2022

Assessing Dialogic Communication Elements in Online Emergency Communication

Lauren Bailey Cain
University of Kentucky, cain.laurenb@gmail.com
Author ORCID Identifier:
https://orcid.org/0000-0003-1547-499X
Digital Object Identifier: https://doi.org/10.13023/etd.2022.216

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Lauren Bailey Cain, Student

Dr. H. Dan O'Hair, Major Professor

Dr. Anthony Limperos, Director of Graduate Studies

ASSESSING DIALOGIC COMMUNICATION ELEMENTS
IN ONLINE EMERGENCY COMMUNICATION

THESIS

A thesis submitted in partial fulfillment of the
requirements for the degree of Master of Arts in the
College of Communication and Information
at the University of Kentucky

By

Lauren Bailey Cain

Lexington, Kentucky

Director: Dr. H. Dan O'Hair, Professor of Communication

Lexington, Kentucky

2022

https://orcid.org/0000-0003-1547-499X

ABSTRACT OF THESIS

ASSESSING DIALOGIC COMMUNICATION ELEMENTS IN ONLINE EMERGENCY COMMUNICATION

Social media have been identified as powerful tools for two-way crisis communication, allowing officials to reach, inform, and motivate at-risk publics during emergencies. However, government use of social media during emergencies is a relatively new area of study and is thus understudied and undertheorized, with little evidence-based guidance for online messaging strategies during emergencies. Dialogic communication theory has recently been used as a framework to investigate the utility of social media as channels for facilitating two-way, cocreational communication. This study assesses the use and impact of dialogic communication elements at each stage of the crisis and emergency risk communication model (CERC) using a content analysis of tweets from 10 state emergency management agencies (EMAs) over a 12-month period, expanding upon W. Liu et al.'s (2020) multi-level framework for dialogic communication in social media-mediated disaster communication. There were statistically significant differences in the means or frequencies of use for all dialogic communication elements and in engagement between CERC stages. Results highlight opportunities for state EMAs to increase use of message attributes such as information specificity, themes of community, and explicit invitations to engage or interact with content or resources. There were few significant associations between dialogic communication elements and engagement metrics when control variables (e.g., hazard topic, tweet type, and CERC stage) were included in a negative binomial regression model, emphasizing the importance of message form and context in online emergency communication.

KEYWORDS: dialogic communication theory, emergency communication, social media

Lauren Bailey Cain

05/12/2022

Date

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By
Lauren Bailey Cain

Dr. H. Dan O'Hair
Director of Thesis

Dr. Anthony Limperos
Director of Graduate Studies

05/12/2022

ACKNOWLEDGMENTS

I must begin by thanking my advisor, Dr. Dan O'Hair. Your wisdom, guidance, and ineffable support have meant the world to me. Whether you knew it or not, every time I felt down or discouraged you said something that reminded me that I am capable of doing what needs to be done.

To Dr. Deborah Chung, for jumping on to my committee with enthusiasm and encouragement, imparting your content analysis wisdom to me, and talking me out of coding 6,400 tweets!

To Dr. Nancy Harrington, for pushing me when I needed it most, encouraging me to start fresh when necessary, and helping me become a better writer and scholar.

To all my other academic mentors, including Dr. Jennifer Scarduzio, Dr. Anthony Limperos, Dr. Emily Walpole, and especially Dr. Emina Herovic. Emina, I simply would not be where I am today without you. Thank you for introducing me to the world of risk and crisis communication and showing me that I can succeed here.

To Mallory and Madelyn, my "mini-cohort", for our (semi-)weekly meetings/vent sessions at Cornerstone. I am so glad I got to do this with you two.

To my family, for granting me the opportunity to pursue higher education, being on board every time I've changed direction, and instilling my love of reading and knowledge at an early age.

To my mental saviors (biking Kentucky backroads, my cat, and North Lime donuts, to name a few) and all the people who have loved and supported me unconditionally. To James, in particular– you go above and beyond even when I think you can't go any farther. I quite literally could not have done this without you.

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CHAPTER 1. INTRODUCTION

As natural disasters increase in frequency and intensity (World Meteorological Organization, 2021), communication serves as a means for government leaders to build community resilience during times of crisis (B. F. Liu et al., 2020). However, scholars have not yet fully explicated the extent to which various messaging strategies influence disaster recovery and community resilience outcomes (Fraustino et al., 2018). Social media have emerged as a valuable tool for rapid and direct two-way dialogic communication and engagement between governments and publics during emergencies (Lin et al., 2016; Lovari & Bowen, 2020), allowing officials to meet the expectations that they inform and engage the public via social media (Fraustino & Liu, 2018; B. F. Liu et al., 2015; Xu, 2020). With these new opportunities comes an essential need to reconsider traditional one-way communication practices of sharing risk and crisis information to publics during emergencies (Lin et al., 2016) and to rigorously evaluate the impact and merit of dedicating resources toward social media crisis communication (B. F. Liu et al., 2015).

Few studies within the realm of emergency communication take similar approaches in terms of theoretical frameworks, constructs, and variables, and many do not derive experimental message design choices from theory. However, scholars (e.g., W. Liu et al., 2020; Olson et al., 2019) have recently begun to systematically assess the influence of specific dialogic message features in social media-mediated emergency communication and their impacts on public engagement outcomes. At present, no studies have answered W. Liu et al.'s (2020) call for future work to apply their multi-level framework of social media-mediated dialogic communication during disasters to other emergency contexts or to assess the influence of dialogic communication elements on public engagement during various emergency stages. This study answers that call using a content analysis of 1,185 tweets from official state emergency management agency (EMA) accounts over a 12-month period of observation and incorporating the crisis and emergency risk communication (CERC) model as a framework to assess the influence of dialogic elements at each stage of an emergency. In this paper, I will review extant literature related to emergency communication, dialogic communication theory, and social media; summarize data collection and analysis methods; report results; and discuss limitations and contributions to the literature.

CHAPTER 2. LITERATURE REVIEW

2.1 Emergency communication

Before reviewing literature related to dialogic communication theory, it is important to establish some conceptual differences between crisis and disaster or emergency communication. For the purposes of this study, the terms "disaster" and "emergency" will be used somewhat interchangeably, as many of the frameworks for crisis and disaster communication can be applied to hazards and emergencies generally. The study and understanding of crises have benefitted from interdisciplinary theories and approaches, including 20 years of communication-based theoretical approaches to organizational crisis response (Ulmer et al., 2018). Crises and disasters are similar but can be differentiated by their emphasis on organizational and community outcomes, respectively. Disasters can be considered operational crises (Coombs, 2017) because both natural and human-made disasters pose threats to "a community's ability to adequately respond [to the threat] and protect itself" (Fraustino & Liu, 2018, p. 130). However, the bulk of crisis communication terms and theory reflect an emphasis on organizations and the reputational threats stemming from crises. As a result, dominant theories in crisis communication literature are primarily concerned with outcomes related to organizational legitimacy and image (Fraustino & Liu, 2018; B. F. Liu et al., 2016).

Reputational crises are notably different from operational crises such as natural disasters, which cannot be attributed to any one organization's wrongdoing (Stewart & Young, 2018). When officials are not at fault for a disaster, their primary goal of emergency communication is to share potentially life-saving information rather than reputation management. In other words, whereas crises have typically been viewed as organization-centered in crisis communication scholarship, disasters are community-centered (B. F. Liu et al., 2016), challenging the tendency of many crisis communication theories to emphasize evaluations and outcomes pertinent to the organization (Stewart & Young, 2018). Of course, operational crises such as natural disasters can spawn reputational crises and threaten an organizations' image (Coombs, 2017) if the public finds an organization's preparation or response to be inadequate (Adkins, 2010; B. F. Liu et al., 2016).

Considering these distinctions, B. F. Liu et al. (2016) define disaster communication as "information creation, seeking, and/or sharing among individuals, organizations, and the media surrounding an event involving largely damaging violations of publics' expectations" (p. 628). Emphasizing the audience-centered nature of disasters and emergencies, recent work has emphasized a shift from traditional one-way information sharing toward two-way, cocreational communication. With an audience-centered or two-way communication approach, organizations can communicate with publics rather than communicating to them and facilitate the creation of shared meaning through interaction (Fraustino & Liu, 2018). Dialogic communication theory has been identified as a valuable cocreational framework for guiding emergency message design in online contexts by capitalizing on the interactivity affordances of social media (Fraustino & Liu, 2018).

2.2 Dialogic communication theory

Dialogic communication theory proposes a two-way cocreational framework in which exchanges between organizations and publics facilitate cocreation of meaning (Fraustino & Liu, 2018). From this perspective, an organization's capacity to engage in dialogue is not attributed as a static characteristic of the organization but as a dynamic and strategic process (W. Liu et al., 2020) in which organizations orient themselves to their audience members, as opposed to promoting one-way persuasive messages (Fraustino & Liu, 2018). With roots in public relations scholarship, the concept of dialogic communication is centered around "a process of negotiated communication, [and] is considered to be an especially ethical way of conducting public dialogue and public relations" (Kent & Taylor, 1998, p. 325).

Engagement is a key component of dialogic communication theory as it allows communicators to include publics in co-creation of meaning and decision-making processes (Olson et al., 2019). According to Tang et al. (2021), public engagement is "the various forms of communicative interaction between the public and government agencies, such as the public sharing or replying to governmental agencies' messages" (p. 2), and this engagement can be used to assess the effectiveness of agencies' communication efforts. Officials can facilitate audience engagement and, in turn, more positive crisis outcomes by sharing messages that reflect invitational rhetoric, or indications of openness to dialogic communication (Yang et al., 2010). Engagement is particularly important during emergencies when uncertainty is high as it allows users to interact directly with official information sources (Xu, 2020).

Through engagement, officials can also gain deeper understanding and perspectives to factor into future decision-making (Kent & Taylor, 2002). For example, engaging in dialogue with publics can help officials understand population-specific challenges and needs during emergencies and thus include tailored assessments of such needs into future warning and response plans (Campbell et al., 2020). Additionally, engaging in online dialogic processes with officials can improve publics' future confidence in both the message source and medium, a particularly useful outcome for officials who are responsible for emergency communication in areas frequently impacted by natural hazards (Lachlan et al., 2018). However, the evaluation of specific dialogic communication practices such as actively engaging in conversations with the public, listening to concerns, and replying to requests for assistance on social media in crisis contexts appears to be infrequent in disaster communication scholarship (B. F. Liu et al., 2020).

2.2.1 Dialogic communication elements

Dialogic communication theory points to several message features that can facilitate public engagement without sacrificing the quality of a message (W. Liu et al., 2020). Broadly speaking, message content and message structure are crucial components of engagement (Olson et al., 2019). Message content can facilitate online engagement via sharing information, instructing followers to engage in recommended behaviors and building community through connections between organizations and users (Olson et al., 2019). Providing relevant and accessible information is a foundational necessity for dialogic communication (Kent & Taylor, 1998; Olson et al., 2019), meaning frameworks for dialogic communication should include the content of messages (W. Liu et al., 2020).

