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INVESTIGATING HEAT RISK MESSAGING USING SOCIAL MEDIA
STUDIES AND A SURVEY EXPERIMENT

by

Yajie Li

A dissertation submitted in partial fulfillment
of the requirements for the degree

of

DOCTOR OF PHILOSOPHY

in

Environment and Society

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2021

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ABSTRACT

Investigating Heat Risk Messaging Using Social Media Studies and a Survey Experiment

by

Yajie Li, Doctor of Philosophy

Utah State University, 2021

Major Professor: Dr. Peter D. Howe
Department: Environment and Society

Extreme heat causes hundreds of deaths each year in the United States even though cost-effective protective measures are available. Heat warning messages sent by government agencies have the potential to reduce the negative impacts by motivating people to take protective actions. However, little is known about how to reach the potential. To fill the gap and inform risk messaging, this dissertation research examined warning message content and public responses to warning messages with four studies in the US. The research performed qualitative and quantitative analyses using three datasets: 1) heat warning messages posted on Twitter, 2) public comments on heat warning messages posted on Facebook, and 3) data from a survey experiment.

Drawing on fear appeal theories, the research identified several types of descriptions—such as health risk susceptibility and health impacts—that are theoretically persuasive and applicable to natural hazards. Results show that heat warning messages that mentioned more types of these descriptions are more effective in terms of message diffusion on Twitter. In addition, compared to listing vulnerable populations, a statement that “anyone can be at risk” appears to be more effective in making heat warning

messages personally relevant to the general public. The research also shows that Facebook comments provide unexpected public input about how they perceive the risks and the messages, which complements what has been found using traditional methods. The research, on the whole, speaks to the importance of message persuasion for risk communication in the context of extreme heat and more generally natural hazards.

(168 pages)

PUBLIC ABSTRACT

Investigating Heat Risk Messaging Using Social Media

Studies and a Survey Experiment

Yajie Li

Extreme heat causes hundreds of deaths each year in the United States even though cost-effective protective measures are available. Heat warning messages sent by government agencies have the potential to reduce the negative impacts by motivating people to take protective actions. To help reach the potential, this dissertation examined the content of warning messages and public responses to warning messages in the US. This research analyzed three kinds of data: 1) heat warning messages posted on Twitter, 2) public comments on heat warning messages posted on Facebook, and 3) experimental results collected using an online survey.

Results show that, for heat warning messages posted on Twitter, most messages mentioned temperatures and/or Heat Index. Half of messages mentioned heat-safety tips. Less than one-third of messages mentioned heat-health impacts and people's vulnerability (who is at risk and/or which behavior is at risk). For these four types of mentions, heat warning messages that mentioned more types were retweeted more frequently. In addition, compared to listing specific vulnerable subgroups such as older adults, a statement that "anyone can be at risk" appears to be more effective in making heat warning messages personally relevant to the public. The research also shows that Facebook comments on heat warning messages can suggest people's needs for risk

messaging. The findings can inform researchers and practitioners of how to better communicate risks in the context of extreme heat and other natural hazards.

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Yajie Li

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CHAPTER I

INTRODUCTION

Heat hazards pose serious threats to public health (Mora et al., 2017). In the United States, the number of deaths from heat hazards is more than twice that of hurricanes, tornadoes, and floods combined (Centers for Disease Control and Prevention, 2020). Adverse health impacts of heat are also widespread across geographic areas, age groups, and income levels (Hess et al., 2014). Government agencies issue heat warning messages shortly prior to and during extreme heat events to inform the public of the risks. While the public are usually aware of heat warnings and cost-effective protective measures are available, the warning messages do not necessarily lead to protective actions (Mayrhuber et al., 2018; Sheridan, 2007; Toloo et al., 2013). Underestimation of personal risks from the heat has been acknowledged as a psychological barrier of warning compliance (Mayrhuber et al., 2018; Sampson et al., 2013). To overcome the psychological barrier and enhance heat warning compliance, this dissertation examined how to improve heat risk messaging through three social media studies and one survey experiment. In spite of severe and widespread heat-health impacts, little research attention has been paid to how to effectively communicate the risks from heat hazards. This dissertation bridges the knowledge gap and informs heat risk communication practices.

Social media have been a complementary communication channel between government agencies and the public in the face of hazardous events and disasters (Poljanšek et al., 2017; Reuter & Kaufhold, 2018). Social media have also been an important data collection platform for researchers to investigate real-life official risk messages and public

responses to these messages. Using this platform, Study 1 (Chapter 2) investigated the content of heat risk messages on Twitter, and Study 2 (Chapter 3), and Study 4 (Chapter 5) investigated public responses to heat risk messages on Twitter and on Facebook respectively. Study 3 (Chapter 4) investigated public responses to proposed messaging strategies using a survey experiment. The broad idea of improving heat risk messaging to promote protective actions ties these studies together.

More specifically, drawing on persuasion theories in health communication literature, Study 1 identified five types of message content that are theoretically important to message persuasion (called persuasive message factors) in the context of natural hazards. Study 1 also examined the usage of the persuasive message factors in heat risk messages posted by U.S. National Weather Service offices on Twitter. Building on Study 1 and using the same data set, Study 2 examined how mentioning the persuasive message factors in heat risk messages predict message diffusion which is another aspect of message success. Using a survey experiment, Study 3 compared the persuasive effect of statements varied in depicted susceptibility of heat-health impacts. Depicted susceptibility of heat-health impacts is one of the persuasive message factors identified in Study 1. Study 4 explored the needs and potential solutions for message improvement by inductively coding Facebook comments on heat risk messages on official Facebook pages for U.S. National Weather Service offices. Heat warning messages about extreme heat events are the common type of heat risk messages across studies, although Study 1 and Study 2 include additional types of heat risk messages. The four studies are within the domain of risk communication, although Study 1 uses the terminology of “crisis” instead

of “risk” (e.g., crisis communication and crisis messages) to fit the specific topic of its target conference.

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CHAPTER II

COMMUNICATING CRISIS WITH PERSUASION: EXAMINING OFFICIAL TWITTER MESSAGES ON HEAT HAZARDS^{1 2}

ABSTRACT

Official crisis messages need to be persuasive to promote appropriate public responses. However, little research has examined the content of crisis messages from a persuasion perspective, especially for natural hazards. This study deductively identifies five persuasive message factors (PMFs) applicable to natural hazards, including two under-examined health-related PMFs: *health risk susceptibility* and *health impact*. Using 2016 heat hazards as a case study, this paper content-analyzes heat-related Twitter messages (N=904) posted by eighteen U.S. National Weather Service Weather Forecast Offices according to the five PMFs. We find that the use of descriptions of *hazard intensity* is disproportionately high, with a lack of use of other PMFs. We also describe different types of statements used to signal the two health-related PMFs. We conclude with implications and recommendations relevant to practitioners and researchers in social media crisis communication.

¹ The previous version of this chapter was published in *Proceedings of the 15th International Conference on Information Systems for Crisis Response and Management ISCRAM2018*. The co-authors of the article are Amanda Lee Hughes and Peter D. Howe. The copyright of the published article is maintained by the authors.

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INTRODUCTION

Government agencies often communicate messages to the public during a crisis to help the public appropriately respond and thus decrease adverse impacts. Previous studies have recognized that crisis messaging should be constructed in an up-to-date and informative manner (Mileti and Sorensen, 1990; Reynolds and Seeger, 2005). However, little research attention has been paid to probing the content of crisis messages for its potential contribution to persuasion, especially when those messages are sent through social media. The persuasive effect of crisis messages refers to a message's ability to persuade members of the public to take appropriate action. The lack of recognition of message content that potentially contributes to message persuasion (i.e., persuasive message factors, PMFs) may result in noncompliance to lifesaving crisis messages by members of the public. To bridge this knowledge gap, we identify five PMFs indicative of effective persuasion for natural hazards. We then investigate the usage of these PMFs in crisis messaging by analyzing the content of Twitter messages ('tweets') posted by National Weather Service (NWS) Weather Forecast Offices (WFOs) about heat hazards.

Some PMFs that play different and potentially critical roles in persuasion are often overgeneralized in previous studies with an emphasis on the informativeness of crisis messages. For example, studies in the natural hazards field often combine descriptions of the physical characteristics of a hazard itself and descriptions of hazard impacts as one content theme regarding hazard information (Mileti and Sorensen, 1990; Sutton et al., 2015a). However, this theme includes multiple PMFs such as the intensity of a hazard, the uncertainty of a hazard, the subgroups that are vulnerable to hazard impacts, and the potential consequences of being affected. From an informative

perspective, the nuances of message content may not be significant enough to be separate content themes. However, from a persuasive perspective, descriptions of hazard intensity, hazard uncertainty, sensitive groups, and potential health impacts can be viewed as four types of message content because they may have varying roles in message persuasion.

PMFs warrant greater attention in crisis messaging because they have been shown to have significant effects on message compliance in other communication fields such as health communication (Maddux and Rogers, 1983; Murray-Johnson and Witte, 2003). A lack of investigation and recognition of PMFs in the context of natural hazards may result in the absence of well-designed PMFs in crisis messages, especially when messages are communicated via short messaging channels such as Twitter. This research deductively identifies five PMFs indicative of persuasion in the context of natural hazards, especially two under-recognized PMFs: *health risk susceptibility* and *health impact*. We then, for the first time, investigate to what extent each of the PMFs is included in crisis messages and what typical statements are used to communicate the two under-examined PMFs. To our knowledge, such investigations have not been conducted for crisis messages communicated through any platforms, no matter social media or traditional media. Our investigation of PMFs through social media could have implications to promote crisis messaging communicated via other platforms such as word-of-mouth and television. For some vulnerable subgroups, such as the elderly who may be less reachable via social media messages, our research findings could benefit them by contributing to better crisis messaging communicated via other platforms.

Crisis Messaging over Social Media

In recent years, social media have provided an expanded communication channel where emergency responders can share and gather timely information during crisis events (Hughes and Palen, 2012). Past research has looked at how emergency responders and other sources of official information have used social media to communicate with the public (Chauhan and Hughes, 2017; Deneff et al., 2013; Hughes et al., 2014). Studies have focused on the informational content of responder messages (Chauhan and Hughes, 2017; Hughes et al., 2014), the style of communication that responders use (Deneff et al., 2013), or the ways that responders seek to foster trust in their messaging (Hughes and Chauhan, 2015). No studies have examined how crisis messages, shared through responder social media, persuade members of the public toward protective action.

Crisis messages on Twitter, Wireless Emergency Alerts, and text messages are brief due to character limits (Sutton et al., 2015b). However, character limitation should not compromise the persuasiveness of messages, but highlight the urgency of providing evidence-based suggestions on which PMFs are critical for effective communication.

Identifying Five PMFs

The five PMFs deductively identified in this paper are 1) *hazard intensity*, 2) *hazard uncertainty*, 3) *health risk susceptibility*, 4) *health impact*, and 5) *response instruction*. Among them, *health risk susceptibility* and *health impact* are also called health-related PMFs. This study identifies the five PMFs based on previous research, following the deductive approaches outlined by Schreier (2014).

Hazard Intensity and Hazard Uncertainty

Hazard intensity refers to the intensity of a hazard itself, e.g., the temperature during heat hazards. *Hazard uncertainty* is the uncertainty of an event occurring, e.g., the possibility of a flood happening. The intensity and the uncertainty of a hazard itself are components commonly involved in crisis messages. Although a growing body of literature tests the effectiveness of alternative ways of communicating hazard uncertainty (Spiegelhalter et al., 2011), it is unclear to what extent *hazard uncertainty* and *hazard intensity* are communicated in crisis messages. Previous studies for natural hazards often combined the two PMFs and other message content such as impacted areas as one single theme (Sutton et al., 2015a; Vos, 2016), and as a result little is known about the degree to which each of the two PMFs was included in crisis messages. This paper separately examines the usage of *hazard intensity* and *hazard uncertainty* because they may influence different psychological aspects of how the public processes crisis messages.

According to the Extended Parallel Process Model (EPPM) and related empirical studies, perceived susceptibility and perceived severity are two critical persuasive concepts for information-processing and decision-making under risks (Murray-Johnson and Witte, 2003; Witte, 1992). Perceived susceptibility describes an individual's belief regarding the likelihood of experiencing the adverse impact of a threat, and perceived severity refers to the magnitude of harm an individual feels as the result of the threat (Murray-Johnson and Witte, 2003; Witte, 1992). People are likely to simply ignore crisis messages if they do not feel themselves to be at risk or that potential impacts are significant (Mileti and Sorensen, 1990; Murray-Johnson and Witte, 2003). Although future research is needed to empirically test how each persuasive concept (i.e., perceived susceptibility and perceived severity) is influenced by descriptions of *hazard intensity*

and *hazard uncertainty*, we hypothesize that communicating the uncertainty of a hazard happening is likely to influence audiences' perceived susceptibility of being impacted since both perceived susceptibility and *hazard uncertainty* are related to probability. On the other hand, *hazard intensity* described in crisis messages may influence an individual's perceived severity of being impacted, and further influence decisions about whether protective action is needed.

Health Risk Susceptibility and Health Impact

The PMF of *health risk susceptibility* refers to message content depicting which subpopulation and/or what behaviors are vulnerable to the health impacts of hazards. The PMF of *health impact* mentions illness or death as health outcomes of hazards. These two PMFs are also called health-related PMFs in this paper.

The message content regarding *health risk susceptibility* and *health impact* have not been well defined and recognized in the field of crisis communication during natural hazards. We identify *health risk susceptibility* in light of communication challenges suggested by previous empirical studies on heat risk perception. Conventional heat-health messages often single-out the elderly as a particular vulnerable subgroup, and several studies on extreme heat hazards have put forward alternative ways to communicate heat-health vulnerability due to undesired outcomes of traditional messaging (Wolf et al. 2010; Sampson et al. 2013). Past studies found that although elderly respondents knew older people are vulnerable to the impacts of heat, many seniors defined older or elderly people as those with ages above their own, not themselves, and thus denied they are personally vulnerable to heat-health impacts (Wolf et al. 2010; Sampson et al. 2013).

According to EPPM theory discussed above, if people think adverse consequences cannot happen to themselves, they may well ignore the risks communicated via crisis messages (Murray-Johnson and Witte, 2003). In addition to specific subgroups such as the elderly and the sick, who are vulnerable to heat-health impacts due to compromised thermoregulatory capacity, everyone can be vulnerable to health impacts from heat hazards caused by risky behavior such as outdoor activities in high-heat conditions (Mora et al., 2017). As a result, it is critical for crisis messages to clarify which subpopulation and what behaviors are vulnerable to health impacts. In response, our study identifies *health risk susceptibility* as one message factor to examine.

We identify the *health impact* PMF based on the affect heuristic theoretical framework and prior empirical research in the natural hazards field. The affect heuristic describes the important role affect plays in influencing decisions and motivating behaviors (Slovic et al., 2007). Negative feelings motivate individuals to take actions that are expected to avoid the negative feelings, and positive feelings stimulate actions predicted to repeat such positive feelings (Slovic et al., 2007). Previous empirical research has found that stronger negative affect associated with the consequences of a flood may explain better flooding preparation for people with previous flood experience, compared to those who were not affected (Siegrist and Gutscher, 2008). Accordingly, scholars called for better communication that “help people to envisage the negative emotional consequences of natural disasters” (Siegrist and Gutscher, 2008, p. 771). In response, we identify *health impact* (which includes mentions of illness and death) as one PMF, because these mentions may invoke unpleasant feelings associated with personal or vicarious adverse health experiences. Such feelings may trigger protective actions to

avoid the adverse health impacts of hazards as well as the negative feelings.

Response Instruction

The last PMF investigated in this paper is *response instruction* (i.e., providing advice on protective actions). *Response instruction* has the potential to improve perceived efficacy of recommended actions (i.e., resulting in higher confidence both in performing recommended actions and in achieving desired outcomes) which may lead to better adaptive behaviors under risks (Murray-Johnson and Witte, 2003). Unlike the other four PMFs, this PMF has been frequently coded as a separate category in crisis messages (e.g., Vos, 2016), and this paper also codes *response instruction* as a separate PMF.

Heat-related Tweets and Heat Warning Tweets

Our investigation focuses on heat hazards, the leading cause of weather-related fatalities in the U.S. over the past few decades (NWS, 2017). We propose two research questions in this study: 1) To what degree are the five PMFs (i.e., *hazard intensity*, *hazard uncertainty*, *health risk susceptibility*, *health impact*, and *response instruction*) included in heat-related tweets and heat warning tweets posted by U.S. NWS WFOs? 2) How do heat-related tweets describe the two health-related PMFs (i.e., *health risk susceptibility* and *health impact*)? For the first research question, we quantify the usage of the five PMFs among two types of messages: heat-related tweets and heat warning tweets. For the second research question, we investigate detailed statements of the two health-related PMFs with heat-related tweets in general, and do not separately investigate detailed statements with heat warning tweets.

Heat-related tweets refer to specific current and/or upcoming heat events. We further separate heat-related tweets into two categories, heat warning tweets and non-warning heat-related tweets. To be considered a heat warning tweet, a heat-related tweet must mention at least one of the three NWS's heat-related watch, warning, and advisory (WWA) products: 1) an Excessive Heat Watch, 2) an Excessive Heat Warning, or 3) a Heat Advisory product. If heat-related tweets do not mention any active heat WWAs, these heat-related tweets are non-warning heat-related tweets. For example, the tweet "LOT continues Excessive Heat Warning for Kendall, Will [IL] till 7:00 PM CDT <https://t.co/fCPmYyYojR>" (the URL linked to a map showing the affected areas of this excessive heat warning) is a heat-related tweet and also a heat warning tweet. However, the following tweets are heat-related tweets but not heat warning tweets, since they alert the public about current and/or upcoming heat events but do not mention any current or upcoming in-effect heat WWAs: "225pm: Now officially a high of 118 in Phoenix. Ties for the 5th hottest temperature ever recorded in Phoenix." and "High of 94 degrees at #Shelton today! Hottest day since June 5. #wawx".

In this paper, we quantify the usage of PMFs for both types of messages: heat-related tweets and heat warning tweets. All heat-related tweets and the subset of heat warning tweets are important types of heat risk messages and need to be persuasive to protect public health from heat hazards. Heat warning tweets alert the public about extreme heat events. The official heat WWAs mentioned in heat warning tweets indicate potentially dangerous conditions for much of the population (NWS, n.d.b). Heat-related tweets contribute to protecting the public from adverse impacts of all heat events, both extreme heat events and non-extreme heat events. Extreme heat events are dangerous. For

non-extreme heat events when heat conditions were not hot enough or their duration was not long enough to issue heat WWAs, negative heat-health impacts are still possible for heat-sensitive populations such as children and the elderly, and those working or being active outside. Prior studies on heat-health impacts have found that in addition to the intensity of temperature and humidity, social vulnerability factors such as age and adaptive behaviors are key determinants of heat-health impacts (Bouchama et al., 2007; Kovats and Hajat, 2008). Measuring usage of these PMFs in heat-related tweets will help describe an aggregate level of factor usage for all tweets alerting the public about heat-health risks. By quantifying factor usage for both heat-related tweets and heat warning tweets, we improve our understanding of factor usage and inform message design for both heat risk messages in general and warning messages about extreme heat events.

METHOD

We selected eighteen NWS WFOs across the U.S. from among the total 123 WFOs using purposive sampling. These sampled offices (see Figure 1) reflect critical variations among the field offices regarding the local climate of forecast areas and regional variation across the four NWS regions in the continental U.S.

