |
| Guidance Adoption Intentions | 1-7 | 4.99 | 1.47 | .798 |
| Crisis Information Seeking Intentions | 1-7 | 3.77 | 1.14 | .739 |
| Crisis Information Sharing Intentions | 1-7 | 3.74 | 1.34 | .927 |
| Source Credibility Perceptions | 1-7 | 5.97 | .924 | .960 |
| Post 1 Message Credibility Perceptions | 1-7 | 5.93 | .895 | .773 |
| Post 2 Message Credibility Perceptions | 1-7 | 6.04 | .904 | .829 |
| Post 3 Message Credibility Perceptions | 1-7 | 5.65 | 1.03 | .834 |
| Post 4 Message Credibility Perceptions | 1-7 | 6.08 | .904 | .806 |
| Post 5 Message Credibility Perceptions | 1-7 | 5.76 | 1.05 | .817 |

*Table 24. Means and Alpha Coefficients for Major Variables 2*

| | *Min – Max* | *Mean* | *SD* | *α* |
|---|---|---|---|---|
| *Crisis Information Seeking Intentions* | | | | |
| Look on Twitter | 1-7[1] | 4.47 | 2.14 | |
| Look on Instagram | 1-7[1] | 3.08 | 1.95 | |
| Look on Pinterest | 1-7[1] | 2.35 | 1.66 | |
| Look on Snapchat | 1-7[1] | 2.29 | 1.69 | |
| Talk to People | 1-7[1] | 5.49 | 1.54 | |
| Email People | 1-7[1] | 3.53 | 1.92 | |
| Text People | 1-7[1] | 5.17 | 1.83 | |
| | | | | .739 |
| *Crisis Information Sharing Intentions* | | | | |
| Email People | 1-7[1] | 3.83 | 1.98 | |
| Call People | 1-7[1] | 5.26 | 1.74 | |
| Text People | 1-7[1] | 5.46 | 1.58 | |
| "Like" Facebook Post | 1-7[1] | 4.93 | 1.98 | |
| "Share" Facebook Post | 1-7[1] | 4.80 | 2.07 | |
| "Comment" on Facebook Page | 1-7[1] | 3.80 | 1.96 | |
| "Retweet" Tweet | 1-7[1] | 4.17 | 2.20 | |
| Tweet | 1-7[1] | 3.74 | 2.12 | |
| Post Blog Post | 1-7[1] | 2.48 | 1.73 | |
| Upload Pictures to Instagram | 1-7[1] | 3.07 | 1.98 | |
| Upload Pictures to Pinterest | 1-7[1] | 2.41 | 1.78 | |
| "Like" Instagram Post | 1-7[1] | 4.25 | 2.19 | |
| "Share" Instagram Post | 1-7[1] | 3.66 | 2.22 | |
| "Comment" on Instagram Post | 1-7[1] | 3.27 | 1.99 | |
| "Like" Pinterest Post | 1-7[1] | 3.28 | 2.22 | |
| "Re-pin" Pinterest Post | 1-7[1] | 2.66 | 1.89 | |
| "Comment" on Pinterest Profile | 1-7[1] | 2.59 | 1.84 | .927 |

*Note*. [1]The "N/A" answer was re-coded as "Strongly Disagree".

*Table 25. Means and Alpha Coefficients for Major Variables 3*

| | *Min – Max* | *Mean* | *SD* | *α* |
|---|---|---|---|---|
| *Source Credibility Perceptions* | | | | |
| Intelligent[1] | 1-7 | 6.14 | 1.17 | |
| Trained | 1-7 | 6.29 | .938 | |
| Expert | 1-7 | 6.22 | 1.10 | |
| Informed[1] | 1-7 | 6.32 | 1.01 | |
| Competent | 1-7 | 6.17 | 1.10 | |
| Bright[1] | 1-7 | 6.00 | 1.15 | |
| "Cares About Me"[1] | 1-7 | 5.64 | 1.33 | |
| "Has My Interest at Heart"[1] | 1-7 | 5.66 | 1.35 | |
| Not Self-Centered | 1-7 | 5.74 | 1.52 | |
| "Concerned with Me"[1] | 1-7 | 5.74 | 1.26 | |
| Sensitive | 1-7 | 5.56 | 1.21 | |
| Understanding | 1-7 | 5.76 | 1.17 | |
| Honest[1] | 1-7 | 5.92 | 1.30 | |
| Trustworthy | 1-7 | 6.17 | 1.14 | |
| Honorable[1] | 1-7 | 5.95 | 1.22 | |
| Moral[1] | 1-7 | 5.95 | 1.23 | |
| Ethical | 1-7 | 6.13 | 1.08 | |
| Genuine | 1-7 | 6.17 | 1.05 | .960 |