Until recently, dialogic communication scholarship focused more on the effects of dialogic communication practices without settling on a clear conceptualization of dialogue itself, treating dialogue as "an attitude or an orientation, rather than a technique" (Ihlen & Levenshus, 2018, p. 391). Drawing from extant work related to social media-mediated engagement, organization-public dialogic communication, and disaster planning and response, W. Liu et al. (2020) developed a multi-level framework for social media-mediated dialogic communication during disasters (see Figure 1). The framework consists of three core components derived from evidence that message structure, content, and style can each influence message effects (W. Liu et al., 2020).

The first component is message structural features, which is broken down into information specificity (i.e., the amount of relevant, accessible information) and media richness (W. Liu et al., 2020). Here, media richness is defined as the variety of media included in a message (W. Liu et al., 2020); this rather simplistic conceptualization of media richness differs from the more widely recognized conceptualization of media richness outlined by Daft and Lengel (1986). The second component is context-specific topical features. W. Liu et al. (2020) identify disaster risk forecasts, correcting misinformation, confirming disaster relief updates, connecting the public to aid resources, and themes of growing community and storytelling as key topics for facilitating dialogue. Lastly, the linguistic features component includes dialogic loops (i.e., posing questions to followers and answering users' questions; Olson et al., 2019), message tone, and message genuineness (W. Liu et al., 2020).

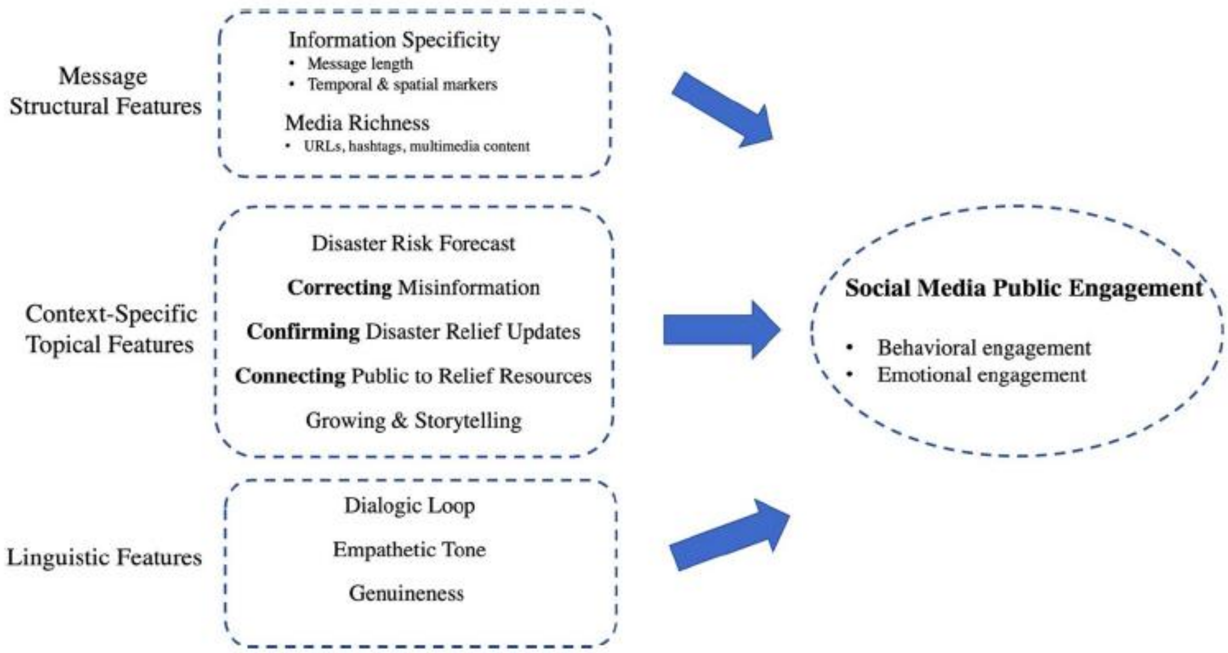

Figure 1. W. Liu et al.’s (2020) multi-level framework of social media-mediated dialogic communication during natural disasters.

Taken together, these three components and their corresponding elements provide a catalog of dialogic communication elements that can be used to facilitate public engagement via social media during emergencies. For example, dialogic loops can establish an openness to dialogic communication (Yang et al., 2010), facilitate relief efforts and a sense of empowerment among publics, and elicit feedback and participation in the form of shares (W. Liu et al., 2020). However, it is important to note that conclusions from analyses of one emergency event cannot necessarily be applied to other emergency contexts or even future similar events (Fraustino et al., 2018; W. Liu et al., 2020). In this case, W. Liu et al.'s (2020) framework was developed and tested using social media messages shared by officials during Hurricane Harvey in 2017. As such, the extent to which different emergency contexts, varying public informational needs, and emergency management priorities can restrict or facilitate online dialogic communication's effects on engagement during different emergency stages remains understudied (W. Liu et al., 2020).

2.2.2 Role of social media in dialogic communication processes

From a two-way or cocreational perspective, social media pose special utility as tools for rapid and interactive two-way communication (i.e., sharing content and engaging in dialogue) between message creators and consumers (Eriksson, 2018; Fraustino et al., 2018; Giroux et al., 2013; Lovari & Bowen, 2020; Spence et al., 2016). Social media allow for interactivity and reciprocal exchanges between officials and their communities during crises (Shahin & Dai, 2019). Such interactions can increase the level and quality of public engagement (Shahin & Dai, 2019) and improve crisis communication efficacy and outcomes (Cheng & Cameron, 2017; Xu et al., 2019). More specifically, social media allow governments to engage in targeted, open, and frequent two-way communication with publics (Graham et al., 2015), listen to public concerns, and respond to requests for assistance in a timely manner (Lin et al., 2016). Online platforms also enable individuals to maintain a sense of community and seek emotional or healing support during disasters (Fraustino et al., 2018). Given the relatively understudied nature of social media as crisis communication tools, some scholars have recommended that social media be used as a component of a multi-channel communication system to supplement traditional channels and enhance the reach of crisis messaging (B. F. Liu et al., 2016; National Academies of Sciences, Engineering, and Medicine, 2021; Veil et al., 2011). Twitter, for example, has been increasingly utilized to share rapid information alongside Wireless Emergency Alerts during imminent threats in recent years (Sutton & Kuligowski, 2019) and is better suited for such uses than other platforms such as Facebook (DeYoung et al., 2019; Lachlan et al., 2018).

Because public attention to public safety accounts increases during emergencies (Olson et al., 2019; Veil et al., 2011), social media can serve as convenient sources of timely, unique, and unfiltered information (Fraustino et al., 2018). And, when used thoughtfully, social media can enhance officials' crisis communication efforts (Veil et al., 2011) and allow them to monitor and correct misinformation (Slavik et al., 2021; Stewart & Young, 2018; Veil et al., 2011). Still, several studies have indicated that social media such as Twitter are generally underutilized by emergency management officials in terms of maximizing two-way communication with publics during emergencies (Lachlan et al., 2016, 2018; B. F. Liu et al., 2020; Lovari & Bowen, 2020; Wukich, 2016). For instance, B. F. Liu et al. (2020) found that officials did not engage in dialogue and feedback with publics to adequately address informational and coping needs during a wildfire, and some officials have reported using social media to engage with the media but not with community members (Lovari & Bowen, 2020). Additionally, the use of social media as tools to monitor public informational needs at different points in the emergency lifecycle and address them accordingly through dialogue warrants further investigation (Zhao et al., 2018).

2.2.3 Role of emergency phase in dialogic communication processes

Public informational needs and topics of public interest shift as crises and emergencies unfold, pointing toward a need for governments to adjust their messaging strategies throughout the lifecycle of an emergency to adequately address publics' informational needs (Xu et al., 2019; Zhao et al., 2018). Traditional approaches to crisis communication have segmented crises and their corresponding response efforts into three broad stages: pre-crisis, crisis, and post-crisis (Coombs, 2010). Engagement is generally lowest during the post-disaster phase and highest in pre- and during-crisis stages, suggesting emergency response should emphasize dialogic and community-building messaging during nonthreat periods to facilitate positive engagement outcomes during emergencies (W. Liu et al., 2020; Olson et al., 2019). These findings align with some of the basic tenets of dialogic communication theory, which encourages organizations to establish dialogic practices with publics during nonthreat periods before a crisis occurs (Ihlen & Levenshus, 2018). As put by Kent and Taylor (2002), a key tenet of dialogic communication is that “dialogue is not something that can take place in one’s spare time or in the periphery” (p. 26).

Reynolds and Seeger (2005) provide a more nuanced segmentation of crises with the crisis and emergency risk communication (CERC) model. The CERC model includes five crisis stages, each with unique recommended communication strategies (Lachlan et al., 2016; Zhao et al., 2018). The first stage, precrisis, involves communicating risk messages, warnings, and information regarding emergency preparations with publics and emergency response organizations (Lachlan et al., 2014; Reynolds & Seeger, 2005). Stage two is the initial crisis event, during which officials should rapidly communicate messages to reduce uncertainty, encourage self-efficacy, and reassure the public (Lachlan et al., 2016; Reynolds & Seeger, 2005; Zhao et al., 2018). In stage three, officials can engage in maintenance behaviors by continuing the steps from stage two (Reynolds & Seeger, 2005) and, additionally, by addressing any misinformation or inaccurate perceptions about the crisis (Neville Miller et al., 2021) and facilitating transactional communication (Lachlan et al., 2016). Transactional communication, as defined by Lachlan et al. (2016), includes the public in the communication process as the public receives information, provides feedback regarding that information, and participates in disseminating information. The fourth stage, resolution, marks the beginning of the post-crisis phase when communication can shift toward updates regarding the resolution, discussions of the cause of the risks, and new understandings of the risk (Reynolds & Seeger, 2005). Communication in this stage "addresses restoration and rebuilding, but also honestly reports findings about factors that caused the crisis" (Neville Miller et al., 2021, p. 4). Lastly, the evaluation stage encourages open discussion and evaluation of the emergency response to reach agreement about lessons learned and new understandings of risks from the crisis (Lachlan et al., 2016; Reynolds & Seeger, 2005).

Each of the CERC stages emphasize the need to inform communication strategies by evaluating the needs of the public as a crisis unfolds (Reynolds & Seeger, 2005). Prior work has demonstrated that Twitter and social media generally can be used throughout all stages of the CERC model to inform and motivate at-risk publics (Lachlan et al., 2016). However, results also point to missed opportunities in terms of engaging in two-way communication and evaluation with publics, particularly during the maintenance stage (Lachlan et al., 2016).

Although the CERC model concepts are not derived directly from dialogic communication theory, the collaborative approaches suggested in the maintenance, resolution, and evaluation stages of the CERC model align well with two-way, cocreational crisis communication frameworks. However, the CERC model does not consider or inform any communication during nonthreat periods, which is encouraged to establish dialogic practices and engagement before a crisis occurs (Ihlen & Levenshus, 2018; W. Liu et al., 2020; Olson et al., 2019).