Second, for each of these sampled offices, the most recent 3200 tweets were collected from their official Twitter accounts using the Twitter Search application programming interface. To narrow the scope to tweets most likely to be heat-related, we extracted tweets containing the English words “heat” or “hot” in the message text. We also restricted the data collection window to the meteorological summer of 2016 (June 1-August 31, 2016, UTC), when most heat events happen. Only original public tweets were

included in the final *Heat Data Set* by removing public retweets and reply tweets. The final *Heat Data Set* contained 1,139 tweets for the next step in the analysis, human coding.

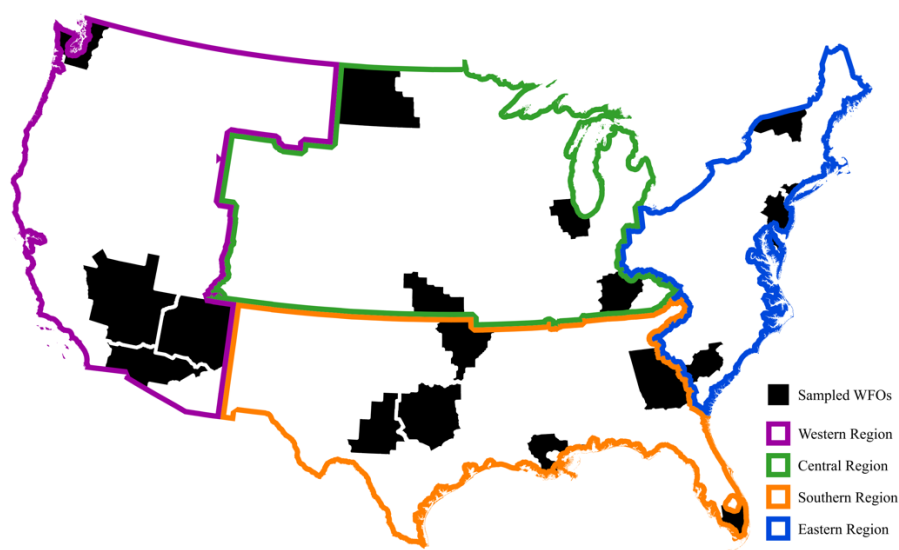


Figure 1. Map showing the distribution of the sampled NWS WFOs, and the NWS regional offices' operational boundaries. White lines separate adjacent WFOs. No WFOs are across NWS regional boundaries.

Each tweet in the *Heat Data Set* was first coded as heat-related tweets, “other on-topic” tweets, or off-topic tweets. No further coding took place for “other on-topic” tweets and off-topic tweets. This topic variable aims to identify heat-related tweets that are suitable and comparable to code for the five PMFs. For example, we found intensity and uncertainty of a specific heat event often were not applicable for general education tweets independent from specific heat events. Heat-related tweets indicated that specific current and/or upcoming heat events either are occurring or will occur in the forecast areas. “Other on-topic” tweets were on the topic of heat but not dependent on specific current or upcoming heat events. These tweets included general education messages

independent from specific heat events, tweets stating a break in recent heat events, and tweets in which it was difficult to tell without local knowledge whether the weather condition reported in the tweets was cool or hot (e.g., tweets reporting forecast heat indices less than 100 °F or temperature less than 95 °F and containing no other information signaling that the forecast condition is hot). Off-topic tweets were not on the topic of heat, for example, tweets posting photos of storms or hail and containing no heat information. The first author was the first coder and an undergraduate researcher worked as the second coder. Two coders split coding tasks. A 20% subset of tweets was randomly selected and both coders coded the subset independently to check the reliability of the coding process. For intercoder reliability, the Cohen's Kappa for this topic variable was 0.83. Among the heat-related tweets, we further coded heat warning tweets which mentioned at least one of heat WWAs that are or will be in effect (Cohen's Kappa = 0.97).

Next, we developed a coding scheme for PMFs. As mentioned earlier in the introduction section, we deductively identified five PMFs as initial coding categories: 1) *hazard intensity*, 2) *hazard uncertainty*, 3) *health risk susceptibility*, 4) *health impact*, and 5) *response instruction*. Based on the initial coding categories and a sample of tweets, we clarified operational definitions for each category. The operational definitions were tailored in response to heat hazards and captured key message content corresponding to each PMF. The coding scheme (see Table 1) was finalized after pilot coding and discussion. All information in each tweet that is visible to Twitter users was included in the coding, including the displayed text (which has a character limit of 140) and textual information in attached images. We coded all heat-related tweets, including heat warning

tweets, for different PMFs. If a single tweet contained more than one PMF, multiple codes responding to each PMF mentioned by the tweet were applied to this single tweet. The intercoder reliability coefficients, Cohen's Kappa, were above 0.93 across these five factor variables.

Table 1. Coding Scheme and Examples for PMFs

PMF	Definition	Tweet Example
<i>Hazard Intensity</i>	Refers to tweets that mention Heat Index (HI) and/or the temperature of current and/or upcoming heat events	"The #heatwave continues w/ heat indices of 105-111 expected today!"
<i>Hazard Uncertainty</i>	Refers to tweets that contain the degree of forecast uncertainty with the temperature or HI for the upcoming weather.	"6-10 DAY OUTLOOK TEMPERATURE PROBABILITY. (With color ramps showing) Probability of Below (Normal) and Probability of Above (Normal)."
<i>Health Risk Susceptibility</i>	Refers to tweets that contain information signaling who, which behaviors and/or which places (e.g., outdoor, on the beach) are vulnerable to heat-health impacts.	"Who's At High Risk? Much of the population, especially those who are heat sensitive and anyone without effective cooling and hydration."
<i>Health Impact</i>	Refers to tweets that contain at least one word indicating heat-related illnesses and/or deaths.	"Take frequent breaks, stay hydrated and wear light-weight clothing to avoid heat-related illnesses."
<i>Response Instruction</i>	Refers to tweets that contain generic and/or specific heat safety tips.	"Stay cool! – Use air conditioning if possible; fans alone DO NOT provide enough cooling when it is very hot outside."

RESULTS

In total, 904 tweets were identified as heat-related tweets. Among them, 224 (25%) were heat warning tweets. All eighteen sampled accounts posted at least thirteen heat-related tweets, with an average of 50 (SD = 30). Fifteen accounts posted heat warning tweets, with the exception of the official Twitter accounts for the NWS WFOs of Atlanta/Peachtree City (Georgia), Bismarck (North Dakota), and Burlington (Vermont). We found in some cases, heat-related tweets did not mention co-occurring heat WWAs.

For example, the Atlanta WFO did issue a heat advisory and the Bismarck WFO issued an excessive heat warning and a heat advisory during the same time period the tweets were collected (Iowa Environmental Mesonet, 2017), but the corresponding heat-related tweets in both accounts did not contain any mention of these heat WWAs. We suspect that a lack of coordinated social media practices may have contributed to these two accounts having missed co-occurring heat WWAs.

Descriptions of Health-related PMFs

We investigated two health-related PMFs including *health risk susceptibility* and *health impact*. Given that previous studies have rarely examined these two health-related PMFs in the field of natural hazard communication, here we provide detailed descriptions on how heat-related tweets communicated these two factors.

For *health risk susceptibility*, four types of statements, separately or jointly, appeared in heat-related tweets to explicitly or implicitly signal susceptibility to heat-health risk. First, some messages indicated that a certain subpopulation such as children and/or the elderly is more vulnerable to health impacts from the heat event. These were “subpopulation” statements. Second, some messages signaled higher heat-health risks associated with certain behaviors and/or certain places such as traveling, working outside, or going to the beach. These were “behavior/place” statements. Third, some messages emphasized that heat can potentially harm everyone without appropriate adaptation (see the susceptibility example in Table 1). These were “anyone” statements. Last, some messages indicated that it is worth paying attention to heat-health risks everywhere, not just in specific places. These were coded as “everywhere” statements. In

“behavior/place” statements and “everywhere” statements, the place does not refer to the administrative areas such as a county or a city, but generic situations such as outdoors, indoors, the workplace, the home, etc. The *health risk susceptibility* PMF either used one type of these statements or simultaneously used several types of statements to illustrate the concept of susceptibility.

For the other health-related PMF, *health impact*, some messages conveyed the health consequences of sickness or death with generic statements such as “Avoid risk of heat related illness” and “deadly heat”. Some messages specifically stated health impact with a long list of symptoms of heat exhaustion and heat stroke, and/or heat-related fatality statistics in recent years.

As an illustrative example, the heat-health message in Figure 2 combines “subpopulation” statements, “behavior/place” statements, and “everywhere” statements for *health risk susceptibility*, and generic statements for *health impact*. This image appears on the NWS heat safety website (<http://www.nws.noaa.gov/os/heat/>), and was also attached to some of the heat-related tweets in our data set. In the message contained in the image, “subpopulation” statements include “Check up on the elderly, sick and those without AC” and “Never leave kids or pets unattended – LOOK before you LOCK” which implicitly indicate that certain subpopulations are vulnerable to heat-health risks. Moreover, “behavior/place” statements were used in this message by listing four places exposed to heat-health risks, i.e., “Job Sites”, “Indoors”, “Vehicles”, and “Outdoors”. Last, the statement “Practice HEAT SAFETY Wherever You Are” is one example of an “everywhere” statement that implies all places have potential for heat-health risks.

Although the statements in Figure 2 implicitly pointed out the associated risks, the

four types of statements (i.e., “subpopulation” statements, “behavior/place” statements, “anyone” statements and “everywhere” statements) can also be explicit. The example of susceptibility found in Table 1 states "Who's At High Risk? Much of the population, especially those who are heat sensitive and anyone without effective cooling and hydration." In this example, the heat-health risks are explicitly linked to heat sensitive populations and anyone with poor adaptation ability by asking, “Who's At High Risk?” Figure 2 also includes a generic statement of *health impact*: “Heat related deaths are preventable.”



Figure 2. A heat-health message posted on the NWS heat safety website and used by some heat-related tweets. This message illustrates how heat-related tweets describe *health risk susceptibility* and *health impact*. Source: <http://www.nws.noaa.gov/os/heat/>

Descriptive Statistics of PMFs

Results indicate (Figure 3) that *hazard intensity* was by far the most frequently used PMF in heat-related tweets (84%) and heat warning tweets (71%) as well. More than half of all heat-related tweets (n=484, 54%) only contained the *hazard intensity*

PMF, without mention of any of the other four PMFs. *Response instruction* was the next most used PMF (heat-related tweets: 37%, heat warning tweets: 46%). A relatively small percentage of tweets contained the PMF of *health risk susceptibility* (heat-related tweets: 20%, heat warning tweets: 29%), and even less for the PMF of *health impact* (heat-related tweets: 11%, heat warning tweets: 17%). *Hazard uncertainty* was rarely mentioned in both heat-related tweets and heat warning tweets, possibly because the forecast of heat is generally perceived as accurate (EPA, 2006). Three PMFs—*health risk susceptibility*, *health impact*, and *response instruction*—were more frequently included in heat warning tweets than overall heat-related tweets, but the differences were small. The use of each PMF had the same position rank in both heat-related tweets and heat warning tweets.

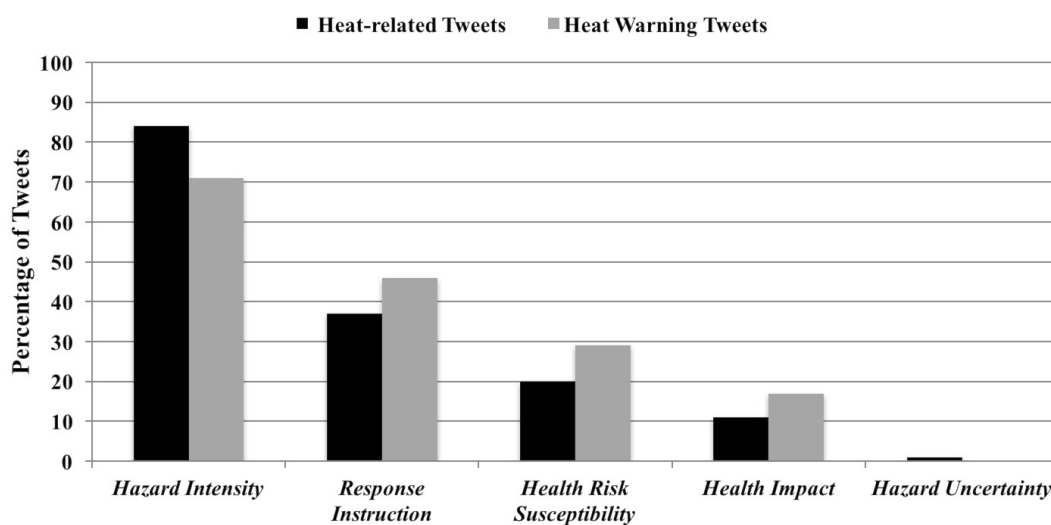


Figure 3. The Percentage of Each Type of Tweet Containing a Certain PMF

For both heat-related tweets and heat warning tweets, tweets using only one of the five PMFs accounted for the largest proportion (heat-related tweets: 56%, heat warning

tweets: 30%; see Table 2). Surprisingly, many heat warning tweets contained none of the PMFs investigated in the paper (n= 53). For example, “LOT continues Excessive Heat Warning till Jul 22, 7:00 PM CDT <https://t.co/fCPmYyYojR>” (the URL linked to a map showing the affected areas of this excessive heat warning). For both types, more than half of the tweets used zero or one PMF (heat-related tweets: 64%, heat warning tweets: 54%). The proportion of tweets containing at least one of the two health-related PMFs were less than two fifths, 24% for all heat-related tweets and 38% for heat warning tweets.

Table 2. The Number of Each Type of Tweet that Contain Varying Numbers of Different PMFs

The Number of PMFs	Number of Heat-related Tweets (n=904)	Number of Heat Warning Tweets (n=224)
0	75(8%)	53(24%)
1	506 (56%)	67(30%)
2	132(15%)	26(12%)
3	157(17%)	66(29%)
4	33(4%)	12(5%)
5	1(0%)	0(0%)

DISCUSSION

During the meteorological summer of 2016, 904 tweets posted by 18 sampled NWS WFOs were heat-related tweets that alerted the public about current or upcoming hot weather. Three quarters of these heat-related tweets were not heat warning tweets, which means only one quarter of heat-related tweets mentioned active heat WWAs. This suggests that although heat warning tweets are a critical subset of social media messages that communicate about heat risks to the public, heat warning tweets—which alert the

public about specific extreme heat events—do not capture all heat-related tweets which alert the public to both extreme heat events and non-extreme heat events. During non-extreme heat events, heat-related tweets were also post-worthy since they address preventing possible extreme health impacts by alerting the heat sensitive population such as the sick and those engaged in potentially risky behaviors such as being physically active outside. To date, little research attention has been paid to crisis messages related to avoiding serious impacts of non-extreme hazards. Compared with crisis messages posted during extreme events, crisis messages surrounding non-extreme events may require different susceptibility statements and behavioral instructions to be effective, which warrants more research attention in the future. During extreme heat events when WFOs did issue heat WWAs, we found some corresponding heat-related tweets missed mentioning co-occurring heat WWAs. An important implication of this finding is that the communication process in social media must be well planned (Veil et al., 2011). In this case, official messages have the responsibility to share information about active heat WWAs to assist the public to make informed decisions.

Our research provides insights into how official crisis messages posted on Twitter communicate two health-related PMFs in the context of natural hazards: *health risk susceptibility* and *health impact*. Most previous studies on crisis messaging for natural hazards, to our knowledge, have not specifically examined the use of health-related PMFs. One exception is a social media study specifically investigating public health messages during the flooding in Boulder, Colorado in 2013 (Sutton et al., 2015b). The health-related content investigated in that paper was limited to health-related instructions such as drinking water safety and hand washing/hygiene, without an investigation of

other health-related PMFs (Sutton et al., 2015b). Drawing on prior theoretical and empirical studies, this paper identified two health-related PMFs: *health risk susceptibility* and *health impact*. We find that Twitter messages about hot weather jointly or separately used four types of statements for pointing out *health risk susceptibility*: “subpopulation” statements, “behavior/place” statements, “anyone” statements and “everywhere” statements. The four types of statements respectively state that certain subpopulations, certain behaviors/places, anyone, or everywhere is vulnerable to heat-health impacts. For both heat-related tweets and heat warning tweets, the two health-related PMFs were much less used than PMFs of *hazard intensity* and *response instruction*.

This paper identifies five PMFs that have the potential to persuade the public to appropriately respond to natural hazards. We find the use of descriptions of *hazard intensity* is disproportionately high among heat-related tweets, with a lack of use of other PMFs. 54% of heat-related tweets exclusively used the *heat intensity* PMF by mentioning the Heat Index and/or temperature (n=484). For both heat-related tweets and heat warning tweets, more than half contained zero or only one of the five investigated PMFs. To enhance the persuasiveness of crisis messages about heat hazards and other types of hazards, future research should empirically test whether the five PMFs persuade or not, which specific statements depicting health-related PMFs are more persuasive, and whether different people respond to the same PMFs differently. This study provides a foundation for future message-testing studies by identifying these five PMFs and by specifying the different types of statements used to communicate health-related PMFs.

CONCLUSION

In this paper, we examine the content of crisis messages from a persuasive perspective. We deductively identify five PMFs that have the potential to persuade the public in the context of natural hazards. Using heat hazards as a case study, we contribute to understanding persuasive content in crisis messaging by quantifying to what degree each PMF is contained in official heat risk tweets. We quantify the use of PMFs not only among tweets mentioning active official heat alert products (e.g., an Excessive Heat Warning), but also among all tweets alerting about specific heat events that may or may not be extremely hot. We also provide insights into the different types of statements used to convey the two under-examined health-related PMFs: *health risk susceptibility* and *health impact*. Future experimental research is needed to empirically test how persuasive the five PMFs are in terms of promoting appropriate public thoughts and behaviors in the context of natural hazards.

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CHAPTER III

TOWARD WIN-WIN MESSAGE STRATEGIES: THE EFFECTS OF PERSUASIVE MESSAGE CONTENT ON RETWEET COUNTS DURING NATURAL HAZARD EVENTS^{3 4}

ABSTRACT

Message diffusion and message persuasion are two important aspects of success for official risk messages about hazards. Message diffusion enables more people to receive lifesaving messages, and message persuasion motivates them to take protective actions. This study helps to identify win-win message strategies by investigating how an under-examined factor, message content that is theoretically important to message persuasion, influences message diffusion for official risk messages about heat hazards on Twitter. Using multilevel negative binomial regression models, the respective and cumulative effects of four persuasive message factors, *hazard intensity*, *health risk susceptibility*, *health impact*, and *response instruction* on retweet counts were analyzed using a dataset of heat-related tweets issued by U.S. National Weather Service accounts. Two subsets of heat-related tweets were also analyzed: 1) heat warning tweets about

³ © American Meteorological Society. Used with permission. This manuscript has been accepted for publication by *Weather, Climate, and Society*. This manuscript is an almost-final version for publication and may be fully cited as “Li, Yajie, Amanda Lee Hughes, and Peter D. Howe. 2021. Toward Win-win Message Strategies: The Effects of Persuasive Message Content on Retweet Counts During Natural Hazard Events. *Weather, Climate, and Society*. Early online release. <https://doi.org/10.1175/WCAS-D-20-0039.1>”. The final typeset copyedited article will replace the early online release when it is published.