*Note*. [1]Reverse-coded.

*Table 26.* Means and Alpha Coefficients for Major Variables 4

| | *Min – Max* | *Mean* | *SD* | *α* |
|---|---|---|---|---|
| *Post 1 Message Credibility Perceptions* | | | | |
| Believable | 1-7 | 6.33 | 1.01 | |
| Accurate | 1-7 | 6.28 | .979 | |
| Trustworthy | 1-7 | 6.28 | .941 | |
| Unbiased[1] | 1-7 | 5.32 | 1.72 | |
| Complete | 1-7 | 5.44 | 1.34 | .773 |
| *Post 2 Message Credibility Perceptions* | | | | |
| Believable | 1-7 | 6.35 | .949 | |
| Accurate | 1-7 | 6.33 | .929 | |
| Trustworthy | 1-7 | 6.30 | .918 | |
| Unbiased[1] | 1-7 | 5.47 | 1.64 | |
| Complete | 1-7 | 5.74 | 1.26 | .829 |
| *Post 3 Message Credibility Perceptions* | | | | |
| Believable | 1-7 | 6.07 | 1.05 | |
| Accurate | 1-7 | 5.95 | 1.13 | |
| Trustworthy | 1-7 | 5.95 | 1.13 | |
| Unbiased[1] | 1-7 | 4.99 | 1.80 | |
| Complete | 1-7 | 5.30 | 1.42 | .834 |
| *Post 4 Message Credibility Perceptions* | | | | |
| Believable | 1-7 | 6.45 | .884 | |
| Accurate | 1-7 | 6.37 | .977 | |
| Trustworthy | 1-7 | 6.37 | .953 | |
| Unbiased[1] | 1-7 | 5.42 | 1.73 | |
| Complete | 1-7 | 5.78 | 1.27 | .806 |
| *Post 5 Message Credibility Perceptions* | | | | |
| Believable | 1-7 | 6.21 | 1.01 | |
| Accurate | 1-7 | 6.11 | 1.08 | |
| Trustworthy | 1-7 | 6.06 | 1.13 | |
| Unbiased[1] | 1-7 | 4.88 | 1.98 | |
| Complete | 1-7 | 5.53 | 1.47 | .817 |

*Note.* [1]Reverse-coded.