2.3 Summary

In sum, research suggests the effectiveness of crisis communication on social media is in part attributed to choosing the “right” message (Eriksson, 2018). Dialogic communication theory provides promising guidance for achieving this goal in the context of emergency communication. However, the impact of government officials’ use of social media during crises remains understudied (DeYoung et al., 2019). Similarly, the application of dialogic communication principles on social media in emergency contexts appears to be infrequent (B. F. Liu et al., 2020) and has not been fully evaluated (Fraustino & Liu, 2018; W. Liu et al., 2020).

Additionally, the impact of government officials’ use of social media during crises and the impact of dialogic communication features on engagement at different stages in the crisis timeline also require further investigation (W. Liu et al., 2020). However, research does indicate that the use of dialogic communication elements in online emergency communication should facilitate public engagement and that such engagement is typically highest during pre- and during-disaster stages than in the post-disaster stage (W. Liu et al., 2020; Olson et al., 2019). These results should translate to engagement being highest during the precrisis, initial event, and maintenance stages of emergencies when using the CERC model as a temporal framework; however, extant literature has not used CERC to complement dialogic communication research. I propose the following hypothesis and research questions to address these gaps in the literature:

RQ1: How frequently are dialogic communication elements used by state emergency management agencies in emergency communication on Twitter?

RQ2: At which stage(s) of the CERC model are dialogic communication elements most frequently applied?

RQ3: At which stage(s) of the CERC model is public engagement the highest?

H1: Tweets with dialogic communication elements will result in higher public engagement.

CHAPTER 3. METHODS

A quantitative content analysis of 1,185 tweets from state EMAs was conducted to address the proposed research questions and hypothesis. State-level analysis was chosen over analysis of communication from local officials because more resources are typically given to social media policy development and implementation at the state level, meaning the resulting dataset should be larger and more diverse than it would at the local level (Wukich, 2016). Because findings from studies of one social media platform cannot be generalized to all social media platforms (Fraustino et al., 2018), Twitter was selected as the primary channel of interest for this proposal to expand upon W. Liu et al.'s (2020) evaluation of their multi-level dialogic communication framework using Facebook. Twitter is a highly useful yet underutilized platform for rapid emergency communication dissemination (Lachlan et al., 2018). However, Twitter restricts the length of posts shared on the platform, meaning tweets function as terse messages (Bean et al., 2015). For this reason, tweets may be limited in their ability to have high information specificity, an element within the message structure component of the multi-level framework that is in part operationalized as the word count of each message (W. Liu et al., 2020).

3.1 Data collection

Following the methodological approach taken by Wukich (2016), official state EMA Twitter accounts were identified through state EMA websites. This approach reduced the risk of selecting unofficial accounts for inclusion in the analysis (Sutton et al., 2014; Wukich, 2016), and it identified 56 relevant accounts. Only one state (Arizona) did not have their official emergency management Twitter account linked on their website; this account was identified through a Google search and verified based on the account credentials. After further review, five accounts were excluded from analysis: two National Guard accounts that did not serve primarily to provide emergency updates (Arizona and Kansas), two inactive accounts (Kansas and Wisconsin), and one account that was used to reshare tweets from the primary account in Spanish (Utah). This left 51 official accounts, with Colorado being the only state to maintain two Twitter accounts both with the sole purpose of sharing emergency preparedness and response information.

After all official accounts were identified, states (not including territories and districts) were divided according to the 10 regions outlined by the Federal Emergency Management Agency (2020), and one account was randomly selected from each region. Both of Colorado’s accounts were listed within the state’s region. The Twitter application programming interface (API) was used to collect all tweets posted in 2021 from the 10 state EMA accounts. This approach sought to ensure that the data would contain tweets pertaining to an assortment of both large-scale and routine emergencies occurring in a diverse range of geographic regions (Wukich, 2016) from accounts with varying online communication strategies, as well as tweets shared during nonthreat periods. These messages were included in the analysis to assess whether and how state EMAs engage in dialogue and build community before emergencies occur.

In addition to collecting tweets themselves, Twitter API was also used to collect metadata such as the tweet source, the date a tweet was posted, public metrics (i.e., retweets, likes, replies, and quote tweets), any related tweets mentioned or linked to the collected tweet, and, if the tweet was a reply, the account to which the tweet replied.

These metadata served as measures for engagement impacts and conversational aspects of each Tweet distributed by state EMAs (Twitter Developer Platform, 2021).

The results of this search yielded 13,943 tweets. Of these, close to half were retweets, which were excluded from the analysis to focus exclusively on the EMAs' communication practices (as opposed to coding content written by other agencies). Additionally, tweet threads (i.e., a chain of messages in which the original poster replies to themselves) were condensed and unitized as one message because they are typically used to convey one continuous message. Thus, each message was analyzed as it would appear to Twitter users encountering the message in the app (Slavik et al., 2021). This left 5,926 original tweets (including threads), quote tweets, and replies.

A stratified random sample was used to select 20% of the tweets from each state to obtain a more manageable sample of tweets to code. A stratified random sample was used to ensure that accounts that tweeted more frequently were not overrepresented and those that tweeted less frequently were not underrepresented. The stratified random sample yielded 1,185 tweets.

3.2 Data analysis

This quantitative content analysis took a deductive directed approach, using extant theory and research findings to guide initial codes (Neuendorf, 2017). A deductive approach is appropriate when testing pre-existing theories or model in different contexts (Elo & Kyngäs, 2008), aligning well with this thesis's aim of assessing W. Liu et al.'s (2020) multi-level framework in various emergency contexts.

3.2.1 Coding scheme

The coding scheme was primarily guided by W. Liu et al.'s (2020) multi-level framework for social media-mediated dialogic communication during natural disasters. Specifically, codes were deductively developed from three core components of dialogic communication: message structural features, context-specific topical features, and linguistic features. Codes are described in the following paragraphs and summarized in the appendix.

Message structural features included information specificity (message length and temporal and spatial markers) and media richness (inclusion of URLs, hashtags, and multimedia content). Message length was recorded numerically to indicate the word count of each tweet. All other elements were coded dichotomously (yes/no) on the basis of their inclusion in the message (W. Liu et al., 2020).

Context-specific topical features included disaster risk forecasts, correcting misinformation, confirming disaster relief updates, connecting the public to relief resources, and growing community and storytelling. These features were also coded dichotomously for their presence in each tweet (W. Liu et al., 2020). These topics are not mutually exclusive, meaning one tweet could be coded for multiple topics (W. Liu et al., 2020).

Lastly, linguistic features included dialogic loops, empathetic tone, and genuineness. Dialogic loops were coded manually if tweets included “phrases that [invite] the public to access information provided, [contact] the organizations, or [contribute] to disaster relief activities” (W. Liu et al., 2020, p. 5). Empathetic tone and genuineness were measured using the Linguistic Inquiry and Word Count (LIWC) analytical framework, which is an efficient and reliable method of assessing textual features of measures (Pan et al., 2018). In this context, LIWC-22 was used to provide counts of positive and negative emotions conveyed in text-based messages and measures of analytic and authentic language to reflect empathetic tone and genuineness, respectively (W. Liu et al., 2020).

In addition to deductive coding, inductive coding was used to assess dialogic elements that were not captured by W. Liu et al.'s (2020) multi-level framework. According to Elo and Kyngäs (2008), inductive content analysis is typically reserved for cases in which “there is not enough former knowledge about the phenomenon or if this knowledge is fragmented” (p. 109); however, if some aspects of the data do not fit within the deductively created coding scheme, such data can be coded inductively to create new concepts. These concepts can inform expansion and revision of existing models developed through inductive content analysis (Elo & Kyngäs, 2008), as was the case with W. Liu et al.'s (2020) multi-level model of dialogic communication. This approach was especially important when analyzing tweets shared during nonthreat periods, the content of which could not be ascribed context-specific topical feature codes from W. Liu et al.'s (2020) framework. Any content during threat periods that did not align well with preestablished codes were also described inductively. Variables were also added to account for message characteristics such as who replies were made to (citizens, officials, or self) and the hazard or threat topic of each tweet.

To investigate the effects of dialogic communication elements at various phases of the emergency lifecycle, tweets were coded using a framework derived from the CERC model. Tweets for each incident that occurred within the designated data collection time frame were coded by the CERC stage they corresponded to (precrisis, initial event, maintenance, resolution, and evaluation), with code definitions derived from Lachlan et al. (2016) and Reynolds and Seeger (2005) conceptualizations of each stage. Tweets that were not related to any particular hazard were coded as nonthreat communication (Olson et al., 2019) and open coded to describe their content to assess dialogic communication practices during nonthreat periods.

3.2.2 Coding process

Once the full sample and subsample of tweets for inter-coder reliability were selected, two graduate students established intercoder reliability. This process began with coder training and practice coding as necessary to ensure both coders shared an understanding of each code definition and when codes should be applied. Once this understanding was established and code definitions were fully developed both coders independently coded 10% of the selected sample (n = 120) to determine intercoder reliability (Neuendorf, 2017). Krippendorf's Alpha was calculated for each measure using ReCal OIR (Freelon, 2013). Coders reached sufficient reliability after one round of reliability coding. The author coded the remaining tweets in the sample, referring to the co-coder for a second opinion for tweets that were difficult to code.

CHAPTER 4. RESULTS

4.1 Intercoder reliability

Intercoder reliability was calculated for nominal and ordinal variables using Krippendorf's alpha. Percent agreement was used as an indicator of intercoder reliability for the two open code variables, tweet topic and nonthreat tweet description. All variables reached acceptable reliability ($\alpha > .800$) after thorough coder training and pilot coding (Neuendorf, 2017). Krippendorf's alpha values and percent agreement are reported in Table 1.

Table 1. Intercoder Reliability Values

Variable	Percent Agreement	Krippendorf's Alpha Value
CERC stage	91.7	.95
In reply to	100	1
Tweet topic (open code)	98.3	n/a
Nonthreat tweet content (open code)	96.7	n/a
Message structural features		
Specific time	94.2	.88
Specific location	94.2	.88
Media richness	100	1
Context-specific topical features		
Disaster risk forecast	96.7	.95
Correcting misinformation	95.0	.88
Confirming disaster relief updates	87.5	.80
Connecting public to relief resources	90.0	.82
Growing and storytelling	96.7	.92
Linguistic features		
Dialogic loops	92.5	.84

4.2 Sample statistics

The stratified random sample was approximately 75.3% original tweets (including threads), 19.7% quote tweets, and 5.1% replies. A summary of tweet types, broken down by tweet and reply type and account, is provided in Table 2.