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current or anticipated extreme heat events and 2) tweets about non-extreme heat events. This study found that heat-related tweets that mentioned more types of persuasive message factors were retweeted more frequently, and so were two subtypes of heat-related tweets. Mentions of hazard intensity also consistently predicted increased retweet counts. Mentions of health impacts positively influenced message diffusion for heat-related tweets and tweets about non-extreme heat events. Mentions of health risk susceptibility and response instructions positively predicted retweet counts for tweets about non-extreme heat events and tweets about official extreme heat warnings respectively. In the context of natural hazards, this research informs practitioners with evidence-based message strategies to increase message diffusion on social media. Such strategies also have the potential to improve message persuasion.

1. Introduction

Risk communication is a vital element in risk management and a promising way to protect public health and safety across a range of domains, including environmental hazards and health (Leiss 1996; Demeritt and Nobert 2014). As a component of risk communication, public risk messages issued by government agencies in the context of natural hazards are important because such messages inform affected populations about hazardous situations and may stimulate protective actions. In recent years, social media have been increasingly used by agencies and organizations to communicate with the public about natural hazards and disasters (Hughes and Palen 2012; Palen and Hughes 2018; Sutton and Kuligowski 2019). Federal, state, and local governments, via emergency management agencies, meteorological departments, and health departments

have used social media like Twitter and Facebook to share and collect timely information before, during, and after a variety of hazardous events (Hughes et al. 2014; St. Denis et al. 2014; Li et al. 2018; Scott and Errett 2018).

Message diffusion in the context of natural hazards enables people who are beyond the direct contacts of the initial sender to receive lifesaving messages. Receiving public risk messages enhances the likelihood of taking protective actions (Mileti and Sorensen 1990), although barriers exist between the point of receiving messages and the point of taking actions. Public risk messages disseminated via social media can be retransmitted more easily, to more individuals, and with higher fidelity than via mass media channels such as radio and television (Sutton et al. 2014, 2015). This highlights the need to understand what factors facilitate or suppress retransmission of official risk messages in social media. The present research investigates how an under-examined factor, persuasive message content, influences message diffusion on Twitter in the context of heat hazards. In this study, persuasive message content refers to specific message content that, suggested by theories or empirical studies, has the potential to influence receivers' attitudes, intentions, or behaviors. This research can benefit public officials especially communication practitioners by identifying evidence-based strategies about risk messaging to increase message diffusion on Twitter. Such strategies also have the potential to motivate people to take protective actions, since these strategies are persuasive message content whose persuasiveness has been suggested by previous studies.

2. Background

a. Message diffusion on social media

Social media sites such as Twitter and Facebook enable message retransmission via functions such as “retweeting” on Twitter and “sharing” on Facebook. Using these functions, people who consume information can also actively promote information to the broader public on social media (Lin et al. 2016b). The number of times the original message was retransmitted is recorded on social media sites, which allows investigation of factors predicting message retransmission with precision unachievable by traditional data sources (Sutton et al. 2015). There is a growing body of research investigating predictors of message retransmission on social media across contexts such as natural hazards (Sutton et al. 2015; Lin et al. 2016a), emerging infectious disease (Vos et al., 2018), software vulnerability (Syed et al. 2018), and marketing (Cvijikj and Michahelles 2013; Walker et al. 2017). Due to limited data availability through other social media platforms (such as Facebook), previous studies have heavily relied on Twitter to investigate retransmission mechanisms. Twitter is a microblogging service, and around a fifth U.S. adults (22%) use Twitter (Wojcik and Hughes 2019).

Across research domains, factors related to message retransmission on Twitter can be categorized into two main groups: intrinsic message features and extrinsic factors beyond the messages themselves. For intrinsic message features, previous studies have examined how message retransmission on Twitter is affected by thematic content (Sutton et al. 2014, 2015), message style such as the use of imperative sentence style (Sutton et al. 2015; Vos et al. 2018; Lachlan et al. 2019), message structure such as inclusion of images and URLs (Sutton et al. 2015; Lachlan et al. 2019), and message sentiment (Walker et al. 2017; Yang et al. 2018). Extrinsic message retransmission factors include

network features such as the number of followers of the sending account (Vos et al. 2018), authorship of Twitter messages (tweets, Wang et al. 2020), and the created time of tweets (Zhu et al. 2011).

b. A knowledge gap about win-win message strategies

Some of the factors related to message diffusion also influence message persuasion, or the message's ability to influence recipients' attitudes, behavioral intentions, and behaviors. For example, images in health communication can not only predict increased message diffusion on Twitter (Vos et al. 2018), but also increase intentions to adopt suggested behaviors (Anderson 1983). Message sources also matter for both message diffusion and message persuasion (Wilson and Sherrell 1993; Wang et al. 2020). Investigating message factors which may influence both message diffusion and message persuasion is important, because it helps identify message strategies that achieve two kinds of message success (persuasion and diffusion). When it comes to message content, limited research attention has been paid to identifying such win-win message content. When investigating message content as a potential factor of message diffusion, researchers across a variety of domains typically inductively categorize message content into thematic content (Sutton et al. 2014; Syed et al. 2018), rather than deductively coding messages into persuasive message content. As a result, much less is known about what persuasive message content enhances message diffusion than what informative themes enhance message diffusion.

Thematic content is usually different from persuasive message content because it is identified based on different considerations. Thematic content is identified based on

patterns of meaning within messages, but persuasive message content is identified based on what has been found by previous theories and empirical studies to increase persuasion. Nuanced message content that is persuasive may not be distinguished as separate content themes using an inductive coding method, and thus data-driven thematic content is usually overrepresented relative to concept-driven persuasive message content. For example, hazard information is one type of thematic content that has been positively related to retweet counts across four types of natural hazards (Sutton et al. 2014, 2015). The theme of hazard information includes descriptions about physical characteristics of the hazard itself and/or hazard impacts (Sutton et al. 2015). There is little doubt that risk messages need information about the hazard itself and hazard impacts (Mileti and Sorensen 1990). However, we hesitate to say that the theme of hazard information is persuasive message content. This is because past studies typically disaggregated the hazard information theme into several components and examined the persuasive effects of its components (Morss et al. 2015; Lebel et al. 2018; Potter et al. 2018), instead of examining the persuasive effects of the hazard information theme itself. A possible reason is that studies comparing the presence and absence of the hazard information theme would not provide useful suggestions for risk messaging since risk messages would include hazard information anyway. The hazard information theme may be too broad to be a meaningful unit of persuasive message content. According to previous theoretical and empirical studies about persuasion, what components of the hazard information theme are persuasive message content will be described in the next subsection.

To our knowledge, no study has investigated how persuasive message content influences message diffusion in the context of natural hazards, and the present study is the first study to do so. In the related field of health communication, only one study (Vos et al. 2018) deductively identified specific persuasive message content based on a persuasion theory, the Extended Parallel Process Model (Witte 1992). The study found that depicted severity (the depicted magnitude of harm that could happen from Zika virus) and efficacy (information about protective actions recommended for individuals) enhanced retransmission of official risk messages on Twitter, but no effect was observed regarding depicted susceptibility (who is at risk for negative consequences from Zika virus) (Vos et al. 2018). The present study was designed in a different context, heat hazards, and used persuasive message content that is suitable to natural hazards.

c. Persuasive message content about natural hazards

Previous studies have suggested some persuasive message content about natural hazards. In recent years, experimental studies disaggregated the theme of hazard information into two components, hazard-based messages and impact-based messages, and compared their persuasive effects (Morss et al. 2015, 2018; Potter et al. 2018). For example, impact-based messages that only contain descriptions about hazard impacts (e.g., potential damage posed to infrastructure) increased risk perceptions of the hazardous event relative to hazard-based messages that only contain descriptions about characteristics of the hazard itself (e.g., wind speed) (Potter et al. 2018). Drawing on fear appeal theories, commonly used in the health communication literature (Witte 1992; Tannenbaum et al. 2015), our prior work (Li et al. 2018) further disaggregated the theme

of hazard information into four types of persuasive message content applicable for natural hazards: *hazard uncertainty*, *hazard intensity*, *health risk susceptibility*, and *health impact*. Our work also identified a fifth type of persuasive message content that was about guidance, termed *response instruction* (see details in Table 3). We called these five types of persuasive message content persuasive message factors (PMFs) (Li et al. 2018). The present study builds on this prior study and investigates how these PMFs respectively and cumulatively predict the retweet counts of official risk messages about heat hazards.

TABLE 3. Definition, Coding Scheme, and Examples for Persuasive Message Factors. Adapted from (Li et al. 2018).

PMF	Definition	Coding scheme for heat	Tweet example
<i>Hazard Uncertainty</i>	Probability information about a hazardous event occurring	Descriptions about the degree of forecast uncertainty with the temperature or Heat Index (HI) for the upcoming weather.	“6-10 DAY OUTLOOK TEMPERATURE PROBABILITY. (With color ramps showing) Probability of Below (Normal) and Probability of Above (Normal).”
<i>Hazard Intensity</i>	Descriptions about the physical severity of a hazardous event itself	Information about HI and/or the temperature of current and/or upcoming heat events	“The #heatwave continues w/ heat indices of 105-111 expected today!”
<i>Health Risk Susceptibility</i>	Message content depicting susceptibility to health-related consequences of a hazardous event	Message content signaling who, which behaviors and/or which places (e.g., outdoor, on the beach) that are vulnerable to heat-health impacts.	“Who’s At High Risk? Much of the population, especially those who are heat sensitive and anyone without effective cooling and hydration.”
<i>Health Impact</i>	Mentions about the severity of health-related consequences of a hazardous event	At least one word indicating heat-related illnesses and/or deaths.	“Take frequent breaks, stay hydrated and wear light-weight clothing to avoid heat-related illnesses.”
<i>Response Instruction</i>	Descriptions about recommended actions	Information about generic and/or specific heat safety tips.	“Stay cool! – Use air conditioning if possible; fans alone DO NOT provide enough cooling when it is very hot outside.”

The persuasive effects of these five PMFs have been suggested by previous studies. With respect to the four PMFs that belong to the broad hazard information theme, meta-analyses of fear appeal studies have found that the independent and joint inclusion of depicted susceptibility (descriptions emphasizing how likely message recipients will be adversely impacted) and depicted severity (descriptions emphasizing negative consequences) in risk messages were persuasive (De Hoog et al. 2007; Tannenbaum et al. 2015). For example, health messages emphasizing the recipient's personal risk and serious consequences of maladaptation positively influence people's behavioral intentions and behaviors compared to messages depicting lower susceptibility and lower severity of the negative consequences (Tannenbaum et al. 2015). Li et al. (2018) adapted depicted susceptibility and severity to natural hazards. *Hazard uncertainty* and *health risk susceptibility* respectively indicate depicted susceptibility of the hazard itself and depicted susceptibility of hazard impacts, and *hazard intensity* and *health impact* respectively indicate depicted severity of the hazard itself and depicted severity of hazard impacts. Definitions of these terms are provided in the Table 3. With respect to the PMF of *response instruction*, meta-analyses of fear appeal studies also suggested the persuasive effects of such efficacy statements (Tannenbaum et al. 2015). Compared to risk messages without efficacy statements, risk messages with efficacy statements improve people's behavioral intentions and tendency to engage in behaviors through increased perceived self-efficacy (belief in one's capacity of performing recommended actions) and/or increased perceived response-efficacy (belief that the recommended actions will achieve desirable outcomes) (Floyd et al. 2000; Milne et al. 2000; Witte and Allen 2000; Tannenbaum et al. 2015).

Previous empirical studies in the context of natural hazards also suggested the persuasive effects of some PMFs investigated in the present study. These previous studies may not use the exact terms as we used to describe their manipulation. However, we found these previous studies manipulated a certain PMF described in the present study after comparing their control messages and treatment messages using the definitions of PMFs. These previous studies have found that intentions to take recommended actions can be elevated by each mention of hazard uncertainty (Lebel et al. 2018), hazard intensity (Casteel 2016), impact severity (e.g., negative consequences on health and property, Casteel 2016), and response instructions (Wong-Parodi et al. 2018). In addition, mentions of *health risk susceptibility* have the potential to address issues that have been identified from previous studies. Failure to personalize heat-health risks has been identified as a main reason why people did not take recommended actions in heat risk messages (Kalkstein and Sheridan 2007; Sheridan 2007; Bassil and Cole 2010). *Health risk susceptibility* has the potential to avoid the misperception of “it can’t happen to me” by clarifying who and/or which behavior are at risk for negative impacts from heat events (Li et al. 2018). However, the persuasive effects of *health risk susceptibility* need future research about natural hazards to provide empirical evidence.

In addition to identifying these five PMFs, our prior work also content-analyzed 904 tweets related to heat hazards issued by a sample of eighteen U.S. NWS Weather Forecast Offices (WFOs) in 2016 (Li et al. 2018). We examined the degree to which the five PMFs were mentioned in these official heat risk tweets (Li et al. 2018). The present study expands on this prior study and investigates how four of the five PMFs respectively and cumulatively predict the retweet counts of the official risk messages for heat hazards.

The PMF that we removed from the analyses was *hazard uncertainty*, since heat-related tweets mentioning *hazard uncertainty* were too rare (only 5 of 904 tweets) to reliably estimate its effects. Our models also controlled for some extrinsic factors of message retransmission such as network features, which will be described in detail in the method section.

d. Different message types

To analyze the respective and cumulative effects of PMFs, this study built models predicting retweet counts for all heat-related tweets. In addition, this study also built separate models for a subset of heat-related tweets that alerted about extreme heat events (*heat warning tweets*) and for another subset of heat-related tweets that alerted about non-extreme heat events (*non-warning tweets*). In this study, extreme and non-extreme heat events were mainly distinguished by whether heat events are accompanied by NWS's heat watch, warning, and advisory (WWA) products. If a heat-related tweet alerted about a heat event that was accompanied by any of the heat WWAs and also mentioned active heat WWAs in the tweet, this heat-related tweet was categorized as a "heat warning tweet." If a heat-related tweet alerted about a heat event whose conditions were not hot enough and/or long enough in duration to issue heat WWAs, this tweet was categorized as a "non-warning tweet."

Heat hazards pose a serious threat to people in the United States, causing more deaths than floods, hurricanes, and tornadoes combined during 2009 to 2018 (Centers for Disease Control and Prevention 2020). Widespread heat-health impacts affect people across age groups and geographic areas (Hess et al. 2014; Mora et al. 2017). Both heat

warning tweets and non-warning tweets are important to protect the public from negative health impacts from heat. Although local WFOs have highly variable criteria regarding conditions favorable to issue heat WWAs for their forecast areas, conditions that warrant heat WWAs in each WFO indicate that, in general, such conditions are dangerous for the local population within the WFO's forecast area (Hawkins et al. 2017). Extreme heat events can harm anyone without appropriate actions (Mora et al. 2017), and heat warning tweets communicate such dangerous conditions with the general public in order to motivate protective actions. Non-warning tweets alert about non-extreme heat events during which negative heat effects are still likely for vulnerable populations such as the elderly, those exercising or working outdoors, and those without adequate hydration (Kovats and Hajat 2008; Mora et al. 2017). Investigating the PMF effects separately for heat warning tweets and non-warning tweets allows targeted messaging suggestions for risk communicators to create different message types for different heat conditions. Investigating the PMF effects for all heat-related tweets allows description of effects at an aggregate level for all tweets that aim to protect the public from heat-health risks.

We propose two research questions in this study:

- 1) How does the inclusion of the persuasive message factors of *hazard intensity*, *health risk susceptibility*, *health impact*, and *response instruction* influence message retransmission respectively for heat-related tweets, heat warning tweets, and non-warning tweets posted by U.S. NWS WFOs?
- 2) What are the cumulative impacts of the inclusion of the persuasive message factors of *hazard intensity*, *health risk susceptibility*, *health impact*, and *response*

instruction on message retransmission for heat-related tweets, heat warning tweets, and non-warning tweets posted by U.S. NWS WFOs?

3. Method

a. Data

Official heat-related tweets (N=904) were collected by our prior work (Li et al. 2018). Using the Twitter Search application programming interface (API), tweets and their retweet counts were collected if tweets were posted between June 1 and August 31, 2016 by each official Twitter account of the eighteen sampled NWS WFOs. These sampled offices (see Fig. 4) were chosen using theoretical sampling (Singleton and Straits 2010) and these offices demonstrate important variations among the total of 123 U.S. WFOs in terms of local climate and NWS regions. Our prior study (Li et al. 2018) extracted original tweets that contained the English words “hot” or “heat” in the displayed text, and further manually coded the extracted tweets as “heat-related tweets” if the extracted tweets (including the displayed text and text in attached images) indicated that specific heat events either were occurring or upcoming in the forecast areas (intercoder reliability coefficients, Cohen’s Kappa = 0.83). This human coding process removed some extracted tweets which, although containing the words “hot” or “heat”, were not heat-related tweets, for example, tweets only stating an expired heat warning. In addition, each of the five PMFs were deductively coded in our prior work (Li et al. 2018). All heat-related tweets (N=904) were coded based on not only the displayed text but also textual information in attached images. For each heat-related tweet, the five PMFs (*hazard uncertainty, hazard intensity, health risk susceptibility, health impact, and*

response instruction) had its own code (1: presence versus 0: absence). Each tweet could contain one or more PMFs. With respect to intercoder reliability, the Cohen's Kappa of the five PMFs were all above 0.93 (Li et al. 2018).

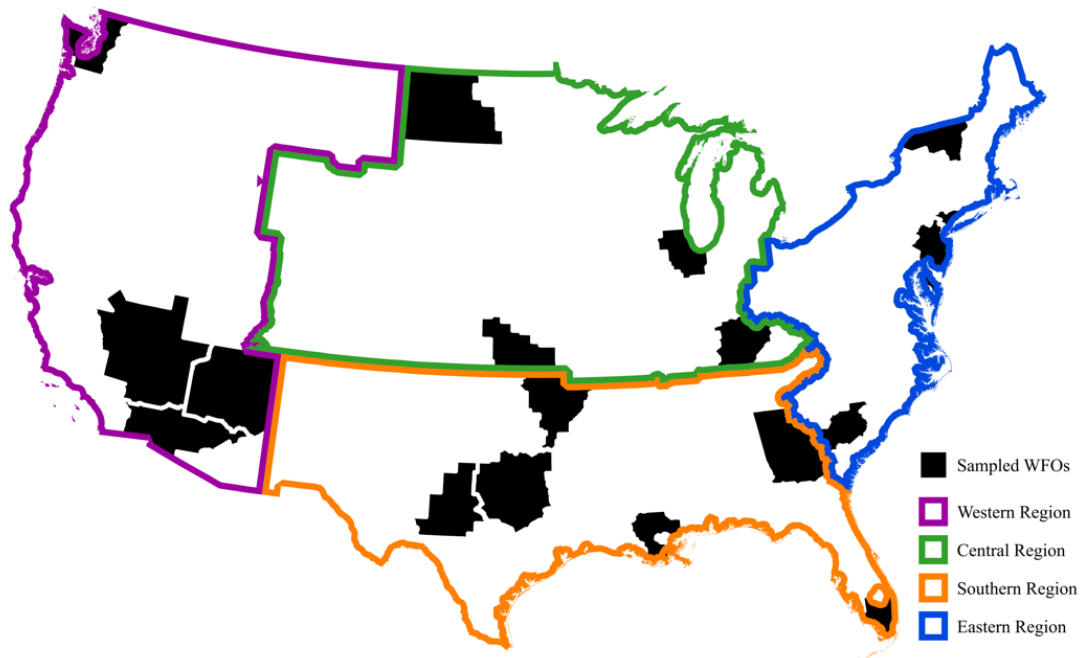


FIG. 4. A map showing the distribution of the sampled NWS WFOs, and the NWS regional offices' operational boundaries. White lines separate adjacent WFOs. No WFOs are across NWS regional boundaries. After (Li et al. 2018).

b. Operationalization

The dependent variable of retweet counts is the number of times a tweet was retransmitted. The respective effects of the PMFs were operationalized as four variables indicating the presence or absence of each PMF (*hazard intensity*, *health risk susceptibility*, *health impact*, and *response instruction*). As mentioned earlier, we removed the PMF of *hazard uncertainty* when modeling the respective and cumulative effects of PMFs because the tweets containing the PMF of *hazard uncertainty* were rare

(only 5 of 904 tweets). The cumulative effect of the PMFs was operationalized as the number of PMFs (*hazard intensity, health risk susceptibility, health impact, or response instruction*) mentioned in a risk message, which ranged from zero to four.