*Table 27. Post Credibility Means by Experiment Condition*

| *Condition* <br> *N =* | *1* <br> *36* | *2* <br> *34* | *3* <br> *32* | *4* <br> *36* | *5* <br> *36* | *6* <br> *37* | *7* <br> *34* |
|---|---|---|---|---|---|---|---|
| *Post 1* | | | | | | | |
| Believable | 6.30 | 6.35 | 5.90 | 6.47 | 6.63 | 6.24 | 6.41 |
| Accurate | 6.38 | 6.35 | 5.75 | 6.41 | 6.36 | 6.29 | 6.38 |
| Trustworthy | 6.30 | 6.26 | 5.75 | 6.50 | 6.38 | 6.32 | 6.44 |
| Unbiased[1] | 5.00 | 5.35 | 4.59 | 5.30 | 5.61 | 5.67 | 5.67 |
| Complete | 5.55 | 5.11 | 5.09 | 5.44 | 5.72 | 5.43 | 5.70 |
| Total | 5.91 | 5.88 | 5.41 | 6.02 | 6.14 | 5.99 | 6.12 |
| *Post 2* | | | | | | | |
| Believable | 6.25 | 6.41 | 6.00 | 6.38 | 6.55 | 6.37 | 6.44 |
| Accurate | 6.16 | 6.35 | 5.96 | 6.52 | 6.55 | 6.32 | 6.44 |
| Trustworthy | 6.27 | 6.32 | 5.87 | 6.41 | 6.55 | 6.32 | 6.29 |
| Unbiased[1] | 5.27 | 5.79 | 5.03 | 5.38 | 5.52 | 5.67 | 5.58 |
| Complete | 5.50 | 5.61 | 5.50 | 5.77 | 6.13 | 5.67 | 6.00 |
| Total | 5.89 | 6.10 | 5.67 | 6.10 | 6.26 | 6.07 | 6.15 |
| *Post 3* | | | | | | | |
| Believable | 6.13 | 6.23 | 5.50 | 6.19 | 6.30 | 6.13 | 5.97 |
| Accurate | 5.94 | 6.02 | 5.59 | 6.11 | 6.16 | 5.94 | 5.82 |
| Trustworthy | 6.05 | 6.08 | 5.43 | 6.22 | 6.02 | 5.89 | 5.91 |
| Unbiased[1] | 5.00 | 5.08 | 4.40 | 4.80 | 5.19 | 5.43 | 4.94 |
| Complete | 5.47 | 5.14 | 5.18 | 5.30 | 5.61 | 5.10 | 5.29 |
| Total | 5.72 | 5.71 | 5.22 | 5.72 | 5.86 | 5.70 | 5.58 |
| *Post 4* | | | | | | | |
| Believable | 6.50 | 6.41 | 6.09 | 6.52 | 6.63 | 6.43 | 6.52 |
| Accurate | 6.44 | 6.26 | 6.06 | 6.47 | 6.44 | 6.37 | 6.50 |
| Trustworthy | 6.47 | 6.38 | 6.00 | 6.44 | 6.44 | 6.35 | 6.50 |
| Unbiased[1] | 5.36 | 5.76 | 5.09 | 5.44 | 5.36 | 5.54 | 5.38 |
| Complete | 5.83 | 5.55 | 5.62 | 5.83 | 5.88 | 5.72 | 6.00 |
| Total | 6.12 | 6.07 | 5.77 | 6.14 | 6.15 | 6.08 | 6.18 |
| *Post 5* | | | | | | | |
| Believable | 6.00 | 6.14 | 5.84 | 6.38 | 6.41 | 6.32 | 6.32 |
| Accurate | 6.02 | 6.17 | 5.62 | 6.27 | 6.19 | 6.24 | 6.20 |
| Trustworthy | 5.97 | 6.00 | 5.56 | 6.38 | 6.25 | 6.13 | 6.08 |
| Unbiased[1] | 4.55 | 5.44 | 4.62 | 4.52 | 4.86 | 5.16 | 5.02 |
| Complete | 5.41 | 5.47 | 5.40 | 5.58 | 5.63 | 5.51 | 5.67 |
| Total | 5.59 | 5.84 | 5.41 | 5.83 | 5.87 | 5.87 | 5.86 |

*Note*. [1]Reverse-coded.