Table 2. Summary of Tweet Types by State

Tweet type	State										
	CA	IL	MD	ME	MO	MS	MT	NJ	OK	OR	Total
Original	193	44	216	76	87	72	69	37	32	66	892
Threads	2	0	16	11	9	3	0	3	1	17	62
Quotes	21	10	45	20	28	16	2	11	21	59	233
Citizens	0	0	0	0	1	0	0	0	0	0	1
Officials	19	10	43	20	26	16	2	11	21	59	227
Self	2	0	2	0	1	0	0	0	0	0	5
Replies	0	1	14	7	5	1	0	19	0	13	60
Citizens	0	1	9	2	4	1	0	9	0	10	36
Officials	0	0	5	5	1	0	0	10	0	3	24
Total	214	55	275	103	120	89	71	67	53	138	1,185

Tweet topics were open coded and assigned numerical codes during the data cleaning process. A summary of tweet topic counts and percentages, listed from most to least frequent, is presented in Table 3.

Table 3. Summary of Tweet Topic Frequencies and Percentages

Topic	Frequency	Percentage
Severe weather	346	29.2
Wildfires/heat/drought	218	18.4
Health	214	18.1
Winter weather	117	9.9
None	114	9.6
General hazards	76	6.4
Earthquakes	39	3.3
Recreation/safety	22	1.9
Infrastructure/environment	15	1.3
Cybersecurity/scams	13	1.1
Multiple	11	0.9

Note. Percentages reflect the proportion of each topic in the full sample.

4.3 RQ1

The first research question sought to determine how frequently dialogic communication elements were used by state EMA accounts. Results are organized by the three feature levels established by W. Liu et al. (2020).

4.3.1 Message structural features

Tweets from state EMAs averaged 33.8 words per message (*SD* = 25.5). Specific time markers (*n* = 599, 50.5%) were present more frequently than specific location markers (*n* = 550, 46.4%). Tweets most frequently included text with photos or visuals (*n* = 779, 65.7%), followed by text with links, mentions, or hashtags (*n* = 267, 22.5%), text with videos, gifs, or live streams (*n* = 113, 9.5%), and text only (*n* = 26, 2.2%).

4.3.2 Context-specific topical features

The codes derived from W. Liu et al.'s (2020) social media-mediated dialogic communication framework to describe message content were only appropriate to apply to tweets related to imminent or active emergencies. In other words, these codes could not be applied to tweets shared during nonthreat periods (*n* = 375), which were instead open coded to describe their content. Consequently, the frequencies reported for these elements are reported in terms of the percentage of the threat period subsample (*n* = 810) rather than the entire sample.

"Disaster risk forecast" (*n* = 438, 54.1%) was the most commonly used topical feature among tweets shared during threat periods, followed by "confirming disaster relief updates" (*n* = 309, 38.2%), "connecting the public to relief resources" (*n* = 177, 21.9%), "growing and storytelling" (*n* = 65, 8.0%), and "correcting misinformation" (*n* = 8, 1.0%).

4.3.3 Linguistic features

Dialogic loops were present in 35.8% (*n* = 424) of tweets in the sample. LIWC counts of positive (*M* = 2.5, *SD* = 4.1) and negative (*M* = 6.3, *SD* = 4.2) tone were used as a proxy for empathy. "Analytic" (*M* = 84.6, *SD* = 19.2), a summary variable reflecting the degree of formal, analytic, and logical thinking, and "authenticity" (*M* = 31.2, *SD* = 30.3), a summary variable reflecting the degree of self-monitoring and spontaneity, were used to reflect genuineness. These measures differ slightly from the measures used by W. Liu et al. (2020) to reflect empathy and genuineness to account for changes in variable conceptualization in the most recent version of LIWC.

4.4 RQ2

The second research question concerned differences in dialogic communication element use between different stages of the CERC model. Chi-square tests of independence were used to test for significant associations between categorical variables and CERC stages. Fisher's exact tests were used for several variables (media richness, correcting misinformation, confirming disaster relief updates, connecting public to relief resources, growing and storytelling, and dialogic loops) which violated the Chi-square assumption that expected values of cells would exceed five. Kruskal-Wallis H tests were used to test for differences in dialogic communication element usage between CERC stages for continuous variables, which were not normally distributed. Distributions of these variables were normal as assessed by visual assessment of boxplots, and results are presented using adjusted *p*-values. All pairwise comparisons for Kruskal-Wallis tests were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons. Results are organized by the three feature levels established by W. Liu et al. (2020).

4.4.1 Message structural features

Specific time markers were used in 27.5% (*n* = 103) of nonthreat tweets, 80.4% (*n* = 262) of precrisis tweets, 47.4% (*n* = 64) of initial event tweets, 51.1% (*n* = 135) of maintenance tweets, 34.2% (*n* = 25) of resolution tweets, and 83.3% (*n* = 10) of evaluation tweets. These differences were statistically significant, χ^2 (5) = 209.38, $p < .001$. Post hoc analysis was conducted with pairwise comparisons using the z-test of two proportions with a Bonferroni correction. The proportion of time markers used during the following CERC stages were statistically significantly higher ($p < .05$) than in other stages: evaluation (higher than nonthreat, maintenance, and resolution), precrisis (higher than nonthreat, initial event, maintenance, and resolution), maintenance (higher than nonthreat and resolution), and initial event (higher than nonthreat).

Specific location markers were used in 11.7% (*n* = 44) of nonthreat tweets, 77.0% (*n* = 251) of precrisis tweets, 52.6% (*n* = 71) of initial event tweets, 51.5% (*n* = 136) of maintenance tweets, 50.7% (*n* = 37) of resolution tweets, and 91.7% (*n* = 11) of evaluation tweets. These differences were statistically significant, χ^2 (5) = 319.17, $p < .001$. Post hoc analysis was conducted with pairwise comparisons using the z-test of two proportions with a Bonferroni correction. The proportion of location markers used during the following CERC stages were statistically significantly higher ($p < .05$) than in other stages: evaluation (higher than nonthreat), precrisis (higher than nonthreat, initial event, maintenance, and resolution), initial event (higher than nonthreat), maintenance (higher than nonthreat), and resolution (higher than nonthreat). Use of location markers during nonthreat periods was significantly lower than in all other stages.

A Kruskal-Wallis H test showed that there were statistically significant differences in word count between CERC stages, $\chi^2(5) = 66.41$, $p < .001$. Post hoc analysis showed statistically significant differences using in word count between precrisis stages (*Mdn* = 19.0) and the following stages: maintenance (*Mdn* = 36.0, $p = .001$), initial event (*Mdn* = 33.0, $p = .002$), nonthreat (*Mdn* = 35.0, $p < .001$), resolution (*Mdn* = 42.0, $p < .001$), and evaluation (*Mdn* = 39.5, $p = .046$). Significant differences were also observed between resolution stages (*Mdn* = 42.0) and maintenance (*Mdn* = 36.0, $p = .001$), initial event (*Mdn* = 33.0, $p = .015$), and nonthreat (*Mdn* = 33.0, $p = .001$) stages.

Media richness also significantly differed between CERC stages ($p < .001$). Post hoc analysis involved pairwise comparisons using multiple Fisher's exact tests (2 x 2) with a Bonferroni correction. Statistical significance was accepted at $p < .003$. The proportion of tweets with text and photos or visuals was significantly lower during precrisis (38.7%, $n = 126$) than during nonthreat (73.9%, $n = 277$), initial event (74.8%, $n = 101$), maintenance (78.4%, $n = 207$), and resolution (80.8%, $n = 59$) stages ($p < .001$). The proportion of tweets with text and links was significantly higher in the precrisis stage (56.1%, $n = 183$) than in initial event (7.4%, $n = 10$), maintenance (9.8%, $n = 26$), and resolution (6.8%, $n = 5$) stages ($p < .001$). Lastly, the proportion of tweets with text and videos was significantly higher during the resolution (80.8%, $n = 59$) stage than during the precrisis stage (38.7%, $n = 126$, $p < .001$).

4.4.2 Context-specific topical features

Because tweets from nonthreat periods could not be assigned context-specific topical feature codes derived from W. Liu et al.'s (2020) framework, associations between CERC stages and topical feature use were calculated only between tweets sent during threat periods (n = 810). Disaster risk forecasts were most frequently used during the precrisis stage (71.9%, n = 315, p < .001), and the remaining topical features were most frequently used during the maintenance stages. These results are summarized in Table 4.

Table 4. Frequencies and Percentages of Context-Specific Topical Features by CERC Stage

Context-specific topical feature	CERC stage										Total		*p*
	Precrisis		Initial event		Maintenance		Resolution		Evaluation				
	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	
Disaster risk forecast	315	71.9	85	19.4	33	7.5	3	0.1	2	0.1	438	100	< .001
Correcting misinformation	0	0	0	0	7	87.5	0	0	1	12.5	8	100	.001
Confirming disaster relief updates	10	3.2	55	17.8	185	59.9	56	18.1	3	1.0	309	100	< .001
Connecting public to relief resources	9	5.1	29	16.4	103	58.2	30	16.9	6	3.4	177	100	< .001
Growing and storytelling	7	10.8	2	3.1	40	61.5	13	20.0	3	4.6	65	100	< .001

4.4.3 Linguistic features

Use of dialogic loops differed significantly by CERC stage ($p < .001$) and were most frequently used during nonthreat periods ($n = 158$, 37.3%), followed by maintenance ($n = 115$, 27.1%), initial event ($n = 55$, 13.0%), resolution ($n = 51$, 12.0%), precrisis ($n = 37$, 8.7%), and evaluation ($n = 8$, 1.9%) stages ($p < .001$). Post hoc analysis involved pairwise comparisons using multiple Fisher's exact tests (2 x 2) with a Bonferroni correction. Statistical significance was accepted at $p < .003$. Significant differences were observed between nonthreat ($n = 158$, 37.3%) and precrisis ($n = 37$, 8.7%) and resolution ($n = 51$, 12.0%) stages ($p < .001$); precrisis ($n = 37$, 8.7%) and initial event ($n = 55$, 13.0%), maintenance ($n = 115$, 27.1%), resolution ($n = 51$, 12.0%), and evaluation ($n = 8$, 1.9%) stages ($p < .001$); initial event ($n = 55$, 13.0%) and resolution ($n = 51$, 12.0%) stages ($p < .001$); and maintenance ($n = 115$, 27.1%) and resolution ($n = 51$, 12.0%) stages ($p < .001$).

LIWC summary measures of analytic and authentic language were used as a proxy for genuineness. A Kruskal-Wallis H test showed that there was a statistically significant difference in analytic language scores between CERC stages, $\chi^2(5) = 54.90$, $p < .001$. Analytic language during nonthreat periods ($Mdn = 89.5$) was significantly different than maintenance ($Mdn = 89.5$, $p = .015$), initial event ($Mdn = 93.0$, $p = .013$), and precrisis ($Mdn = 95.3$, $p < .001$) stages. Analytic language was significantly higher during precrisis stages ($Mdn = 95.3$) than maintenance ($Mdn = 89.5$) stages ($p = .007$). Statistically significant differences in authentic language scores between CERC stages were also observed, $\chi^2(5) = 63.10$, $p < .001$. Significant differences were observed between precrisis stages ($Mdn = 28.6$) and nonthreat ($Mdn = 12.4$, $p < .001$), maintenance

(*Mdn* = 16.6, $p < .001$), and resolution (*Mdn* = 16.6, $p = .033$) stages. Significant differences were also observed between initial event stages (*Mdn* = 26.8) and nonthreat (*Mdn* = 12.4, $p < .001$) and maintenance (*Mdn* = 16.6, $p = .008$) stages.