In addition to heat-related tweets overall (N=904), the other two message types were two subsets of heat-related tweets: heat warning tweets (N=223) and non-warning tweets (N=436). First, as mentioned earlier, heat warning tweets alerted about current or anticipated extreme heat events that warrant heat WWAs, and non-warning tweets alerted about current or anticipated non-extreme heat events that did not warrant heat WWAs. For the present study, to be considered a heat warning tweet, a heat-related tweet must 1) be posted within at least one heat WWA's active period (from issuance time to expiration time) in its respective WFO, and 2) mention at least one heat WWA that has been issued, is currently in effect, or will be in effect in the displayed text or text in attached images. About a quarter of heat-related tweets (N=223) met the two criteria and were categorized as heat warning tweets. Second, some of the heat-related tweets (N=245) only met the first criterion which means they were posted when at least one heat WWA was issued in their respective WFOs but these tweets did not mention the co-occurring heat WWAs. On the one hand, some of these 245 tweets may alert about non-extreme heat events. For example, consider a case in which a heat warning product is issued this morning and indicates that the start time of an extreme heat event is tomorrow. An official tweet may be posted at noon and only mention today's non-extreme heat situation that does not warrant a watch, warning, or advisory product. On the other hand, some of these 245 tweets may alert about extreme heat events, but they did not mention co-occurring heat WWAs. In this situation, the diffusion mechanism of the tweets may be different from

those that met both criteria to be considered heat warning tweets. As a result, we did not identify these 245 heat-related tweets as either heat warning or non-warning tweets. In other words, although the 245 heat-related tweets were included when we built models using all heat-related tweets, the 245 heat-related tweets were excluded when we built models using the subsets of heat-related tweets: heat warning tweets and non-warning tweets, because they could not be definitively included in either category. Third, to be considered a non-warning tweet, a heat-related tweet must have been posted prior to the issuance time of heat WWAs and after the expiration time of heat WWAs in respective WFOs. Data about the issuance/expiration time of archived heat WWAs were collected from the Iowa Environmental Mesonet (n.d.). About half of heat-related tweets (N=436) were categorized as non-warning tweets, and there is no overlap between heat warning tweets and non-warning tweets.

We also considered control variables (Table 4) to help isolate the relationship between mentions of PMFs and message diffusion. These include the time of day, day of week, and the month the tweet was issued, the sending account and its number of followers, the region of origin, the population of the office's jurisdiction, and environmental variables (monthly normal temperature and temperature anomaly). The created time of tweets (except created month), network features, and authorship have each been found to have an influence on message retransmission (Zhu et al. 2011; Sutton et al. 2015; Hu et al. 2019; Wang et al. 2020). Seasonality (created month) and environmental variables (monthly normal temperature and monthly temperature anomaly) could influence the sharing behavior of local Twitter users through a mediator, heat risk perception. Early in the warm season, higher mean temperature, and increased

temperature anomaly have been associated with higher heat risk perception (Schoessow 2018), and the higher heat risk perception among local Twitter users could motivate more message sharing behaviors regardless of the mention of PMFs among such messages.

Aligned with previous studies (Howe et al. 2019), we used mean temperatures (instead of maximum and minimum temperatures) to calculate monthly normal temperatures and temperature anomalies. Mean temperatures were highly correlated with maximum and minimum temperatures in our data sets (Pearson correlation coefficient ranging from 0.88 to 0.97).

TABLE 4. Description of Control Variables

Variable	Description	Data source
Created time of day	The local time of day when the tweet was posted, which was classified into four categories: 0am - 6am, 6am - 12pm, 12pm - 6pm, and 6pm - 12am.	Collected using Twitter Search API
Created day of week	The local time of week when the tweet was posted, which was classified into seven categories: Monday, Tuesday, ... Saturday, and Sunday.	Collected using Twitter Search API
Created month	The local time in month when the tweet was posted, which had three categories: June, July, and August.	Collected using Twitter Search API
Sending WFO	The WFO which is the sending account. The eighteen WFO names can be found in appendix A.	Collected using Twitter Search API
NWS region	The NWS regional office to which the sending WFO belongs, which had four categories: Western Region, Central Region, Southern Region, and Eastern Region.	Collected using Twitter Search API
Monthly normal temperature	The average monthly long-term mean temperature (1981-2010) in the forecast area of each sampled WFO.	PRISM Climate Group (n.d.)
Monthly temperature anomaly	Subtracting monthly normal temperature from the average monthly mean temperature of the study year 2016 for the forecast area of each sampled WFO. This variable was rescaled by multiplying by ten when fitting in models.	PRISM Climate Group (n.d.)
Follower count	The number of followers in the sending account on September 1st, 2016. This variable was rescaled by taking natural log when fitting in models.	Provided by NWS Social Media and Digital Strategy Lead via an email on February 11th, 2020
Population size	The number of individuals living within the forecast area of each sampled WFO in 2016. This variable was rescaled by taking natural log when fitting in models.	U.S. Census Bureau (2017)

c. Analytic approach

We modeled the effects of PMFs on message diffusion through a multilevel negative binomial regression model in the R statistical computing environment using the

lme4 package (Bates et al. 2015). Respective effects and cumulative effects were modeled separately. For each type of effect, we also modeled each of the three data sets which correspond to heat-related tweets, heat warning tweets, and non-warning tweets respectively. The two subsets of heat-related tweets were modeled separately to find out whether the effects of PMFs on message diffusion are different between heat warning tweets and non-warning tweets. We used negative binomial regression models (Gelman and Hill 2006) because retweet counts in our data sets were overdispersed count data (dispersion parameters ranging from 2.2 to 7.5). Our data were collected with multilevel structures (e.g., tweets within WFOs and WFO regions). Multilevel modeling, compared to classical regression, provided more reasonable estimates because multilevel modeling accounts for group-level variability by including indicators at different levels and also accounts for group-level dependency through partial pooling (Gelman and Hill 2006).

Each of the six multilevel negative binomial models was fit using a combination of individual-level predictors, grouping variables, and group-level predictors. The individual-level predictors were the variables regarding the respective or cumulative effects of the PMFs. These individual-level predictors were treated as fixed effects, which means that their coefficients were estimated using classical maximum likelihood methods (Gelman and Hill 2006). Individual tweets were also grouped according to their created time of day, created day of week, created month, sending WFO, and NWS region. In our study, these grouping variables were treated as random effects and multilevel regression models were restricted to a varying-intercept and constant-slope model. This means that each group within these grouping variables (e.g., each WFO within the grouping variable of sending WFO) could have different intercepts in the multilevel model, and the varying

intercepts were estimated using partial pooling (Gelman and Hill 2006). Some of these grouping variables also have group-level predictors: follower counts and population size were two group-level predictors for the group of the sending WFO. Monthly normal temperature and monthly temperature anomaly were group-level predictors across the groups of sending WFO level and created month. These group-level predictors were treated as fixed effects in our models.

The continuous predictors in this study were on different scales. To reduce their impact on parameter estimates, we multiplied the variable of monthly temperature anomaly ($^{\circ}\text{C}$) by a factor of 10, and transformed the variables of follower counts and population size using the natural log function. For each of the six models, variables treated as fixed effects did not have serious multicollinearity problems, according to the generalized variance-inflation factor (GVIF, Fox and Monette 1992). The highest GVIF among fixed-effect variables in the six models was 2.4. Aligned with GVIF, the highest Pearson correlation between logged follower counts and logged population size was 0.61. All fixed effects were kept in all models regardless of their explanatory effects. For each model, we dropped the random effects which provided little explanatory effect (i.e., with an Intraclass-Correlation Coefficient less than 0.0001).

For model diagnostics, we used the plot of Pearson residuals against fitted values on the scale of the linear predictor for our multilevel negative binomial models. This plot is the equivalent of the plot of residuals against fitted values for general linear models (Faraway 2016). For each of the six models, points in the plot of Pearson residuals against fitted values in the scale of the linear predictor were around the horizontal line of zero, with a roughly constant variance, which means that the assumptions of linearity (in

the scale of linear predictors) and equal variance of errors (scaling out the variance function) were met for all multilevel negative binomial models.

4. Results

a. Distribution of PMFs

Retweet counts of the heat-related tweets in our data set ranged from 0 to 217, with a mean of 13.6 (SD=14.9). For the two subsets of heat-related tweets, heat warning tweets had higher retweet counts (mean=15.5, SD=13.5) than non-warning tweets (mean=10.6, SD=7.2; $t(289.3)=5$, $p < 0.001$) without controlling for other variables. Overall, the use of PMFs across message types was quite consistent. Across message types, information about temperature or heat index (the PMF of *hazard intensity*) was by far the most used PMF and descriptions about the severity of health impacts from heat (the PMF of *health impact*) was the least frequently mentioned PMF (Fig. 5). About two-thirds of heat warning tweets (N=158, 70%) mentioned *hazard intensity*, as did more than four-fifths of heat-related tweets (N=760, 84%) and nearly 90% non-warning tweets (N=392). However, less than one-fifth of tweets mentioned *health impact* in each category of tweet. The next most used PMF was *response instruction* across message types, followed by the PMF of *health risk susceptibility* that describes who, which behavior, or certain places that are at risk from heat.

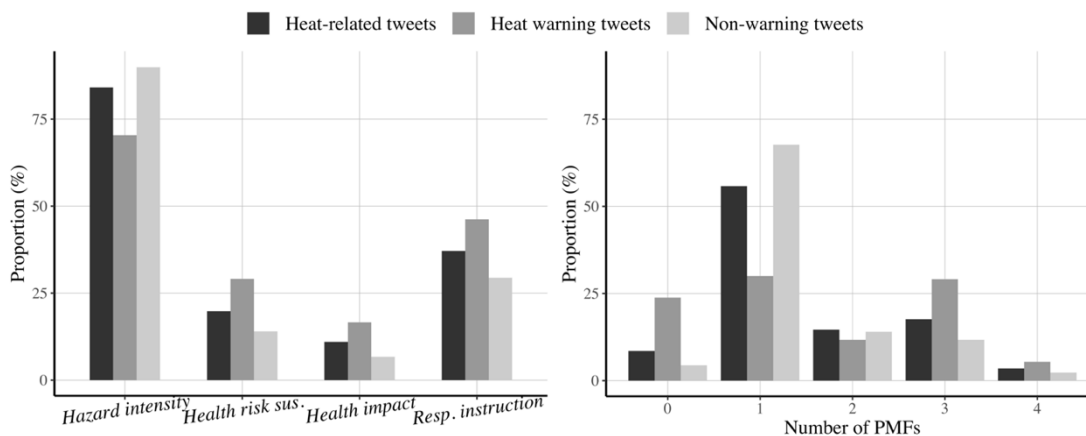


FIG. 5. The percentage of each type of tweet containing a certain PMF and containing varying numbers of different PMFs. Heat-related tweets refer to official tweets alerting about any heat events, and heat warning tweets and non-warning tweets are subsets of heat-related tweets which alert about extreme heat events and non-extreme heat events respectively.

A majority of tweets used zero or only one PMF in each type of tweet. This was especially the case for non-warning tweets (N=314, 72%). For tweets that used one PMF, the percentage of each type of tweet that used the PMF of *hazard intensity* ranges from 96% to 97%. For tweets that used two PMFs across message types, the percentage of each type of tweet that used the combination of *hazard intensity* and *response instruction* ranges from 73% to 85%. Less than 6% tweets used all of the four PMFs in each message type. Descriptive statistics of each type of tweet across grouping variables and group-level predictors can be found in appendix A. Across message types, the number of tweets posted by each sending WFO varied substantially (e.g., heat-related tweets: min.=13, max.=98, mean=50, SD=30). In contrast, the number of tweets was distributed almost evenly across days of the week. For other grouping variables, more tweets were posted in July but fewer in August. Fewer tweets were posted between 6 pm and 12 am relative to other times of day. WFOs in the NWS Eastern Region posted, on average, fewer tweets than WFOs in other regions.

b. Respective and cumulative effects of PMFs

Regarding the respective effect of PMFs, *hazard intensity* was a consistently positive predictor of retransmission across all types of tweets (Table 5). The other three PMFs, *health risk susceptibility*, *health impact*, and *response instruction*, had statistically significant and positive influence on retweet counts for one or two message types. No PMFs showed negative respective effects on retweet counts. The mention of *health risk susceptibility* was a statistically significant and positive predictor of retweet counts for non-warning tweets. The inclusion of *health impact* had a statistically significant and positive effect on retweet counts in all heat-related tweets and the subset of non-warning tweets. The mention of *response instruction* had a statistically significant and positive effect on retweet counts for the heat warning tweets. The effect size of these statistically significant, respective effects was similar, ranging from a 21% increase to a 33% increase in retweets. Given the exploratory nature of this analysis, it is worth noting that, for heat-related tweets, the effect of mentioning *health risk susceptibility*, IRR=1.13 [95% CI: 1.00 -1.28], $p = 0.055$, and mentioning *response instruction*, IRR=1.10 [95% CI: 0.99-1.23], $p = 0.087$, approached statistical significance.

TABLE 5. Multilevel Negative Binomial Regression Predicting the Respective Effect of PMFs on Retweet Counts for Each Type of Tweet. P values less than 0.05 are in bold. Note that b is the unstandardized regression coefficient, S.E. is the standard error, IRR is the incidence rate ratio, CI is the confidence interval, N is the number of groups within a grouping variable, σ^2 is the component of variance, and ICC is the intra-class correlation coefficient.

<i>Individual-level Predictor</i>	Heat-related tweets				Heat warning tweets				Non-warning tweets			
	b (S.E.)	IRR [95%CI]	p value	b (S.E.)	IRR [95%CI]	p value	b (S.E.)	IRR [95%CI]	p value	b (S.E.)	IRR [95%CI]	p value
(Intercept)	-4.81 (0.83)	0.01 [0.00, 0.04]	< 0.001	-3.55 (1.30)	0.03 [0.00, 0.37]	0.006	-3.18 (1.23)	0.04 [0.00, 0.47]	0.010			
<i>Hazard intensity</i>	0.20 (0.06)	1.22 [1.09, 1.37]	< 0.001	0.23 (0.09)	1.26 [1.04, 1.51]	0.016	0.24 (0.08)	1.28 [1.10, 1.49]	0.002			
<i>Health risk susceptibility</i>	0.12 (0.06)	1.13 [1.00, 1.28]	0.055	0.01 (0.12)	1.01 [0.81, 1.27]	0.929	0.22 (0.08)	1.25 [1.07, 1.46]	0.006			
<i>Health impact</i>	0.19 (0.07)	1.21 [1.05, 1.39]	0.007	0.05 (0.12)	1.05 [0.83, 1.33]	0.694	0.28 (0.09)	1.33 [1.10, 1.60]	0.003			
<i>Response instruction</i>	0.10 (0.06)	1.10 [0.99, 1.23]	0.087	0.24 (0.12)	1.27 [1.01, 1.60]	0.043	0.04 (0.06)	1.04 [0.92, 1.18]	0.513			
<i>Group-level predictor</i>	b (S.E.)	IRR [95%CI]	p value	b (S.E.)	IRR [95%CI]	p value	b (S.E.)	IRR [95%CI]	p value			
Monthly normal temperature	-0.01 (0.01)	0.99 [0.96, 1.02]	0.524	-0.05 (0.02)	0.95[0.92, 0.99]	0.011	-0.01 (0.02)	0.99 [0.95, 1.02]	0.435			
Monthly temperature anomaly (multiplied by ten)	0.01 (0.00)	1.01 [1.00, 1.02]	0.008	0.00 (0.01)	1.00 [0.99, 1.02]	0.794	0.00 (0.00)	1.00 [0.99, 1.00]	0.388			
Follower count (logged)	0.38 (0.12)	1.46 [1.15, 1.85]	0.002	0.24 (0.17)	1.27 [0.91, 1.77]	0.165	0.21 (0.19)	1.24 [0.86, 1.78]	0.250			
Population size (logged)	0.23 (0.06)	1.26 [1.11, 1.43]	< 0.001	0.31 (0.09)	1.37 [1.14, 1.63]	0.001	0.23 (0.10)	1.26 [1.04, 1.53]	0.020			
<i>Grouping variable</i>	N	σ^2	ICC	N	σ^2	ICC	N	σ^2	ICC			
Created time of day	—	—	—	—	—	—	4	0.003	0.008			
Created day of week	7	0.008	0.019	7	0.013	0.034	—	—	—			
Created month	3	0.016	0.038	3	0.054	0.141	3	0.002	0.007			
Sending WFO	18	0.029	0.069	15	0.025	0.064	18	0.078	0.241			
NWS region	4	0.075	0.180	4	0.076	0.198	4	0.053	0.165			
Number of observations		904			223			436				
Marginal R^2		0.261			0.298			0.250				
Conditional R^2		0.443			0.570			0.537				

Compared to the respective effects of individual PMFs, the cumulative effect of PMFs was a more consistent and precise predictor of retweet counts across message types. The number of PMFs was a statistically significant, positive predictor for all types of tweets, and its 95% confidence intervals were consistently narrower than those of the respective effects of separate PMFs (Table 6 and Fig. 6). Every additional type of PMF mentioned in official tweets increased the predicted retweet counts for each type of tweet by a factor of about 1.15, controlling for other variables in the models. Heat-related tweets mentioning four PMFs were estimated to have 48% more retweets than heat-related tweets mentioning one PMF, regardless of the PMF type. For heat warning tweets and non-warning tweets, tweets containing four PMFs were associated with 53% and 57% more predicted retweets respectively than tweets containing only one PMF. To check whether the effects of the number of PMFs were dependent on a single influential PMF, we conducted 12 additional models (for each PMF and tweet type) dropping tweets mentioning one of the four PMFs from one of three message types. Overall, the effects of the number of PMFs were not driven by a single PMF across message types (see appendix B for details of the statistical analysis). In addition, the cumulative effects of PMFs, as well as the respective effects of each individual PMF, were not statistically significantly different across message types. This is suggested by the overlapped confidence intervals of each predictor for the three data sets (see Fig. 6) and confirmed using a standard method of testing the significance of differences between point estimates (Schenker and Gentleman 2001).

TABLE 6. Multilevel Negative Binomial Regression Predicting the Cumulative Effect of PMFs on Retweet Counts for Each Type of Tweet. P values less than 0.05 are in bold. Note that b is the unstandardized regression coefficient, S.E. is the standard error, IRR is the incidence rate ratio, CI is the confidence interval, N is the number of groups within a grouping variable, σ^2 is the component of variance, and ICC is the intra-class correlation coefficient.