FIGURES

*Figure 1. The Social-Mediated Disaster Information Amplification (SMDIA) Model*

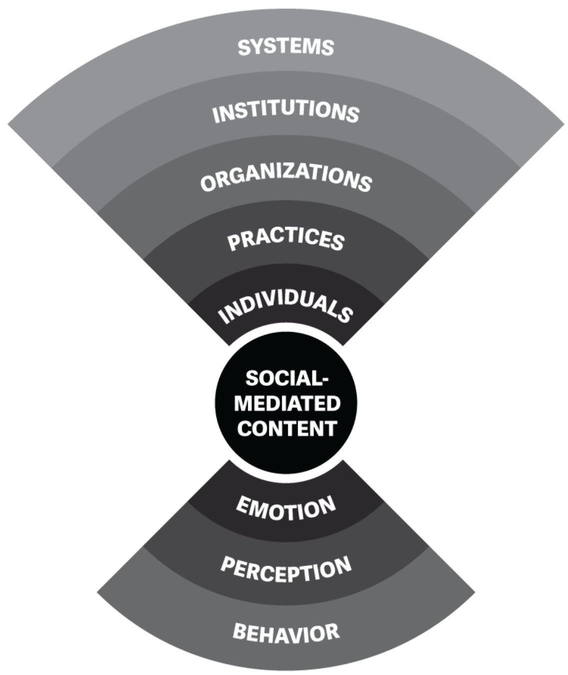

*Figure 2. Hurricane Matthew Timeline*

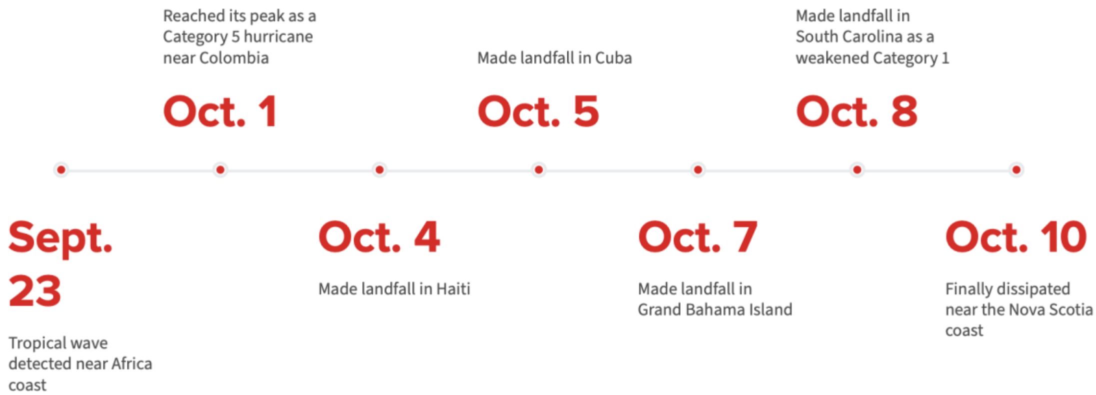

*Figure 3. Blank version of the NFHMC Twitter profile*