LIWC counts of positive and negative tone words were used as a proxy measure for empathy. A Kruskal-Wallis H test showed that there was a statistically significant difference in positive tone counts between CERC stages, $\chi^2(5) = 137.50$, $p < .001$. Significant differences were observed between precrisis stages (*Mdn* = 0.0) and the following stages: nonthreat (*Mdn* = 2.6, $p < .001$), maintenance (*Mdn* = 0.0, $p < .001$), and resolution (*Mdn* = 2.2, $p < .001$). Significant differences were also observed between initial event stages (*Mdn* = 0.0) and resolution (*Mdn* = 2.2, $p = .029$) and nonthreat (*Mdn* = 2.6, $p < .001$) stages. Lastly, significant differences were observed between maintenance stages (*Mdn* = 0.0) and nonthreat periods (*Mdn* = 2.6, $p < .001$).

There were also statistically significant differences in negative tone counts between CERC stages, $\chi^2(5) = 36.42$, $p < .001$. Significant differences were observed between resolution stages (*Mdn* = 4.3) and the following stages: precrisis (*Mdn* = 6.1, $p < .001$), initial event (*Mdn* = 6.3, $p < .001$), and maintenance (*Mdn* = 5.0, $p = .012$) stages. Significant differences were also observed between nonthreat periods (*Mdn* = 5.0) and precrisis (*Mdn* = 6.1, $p = .005$) and initial event (*Mdn* = 6.3, $p = .022$) stages.

4.5 RQ3

Kruskal-Wallis H tests were also used to determine if there were differences in engagement (represented by retweets, likes, replies, and quote tweets) between CERC stages. These tests revealed statistically significant differences for all engagement metrics between CERC stages. All distributions were similar for all groups as assessed by visual inspection of a boxplot. Pairwise comparisons were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons. Adjusted *p*-values are reported.

Statistically significant differences were observed for retweets, $\chi^2(5) = 118.29$, $p < .001$. Retweets during nonthreat periods (*Mdn* = 2.0) were significantly different from the following stages: maintenance (*Mdn* = 4.0, $p < .001$), precrisis (*Mdn* = 4.0, $p < .001$), resolution (*Mdn* = 5.0, $p < .001$), initial event (*Mdn* = 8.0, $p < .001$), and evaluation (*Mdn* = 12.0, $p < .001$). Retweets during maintenance stages (*Mdn* = 4.0) were significantly different from initial event (*Mdn* = 8.0, $p < .001$) and evaluation (*Mdn* = 12.0, $p = .014$) stages. Lastly, there were significant differences in retweets between precrisis (*Mdn* = 4.0) and initial event (*Mdn* = 8.0) stages ($p < .001$).

Statistically significant differences in likes between CERC stages were also observed, $\chi^2(5) = 91.74$, $p < .001$. Likes during nonthreat periods (*Mdn* = 4.0) were significantly different from the following stages: precrisis (*Mdn* = 6.0, $p = .012$), resolution (*Mdn* = 10.0, $p < .001$), initial event (*Mdn* = 14.0, $p < .001$), and evaluation (*Mdn* = 19.0, $p < .001$). Likes during maintenance stages (*Mdn* = 5.0) were significantly different than initial event (*Mdn* = 14.0, $p < .001$) and evaluation (*Mdn* = 19.0, $p = .006$). Lastly, likes during precrisis stages (*Mdn* = 6.0) were significantly different than initial event (*Mdn* = 14.0, $p < .001$) and evaluation (*Mdn* = 19.0, $p = .012$).

Differences in replies between CERC stages were statistically significant, $\chi^2(5) = 41.37$, $p < .001$. Replies during precrisis stages (*Mdn* = 0.0) were significantly different from the following stages: initial event (*Mdn* = 0.0, $p = .004$), maintenance (*Mdn* = 0.0, $p = .001$), and evaluation (*Mdn* = 1.0, p = .001). Replies during nonthreat periods (*Mdn* =

0.0) were significantly different from maintenance (*Mdn* = 0.0, $p = .002$), initial event (*Mdn* = 0.0, $p = .009$), and evaluation (*Mdn* = 1.0, $p = .001$) stages. Lastly, replies during resolution stages (*Mdn* = 0.0) were significantly different from evaluation stages (*Mdn* = 1.0, p = .014).

Differences in quotes between CERC stages were statistically significant $\chi^2(5) = 37.25$, $p < .001$. Replies during nonthreat periods (*Mdn* = 0.0) were significantly different from initial event (*Mdn* = 1.0, $p < .001$) and evaluation (*Mdn* = 1.0, $p = .008$) stages. Replies during maintenance stages (*Mdn* = 0.0) were significantly different from initial event (*Mdn* = 1.0, $p < .001$) and evaluation (*Mdn* = 1.0, $p = .026$) stages. Replies during precrisis stages (*Mdn* = 0.0) were significantly different from initial event (*Mdn* = 1.0, $p < .001$) and evaluation (*Mdn* = 1.0, $p = .029$) stages. Lastly, replies during resolution stages (*Mdn* = 0.0) were significantly different from initial event stages (*Mdn* = 1.0, $p = .019$).

4.6 H1

Negative binomial regressions were used to test the hypothesis that tweets with dialogic communication elements would receive higher public engagement. This test is similar to normal multiple regression but is used when the dependent variable (here, engagement as measured by likes, retweets, replies, and quote tweets) is not normally distributed, as was the case in W. Liu et al.'s (2020) analysis. In models including only the dialogic communication elements in W. Liu et al.'s (2020) framework, several elements had positive statistically significant associations with engagement. All models were significant improvements from the intercept-only model ($p < .001$). These results are summarized in Table 5.

Table 5. Negative Binomial Regression Results Predicting Engagement using Dialogic Communication Element Variables

Variable	Retweets	Likes	Replies	Quotes
Message structural features				
Information specificity				
Word count	0.01(0.00)***	0.01(0.01)***	0.01(0.00)*	0.01(0.00)***
Time markers	0.12(0.09)	0.06(0.09)	–0.04(0.17)	0.14(0.14)
Location markers	0.06(0.10)	0.20(0.09)	–0.26(0.18)	0.18(0.15)
Media richness				
Text + videos	2.57(0.40)***	1.73(0.31)***	0.73(0.60)	2.46(0.74)***
Text + visuals	2.33(0.38)***	1.48(0.29)***	0.67(0.57)	2.03(0.73)**
Text + links	1.65(0.39)***	0.77(0.30)**	–0.02(0.60)	1.35(0.74)
Text only (reference group)				
Context-specific topical features				
Disaster risk forecast	0.67(0.10)***	0.52(0.10)***	0.28(0.19)	0.42(0.16)**
Correcting misinformation	1.21(0.52)*	0.34(0.45)	0.29(0.84)	1.23(0.69)
Confirming disaster relief updates	0.21(0.10)*	0.36(0.10)***	0.11(0.19)	0.04(0.15)
Connecting public to relief resources	0.51(0.12)***	0.14(0.01)	0.45(0.21)*	0.20(0.17)
Growing and storytelling	–0.03(0.17)	0.32(0.16)$^{+}$	0.58(0.30)$^{+}$	–0.12(0.26)
Linguistic features				
Dialogic loops	0.13(0.09)	0.14(0.09)	0.33(0.16)*	0.25(0.13)
Analytic language	0.01(0.00)**	0.01(0.00)***	0.01(0.00)*	0.01(0.00)
Authentic language	0.00(0.00)	0.00(0.00)	0.00(0.00)	–0.00(0.00)
Positive tone	–0.01(0.01)	0.03(0.01)**	–0.01(0.02)	–0.01(0.02)
Negative tone	–0.03(0.01)**	–0.04(0.01)***	–0.07(0.02)***	–0.05(0.02)**

Note. Standard errors are reported in parentheses.

*** $p < .001$, ** $p < .010$, * $p < .050$, $^{+}$approaching significance

However, when control variables such as tweet type, CERC stage, and hazard type were added to the model, many of these significant associations became nonsignificant. Including these controls improved the overall fit of the models, and all were significant improvements from the intercept-only model ($p < .001$); results are presented in Table 6. Only use of text and videos was positively associated with the number of quote tweets ($\beta = 1.11$, $p = .028$). Word count was positively associated with replies ($\beta = 0.01$, $p = .026$) and approached significance with the number of likes received ($\beta = 0.01$, $p = .052$). Of the five topical codes, only tweets that connected the public to relief resources were positively associated with retweets ($\beta = 0.41$, $p = .004$), while "growing and storytelling" was positively associated with likes ($\beta = 0.41$, $p = .023$). Tweets that contained dialogic loops were positively associated with the number of times a tweet was quoted ($\beta = 0.27$, $p = .032$). Positive tone was positively associated with likes ($\beta = 0.04$, $p = .028$). Only one dialogic element had significant negative associations with engagement: negative tone (a proxy for empathy) was negatively associated with retweets ($\beta = –0.04$, $p = .003$), likes ($\beta = –0.05$, $p < .001$), replies ($\beta = –0.06$, $p = .005$), and quotes ($\beta = –0.06$, $p = .006$).