<i>Individual-level Predictor</i>	Heat-related tweets			Heat warning tweets			Non-warning tweets		
	b (S.E.)	IRR [95%CI]	p value	b (S.E.)	IRR [95%CI]	p value	b (S.E.)	IRR [95%CI]	p value
(Intercept)	-4.72 (0.81)	0.01 [0.00, 0.04]	<0.001	-3.95 (1.36)	0.02 [0.00, 0.27]	0.004	-3.10 (1.24)	0.04 [0.00, 0.51]	0.013
Number of PMFs	0.13 (0.02)	1.14 [1.10, 1.18]	<0.001	0.14 (0.03)	1.15 [1.08, 1.23]	<0.001	0.15 (0.03)	1.16 [1.11, 1.22]	<0.001
<i>Group-level predictor</i>	b (S.E.)	IRR [95%CI]	p value	b (S.E.)	IRR [95%CI]	p value	b (S.E.)	IRR [95%CI]	p value
Monthly normal temperature	-0.01 (0.01)	0.99 [0.97, 1.02]	0.547	-0.05 (0.02)	0.95 [0.92, 0.99]	0.022	-0.01 (0.02)	0.99 [0.95, 1.03]	0.542
Monthly temperature anomaly (multiplied by ten)	0.01 (0.00)	1.01 [1.00, 1.02]	0.005	0.00 (0.01)	1.00 [0.99, 1.02]	0.656	0.00 (0.00)	1.00 [0.99, 1.00]	0.428
Follower count (logged)	0.38 (0.12)	1.46 [1.16, 1.84]	0.001	0.27 (0.18)	1.31 [0.92, 1.86]	0.136	0.21 (0.19)	1.24 [0.86, 1.79]	0.259
Population size (logged)	0.23 (0.06)	1.25 [1.11, 1.42]	<0.001	0.32 (0.09)	1.37 [1.14, 1.65]	0.001	0.23 (0.10)	1.25 [1.03, 1.53]	0.024
<i>Grouping variable</i>	N	σ^2	ICC	N	σ^2	ICC	N	σ^2	ICC
Created time of day	—	—	—	—	—	—	4	0.003	0.010
Created day of week	7	0.008	0.021	7	0.011	0.028	—	—	—
Created month	3	0.015	0.036	3	0.052	0.134	3	0.002	0.006
Sending WFO	18	0.027	0.066	15	0.031	0.079	18	0.080	0.248
NWS region	4	0.073	0.178	4	0.072	0.187	4	0.049	0.150
Number of observations		904			223			436	
Marginal R^2		0.260			0.304			0.243	
Conditional R^2		0.439			0.568			0.528	

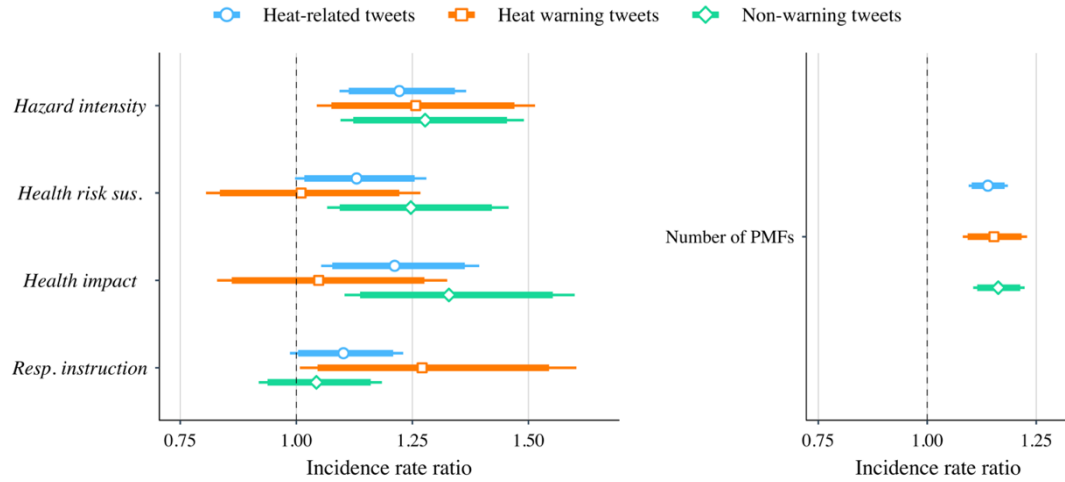


FIG. 6. Estimated respective and cumulative effects of PMFs for each type of tweet. Points, squares, and diamonds indicate the estimated effect; lines indicate 95% confidence intervals with the 90% confidence interval in bold.

c. Effects of control variables

With respect to the control variables included in the regression models, it is worth noting that population size in the forecast area of WFOs consistently had a positive influence on retweet counts across message types. After controlling for other variables including population size, the follower count of the sending account was not a statistically significant predictor of retweet counts for heat warning tweets and non-warning tweets, but had positive effects on retweet counts for heat-related tweets. With respect to the two environmental variables, heat-related tweets posted in places and during months with a higher monthly temperature anomaly predicted slightly increased retweet counts. Heat warning tweets posted in places and during months with higher monthly normal temperature predicted slightly decreased retweet counts. After controlling for other variables in the models, the NWS region, sending WFO, created month of the tweet, and created day of week played varying roles in affecting message

diffusion for different message types. The time of day the tweet was posted had only a small influence on message diffusion across message types.

5. Discussion and conclusions

Using official risk messages about heat hazards as a case study, this study investigated the respective and cumulative effects of four types of persuasive message content on message retransmission via social media. We found that official tweets containing more types of PMFs were retweeted more frequently. This finding held true for all heat-related tweets at an aggregate level, and was also observed separately among its subsets: heat warning tweets and non-warning tweets. In respect to the respective effects, the mention of *hazard intensity* was a positive predictor of retweet counts for heat-related tweets and its two subsets. The mention of *health impact* was a positive predictor for heat-related tweets and non-warning tweets. The mention of *health risk susceptibility* and the mention of *response instruction* were positive predictors of retweet counts for non-warning tweets and heat warning tweets respectively. While some PMFs, as indicated above, showed statistically significant influence for one or two types of tweets and showed statistical insignificance for the other type(s) of tweet(s), each PMF did not show statistically significant differences in its respective effects across three types of tweets.

a. Contributions to theory

Our findings provide insights into how specific message content that is theoretically important to message persuasion influenced message diffusion on social

media in the context of natural hazards. To our best knowledge, this is the first study to identify persuasive message content as factors of message retransmission about natural hazards. In the context of health communication, as mentioned earlier, one study about Zika virus has suggested that depicted severity and efficacy statements were not only persuasive according to a persuasion theory but also effective in terms of message diffusion on Twitter (Vos et al. 2018). In addition, this previous study did not observe the effect of depicted susceptibility on message diffusion, although depicted susceptibility was also persuasive message content (Vos et al. 2018). Our findings about the respective effects of *health risk susceptibility*, *health impact*, and *response instruction* generally align with this previous study, although we did detect a positive effect of *health risk susceptibility* for tweets alerting non-extreme heat events.

Our research also contributes to understanding the cumulative effects of message content. Previous studies have found that a combined theme of hazard information, which was the equivalent of mentioning at least one of the PMFs among *hazard uncertainty*, *hazard intensity*, *health risk susceptibility*, and *health impact*, was a positive predictor of message diffusion across four natural hazard events (Sutton et al. 2015). Although this finding sheds some light on the overall effects of persuasive message content, little research attention has been paid specifically to the cumulative effects of message content. The cumulative effects of message content reflect an important message style: specificity. For risk messages, specificity refers to specific information regarding the hazard's nature and possible consequences, time of impact, location, source, and instructions about protective actions (Mileti and Sorensen 1990). This style of messaging has been found to be persuasive in the context of natural hazards (Mileti and Sorensen 1990; Sutton et al.

2018). Tweets containing a higher number of PMFs are more specific. The positive effects of the number of PMFs detected in the current study suggest that the persuasive message style, specificity, has the potential to enhance message diffusion as well.

In addition to message factors, our study found that audience population size was also a consistent and positive factor of message diffusion, which is in line with one previous study (Hu et al. 2019). A possible explanation of the effect of population size is: when a WFO posts a tweet about hazardous weather in its forecast area and if more individuals live in the forecast area, any reader of the tweet would be more likely to have family members, friends, and co-workers living in the affected area, and thus it would be more likely for the reader to think of someone who needs this message and thus retweet it. However, the follower count of sending accounts was not a consistent predictor of message diffusion. Although positive effects of follower counts on message diffusion were found for all heat-related tweets, follower counts did not predict message diffusion for heat warning tweets and non-warning tweets. Previous studies have also found inconsistent effects of follower counts on message diffusion. Some studies have found positive effects of follower counts on message diffusion (Sutton et al. 2015; Vos et al. 2018; Hu et al. 2019), but some studies have found small negative effects of follower counts on message diffusion (Sutton et al. 2015; Wang et al. 2020). In addition, most previous studies have investigated the effects of follower counts without controlling for the factor of audience population size (Sutton et al. 2015; Vos et al. 2018; Wang et al. 2020). To better understand the effects of follower counts and population size on message diffusion, future research should consider both factors—population size and follower counts—when modeling message diffusion.

b. Contributions to practice

This research informs evidence-based strategies about official risk messaging to enhance message retransmission, thus allowing more people to receive lifesaving messages in the context of natural hazards. When designing official tweets alerting about heat events, no matter whether these events are technically extreme or not, our results about cumulative effects suggest that communicators should use all four PMFs (*hazard intensity*, *health risk susceptibility*, *health impact*, and *response instruction*) to maximize message diffusion. For official tweets alerting about extreme heat events that are accompanied by heat WWAs, it is especially important to mention the PMFs of *hazard intensity* and *response instruction* to enhance message retransmission. Such official tweets should also mention co-occurring heat WWAs in their messages. For official tweets alerting about non-extreme heat events, it is particularly important to mention the PMFs of *hazard intensity*, *health risk susceptibility*, and *health impact* to enhance message diffusion. In addition to contributions on message diffusion, the strategies suggested in our findings also have the potential to promote message persuasion since, in origin, such PMFs were deductively identified based on theoretical and empirical studies about persuasion.

In our data sets, a majority of tweets used zero or only one PMF, and the use of *hazard intensity* was disproportionately high compared to other PMFs. This fact does not mean that it is infeasible to mention all four types of PMFs in content constrained messages like tweets. In contrast, 280 characters in the displayed text and text in attached images provide ample room to describe each PMF. For example, the hypothetical

statement below describes all four PMFs within 140 characters: “Excessive Heat Warning today! Respect the triple-digit heat by drinking enough water and keeping cool! Otherwise everyone is vulnerable to heat-related illnesses.”

c. Limitations and future research

This study had several limitations. First, when predicting the effects of PMFs on message diffusion, we controlled for some extrinsic factors such as network features and authorship of tweets, but our models did not include some intrinsic factors that have been related to message diffusion. For example, we did not consider factors of capitalization of words, inclusion of hashtags, and the imperative sentence style, which have been found to enhance message retransmission in the context of natural hazards (Sutton et al. 2015; Lachlan et al. 2019). These factors—especially the imperative sentence style—may also improve message clarity and message certainty, which are important message styles for risk messages (Mileti and Sorensen 1990; Lachlan et al. 2019). Although our models already explained 44% ~ 57% of the variance in the retweet counts, future research should consider more intrinsic factors to provide a more accurate estimation of the effects of persuasive message content on message diffusion.

Second, our findings about the effects of PMFs were based on data from Twitter. In the U.S., Twitter users are younger compared with the general public and users of some other social media sites, such as Facebook (Perrin and Anderson 2019; Wojcik and Hughes 2019). For example, about three quarters (73%) of Twitter users are less than 50 years old (compared with 54% of all U.S. adults) (Wojcik and Hughes 2019). Although Twitter users, in themselves, are an important audience of heat-related messages since

even younger adults can be at risk of heat-related illnesses and deaths due to maladaptation (Hess et al. 2014; Mora et al. 2017), Twitter users are not representative of the elderly who are at greater risk from heat hazards. To benefit those who are less reachable via Twitter messages, especially the elderly, future research should examine the relationship between message diffusion on Twitter and message diffusion via other communication channels. For example, it is important to understand whether messaging strategies that improve message diffusion on Twitter also improve message diffusion via other channels, such as Facebook and word-of-mouth. It is also important to understand to what degree those who retweet a message on Twitter further share the information with non-Twitter users via other channels.

Although this study examined the effects of PMFs on message diffusion in the context of heat hazards, the five PMFs were originally designed for natural hazards in general, not limited to heat hazards. To be more applicable to different types of natural hazards beyond those that are primarily health threats, further studies could rename *health risk susceptibility* and *health impact* as *impact susceptibility* and *impact severity*. These two PMFs could then refer to not only the susceptibility and severity of health-related consequences but also the susceptibility and severity of other aspects of hazard impacts such as infrastructure impacts. Future studies should examine how these five PMFs influence message diffusion for other types natural hazards such as floods and winter storms. In addition, scholars should continue research to understand the relationship between message persuasion and message diffusion in order to identify win-win communication practices in the context of natural hazards.

A wide variety of natural hazard events will continue to happen due to natural climate variability, with certain hazards like extreme heat being particularly exacerbated by anthropogenic climate changes (Intergovernmental Panel on Climate Change 2012). Effective risk communication about natural hazards is important to stimulate individual protective actions and thus reduce adverse impact on public health and property. To improve official risk messaging, this research empirically tested the influence of persuasive message content on message retransmission on Twitter in the context of heat hazards. We found that official tweets mentioning more types of persuasive message factors and mentioning *hazard intensity* were respectively associated with higher rates of message retransmission for heat-related tweets and its two subtypes, heat warning tweets and non-warning tweets. Mentions of *health risk susceptibility*, *health impact*, and *response instruction* respectively demonstrated positive effects on message diffusion for some message types about heat hazards. Our findings could have implications for official risk messages about other types of natural hazards and for those disseminated through other channels such as Facebook and television to maximize message diffusion.

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CHAPTER IV

MOVING BEYOND LISTING VULNERABLE POPULATIONS: AN
EXPLORATORY EXPERIMENT ABOUT HEAT RISK MESSAGING^{5 6}

ABSTRACT

Extreme heat causes more deaths than tornadoes and floods combined in the United States. While vulnerable populations are at higher risk of heat-health impacts, anyone can be at risk from extreme heat without appropriate actions. Heat risk messages need to effectively depict people's susceptibility and engage those in affected areas. Using a survey experiment (N=1386), this study compared the effectiveness of four statements that varied how they depicted which types of people were susceptible to heat-health impacts. Relative to traditional messaging that lists specific vulnerable subgroups, a statement that "anyone can be at risk" and a statement without susceptibility information were respectively more effective in making messages personally relevant. Mentioning the "anyone can be at risk" statement and the "certain subgroups are at more risk" statement together reduced belief in the hazard happening compared to mentioning the latter statement individually. Implications for risk communication in broader domains are discussed.

Introduction

⁵ The target journal for this manuscript is *Environmental Communication*. Peter D. Howe will serve as a co-author.

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Many hazards, ranging from environmental hazards to pandemic diseases, pose higher risk to some subgroups who are disadvantaged by physical or socioeconomic status. Information about who is at higher risk helps emergency managers prioritize resource allocation and meet the special needs of the vulnerable populations (Phillips & Morrow, 2007). However, mentions of vulnerable populations in official risk messages may produce undesired effects on how the target audience respond to hazards. Using a survey experiment, this study examined how to effectively depict who is at risk in the context of natural hazards and more specifically heat hazards.

Severe heat-health impacts and one contributor

Extreme heat has been associated with excess mortality worldwide and is projected to increase in frequency and intensity in the 21st century (Intergovernmental Panel on Climate Change, 2012; Mora, Dousset, et al., 2017). In the United States, extreme heat caused an average of 430 deaths every year from 2009 to 2018, more than twice the number of deaths from tornadoes, hurricanes, floods, and earthquakes combined (Centers for Disease Control and Prevention, 2020). In addition to heat-related deaths, heat-related illnesses such as heat exhaustion and heat stroke led to an average of 65,299 emergency department visits per year in the U.S. during 2006-2010 (Hess et al., 2014). With respect to affected populations, negative health impacts from extreme heat are not restricted to the elderly, people in the South, or the poor, but widespread across age groups, geographic areas, and income levels (Hess et al., 2014). Taking affected age groups as an example, all age groups are subject to mortality risk from extreme heat, although elderly people are at greater mortality risk than younger adults (Anderson &

Bell, 2009; Centers for Disease Control and Prevention, 2020). When it comes to heat-related emergency department visits, adolescents and young adults (15-44 years of age) even have a higher incidence rate than adults 65 years or older (Harduar Morano et al., 2016; Hess et al., 2014; Lippmann et al., 2013).

In contrast to the serious and widespread heat-health impacts, heat-related mortality and morbidity are commonly viewed as largely preventable, given accurate weather forecasts and the availability of effective protective measures (U.S. Environmental Protection Agency, 2006). Assuming that health risks from extreme heat are preventable yet mortality and morbidity rates remain high, what factors might cause this paradox? This circumstance has been attributed, at least partly, to the fact that people tend to underestimate personal risks posed by extreme heat, and are thus less likely to take protective actions (Kalkstein & Sheridan, 2007; Mayrhuber et al., 2018). For example, many elderly people do not think of themselves as part of a vulnerable population for extreme heat (Sampson et al., 2013; Sheridan, 2007). Even when some elderly respondents recognized that “the elderly” is a population vulnerable to heat, they defined “the elderly” or “older adults” as those older than themselves and in a worse health or social situation and thus did not associate heat-health risks directly with themselves (Sampson et al., 2013; Wolf et al., 2010).

Research gaps about heat risk messaging

Informed by findings about heat-risk perceptions, researchers have reconsidered traditional messaging that lists vulnerable subgroups such as older adults as being at greater risk from extreme heat (i.e., the subgroup statement) (Sampson et al., 2013; Wolf

et al., 2010). For instance the elderly, as mentioned earlier, disassociate themselves from being part of a vulnerable population (Sampson et al., 2013; Wolf et al., 2010). Following the logic of this finding, researchers proposed that the elderly may perceive messages singling out the elderly as a vulnerable group to be irrelevant to themselves and subsequently deny the heat-health risks warned about in such messages (Wolf et al., 2010). For younger people, statements depicting the elderly and some other subgroups as being vulnerable to extreme heat may build a false sense of security for younger people, especially if they also do not belong to other vulnerable subgroups such as outdoor workers (Mora, Counsell, et al., 2017). Researchers have also proposed an “anyone” statement, that anyone can be at risk from extreme heat, as a promising alternative to communicate heat-health risks (Sampson et al., 2013). They argued that the anyone statement may make heat risk messages more relevant to people of all ages (Mora, Counsell, et al., 2017; Sampson et al., 2013). The anyone statement, as with the subgroup statement, is true according to medical evidence in the context of extreme heat (Mora, Counsell, et al., 2017). However, there is little empirical evidence about how recipients respond to the anyone statement and the subgroup statement in heat risk messages.

In the field of risk communication, extreme heat is an under-examined natural hazard in spite of its relatively severe and widespread impacts on public health. Past experiments about heat risk messages have been limited to investigating whether the availability of heat risk messages (versus no heat risk messages) influences responses among vulnerable populations (Mehiriz et al., 2018; Nitschke et al., 2017; Takahashi et al., 2015). The heat risk messages under test in these experiments did not appear to mention subgroup statements or anyone statements. To our knowledge, only one

experiment has moved beyond simple message availability and compared the effectiveness of certain types of statements in heat risk messages (Bruine de Bruin et al., 2016); it found that reminding residents in United Kingdom of the most unpleasant highest temperature promotes behavioral intention to take protective actions compared with no statements about temperature recall (Bruine de Bruin et al., 2016).