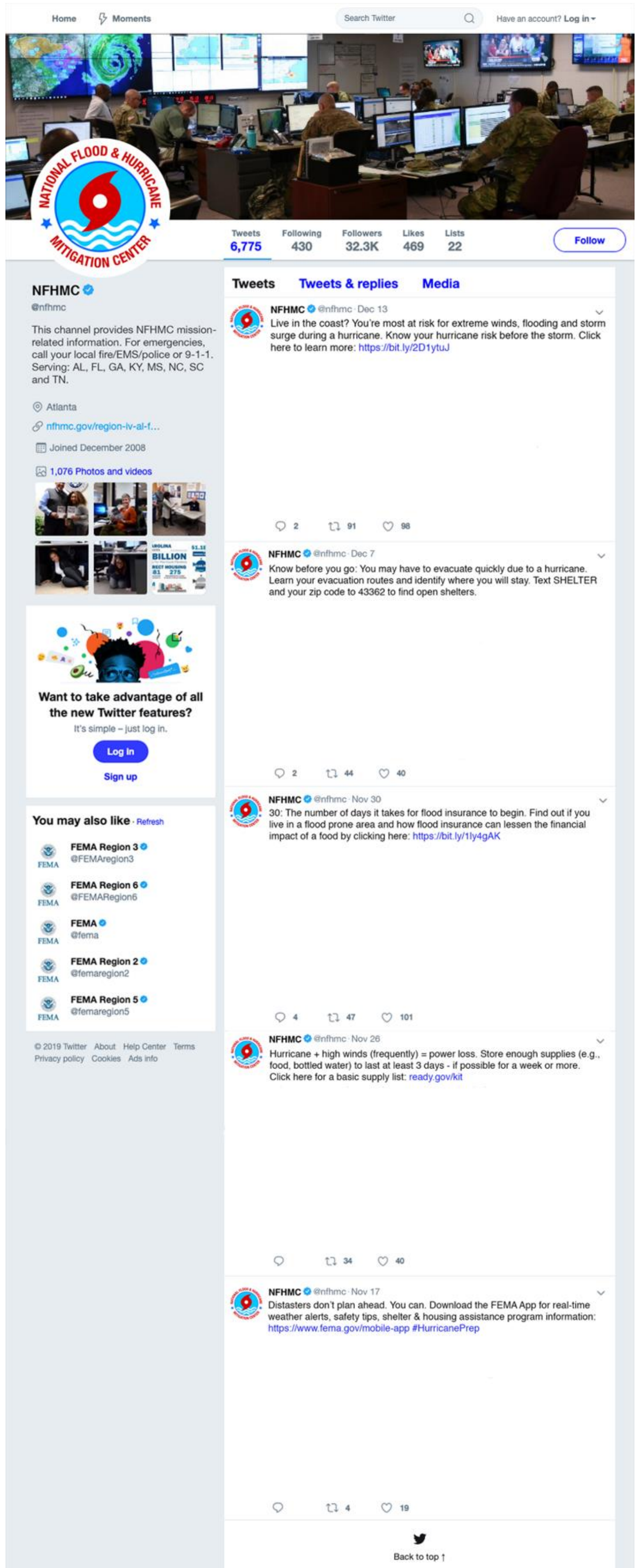

*Figure 4. Mediation Model 1*

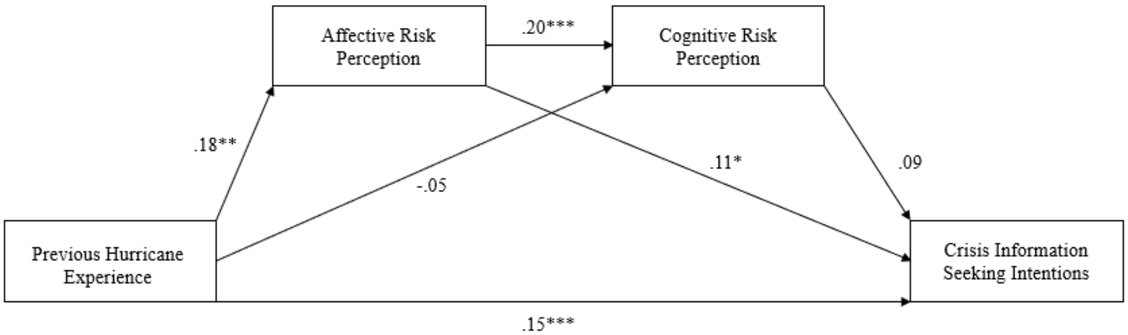

*Figure 5. Mediation Model 2*

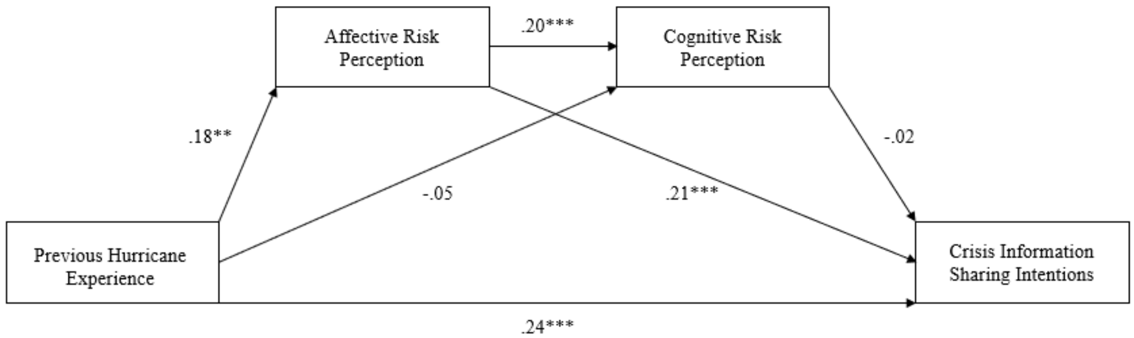

*Figure 6. Mediation Model 3*