Table 6. Negative Binomial Regression Predicting Engagement using Dialogic Communication Element and Control Variables

Variable	Retweets	Likes	Replies	Quotes
Message structural features				
Information specificity				
Word count	0.01(0.00)$^{+}$	0.01(0.00)$^{+}$	0.01(0.00)*	0.01(0.01)
Time markers	0.14(0.10)	0.09(0.11)	0.05(0.18)	0.131(0.14)
Location markers	–0.06(0.10)	0.02(0.11)	–0.22(0.17)	0.081(0.14)
Media richness				
Text + videos	0.86(0.44)$^{+}$	0.67(0.39)	0.62(0.47)	1.11(0.51)*
Text + visuals	0.54(0.44)	0.34(0.38)	0.54(0.49)	0.66(0.49)
Text + links	–0.11(0.45)	–0.29(0.39)	0.05(0.50)	–0.11(0.52)
Text only (reference group)				
Context-specific topical features				
Disaster risk forecast	–0.10(0.17)	0.01(0.17)	0.16(0.32)	–0.01(0.25)
Correcting misinformation	0.38(0.34)	0.05(0.33)	–0.24(0.54)	1.01(0.61)
Confirming disaster relief updates	–0.02(0.15)	0.24(0.16)	–0.26(0.26)	0.03(0.21)
Connecting public to relief resources	0.41(0.14)**	0.16(0.17)	0.20(0.23)	0.11(0.17)
Growing and storytelling	–0.01(0.16)	0.41(0.18)*	0.47(0.26)	–0.09(0.23)
Linguistic features				
Dialogic loops	0.14(0.10)	0.13(0.10)	0.31(0.17)	0.27(0.13)*
Analytic language	0.00(0.00)	0.00(0.00)	0.01(0.00)	0.00(0.00)
Authentic language	–0.00(0.00)	0.00(0.00)	–0.00(0.00)	–0.00(0.00)
Positive tone	0.01(0.02)	0.04(0.01)**	0.00(0.02)	0.02(0.02)
Negative tone	–0.04(0.01)**	–0.05(0.01)***	–0.06(0.02)**	–0.06(0.02)**

Table 6 (continued)

Variable	Retweets	Likes	Replies	Quotes
Hazard topic				
Multiple	0.17(0.53)	–0.32(0.39)	–0.24(0.74)	0.57(0.57)
General	–0.25(0.25)	–0.43(0.22)*	–0.68(0.44)	–0.08(0.34)
Infrastructure/environmental	0.21(0.38)	0.41(0.40)	–0.59(0.65)	0.12(0.54)
Cybersecurity/scams	–0.79(0.45)	–1.22(0.38)**	–2.45(1.09)*	–1.81(0.89)*
Recreation/home safety	–0.26(0.38)	–0.26(0.48)	0.08(0.81)	0.00(0.55)
Winter weather	0.16(0.25)	0.06(0.24)	–0.36(0.42)	0.72(0.33)*
Wildfire, heat, drought	0.63(0.24)*	0.53(0.23)*	0.31(0.41)	0.98(0.30)***
Earthquakes	1.16(0.33)***	0.68(0.31)*	0.30(0.53)	1.28(0.38)***
Severe weather	0.26(0.24)	0.01(0.21)	–0.38(0.39)	0.91(0.31)**
Health	0.13(0.29)	0.43(0.28)	1.35(0.48)**	0.83(0.38)*
None (reference group)				
CERC stage				
Evaluation	0.64(0.56)	0.85(0.58)	1.25(0.70)	0.84(0.64)
Resolution	–0.23(0.22)	–0.52(0.26)*	–0.47(0.44)	–0.58(0.33)
Maintenance	0.26(0.23)	–0.41(0.25)	–0.75(0.40)	–0.36(0.33)
Initial event	0.91(0.22)***	0.60(0.24)*	0.59(0.37)	0.57(0.28)*
Precrisis	0.83(0.21)***	0.45(0.23)+	–0.04(0.38)	0.33(0.32)
Nonthreat (reference group)				
Tweet type				
Quote tweet	–0.55(0.12)***	–0.55(0.11)***	–0.87(0.19)***	–0.71(0.17)***
Reply	–3.30(0.33)***	–1.69(0.31)***	–0.33(0.31)	–3.91(1.04)***
Original (reference group)				

Note. Standard errors are reported in parentheses.

*** $p < .001$, ** $p < .010$, * $p < .050$, +approaching significance

Several controls also had significant associations with engagement. Topics related to cybersecurity and scams were negatively associated with likes (β = –1.22, p = .001), replies (β = –2.45, p = .025), and quotes (β = –1.81, p = .041), and tweets about general hazards were negatively associated with likes (β = –0.43, p = .048). Winter weather topics (β = 0.72, p = .006) and severe weather (β = 0.91, p = .003) were positively associated with quotes, while tweets about wildfires, heat, and drought were positively associated with retweets (β = 0.63, p = .010), likes (β = 0.53, p = .020), and quotes (β = 0.98, p < .001). Tweets about earthquakes were positively associated with retweets (β = 1.16, p < .001), likes (β = 0.68, p = .026), and quote tweets (β = 1.28, p < .001). Tweets about health threats, including COVD-19, were positively associated with replies (β = 1.35, p = .005) and quote tweets (β = 0.81, p = .029).

Tweet type was also included in the model and saw significant associations with engagement. With original tweets serving as the reference group, quote tweets from EMAs were negatively associated with retweets (β = –3.30, p < .001), likes (β = –1.69, p < .001), and quote tweets (β = –3.91, p < .001). Replies from EMA accounts were negatively associated with retweets (β = –0.55, p < .001), likes (β = –0.55, p < .001), replies (β = –0.87, p < .001), and quotes (β = –0.71, p < .001).

Lastly, some CERC stages had significant associations with engagement. Tweets from precrisis stages were positively associated with retweets (β = 0.83, p < .001) and approached significance for likes (β = 0.45, p = .052). Tweets sent during initial events were positively associated with retweets (β = 0.91, p < .001), likes (β = 0.60, p = .011), and quote tweets (β = 0.57, p = .042). Tweets sent during evaluation stages were negatively associated with likes (β = –0.52, p = .041).

4.7 Inductive findings

Open codes were assigned to tweets shared during nonthreat periods to reflect their content. Once coding was complete, these codes were grouped and categorized based on their content. This process generated six categories: “providing additional or clarifying information” (*n* = 12, 3.2%), “engagement” (*n* = 25, 6.7%), “advertising public events/programs” (*n* = 27, 7.2%), “advertising job openings, trainings, or funding opportunities” (*n* = 27, 7.2%), “sharing agency information” (*n* = 70, 18.7%), and “general preparedness/safety tips” (*n* = 214, 57.1%). These codes did not improve the fit of the negative binomial regression model when added as predictor variables. Additionally, some of these codes were marked as “redundant”, indicating that they may have overlapped with existing codes derived from W. Liu et al.'s (2020) framework.

Additionally, two inductive codes were added to the codebook after some common trends were observed during the data cleaning process. First, the author added a code to capture EMAs thanking responders during emergencies (n = 28, 3.5%). These tweets were often coded as “confirming disaster relief updates” but also contained themes that aligned well with the “growing and storytelling” code from W. Liu et al.'s (2020) framework, but did not explicitly fit this code definition. Second, some tweets were coded as “acknowledging thanks and/or feedback” (*n* = 12, 1.0%). These tweets were typically replies to members of the public who provided an EMA with feedback or thanked them for their efforts. These messages did not fit the definition of a dialogic loop established by W. Liu et al. (2020) but may have reflected invitational rhetoric, thus serving as implicit indicators to the public that the agencies were willing to interact with citizens through their account and, in turn, facilitate audience engagement (Yang et al., 2010).

CHAPTER 5. DISCUSSION

This study contributes to emergency communication and dialogic communication theory scholarship by directly addressing the role of dialogic elements at each CERC phase and the impact of CERC phase on engagement. A thorough review of emergency communication literature did not yield any studies that have utilized the CERC model to supplement dialogic communication theory. By assessing dialogic communication elements in the context of a variety of hazards, this work increases the generalizability of the multi-level framework for social media-mediated dialogic communication during disasters by applying the framework to a variety of emergencies and hazards occurring in diverse geographic locations.

In doing so, this analysis also provided a descriptive overview of the types of tweets shared by state EMAs, as well as their content. Tweets were generally high in media richness, with 75.2% of the sample using visuals or videos and only 2.2% only using text. Nearly 60% of the sample (n = 709) included either a time or location marker, and 37.1% of the sample included both (n = 440). "Disaster risk forecast" was the most common topical feature for tweets sent during threat periods, whereas "correcting misinformation" and "growing and storytelling" were less commonly used. The sample mean for negative tone scores (M = 6.3, SD = 4.2) was more than twice that that of positive tone (M = 2.5, SD = 4.1), and average analytic scores reflecting more formal and rigid language (M = 84.6, SD = 19.2) were more than double the average scores for authenticity (M = 31.2, SD = 30.3). Dialogic loops were present in 35.8% (n = 424) of the tweets included in this analysis. These basic frequencies point to opportunities to increase use of message attributes such as information specificity, themes of community, and explicit invitations to engage or interact with content or resources.

Additionally, this study provides a more comprehensive understanding of engagement. Past studies have looked at public interaction with posts (e.g., likes, comments, shares; W. Liu et al., 2020) and officials' use of mentions and replies (Olson et al., 2019) as indicators of engagement, but not both. This method expands current understanding of the capacity of social media as facilitators of two-way dialogic communication. In all, engagement was relatively low throughout the sample, and qualitative observations of state EMAs' tweets and the replies they received showed that many questions from members of the public (in the form of replies) went unacknowledged. Along with the infrequent observations of "correcting misinformation" topics during threat periods, these findings indicate that state EMAs may not be capitalizing on the affordances of social media that can facilitate community building and allow agencies to monitor and address misinformation.

The hypothesis that tweets containing dialogic communication elements would have higher engagement received partial support at best, as there were few significant associations between dialogic communication elements and engagement metrics when control variables (hazard topic, tweet type, and CERC stage) were included in the negative binomial regression model. In this model, only five of the dialogic communication elements (high information specificity, high media richness, connecting public to resources, growing and storytelling, and dialogic loops) had positive significant associations with at least one engagement metric. Instead, this model revealed more consistent influences of variables such as hazard topic, CERC stage, and tweet type.

It is worth noting here that the strong negative associations between engagement and reply tweets from EMAs should not discourage practitioners from engaging with other accounts through replies. These tweet forms are typically directed to a single user or a handful of users and thus do not reach an EMA's larger audience. Quote tweets, however, are typically used to communicate with a larger audience and were negatively associated with all engagement metrics. This suggests that when choosing between sharing information in an original tweet or sharing information from another account by quoting them, state EMAs should choose the former. Future research should further investigate message elements that improve engagement outcomes for quote tweets.

Chi-square analysis and Kruskal-Wallis H tests showed that there were significant differences in the use of all dialogic communication elements between CERC stages. Additionally, results of the negative binomial regression reflect positive significant associations between precrisis tweets and retweets and between initial event tweets and retweets, likes, and quotes. There was also a negative association between tweets from resolution stages and likes. Practitioners may consider including more dialogic communication efforts and explicit invitations to engage with content in tweets shared during this stage.

The negative binomial regression also showed that hazard topics regarding general hazards and cybersecurity or scams had significant negative relationships with engagement, again pointing to an opportunity to increase use of dialogic communication elements when discussing these topics.

This study additionally increases the generalizability of W. Liu et al.'s (2020) social media-mediated dialogic communication framework by applying it to nonthreat periods. Open coding the topic of nonthreat tweets provided a more descriptive summary of the topics discussed during nonthreat periods. However, the redundant results obtained after including the condensed nonthreat open code descriptors in the negative binomial regression model point to some overlapping constructs between threat and nonthreat content codes. Indeed, codes such as “general preparedness/safety tips” are functionally the equivalent of “disaster risk forecasts” in nonthreat times, intending to educate the public about specific hazards and the actions they could take to prepare for them and mitigate damages. Similarly, some of the nonthreat tweets coded as “agency information” (e.g., employee spotlights) closely align with the narratives and themes of community coded as “growing and storytelling” during threat periods. These qualitative observations indicate that the topics of nonthreat tweets may not stray too far from the topics of tweets shared during threat periods. Future work should consider attempting to expand the context-specific topical feature codes to include both threat and nonthreat topics instead of coding them separately.