Despite lacking empirical testing, the anyone statement has appeared in official heat risk messages in the U.S. (Li et al., 2018). Furthermore, a statement combining an “anyone can be at risk” message and a “certain subgroups are at more risk from extreme heat” message (i.e., the anyone+subgroup statement) has been recommended for use by the health department of Canada (Health Canada, 2011). The U.S. National Weather Service (NWS) has also used the anyone+subgroup statement in its experimental HeatRisk product to communicate heat-health risks (National Weather Service, n.d.). The use of these alternative statements in official messages precedes empirical testing, which may result in unintended adverse effects on public response.

Research gaps about natural hazard communication

One psychological barrier to taking protective actions in the context of heat hazards is the underestimation of personal risks from extreme heat. This barrier can be called a lack of “personalization” or more precisely low “perceived susceptibility.” Personalization and perceived susceptibility both describe people’s belief in the likelihood of experiencing negative impacts from a threat (Mileti & Sorensen, 1990; Witte, 1992). The differences between these two concepts are 1) personalization considers the implication of the risk not only for oneself but also for one’s family and

community but perceived susceptibility only considers the implication for oneself, and 2) personalization is a term commonly used in the field of natural hazard communication but perceived susceptibility is a term commonly used in the field of health communication (Mileti & Sorensen, 1990; So et al., 2016; Sutton et al., 2018; Witte, 1992). In addition, the traditional and alternative statements about who is at risk from extreme heat (the subgroup, anyone, and anyone+subgroup statements) fit into a commonly investigated message component in health communication literature: depicted susceptibility. Depicted susceptibility refers to descriptions about how likely the message audience will experience negative consequences of a threat (Witte, 1993). High levels of depicted susceptibility emphasize the intended audience's susceptibility via intense and emotional language, vivid presentation, or mentioning reference groups less susceptible than the audience, while low levels of depicted susceptibility describe the intended audience as relatively less susceptible via impartial language, bland presentation, a vague reference group, or mentioning reference groups more susceptible than the audience (Tannenbaum et al., 2015; Witte, 1993). Low levels of depicted susceptibility also include no messages or neutral messages about depicted susceptibility (Tannenbaum, 2015). High levels of depicted susceptibility usually act as stimuli to arouse high levels of perceived susceptibility in past experiments about health communication (Siero et al., 1984; So et al., 2016; Witte, 1993). High levels of depicted susceptibility are also more likely to produce better behavioral intention and actual behavior than low levels of depicted susceptibility according to fear appeal theories and meta-analyses of related empirical studies (Tannenbaum et al., 2015).

The term depicted susceptibility lacks a counterpart in the field of natural hazard communication, although it fits the generic topic of “hazard” in the field. “Hazard” describes the characteristics of the hazard, and has been recognized as a required component of warning messages of natural hazards (Mileti & Sorensen, 1990). Within this, however, depicted susceptibility is not a must-have subcomponent and has drawn much less attention from researchers and practitioners than other subcomponents such as descriptions of hazard uncertainty (e.g., the hurricane cone of uncertainty) and the physical intensity of a hazard itself (e.g., wind speeds and temperatures) (Li et al., 2018; Morss et al., 2018; Potter et al., 2018). Although depicted hazard uncertainty and depicted susceptibility both communicate the likelihood of being negatively affected, depicted possibility of the hazard happening emphasizes physical vulnerability to the hazard itself but depicted susceptibility emphasizes social vulnerability to hazard impacts which involves social factors such as age, economic status, and preparedness. Past experiments about natural hazard communication have widely investigated how to effectively depict hazard uncertainty (Cox et al., 2013; E. E. H. Doyle et al., 2011; J. K. Doyle, 2006; Keller et al., 2006), but little research attention has been paid to how to effectively depict people’s susceptibility to natural hazards. A few recent experiments about hurricanes and drought found that combined descriptions about the susceptibility and severity of hazard impacts (e.g., “Your farm is susceptible and you will lose a lot if drought occurs”) produce higher intentions to take recommended actions than a lack of the combined descriptions (Lebel et al., 2018; Morss et al., 2018). However, to our knowledge, no study in the context of natural hazards has investigated the respective effects of depicted susceptibility on behavioral intention, personalization (or perceived

susceptibility) or belief in hazard happening. A lack of investigation on how to effectively depict people's susceptibility to natural hazards leaves the potential for under-informed risk messaging and suboptimal rates of warning compliance.

The current study

To bridge these research gaps, this study compared the effectiveness of different types of depicted susceptibility in the context of natural hazards and more specifically heat hazards using an online survey-based experiment. The four treatments were the subgroup statement, the anyone statement, the anyone+subgroup statement, and a “no depicted susceptibility” statement. The no depicted susceptibility statement was a neutral statement without any descriptions about who is at risk from extreme heat. We included this statement because heat risk messages without any depicted susceptibility are frequently issued by local weather forecast offices on social media in the U.S. (Li et al., 2018). In the current experiment, heat risk messages specifically refer to heat warning messages that warn the whole population in affected areas about specific upcoming and/or current extreme heat. The intended audience is the general public and thus our participants were not limited to those particularly vulnerable to extreme heat. Four outcome variables used to compare the effectiveness among all pairs of treatments were 1) perceived personal relevance of a message, 2) belief in whether a predicted extreme heat event will happen, 3) perceived susceptibility to heat-health problems (perceived likelihood that the predicted extreme heat event can adversely impact personal health), and 4) behavioral intention to protect oneself from heat-health impacts.

In the prior subsection, we reviewed the current knowledge of how depicted susceptibility influences perceived susceptibility and behavioral intention in the field health communication. We also highlighted the current lack of knowledge about how depicted susceptibility influences belief in a hazard happening, perceived susceptibility, and behavioral intention in the field of natural hazard communication. Perceived message relevance is not a typical outcome variable used to measure the effectiveness of depicted susceptibility. However, we selected perceived message relevance as one of our outcome variables for two reasons. First, perceived message relevance has been used to explain why messages tailored to individual demographics and beliefs produce better behavioral intention or behaviors than non-tailored messages in the context of fruit and vegetable consumption and breast cancer screening (Jensen et al., 2012; Ko et al., 2011). Compared to depicted susceptibility, tailoring is a different but related messaging strategy since some tailored messages—especially those using personalized language—may respond to higher levels of depicted susceptibility. Second, as mentioned earlier, making messages personally relevant is one of expected benefits of using anyone statements in heat risk messages (Wolf et al., 2010). The current study is the first study to empirically compared the relative effectiveness of statements that vary in depicted susceptibility to heat-health impacts. Our findings could therefore have implications for messaging strategies for heat hazards and other natural hazards.

Method

An online survey experiment was conducted using a post-test-only, between-subjects design. Participants (N = 1386) were recruited from the SurveyMonkey

Audience panel and took our survey using the SurveyMonkey platform. This panel has millions of panelists who are part of the U.S. population aged 18 or older and volunteer to join the panel. The panelists take online surveys in order to donate to charity, get gift cards, and/or gain chances to win sweepstakes. This study ran during autumn (from November 5 to November 13, 2018) and was approved by the Utah State University Institutional Review Board (the protocol number is 9708).

Procedure and materials

After reading a letter of information, participants who agreed to take the survey were presented with an introduction about a hypothetical situation that, one day during the past summer, participants saw a heat warning message from their local office of the NWS. Each participant was randomly assigned to a graphic heat warning message that contained one of the four treatments: the subgroup, anyone, anyone+subgroup, or no depicted susceptibility statement. The random assignment of treatment groups was enabled by the A/B test feature of the SurveyMonkey platform, which has been used by other experimental studies to assign participants randomly (Saunders et al., 2016; Talley & Temple, 2015). Table 7 shows treatment text, and appendix C shows the description of the hypothetical situation and full graphic messages in the four treatment groups.

Although messages assigned to treatment groups varied in depicted susceptibility, messages used the same textual and visual information describing other aspects of the upcoming extreme heat event such as the affected area that is participants' local area and response instructions. Messages were closely adapted from existing official heat warning messages. The no depicted susceptibility statement acted as a proxy for not mentioning

either “anyone can be at risk” or “certain subgroups are at more risk”. The neutral statement was also like a placebo which made the full graphic message similar to those in other treatment groups in terms of message length, specificity, and layout.

Table 7. Descriptions of experimental conditions

Condition	Treatment text	No. of respondents
Subgroup statement	Older adults, children, people with chronic diseases, and outdoor workers are more at risk. Heat-related illness can set in sooner for these groups.	357
Anyone statement	Everyone can be at risk. Heat-related illness can happen to anyone without protective actions.	331
Anyone+subgroup statement	Everyone can be at risk without protective actions. Older adults, children, people with chronic diseases, and outdoor workers are at greater risk.	354
No depicted susceptibility	People get heat-related illness when the body’s temperature control system is overloaded, and sweating just isn’t enough.	344

After reading the message, a screening attention check question was placed to catch and remove participants who did not read the graphic message. The screener asked whether the number of words in ***bold italic*** in the above message is greater than, equal to, or less than forty. This unobtrusive screener had an objective right answer, because the words in bold italic were treatment text which varied from 14 words to 23 words. Participants had access to the graphic message when they answered this screener. Regardless of participants’ response to the screener, they were then asked to answer survey questions measuring outcome variables and demographic information. Participants who failed the screener were later removed from the analysis.

Participants

A total of 1722 participants completed the survey. The screener failure rate was 19.4% (N = 334), within the range of rates observed in other online samples (2%~63%) (Thomas & Clifford, 2017). Compared to those who passed the screening test, those who failed were less educated, less wealthy, less likely to be non-Hispanic White people, more likely to answer the survey using Phone or Tablet (versus Desktop or Laptop), and spent less time to complete the survey. To improve data quality, we excluded participants who failed the screener and another two participants whose answers were “Don’t know” for all survey items measuring outcomes. After the exclusion, there were 1386 participants in our sample for the subsequent analyses. Table 8 shows that the distribution of our sample was similar to that of the U.S. adults in sex, age, race/ethnicity, household income, and region, but our sample was more educated than the U.S. adult population. We also performed chi-square tests to check the random assignment of treatment groups. We found that all pre-treatment variables listed in the Table 8 were well balanced across treatment groups (see Table 14 in appendix C for details).

Table 8. Characteristics of sample compared to U.S. adult population

	Sample ¹	Population ²
	N (%)	%
Sex		
Male	640 (46.2%)	48.7%
Female	745 (53.8%)	51.3%
Missing data	1	
Age (years)		
18-29	365 (26.4%)	21.3%
30-44	313 (22.6%)	25.0%
45-60	416 (30.0%)	26.7%
Over 60	291 (21.0%)	27.0%
Missing data	1	
Race/ethnicity		
White, non-Hispanic	1015 (76.0%)	63.3%
Black, non-Hispanic	77 (5.8%)	12.1%
Hispanic	103 (7.7%)	16.2%
Other or 2+ races, non-Hispanic	140 (10.5%)	8.3%
Missing data	51	
Education		
High school or less	188 (13.7%)	39.3%
Some college	355 (25.8%)	22.5%
College graduate	556 (40.5%)	27.1%
Graduate degree	275 (20.0%)	11.2%
Missing data	12	
Household income		
Less than \$25,000	237 (18.9%)	19.6%
\$25,000-\$49,999	287 (22.9%)	21.3%
\$50,000-\$74,999	258 (20.6%)	17.4%
\$75,000-\$99,999	176 (14.1%)	12.6%
\$100,000 or more	294 (23.5%)	29.2%
Missing data	134	
Region		
Northeast	247 (18.0%)	17.5%
Midwest	305 (22.3%)	20.8%
South	477 (34.8%)	37.9%
West	341 (24.9%)	23.7%

Missing data	16	
Device used to take the survey		
Desktop or Laptop	494 (35.7%)	n/a
Phone or Tablet	876 (63.2%)	n/a
Other devices	15 (1.1%)	n/a
Missing data	1	
Total observations	1386	

¹ Each participant's race/ethnicity and education data were collected using survey questions. Each participant's sex, age group, and other information in this table was provided by the SurveyMonkey Audience panel.

² 2018 U.S. population data from U.S. Census Bureau (2019)

Outcome measures and data analysis

Table 9 shows the measures and summary statistics of the four outcome variables:

1) perceived message relevance, 2) belief, 3) perceived susceptibility, and 4) behavioral intention. Belief and behavioral intention are traditionally important outcomes in natural hazard communication (Mileti & Sorensen, 1990). The measures of perceived message relevance and perceived susceptibility were adapted from health communication studies (Gallagher et al., 2011; Jensen et al., 2012). Behavioral intention to protect oneself originally had a four-item scale, and one survey item about wearing dark-colored clothes was removed since its reverse coded item had a low correlation with the overall scale (the corrected item-total correlation was 0.21).

Table 9. Measures and summary statistics of outcome variables

Outcome variable	Survey item ^{1,2}	Summary statistics			
		N	Min~Max	Mean (SD)	Median
Perceived message relevance	1. How much do you agree or disagree with the following statement? “If I received this message, I would think that this message was meant for me.”	1374	1~5	3.81 (1.13)	4
Belief	1. If you received this message, how likely would you think that there would be extreme heat conditions tomorrow in your local area?	1374	1~4	3.53 (0.76)	4
Perceived susceptibility ³ (Cronbach’s alpha = 0.8)	1. How much do you agree or disagree with the following statement? “If I received this message, I would think that my health was likely to be harmed tomorrow.” 2. How much do you agree or disagree with the following statement? “If I received this message, I would think that I might experience heat-related illness tomorrow (such as dehydration, heat exhaustion, or heat stroke).”	1384	1~5	2.96 (1.18)	3
Behavioral intention ⁴ (Cronbach’s alpha = 0.69)	1. If you received this message, how likely would you be to spend time in air-conditioned buildings (either at home or elsewhere) tomorrow? 2. If you received this message, how likely would you be to drink plenty of fluids to stay hydrated tomorrow? 3. If you received this message, how likely would you be to avoid strenuous outdoor activities during the hottest parts of the day tomorrow?	1383	1~4	3.52 (0.60)	3.67

¹ Response options of perceived message relevance and perceived susceptibility: 1 (Strongly disagree); 2 (Somewhat disagree); 3 (Neither agree nor disagree); 4 (Somewhat agree); 5 (Strongly agree); NA (Don’t know).

² Response options of belief and behavioral intention: 1 (Very unlikely); 2 (Somewhat unlikely); 3 (Somewhat likely); 4 (Very likely); NA (Don’t know).

^{3,4} Scale construction for perceived susceptibility and behavioral intention: the intraindividual mean of non-missing survey items.

The effect of statement type on each outcome variable was examined using one-way ANOVA. Post-hoc pairwise comparisons were performed using the Tukey’s Honest Significant Difference (HSD) test. We also performed unadjusted pairwise t tests (pooled standard deviation and two-sided tests) to compare the differences in mean outcomes

between all pairs of treatments. The use of one-way ANOVA and Tukey's HSD tests is to control the type I error rate, and the use of unadjusted pairwise t tests is to reduce the chances of committing type II errors and generate more hypotheses for future testing (Jaeger & Halliday, 1998). The magnitudes of pairwise differences were assessed using Hedges' g , a correction for Cohen's d in estimating population variance. Hedges' g is a preferable measure of effect size even though Hedges' g and Cohen's d are almost equivalent in sample sizes larger than 20 (Lakens, 2013).

Results

Means and standard deviations for each treatment group are shown in Table 10 for each outcome. The results of ANOVA indicated that perception of message relevance was statistically significantly different among participants viewing the subgroup, anyone, anyone+subgroup, and no depicted susceptibility statements, $F(3, 1370) = 3.52, p = 0.015$. Post-hoc comparisons using the Tukey's HSD test indicated that participants who read messages mentioning the anyone statement ($M = 3.95, SD = 1.11$) perceived the message as more personally relevant than participants who read messages mentioning the subgroup statement ($M = 3.68, SD = 1.14, p = 0.011$). The Hedges' g of the difference was 0.24, indicating a small effect size. The Tukey's HSD test did not find other pairs of statement types that resulted in statistically significantly different perception of message relevance. Unadjusted pairwise t tests suggested another two pairs of treatment types that tended to produce differences in perceived message relevance. Participants who viewed messages with the subgroup statement ($M = 3.68, SD = 1.14$) reported lower perceived message relevance than participants who viewed messages with the no depicted

susceptibility statement ($M = 3.86$, $SD = 1.06$, $p = 0.034$, Hedges' $g = 0.17$). The differences in perceived message relevance between the anyone statement condition ($M = 3.95$, $SD = 1.11$) and the anyone+subgroup statement condition ($M = 3.78$, $SD = 1.18$, $p = 0.050$, Hedges' $g = 0.15$) approached statistical significance.

Table 10. Means of outcome variables by experimental conditions

Outcome variable	Subgroup statement		Anyone statement		Anyone+subgroup statement		No depicted susceptibility	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Perceived message relevance	3.68^a	1.14	3.95^b	1.11	3.78 ^{ab}	1.18	3.86 ^b	1.06
Belief	3.58 ^a	0.67	3.55 ^{ab}	0.74	3.46 ^b	0.85	3.52 ^{ab}	0.78
Perceived susceptibility	2.95 ^a	1.16	3.04 ^a	1.19	2.91 ^a	1.17	2.96 ^a	1.19
Behavioral intention	3.53 ^a	0.60	3.53 ^a	0.58	3.50 ^a	0.60	3.51 ^a	0.62

Notes: Means in bold are statistically significantly different which are determined by Tukey's HSD tests ($p < 0.05$). The only pair of means in bold had a small magnitude of difference (Hedges' $g = 0.24$). Statistically significant differences determined by unadjusted p -values are also reported using superscripts. In the same row, means without common superscripts are statistically significantly different from each other (pairwise t tests with pooled SD , $p < 0.05$). In the same row, means with shared superscripts are not statistically significantly different (pairwise t tests with pooled SD , $p \geq 0.05$). The difference in perceived message relevance between the anyone statement and the anyone+subgroup statement approached statistical significance (unadjusted $p = 0.050$).

For other outcome variables, the results of ANOVA indicated that participants viewing different statement types did not have statistically significantly different belief in the hazard happening, $F(3, 1370) = 1.50$, $p = 0.213$, perceived susceptibility to heat-health impacts, $F(3, 1380) = 0.72$, $p = 0.538$, and behavioral intention to protect themselves from heat-health problems, $F(3, 1379) = 0.25$, $p = 0.860$. Unadjusted pairwise t tests found that, compared to the subgroup statement ($M = 3.58$, $SD = 0.67$), the anyone+subgroup statement ($M = 3.46$, $SD = 0.85$, $p = 0.041$, Hedges' $g = 0.15$) resulted in a lower degree of belief that the extreme heat event warned about in the message will

actually occur. Unadjusted pairwise t tests found no other differences that were statistically significant or approached statistical significance.

Discussion

Findings in this exploratory experiment provide two insights into how to effectively communicate heat risk susceptibility with the general public. The first insight is that mentions of vulnerable subgroups appear to be not only a less effective strategy but also a harmful strategy when it comes to making heat warning messages personally relevant to the public. We found that messages mentioning the subgroup statement were perceived as less personally relevant than messages mentioning the anyone statement. Furthermore, message relevance ratings of the subgroup statement were even lower than those of the placebo treatment (the no depicted susceptibility statement) suggesting a negative effect of mentioning vulnerable subgroups on perceived message relevance. Perceived message relevance is an important metric of message success. In an era of information explosion, receiving heat risk messages does not necessarily mean paying attention to the content of the messages especially during a prolonged period of extreme heat. A perception of “the message is meant for me” makes people more likely to attend to the message and process the information thoughtfully (Bargh, 1982; Petty et al., 1981).