However, one nonthreat code that could not be easily absorbed by the preestablished content categories is “engagement.” These tweets contained no hazard information, narratives, or news, but instead were simple interactions between state EMAs and other agencies or members of the public. In other words, these tweets served no purpose other than to interact and engage with others (e.g., wishing happy holidays, sharing locally relevant memes or jokes, etc.). Such communication may not serve to help the public become more resilient or prepared for emergencies but may help establish EMAs as a trustworthy and reliable source for the public to turn to in the face of emergencies. Similarly, replying to comments or feedback from members of the public may serve as an implicit dialogic loop, demonstrating that an EMA is open to two-way communication with the public through their social media accounts.

Additionally, this analysis suggests some expanded definitions for the context-specific topical features from W. Liu et al.'s (2020) framework. Specifically, this analysis identified several tweets from state EMAs acknowledging the thanks or feedback they received from the public. These messages may demonstrate invitational rhetoric (Yang et al., 2010), essentially serving as implicit dialogic loops. Additionally, tweets that thanked emergency responders for their efforts but did not explicitly provide disaster relief updates did not fit well within the prescribed definitions of “growing and storytelling” but did serve to highlight relationships within and between emergency management agencies. These tweets, along with others that provided general information about the EMAs themselves (e.g., employee spotlights), would be appropriate to code as dialogic communication topics in future analyses.

Lastly, this analysis also revealed some state-level or regional-level differences in dialogic communication use. For example, some agencies used their accounts almost exclusively to share emergency-related information, whereas other agencies capitalized on the interactivity of Twitter to share memes and community narratives during nonthreat periods. Although not an intended goal of this proposal’s design, these findings echo conclusions from Olson et al. (2019) that engagement content varies across geographical and temporal contexts, emphasizing the need to design messages with target audiences in mind (Slavik et al., 2021).

5.1 Limitations

There are several limitations with this study, the first being that it provides a rather limited view of agencies' holistic emergency communication strategies because the analysis only involved tweets. Scholars have recommended that social media platforms such as Twitter be used in tandem with other forms of communication (B. F. Liu et al., 2016; National Academies of Sciences, Engineering, and Medicine, 2021; Veil et al., 2011). Additionally, the core tenets of dialogic communication theory encourage communicators to engage with all publics who are affected by organizational behaviors (Kent & Taylor, 2002). Certainly, not all individuals affected by the information shared by state EMAs use Twitter; thus, this analysis does not capture engagement efforts with an EMA's entire target audience.

Further, the utility of social media as communication tools during emergencies is contingent on organizations having the resources to run accounts, the public using social media as information sources, and social media being accessible during disasters (B. F. Liu et al., 2016). As Veil et al. (2011) note, social media are considered "free" but the technology required to access them is not always readily available to low-education and low-income populations. Keeping this in mind, some EMAs may prioritize sharing emergency communication via more accessible or popular platforms than Twitter or may lack the resources to utilize social media at all. As a result, this analysis may not accurately reflect state EMAs entire dialogic communication efforts or engagement from the entire target audience population, particularly because random sampling methods were used to select both the accounts that were included in the analysis and the tweets that were analyzed.

A related issue is that this analysis does not capture any complementary or possibly contradictory messaging strategies from other relevant organizations or officials. According to Adkins (2010), "unless we begin to examine disasters and crises from a more holistic perspective that encompasses entire networks of organizations, we will continue to overlook potentially important insights that cannot be explained by analysis of the individual organizations we have typically studied to date" (p. 113). This area of research would benefit from more complex network analyses to gain a more holistic understanding of dialogic communication practices across multiple sources within the context of a singular hazard event.

Lastly, this analysis is limited by relying on engagement metrics that may not accurately reflect public sentiment or response to dialogic messages. Additionally, focusing on engagement as a dependent variable does not provide any indication of the impact of dialogic communication on behavioral outcomes during emergencies. Future studies should consider analyzing public response to official communication (i.e., replies, quotes) and testing dialogic communication elements and strategies in controlled experiments to assess their effects more accurately on emergency communication outcomes.

CHAPTER 6. CONCLUSION

During disasters and emergencies, government officials are often responsible for the complex task of communicating information to the public to promote decisions and behaviors that will mitigate losses and damages (Bostrom et al., 2018). This study assessed the frequency and impact of dialogic communication element use during nonthreat and threat periods, in the context of many different hazards occurring in diverse geographic areas.

Practically, the results of this study point to opportunities to implement dialogic communication elements to facilitate dialogue and public engagement on Twitter at each stage of an emergency and, in turn, increase the likelihood of positive emergency communication outcomes. Specifically, results of the negative binomial regression indicate that emergency communication practitioners can use positive tone words and share specific information, rich media, disaster relief resource information, themes of growing and storytelling, and dialogic loops to increase the likelihood of at least one metric of engagement.

This study presents theoretical contributions by building upon recent efforts to operationalize and empirically study dialogic communication elements and assesses their use and impacts on public engagement. Additionally, this is the first known study to assess dialogic communication elements in the context of multiple hazards and nonthreat periods, and to use the CERC model to assess the use and impact of dialogic communication elements at various stages of an emergency.

In sum, the results of this study reinforce past findings that officials may not be using two-way, cocreational channels like Twitter to their fullest extent (Lachlan et al., 2016, 2018; Lovari & Bowen, 2020; Wukich, 2016) and that *how* information is communicated is just as important as *what* is communicated (B. F. Liu et al., 2020). Future work should continue to critically evaluate the communication strategies used by government officials such as state EMAs and provide theory-driven methods for promoting positive emergency communication outcomes.

APPENDIX

Content analysis coding scheme

Feature level	Message element	Operationalization
Message structural features	Information specificity	Word count; presence of specific time and location markers
	Media richness	Presence of various forms of medium, ranging from least to most rich: text only, with hyperlinks, with photos/visual content, with videos/livestreaming
Context-specific topical features	Disaster risk forecast	Messages conveying weather forecasts and/or instructions for damage control
	Correcting misinformation	Messages clarifying misinformation or dispelling rumors
	Confirming disaster relief updates	Messages updating the status of disaster and rescue efforts
	Connecting public to relief resources	Messages connecting individuals with various resources to ensure safety
	Growing and storytelling	Messages with themes of growing community and/or narratives of community members
Linguistic features	Dialogic loops	Phrases inviting public to access information, contact organizations, or contribute to disaster relief
	Empathetic tone	LIWC count of positive and negative emotions
	Genuineness	LIWC analytic (frequency of articles, prepositions, and conjunctions) and informal (swear words, Netspeak, assent, nonfluencies, and fillers) ratings

Note. Adapted from W. Liu et al. (2020).

REFERENCES

Adkins, G. L. (2010). Organizational networks in disaster response: An examination of the US government network's efforts in Hurricane Katrina. In W. T. Coombs & S. J. Holladay (Eds.), *The handbook of crisis communication* (pp. 93–114). Wiley-Blackwell. https://doi.org/10.1002/9781444314885.ch4

Bean, H., Sutton, J., Liu, B. F., Madden, S., Wood, M. M., & Mileti, D. S. (2015). The study of mobile public warning messages: A research review and agenda. *Review of Communication*, *15*(1), 60–80. https://doi.org/10.1080/15358593.2015.1014402

Bostrom, A., Morss, R., Lazo, J. K., Demuth, J., & Lazrus, H. (2018). Eyeing the storm: How residents of coastal Florida see hurricane forecasts and warnings. *International Journal of Disaster Risk Reduction*, *30*, 105–119. https://doi.org/10.1016/j.ijdrr.2018.02.027

Campbell, N., Roper-Fetter, K., & Yoder, M. (2020). *Principles of risk communication: A guide to communicating with socially vulnerable populations across the disaster lifecycle* (pp. 1–29). Natural Hazards Center, University of Colorado Boulder. https://hazards.colorado.edu/uploads/freeform/Risk%20Communication%20Guide_FINAL_508_Ed%20Feb%202021.pdf

Cheng, Y., & Cameron, G. (2017). The status of social-mediated crisis communication (SMCC) research. In L. Austin & Y. Jin (Eds.), *Social media and crisis communication* (1st ed., pp. 9–20). Routledge. https://doi.org/10.4324/9781315749068-2

Coombs, W. T. (2010). Parameters for crisis communication. In W. T. Coombs & S. J. Holladay (Eds.), *The handbook of crisis communication* (1st ed., pp. 17–53). Wiley-Blackwell. https://doi.org/10.1002/9781444314885.ch1

Coombs, W. T. (2017). Revising situational crisis communication theory. In L. Austin & Y. Jin (Eds.), *Social media and crisis communication* (1st ed., pp. 21–37). Routledge. https://doi.org/10.4324/9781315749068-3

Daft, R. L., & Lengel, R. H. (1986). Organizational information requirements, media richness and structural design. *Management Science*, *32*(5), 554–571. https://www.jstor.org/stable/2631846

DeYoung, S. E., Sutton, J. N., Farmer, A. K., Neal, D., & Nichols, K. A. (2019). "Death was not in the agenda for the day": Emotions, behavioral reactions, and perceptions in response to the 2018 Hawaii Wireless Emergency Alert. *International Journal of Disaster Risk Reduction*, *36*, 1–10. https://doi.org/10.1016/j.ijdrr.2019.101078

Dunn, O. J. (1964). Multiple Comparisons Using Rank Sums. *Technometrics*, *6*(3), 241–252. https://doi.org/10.2307/1266041

Elo, S., & Kyngäs, H. (2008). The qualitative content analysis process. *Journal of Advanced Nursing*, *62*(1), 107–115. https://doi.org/10.1111/j.1365-2648.2007.04569.x

Eriksson, M. (2018). Lessons for crisis communication on social media: A systematic review of what research tells the practice. *International Journal of Strategic Communication*, *12*(5), 526–551. https://doi.org/10.1080/1553118X.2018.1510405

Federal Emergency Management Agency. (2020). *Regions*. Federal Emergency Management Agency. https://www.fema.gov/about/organization/regions

Fraustino, J. D., & Liu, B. F. (2018). Toward more audience-oriented approaches to crisis communication and social media research. In L. Austin & Y. Jin (Eds.), *Social media and crisis communication* (1st ed., pp. 129–140). Routledge. https://doi.org/10.4324/9781315749068-10

Fraustino, J. D., Liu, B. F., & Jin, Y. (2018). Social media use during disasters: A research synthesis and roadmap. In L. Austin & Y. Jin (Eds.), *Social media and crisis communication* (1st ed., pp. 283–295). Routledge. https://doi.org/10.4324/9781315749068-21

Freelon, D. (2013). ReCal OIR: Ordinal, interval, and ratio intercoder reliability as a web service. *Journal of Internet Science*, *8*(1), 10–16. https://www.ijis.net/ijis8_1/ijis8_1_freelon.pdf