The second insight is that mentioning the combined statement (i.e., the anyone+subgroup statement) does not increase effectiveness more than mentioning the anyone statement and the subgroup statement separately. Moreover, the combined statement was inferior to its parts in some ways. On the one hand, compared with the anyone statement, the anyone+subgroup statement produced lower ratings of message

relevance, albeit with only marginal statistical significance (unadjusted $p = 0.050$). This difference suggested that the negative effect of mentioning vulnerable subgroups on people's evaluation of message relevance still holds true when messages mention an "anyone can be at risk" statement simultaneously. On the other hand, compared with the subgroup statement, the anyone+subgroup statement produced lower ratings of belief that the extreme heat event warned about in the message will actually occur. There are two possible explanations of this difference. The anyone+subgroup statement depicted two aspects of susceptibility together which may have made the message seem overblown, or the two aspects of the anyone+subgroup statement may seem contradictory to each other. In either case, a negative spillover effect is possible on whether recipients believe the warning is real or not. Beyond the four differences mentioned in these two paragraphs, we found no other differences between each pair of treatments in our four outcome variables.

Different types of depicted susceptibility produced similar perceived susceptibility and behavioral intention. Based on a post hoc analysis about treatment effects in each age group (see appendix D for details), we suspected that heterogeneous treatment effects by age group may exist and explain why we found no average treatment effect on perceived susceptibility to heat-health impacts and on behavioral intention to protect oneself with the whole dataset. For example, although the anyone and anyone+subgroup statements produced similar behavioral intention in the main analysis, the relative effects of this pair of treatments varied by age group in the post hoc analysis. Specifically, we found that young people aged 18 to 29 were more responsive to the anyone statement, but people aged 30 to 44 were more responsive to the

anyone+subgroup statement. The two differences in behavioral intention were statistically significant (unadjusted $p < 0.05$, Hedges' $g > 0.3$) but in an opposite direction. For people aged 45 to 60 and people over 60, this pair of treatments resulted in similar behavioral intention. Although treatment effect heterogeneity was outside the scope of this study, such preliminary analysis helps us interpret our results.

The magnitudes of the differences in this study were not large but still theoretically and practically meaningful. The difference between the subgroup statement and the anyone statement in perceived message relevance was the only statistically significant difference determined by the Turkey HSD test and its effect size was Hedges' $g = 0.24$. The other three differences were determined by unadjusted pairwise t tests and their effect sizes ranged from $g = 0.15$ to $g = 0.17$. These effect sizes are comparable to those in previous experimental studies about health communication. For example, compared with messages mentioning the loss of not taking a behavior (loss-framed messages), messages mentioning the benefits of taking a behavior (gain-framed messages) are more effective in promoting illness prevention behavior with a mean effect size of Cohen's $d = 0.17$ (Gallagher & Updegraff, 2011). According to another meta-analysis, computer-delivered interventions improve attitude and intention of taking healthy behavior with an effect size of $d = 0.23$ and $d = 0.18$ respectively (Portnoy et al., 2008). In our study, the effect sizes were measured by Hedges' g instead of Cohen's d . However, as long as sample sizes are larger than 20, these two measures produce approximately the same values (Lakens, 2013). This statement was confirmed after we checked respective Cohen's d values in this study. According to the commonly used threshold for small effect sizes, $d = 0.2$ (Cohen, 1988), only one difference in this study

had a small effect size and others had effect sizes less than small. However, these effect sizes can be practically meaningful since the messaging variations tested in this study are cost-effective and easy to implement on a large scale (Litschge et al., 2010).

Contributions to theory and practice

This study contributes to risk communication literature in two ways. First, this study shows how risk messaging about natural hazards can be informed by established persuasive messaging strategies in other communication contexts. Traditionally, “good” risk messages about natural hazards are mainly informative messages which faithfully describe the risk with specificity, accuracy, and clarity (Demeritt & Nobert, 2014; Mileti & Sorensen, 1990; Reynolds & Seeger, 2005). Research in this tradition often implicitly assumes that technical information about the risk, by itself, is sufficient to change the attitudes and behaviors of message recipients (Demeritt & Nobert, 2014). In contrast, “good” risk messages in the field of health communication are mainly persuasive messages which strategically describe the risk with a closer attention to the interaction between technical risk information and social psychological factors of message recipients (Demeritt & Nobert, 2014; Reynolds & Seeger, 2005). These differences may explain why depicted susceptibility has been widely acknowledged as a persuasive messaging strategy in health communication literature but has drawn little research attention in the field of natural hazard communication. This study adapted depicted susceptibility as a persuasive device to the context of natural hazards and empirically compared the effectiveness of statements that vary in depicted susceptibility to heat-health impacts. This study highlights the potential of depicted susceptibility to inform weather risk

messaging by showing that different ways to depict people's susceptibility to heat-health impacts result in differences in people's perception of message relevance or belief in hazard happening.

Second, this study advances understanding about how to effectively depict people's susceptibility by comparing under-examined pairs of statements and using the general public as the intended audience. Although there have been prior studies comparing statements that vary in depicted susceptibility, pairs of statements compared in this study have drawn little research attention even in the context of health communication. Past experiments in health communication literature usually use subpopulations, instead of the general public, as the target audience. In addition, for most past experiments, the purpose of designing statements that vary in depicted susceptibility is to manipulate perceived susceptibility and then test how different levels of perceived susceptibility influence people's responses to messages (So et al., 2016; Witte, 1993). This may explain why pairs of statements in past experiments usually demonstrate clear variations in levels of depicted susceptibility, which means it is easy to tell which statement depicts the target audience as more susceptible than the other statement (see introduction section for detailed explanation about levels of depicted susceptibility). For example, when communicating the threat of meningitis infection with college students, the message high in depicted susceptibility stated that college students are more at risk of contracting meningitis than the general public, and the message low in depicted susceptibility stated that children less than five years old is the most vulnerable subgroup for meningitis infection (So et al., 2016). However, since the treatment design in the current study was problem-driven instead of theory-driven, this study compared

statements with competing levels of depicted susceptibility and used the general public as the intended audience. For instance, the relative levels of the combined statement (the anyone+subgroup statement) and its part (e.g., the anyone statement) are not intuitive. The relative levels of the subgroup statement and the anyone statement are also not clear, since their relative levels depend on the share of vulnerable subgroups in the general public and how people who belong to vulnerable subgroups perceive the pair of statements. Our findings about these under-examined pairs of statements advance understanding of how to effectively depict people's susceptibility when the intended audience is the general public.

Our findings also provide practical implications for risk messaging when risk messages aim to reach the general public. Our findings support the reconsideration of mentioning vulnerable populations in heat risk messages (Sampson et al., 2013) since the presence of such subgroup statements reduced people's perception of message relevance. The "anyone can be at risk" statement appears to be a good substitution as expected (Sampson et al., 2013) because this alternative statement made messages more relevant and performed similarly in other outcome aspects evaluated in this study. In addition, the "more is worse" insight implies that practitioners should reconsider the adoption of the anyone+subgroup statement in official heat risk communication. The combined statement performed worse than the subgroup statement in influencing whether people believe the warning is real and worse than the anyone statement in influencing whether people think the warning is personally relevant. Although the full messages in our experiments were graphic messages, the hypothetical situation did not specify a communication channel and our treatments were textual information. Thus, the practical implications of our

findings do not restrict to a certain communication channel and may be applicable across channels such as television and social media. Our findings could also have implications for risk messaging in other contexts such as infectious disease epidemics when the intended audience of risk messages is not only certain vulnerable subgroups but also the general public.

Limitations and future research

Our exploratory experiment had several limitations. Firstly, this experiment was conducted in the early November, which was in autumn for our participants. Similar to most previous experiments about message testing in the context of natural hazards (e.g., Morss et al., 2018; Potter et al., 2018; Sutton, Vos, Wood, & Turner, 2018), a hypothetical hazardous event was presented to participants in this study (see appendix C for the description). The hypothetical extreme heat event may have seemed artificial for our participants because they were outside the summer season. The lack of realism might reduce external validity of this experiment because how our participants responded in this hypothetical situation may not be generalizable to real-world extreme heat events. To enhance external validity of our findings, future studies should investigate the effects of depicted susceptibility to heat-health impacts during ongoing extreme heat events and in field settings (e.g., a real-world environment where people may be vulnerable to heat).

Secondly, our experiment used an online convenience sample. Although our sample was similar to the general population in terms of sex, age, race/ethnicity, and income, our participants were more educated than the general public. Although average treatment effects estimated using nationally representative samples were very similar to

those estimated using online convenience samples in many social science survey experiments (Coppock et al., 2018), future studies should replicate the current experiment using representative samples to know whether our results are also generalizable to the general public. Although the first and second limitations affected external validity of our experiment, they had little impact on internal validity.

Thirdly, our experiment did not examine actual behavior as an outcome. Although our outcome variables (perceived message relevance, belief in the hazard happening, perceived susceptibility and behavioral intention) could have theoretical and practical implications, actual behavior is a critical outcome to determine practical benefits of messaging strategies. The lack of effects on perceived susceptibility and behavioral intention in our study does not necessarily mean a lack of effects on actual behavior, since these two outcomes may not always well predict behavior. For example, a meta-analysis about gain- and loss-framed messages found that message framing promoted illness prevention behavior but had no effect on attitude and behavioral intention (Gallagher & Updegraff, 2011). To better realize practical benefits, future studies should investigate the effects of different types of depicted susceptibility on people's self-reported or objective behavior to protect oneself. In addition, future studies should also examine actual behavior of checking on others and self-reported heat-health symptoms as outcomes in order to get a more comprehensive understanding about how to effectively depict people's susceptibility in heat risk messages.

Given the exploratory nature of this experiment, our findings should be tested and replicated in future rigorous studies in order to provide strong evidence for theory and practice. Future studies should prioritize testing the difference between the subgroup and

anyone statements in perceived message relevance, since this finding had lower statistical uncertainty and larger effect size. In addition, future studies should investigate how and why the relative effectiveness of susceptibility statements varies by age group. Such studies will benefit heat risk messaging especially when its intended audience is not the general public but people in a certain age group.

Conclusion

Extreme heat is an under-examined hazard in environmental risk communication despite its relatively severe and widespread impacts on public health. This study contributes to the risk communication literature by empirically comparing the effectiveness of different statements about people's susceptibility to extreme heat and showing how to make heat risk messages personally relevant to the general public. Our findings support the reconsideration of listing vulnerable subgroups in heat risk messages due to its negative effects on people's perception of message relevance. Rather than listing specific vulnerable subgroups, a message that anyone can be at risk can be a good substitution, as expected. Practitioners should also be cautious about combining the subgroup and anyone statements in one message because the combined statement appears to be worse than its parts in influencing people's perceived message relevance or belief in the hazard happening. Given the exploratory nature of this experiment, future research with lower methodological uncertainties is needed to test our findings about heat risk messaging. Our findings provide insights into how to effectively communicate people's susceptibility about extreme heat and from which new discoveries might be inspired in

the broader domains of environmental risk communication and public health communication.

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CHAPTER V

ANALYZING FACEBOOK COMMENTS TO IMPROVE OFFICIAL WEATHER
RISK MESSAGES^{7 8}

ABSTRACT

Social media can expand public engagement in risk communication. During hazardous events and disasters, the public play various roles—such as *help-seekers* and *reporters*—in communicating with each other and with government agencies. However, little attention has been paid to the role of the public as *consumers* who leave comments on official risk messages and help message improvement through such feedback. To better understand the role and inform risk messaging, this study inductively coded public comments on heat warning messages posted on Facebook by U.S. National Weather Service offices. Here we show that a small portion of Facebook comments (7%, N=216) provided insights into people’s needs for risk messaging. Comments by 44 Facebook users explicitly or implicitly expressed that the heat condition was normal and the warning seemed unnecessary and/or overblown. These comments suggest a need for messages that justify why the heat condition—which seems normal to these users—warrants the heat warning. This need was not only the most common need but also an unexpected need. Three more-detailed needs were also identified. This study describes a novel and complementary method to assess people’s needs with high ecological validity and low research cost.

⁷ The co-author of this manuscript will be Peter D. Howe.

⁸ We thank Brittany Shield for being a second coder for the intercoder reliability check.

Introduction

Consumer feedback is important for product improvement. Likewise, audience feedback is important for message improvement. In the face of public threats such as environmental hazards and emerging infectious diseases, government agencies often disseminate risk messages in social media to enhance situational awareness and encourage protective actions (Lin et al., 2016). The public sometimes leave comments directly following these messages in social media (Hughes et al., 2014; Raamkumar et al., 2020). Can these public comments act as consumer feedback and help improve risk messages? This study explores this potential by inductively coding public comments on heat warning messages in a sample of official Facebook pages for U.S. National Weather Service (NWS) offices.

Roles of the public in social media risk communication

Social media have been an important channel of risk communication within and between government agencies and the public (Poljanšek et al., 2017; Reuter & Kaufhold, 2018). The public play various and sometimes overlapping roles in social media before, during, and after hazardous events and disasters: *readers* who passively receive information; *reporters* who report on-site observations about hazardous events; *help-seekers* who ask for help like transportation and medical assistance; *helpers* who offer emotional support and information to other social media users; and *digital volunteers* who retransmit, verify, and integrate information usually in the form of neighborly support (Purohit et al., 2014; Reuter & Kaufhold, 2018; Starbird & Palen, 2011). Using

crowdsourcing strategies, user-generated content by *reporters* helps government agencies to detect hazardous events and assess their damage (Zhang et al., 2019). User-generated content by *help-seekers*—especially that containing predefined and structured hashtags—helps government agencies to quickly respond to people’s needs during an emergency (Reuter & Kaufhold, 2018; Starbird & Palen, 2011).

Although a large body of literature has investigated public engagement in risk communication through social media, the role of the public as *consumers* has not been fully recognized. We introduce the role of *consumers* to describe the public who consume products in social media, and may also provide feedback on the products in social media. Drawing on the term “public goods” from economics (Morrell, 2009), the products in this case refer to products or services that are available to social media users for free and typically provided by governments through taxation. In the context of hazardous events and disasters, the products can be emergency services provided in social media, social media accounts managed by agencies, or official risk messages posted in social media. The forms of feedback can be online comments, the number of followers/friends, or share/retweet counts. Since the linkage of consumer feedback and product improvement is intuitive in the context of economics, we describe this type of role as *consumers* to highlight the implication of people’s feedback for improving risk communication in social media. Through the lens of *consumers*, this paper specifically explores how public comments in social media can help researchers and practitioners to understand people’s needs and inform risk message design.

The “consumers” perspective

Social marketing research considers people to be “consumers” even when no commercial transactions occur (Craig Lefebvre & Flora, 1988; Grier & Bryant, 2005). Social marketing is a campaign-planning process that utilizes commercial marketing principles to promote attitudes and behaviors such as healthy eating habits (Craig Lefebvre & Flora, 1988; Grier & Bryant, 2005; Truong, 2014). In social marketing campaigns, the target audience are usually called consumers, the attitudes and behaviors promoted by the campaigns are called “actual products”, and pamphlets and other activities that help behavior changes are called “augmented products” (Grier & Bryant, 2005; Patel & Arya, 2017). The communication channels of social marketing campaigns include, but are not limited to, television, telephone, and social media (Ledford, 2012). One principle in social marketing is “consumer orientation”, which emphasizes the importance of understanding consumer needs (e.g., people’s knowledge gaps and preferences for campaign materials) in campaign planning and implementation (Craig Lefebvre & Flora, 1988; Grier & Bryant, 2005). The same principle motivates the present study to put forward the role of *consumers*: consumer needs matter for product design, or in other words, people’s needs matter for message design.

The present study expands social marketing research in two ways. First, social marketing campaigns heavily rely on traditional methods such as focus groups and surveys to collect consumer input and assess consumer needs (Grier & Bryant, 2005; Patel & Arya, 2017). The present study uses user-generated content in social media—specifically the content of public comments—as a complementary method to hear from the public and identify opportunities for improvement. Although people who leave comments are not representative of social media users who have access to official risk

messages, comments in social media record people's immediate responses to real-life risk messages and such responses are not constrained by questions predefined by researchers or influenced by researchers' intervention. Second, social marketing is used in the context of campaigns, typically health promotion campaigns (Truong, 2014). The present study expands the role of "consumers" to the context of risk communication from government agencies, especially before, during, and after hazardous events and disasters. Although the present study restricts the communication channel to social media, risk communication about hazards and disasters in social media usually has shorter preparation time, less personnel resources, and larger spatiotemporal scope than campaigns (Avery, 2017; Reynolds & Seeger, 2005). These features highlight the necessity for researchers to inform future communication efforts by learning lessons from previous communication efforts.

Outside the field of social marketing, several past studies have examined the content of online comments on official risk messages in social media (Bica et al., 2020; Hughes et al., 2014; Kurian & John, 2017; Lambrecht et al., 2019; Raamkumar et al., 2020; St. Denis et al., 2014). These studies analyzed the same kind of data (i.e., comments) using a few different perspectives. Studies with different perspectives refer to studies that have different research purposes or use different approaches to achieve similar purposes. For example, the research purposes of some studies were to understand the phenomenon, specifically to understand what people talk about via the comments (Hughes et al., 2014; Kurian & John, 2017; St. Denis et al., 2014). Their perspectives are different from the perspective of one study whose research purpose was to solve a practical problem, which is to improve risk communication of weather forecasts with the

public (Lambrecht et al., 2019). To achieve the purpose, this prior study identified the language (beliefs and values) of Facebook comments and explored whether—as suggested by the consensus model of trust (Earle, 2010)—using shared language in the official risk messages builds trust between the public and government agencies (Lambrecht et al., 2019). In the prior study, the specific problem that needs attention (relational trust) and its solution direction (using shared language in messages) were identified by the researchers based on a theory, and the voice of the public (Facebook comments) was analyzed to inform the solution (what was the language used by the public). The present study holds a different perspective from the prior study. In the present study, the voice of the public (Facebook comments) was analyzed to identify what are the specific problems that need to work on (a lack of trust, inconsistent information, or something else) in order to achieve the practical goal (more effective risk communication). We call the perspective applied in the present study “the consumers perspective”, because in economics the typical application of the voice of consumers is to identify product attributes that need to improve. To our knowledge, past studies that analyzed online comments on risk messages have not applied the “consumers” perspective.

Studies with different perspectives contribute to risk communication in different ways. Studies that were to understand the phenomenon may indicate broad topics talked in comments but seldom provide actionable information to improve risk messaging. For example, Kurian and John (2017) found that several Facebook comments “strongly criticise emergency alerts that contain wrong information”, and identified themes such as expressions of gratitude. For the prior finding, it was unclear whether the respective

messages really contained incorrect content, or if such criticism was due to people's misunderstandings. For the latter finding, comments that expressed gratitude for first responders' sacrifice provide little hints about how to improve risk messages. The "consumers" perspective has the potential to complement other perspectives and narrows the gap between knowledge and practice.