Giroux, J., Roth, F., & Herzog, M. (2013). *Using ICT and social media in disasters: Opportunities and risks for government* (pp. 1–28) [Background document]. ETH Zurich. https://doi.org/10.3929/ETHZ-A-009920641

Graham, M. W., Avery, E. J., & Park, S. (2015). The role of social media in local government crisis communications. *Public Relations Review*, *41*(3), 386–394. https://doi.org/10.1016/j.pubrev.2015.02.001

Ihlen, Ø., & Levenshus, A. (2018). Digital dialogue: Crisis communication in social media. In J. D. Fraustino & Y. Jin (Eds.), *Social media and crisis communication* (1st ed., pp. 389–400). Routledge. https://doi.org/10.4324/9781315749068-10

Kent, M. L., & Taylor, M. (1998). Building dialogic relationships through the world wide web. *Public Relations Review*, *24*(3), 321–334. https://doi.org/10.1016/S0363-8111(99)80143-X

Kent, M. L., & Taylor, M. (2002). Toward a dialogic theory of public relations. *Public Relations Review*, *28*(1), 21–37. https://doi.org/10.1016/S0363-8111(02)00108-X

Lachlan, K. A., Spence, P., & Lin, X. (2018). Natural disasters, Twitter, and stakeholder communication. In L. Austin & Y. Jin (Eds.), *Social media and crisis communication* (1st ed., pp. 296–305). Routledge. https://doi.org/10.4324/9781315749068-22

Lachlan, K. A., Spence, P. R., & Lin, X. (2014). Expressions of risk awareness and concern through Twitter: On the utility of using the medium as an indication of audience needs. *Computers in Human Behavior*, *35*, 554–559. https://doi.org/10.1016/j.chb.2014.02.029

Lachlan, K. A., Spence, P. R., Lin, X., Najarian, K., & Del Greco, M. (2016). Social media and crisis management: CERC, search strategies, and Twitter content. *Computers in Human Behavior*, *54*, 647–652. https://doi.org/10.1016/j.chb.2015.05.027

Lin, X., Spence, P. R., Sellnow, T. L., & Lachlan, K. A. (2016). Crisis communication, learning and responding: Best practices in social media. *Computers in Human Behavior*, *65*, 601–605. https://doi.org/10.1016/j.chb.2016.05.080

Liu, B. F., Fraustino, J. D., & Jin, Y. (2015). How disaster information form, source, type, and prior disaster exposure affect public outcomes: Jumping on the social media bandwagon? *Journal of Applied Communication Research*, *43*(1), 44–65. http://dx.doi.org/10.1080/00909882.2014.982685

Liu, B. F., Fraustino, J. D., & Jin, Y. (2016). Social media use during disasters: How information form and source influence intended behavioral responses. *Communication Research*, *43*(5), 626–646. https://doi.org/10.1177/0093650214565917

Liu, B. F., Iles, I. A., & Herovic, E. (2020). Leadership under fire: How governments manage crisis communication. *Communication Studies*, *71*(1), 128–147. https://doi.org/10.1080/10510974.2019.1683593

Liu, W., Xu, W., & Tsai, J.-Y. (2020). Developing a multi-level organization-public dialogic communication framework to assess social media-mediated disaster communication and engagement outcomes. *Public Relations Review*, *46*(4), 1–9. https://doi.org/10.1016/j.pubrev.2020.101949

Lovari, A., & Bowen, S. A. (2020). Social media in disaster communication: A case study of strategies, barriers, and ethical implications. *Journal of Public Affairs*, *20*(1), 1–9. https://doi.org/10.1002/pa.1967

National Academies of Sciences, Engineering, and Medicine. (2021). *Emergency evacuation and sheltering during the COVID-19 pandemic* (pp. 1–32). National Academies Press. https://doi.org/10.17226/26084

Neuendorf, K. A. (2017). *The content analysis guidebook*. SAGE Publications, Inc. https://doi.org/10.4135/9781071802878

Neville Miller, A., Collins, C., Neuberger, L., Todd, A., Sellnow, T., & Bouteman, L. (2021). Being first, being right, and being credible since 2002: A systematic review of crisis and emergency risk communication (CERC) research. *Journal of International Crisis and Risk Communication Research*, *4*, 1–28. https://doi.org/10.30658/jicrcr.4.1.1

Olson, M. K., Sutton, J., Vos, S. C., Prestley, R., Renshaw, S. L., & Butts, C. T. (2019). Build community before the storm: The National Weather Service's social media engagement. *Journal of Contingencies and Crisis Management*, *27*(4), 359–373. https://doi.org/10.1111/1468-5973.12267

Pan, W., Feng, B., & Skye Wingate, V. (2018). What you say is what you get: How self-disclosure in support seeking affects language use in support provision in online support forums. *Journal of Language and Social Psychology*, *37*(1), 3–27. https://doi.org/10.1177/0261927X17706983

Reynolds, B., & Seeger, M. W. (2005). Crisis and emergency risk communication as an integrative model. *Journal of Health Communication*, *10*(1), 43–55. https://doi.org/10.1080/10810730590904571

Shahin, S., & Dai, Z. (2019). Understanding public engagement with global aid agencies on Twitter: A technosocial framework. *American Behavioral Scientist*, *63*(12), 1684–1707. https://doi.org/10.1177/0002764219835248

Slavik, C. E., Buttle, C., Sturrock, S. L., Darlington, J. C., & Yiannakoulias, N. (2021). Examining tweet content and engagement of Canadian public health agencies and decision makers during COVID-19: Mixed methods analysis. *Journal of Medical Internet Research*, *23*(3), 1–18. https://doi.org/10.2196/24883

Spence, P. R., Lachlan, K. A., & Rainear, A. M. (2016). Social media and crisis research: Data collection and directions. *Computers in Human Behavior*, *54*, 667–672. https://doi.org/10.1016/j.chb.2015.08.045

Stewart, M. C., & Young, C. (2018). Revisiting STREMII: Social media crisis communication during Hurricane Matthew. *Journal of International Crisis and Risk Communication Research*, *1*(2), 279–302. https://doi.org/10.30658/jicrcr.1.2.5

Sutton, J., & Kuligowski, E. D. (2019). Alerts and warnings on short messaging channels: Guidance from an expert panel process. *Natural Hazards Review*, *20*(2), 1–10. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000324

Sutton, J., Spiro, E. S., Johnson, B., Fitzhugh, S., Gibson, B., & Butts, C. T. (2014). Warning tweets: Serial transmission of messages during the warning phase of a disaster event. *Information, Communication & Society*, *17*(6), 765–787. https://doi.org/10.1080/1369118X.2013.862561

Tang, L., Liu, W., Thomas, B., Tran, H. T. N., Zou, W., Zhang, X., & Zhi, D. (2021). Texas public agencies' tweets and public engagement during the COVID-19 pandemic: Natural language processing approach. *JMIR Public Health and Surveillance*, *7*(4), e26720. https://doi.org/10.2196/26720

Twitter Developer Platform. (2021). *Twitter API v2 data dictionary*. https://developer.twitter.com/en/docs/twitter-api/data-dictionary/object-model/tweet

Ulmer, R. R., Sellnow, T. L., & Seeger, M. W. (2018). Defining crisis communication. In *Effective crisis communication: Moving from crisis to opportunity* (4th ed., pp. 1–23). SAGE Publications.

Veil, S. R., Buehner, T., & Palenchar, M. J. (2011). A work-in-process literature review: Incorporating social media in risk and crisis communication. *Journal of Contingencies and Crisis Management*, *19*(2), 110–122. https://doi.org/10.1111/j.1468-5973.2011.00639.x

World Meteorological Organization. (2021). *WMO atlas of mortality and economic losses from weather, climate and water extremes (1970-2019)* (WMO-No. 1267; pp. 1–90). World Meteorological Organization. https://library.wmo.int/doc_num.php?explnum_id=10902

Wukich, C. (2016). Government social media messages across disaster phases. *Journal of Contingencies and Crisis Management*, *24*(4), 230–243. https://doi.org/10.1111/1468-5973.12119

Xu, Z. (2020). How emergency managers engage Twitter users during disasters. *Online Information Review*, *44*(4), 933–950. https://doi.org/10.1108/OIR-08-2019-0275

Xu, Z., Lachlan, K., Ellis, L., & Rainear, A. M. (2019). Understanding public opinion in different disaster stages: A case study of Hurricane Irma. *Internet Research*, *30*(2), 695–709. https://doi.org/10.1108/INTR-12-2018-0517

Yang, S.-U., Kang, M., & Johnson, P. (2010). Effects of narratives, openness to dialogic communication, and credibility on engagement in crisis communication through organizational blogs. *Communication Research*, *37*(4), 473–497. https://doi.org/10.1177/0093650210362682

Zhao, X., Zhan, M., & Jie, C. (2018). Examining multiplicity and dynamics of publics' crisis narratives with large-scale Twitter data. *Public Relations Review*, *44*(4), 619–632. https://doi.org/10.1016/j.pubrev.2018.07.004

VITA

Degrees Awarded
Bachelor of Arts, Criminology and Criminal Justice, 2019, University of Maryland

Professional Positions
Graduate Teaching Assistant, Department of Communication, University of Kentucky
Guest Researcher, Professional Research Experience Program, National Institute of Standards and Technology

Scholastic Honors
Sebastian Herbstein Memorial Scholarship in Fiction Writing, University of Maryland, 2019
Second Place, Student Poster Competition, International Crisis and Risk Communication Conference, 2019
Dean's List, University of Maryland, Spring 2017 – Fall 2019 (awarded each semester)

Professional Publications

Cain, L. (2023, in press). How government leaders use social media during disasters: A scoping review. In H.D. O'Hair & M.J. O'Hair (eds.), *Communication and catastrophic events: Strategic risk and crisis management.* Wiley Blackwell.

Cain, L., Herovic, E., & Wombacher, K. (2021). "You are here": Assessing the inclusion of maps in a campus emergency alert system. *Journal of Contingencies and Crisis Management*, *29*(3), 332-340. https://doi.org/10.1111/1468-5973.12358

Walpole, E.H., Kuligowski, E.D., **Cain, L.,** Fitzpatrick, A., & Salley, C. (2020). *Evacuation Decision-Making in the 2016 Chimney Tops 2 Fire: Results of a Household Survey*. (NIST Technical Note 2103). National Institute of Standards and Technology. https://doi.org/10.6028/NIST.TN.2103

Lovrelgio, R., Nilsson, D., Kuligowski, E., **Cain, L.,** Walpole, E., Johnston, D., & Rothas, F. (2020). *The Pigeon Valley Fire: A questionnaire study about the evacuation process*. (FENZ Research Report). University of Canterbury; Massey University.

Cain, L. (2019, March 11-13). *"You are here": Assessing the inclusion of maps in a campus emergency alert system* [Poster presentation]. International Crisis & Risk Communication Conference, Orlando, FL, United States. Advisor: Dr. Emina Herovic.

Lauren Bailey Cain