Process and techniques in product design

Using Facebook comments on heat warning messages as a case study, the present study explores a novel and complementary method to hear from the public and inform risk message design. The complementary method integrates an under-examined data source—public comments following official risk messages in social media—and an under-examined perspective to analyze data, the "consumers" perspective. We borrow the quality function deployment (QFD) process and related techniques in the field of product design to help us apply the "consumers" perspective. QFD is a widely used tool to develop new or improved products, which transforms the customer input to engineering production requirements (Chan & Wu, 2002; Karsak, 2004). Although QFD originally uses "customer" and "customer needs" to describe its process, we replace the word "customer" with the word "consumer" to better fit the context of the present paper. The QFD process is 1) collecting consumer input related to a product, 2) extracting consumer needs—including latent consumer needs—from the raw data, 3) organizing consumer needs into categories and, if necessary, subcategories, 4) prioritizing consumer needs based on consumer's evaluation and marketing considerations, and 5) translating important consumer needs (WHATs) to solutions (HOWs) (Chan & Wu, 2002; Zhou et

al., 2015). The first three steps are the focus of the present study, and other steps are briefly summarized here to provide a whole picture of the QFD process.

A consumer need is a statement describing a benefit that a consumer seeks to get from a product or service (Timoshenko & Hauser, 2019). Latent consumer needs are about benefits which consumers are not fully aware or even not aware that they desire, but consumers are satisfied if those needs are fulfilled in a product or service (Zhou et al., 2015). Informing the public of the risks and promoting protective actions are two basic functions or benefits provided by official risk messages, when considering messages as products. It is likely to be easier for people to notice that they need the prior benefit (risk information) than the latter benefit (persuasion to engage in protective action). In this case, risk messages that are effective at promoting protective actions could be a latent consumer need or a latent need of people. This latent need is described in broader terms, which can be specified using subcategories which are called more-detailed needs. More-detailed needs specify the paths toward solutions (Griffin & Hauser, 1993). For example, compared to “good-looking”, good color and good shape are two more-detailed consumer needs for fried chicken.

Empathic design is a relative new approach in design science to identify consumer needs, especially the latent needs (Postma et al., 2012; Zhou et al., 2015). Using empathic design, experts (e.g., designers, researchers, and engineers) observe the interactions between consumers and products, and interpret consumer needs through empathy as well as experts’ personal insights (Postma et al., 2012). Drawing on empathic design, the present study inductively identified people’s needs for risk messages, including latent needs, through observing the interactions between Facebook comments and their

respective official risk messages and then interpreting the context-dependent meanings of the comments and people's needs. As a hypothetical example, a heat warning message posted in Facebook lists heat-safety tips including "avoid alcohol", and one comment said "Avoid alcohol?? Did all those except this one!". The latent need associated with this comment would be interpreted as "A message that justifies why I need to avoid alcohol during the extreme heat event". Although finding a solution is not the scope of the present study, an improved message that is responsive to this need may express empathy and briefly explain why avoiding alcohol is important to protect oneself from acute heat-related illnesses.

Specifically, we performed a case study using Facebook comments on heat warning messages in 2018 and 2019 from NWS Facebook pages. In the U.S., NWS field offices issue heat watch, warning, and advisory products for their forecast areas when extreme heat events are imminent. In this study, heat warning messages refer to official risk messages that mention at least one of the active heat-related products. Extreme heat events pose serious health threats to people across age groups and geographic areas (Hess et al., 2014; Mora et al., 2017), and heat warning messages need improvement to better stimulate protective actions and protect public health (Mayrhuber et al., 2018). Facebook is an important channel to disseminate heat warning messages because Facebook has a large and diverse user base in the U.S. (Perrin & Anderson, 2019). By identifying people's needs for heat warning messaging, the present study provides actionable information for researchers and practitioners to follow up in order to improve heat risk messaging on Facebook and social media channels more generally.

Method

Facebook comments were collected through the following steps. First, we sampled 31 NWS official Facebook pages (see Table 16 in appendix E). NWS national and regional accounts were all included except those irrelevant to heat hazards (e.g., NWS National Hurricane Center). We also randomly sampled 25 pages from a total of 121 pages for NWS field offices. Although NWS has 123 field offices, our sampling frame contained 121 official Facebook pages. This is because three field offices in Alaska shared one page and their individual pages did not exist until October 2018. Next, we searched posts using the Facebook search bar with keywords including “heat warning”, “heat advisory”, and “heat watch”. We also set another two criteria in the search: 1) date posted within 2018 or 2019, and 2) posts from one of our sampled pages. Further, the returned posts were manually coded as “heat warnings with comments” if the posts 1) contained at least one comment, and 2) mentioned at least one of NWS’s heat watch, warning, and advisory products that was currently in effect or would be in effect in the displayed text or in attached images. We finally identified 354 heat warning posts with comments whose comment sections contained 3,182 comments. There were 23 Facebook pages containing at least one heat warning post with comments. In this study, the word “comments” refers to both comments on posts and replies to comments.

We coded the comments using the empathic design approach and the general inductive approach (Postma et al., 2012; Thomas, 2006). The former approach offers principles in the analysis, and the latter approach provides specific operational guidance. Categories identified by this approach are not only derived from the raw data but also clearly linked to research purposes (Thomas, 2006). Our research purpose is to identify

people's needs for heat risk messaging. Comments irrelevant to the research purpose were not assigned to any categories (Thomas, 2006). Relevant comments were those whose context-dependent meanings suggested people's needs including latent ones. The context of comments includes respective posts and other comments following the same posts. Specified categories were created for common needs and the common needs should be relatively specific for researchers and practitioners to act upon. A residual category was for relevant comments which suggested uncommon needs. We also explored more-detailed needs for one of the specified categories. Compared to other specified categories, comments in this category contain relatively rich information and therefore allow the exploration. However, the number of relevant comments in this category were still limited (N=58), and some of the comments were short. For this reason, the exploration of more-detailed needs was less restrictive than the analysis of primary needs (i.e., the specified categories and residual category). No mutually exclusive subcategories were built for the more-detailed needs.

In most cases, one relevant comment was one unit of coding. One unit of coding was assigned to only one category. Sometimes, multiple comments were combined into one coding unit when a relevant comment was involved in a conversation. In such a situation, one coding unit may contain multiple relevant comments if they interacted with each other and suggested a common need. If relevant comments interacted with irrelevant comments in the conversation, the irrelevant comments were also included in the coding unit in order to facilitate interpretation of the relevant comments in the context. For example, if one comment asked a question, the second comment replied "same question", and the third comment correctly answered the question, the three comments were

combined into one coding unit. The first two comments were relevant comments which suggested an information need, and the third comment was irrelevant because the answer itself did not suggest any need for risk messages. Categories and coding units were developed by the primary coder. To improve credibility, interpretations on comments were frequently discussed with a researcher who also specializes in heat risk research. To test intercoder reliability, a sample of coding units were selected using stratified random sampling (specified categories: N= 50, 64%; residual category: N=10, 10%). The second coder independently assigned one of the developed categories to each unit. The level of intercoder reliability (Cohen's Kappa = 0.72) was acceptable for an exploratory study (Lombard et al., 2002). Discrepancies were resolved after discussion.

Results

Among a total of 3,182 Facebook comments in the comment sections of 345 heat warning messages, a small portion of comments (6.8%, N=216) were relevant comments, which means they suggested explicit needs or latent needs for heat risk messaging. We explain why the proportion of irrelevant comments was large from two aspects. First, when people leave reviews on commercial products on shopping websites (e.g., Amazon.com), the reviews are supposed to evaluate the products and describe whether the products satisfy or dissatisfy the consumers. However, such a norm does not exist when people leave comments on official risk messages. The messages also rarely contain a direct call to engagement, such as "We'd love to hear from you. Share your questions and suggestions." As a result, although comments on heat warning messages record people's responses to the messages, informative comments for people's needs had to be

distilled from thousands of unsolicited and unstructured comments. For example, comments usually expressed feelings about the hot weather or tagged other users to diffuse the message such as “[Name] hot hot”, “Come on Fall.” and “[Name] please read”. Although such comments indicated how people respond to heat warning messages, they seldom provide information about the problems and strengths of the messages. Second, most comments were short, and some comments were generic or even ambiguous. In some cases, limited information did not allow us to tell whether the comment suggested a need or not. For example, we had to avoid overinterpreting “I’d rather heat than flooding.” to mean that the person underestimated the risks from heat.

Needs identification

In respect to relevant comments, although comments containing inquiries or criticism usually informed people’s needs, other possible signs of relevant comments included comments that disagreed with their respective risk messages, comments that praised specific aspects of the respective risk messages, comments that expressed risky behaviors or situations, and comments that suggested misunderstandings. As mentioned earlier, 216 relevant comments were identified, and they were further categorized into four specified categories and one residual category. Table 11 shows the descriptions and examples of the categories, as well as the needs suggested by the categories. Table 12 shows the descriptive statistics for the categories. The first two specified categories, “Normalization” and “Lacking relief measures”, suggested latent needs. The last two categories, “Warning issuance criteria” and “When relief”, suggested people’s needs in a

more obvious way since Facebook users usually directly expressed these needs through questions.

Table 11. Descriptions of categories and the interpreted needs

Category	Description	Interpreted need	Comment example
Normalization	Comments explicitly or implicitly indicating that the heat condition is not unusual to happen, and the warning seems unnecessary or overblown	A message that justifies why the heat condition—which seems normal—warrants the heat warning	Temps above 110 doesn't sound like an excessive heat warning it sounds like a typical AZ [Arizona, a U.S. state] summer.
Lacking relief measures	Comments indicating conditions where no air conditioner is working indoor or in vehicle during heat events	A message that provides alternative coping strategies when no air conditioner is working	Our ac broke last night, too. [slightly frowning face emoji] This heat can kill people.
Warning issuance criteria ¹	Comments indicating a lack of knowledge about the issuance criteria of NWS's heat watch, warning, and advisory products	A message that clarifies the issuance criteria of the heat warning	According to the forecast Big Spring is only going to be 1 degree cooler than Midland and Odessa but isn't part of the heat advisory. (...) I don't understand why.
When relief	Comments suggesting the information need about when the temperature will be cooler.	A message that provides information about when the temperature will be cooler	When will this heat wave stop
Residual	Comments suggesting uncommon consumer needs for heat risk messaging	For example: A message that justifies the use of the Heat Index.	If it's a 100F then it's a 100F... not 110F or anything thing else. STOP the sensationalism [Context: One sentence in the message was "Temperatures will be over 100 degrees in places, with heat index values over 110 degrees. "]

¹ If a comment simultaneously fit descriptions of the “Normalization” category and the “Warning issuance criteria” category, it was coded into the “Normalization” category.

Table 12. Descriptive statistics of comments

Comment type	No. of comments	No. of unique Facebook users	No. of warning messages	No. of Facebook pages
Whole dataset	3182	n/a	354	23
Relevant comments	216	n/a	121	18
Normalization	58	44	30	11
Lacking relief measures	20	18	15	10
Warning issuance criteria	15	13	11	6
When relief	13	12	13	7
Residual	110	n/a	73	17

We explain how comments in the first two categories (“Normalization” and “Lacking relief measures”) suggested people’s needs for risk messaging. For the first category, when Facebook users perceived the warning messages to be unnecessary or overblown, they implicitly expressed needs for messages that justify the necessity of the heat warning. Being irresponsive to the need may result in distrust of the competence and/or integrity of the NWS offices and maladaptation to extreme heat events. When people perceive the heat conditions to be normal, they may act normally (in other words, not changing their behavior to protect themselves) which may be insufficient to protect them from heat-health impacts. Several comments in the “Normalization” category questioned the need for other people to take the heat seriously or even reported maladaptive behaviors during extreme heat events. For example, after arguing with other people who held opposite opinions, a Facebook user stated: “Lol, you people are being silly. Get an air conditioner. I’ll be doing field work.” With respect to the “Lacking relief measures” category, the Facebook users expressed concerns related to air conditioner breakdowns or no access to an air conditioner during the heat. Although they did not

explicitly request tips on how to deal with such extraordinary situations, messages that specify alternative coping strategies could be a latent need of these Facebook users since such messages would reduce people's concern and risks in such situations.

The most common need was suggested by the "Normalization" category which contained 58 comments by 44 unique Facebook users. The comments responded to 30 heat warning messages across 11 official Facebook pages. The other specified categories (i.e., "Lacking relief measures", "Warning issuance criteria" and "When relief") were less common, containing a total of 48 comments. About half of the relevant comments (51%, N=110) were coded into the residual category and suggested diverse needs. In the residual category, the most common need was meeting the information need about humidity levels, which was suggested by eight comments (e.g., "What's the humidity level with that heat?"). A few examples of other uncommon needs were avoiding typos in messages (four comments), using proper font size in infographics to ensure readability (three comments), tackling distrust in the Heat Index (two comments), and improving message consistency about what is the deadliest weather hazard (one comment). One example of comments indicating distrust in the Heat Index is shown in the last row in Table 11.

More-detailed needs exploration

Using comments in the "Normalization" category, we identified three more-detailed needs. They are 1) a message that justifies why a heat condition that happens every year for this area warrants a heat warning, 2) a message that explains why a heat condition that may not be dangerous for southern populations is dangerous for northern

populations, and 3) when justifying the necessity of the heat warning, a message that uses strategies beyond mentions of temperature and/or Heat Index, “excessive/extreme heat”, and intense statements such as “dangerous heat” and “Don’t be a statistic”.

We found that some Facebook users’ definition of what are considered normal conditions was different from the definition of experts. Experts use average conditions (e.g., the average monthly long-term maximum temperature) to define what is normal. For experts, the heat conditions that warrant heat watch, warning, or advisory products are extreme and dangerous for local people (Hawkins et al., 2017). However, some Facebook users called such “extreme” conditions typical summer days. Half of the comments in the “Normalization” category (N=29) provided some hints about their reasons. First, for some Facebook users, if a temperature happens every year or is lower than the highest temperature they have ever known, then the temperature is normal. For example, two Facebook users respectively used “It’s called August. Happens every year (...)” and “(...) I remember even 20 and 30 years ago having days in the 120's (...)” to justify their statements. Second, for several Facebook users, if a heat condition is normal for southern populations, the heat condition is not unusual for northern populations. These users underestimated the severity of heat conditions in northern areas, likely due to misunderstandings about heat acclimatization. For example, in response to a heat warning message posted on the NWS Binghamton New York’s page, a comment said “(...) Lol, they have conditions like this everyday in many parts of the country. This isn’t even terrible.” We identified the first two more-detailed needs in response to the two aspects stated above.

We identified the third more-detailed need from the perspective of message-comment interaction. Mentions of “excessive/extreme heat” and mentions of temperatures and/or Heat Index in the messages were insufficient to convince some Facebook users of the necessity of the warning. Comments in the “Normalization” category respond to 30 different warning messages, and both kinds of mentions appeared in about 80% of messages. Of the 30 messages, mentions of “dangerous” or “danger”, heat-related illness or deaths, and who or which behavior is more vulnerable respectively appeared in about one-third of messages. Since the comments were unsolicited feedback, most of them did not clarify the role of their respective messages in stimulating their comments that belong to the “Normalization” category. Comments by eight Facebook users (18%), however, expressed discontent with perceived exaggerations in messages. For example, a comment on a message (see Figure 7) stated: “If I didn't know better I'd say it's never been hot in Louisiana based off these excessive posts about how hot it is. Of course it's hot & humid. It's Louisiana in August”. It seems that the phrases “very hot”, “dangerous heat index values”, and even “excessive heat warning” can be perceived as exaggerations when people are not convinced of the danger by other descriptions in the message.

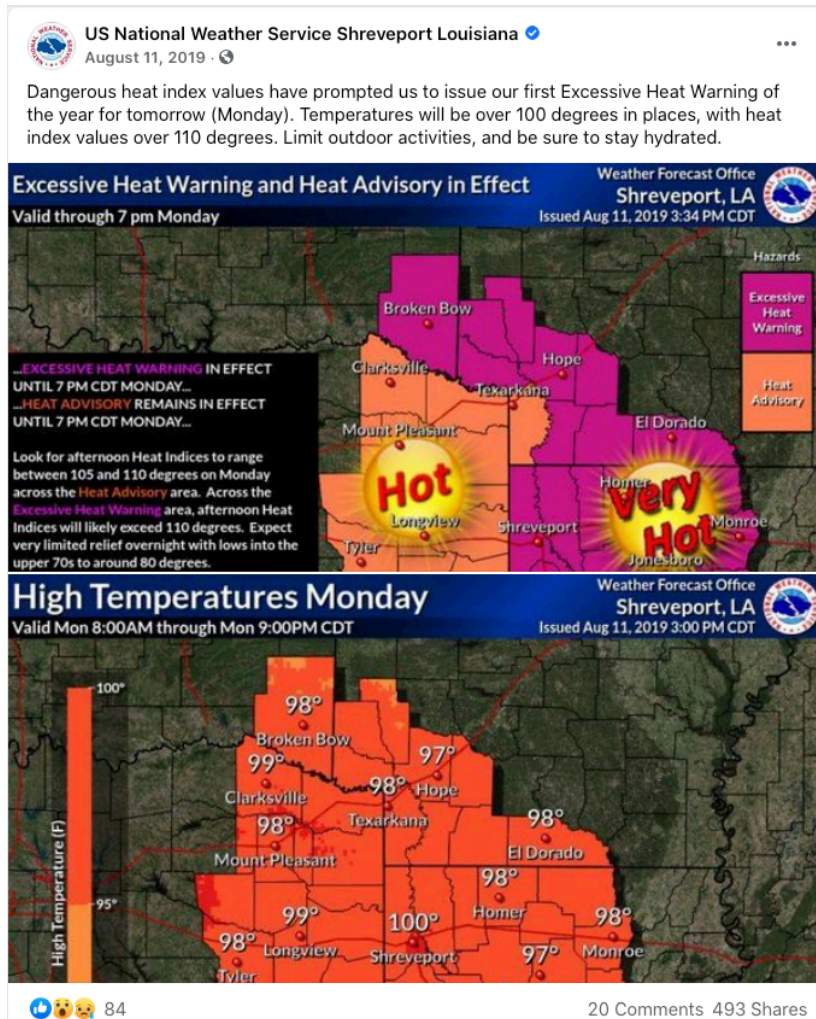


Figure 7. An example of heat warning messages on official Facebook pages

Discussion and conclusions

This study shows that Facebook comments on heat warning messages have the potential to inform people's needs for risk messaging. This study also shows that the "consumers" perspective can be applied to meet the potential through empathic design (Postma et al., 2012) and the general inductive approach (Thomas, 2006). The general inductive approach allows us to directly address the goal of needs identification and only categorize comments that suggested the needs (i.e., relevant comments). Since the density

of relevant comments was low in our study, the general inductive approach saves researcher time from coding a large volume of “noisy” comments. Working with publicly available data—Facebook comments on multiple public pages—using the appropriate approach enables us to reach a geographically diverse population with low research costs.

Although only a relatively small number of comments suggested needs for message improvements, some unexpected findings appear to be valuable. For example, comments in the “Normalization” category provide insights into how people define normal heat conditions and how the perception might affect message processing. Past surveys and in-depth interviews have acknowledged that people tend to underestimate the heat-health risks posed to themselves which has also been associated with noncompliance behaviors of heat warning messages (Mayrhuber et al., 2018). The “Normalization” category opens up a new way to think about why some people do not take protective actions recommended by heat warning messages. In the broader domains of extreme weather and climate change, public perception of weather as either normal or unusual is important to climate change adaptation and mitigation, but related empirical evidence is limited (Moore et al., 2019). Our findings about how people use not only temporal references but also spatial references to define normal heat conditions improve understanding of the under-examined perception. The primary needs and more-detailed needs identified in this study not only contain serendipitous discoveries—unexpected and valuable findings—but also have high ecological validity. This is because Facebook comments record people’s immediate responses to a variety of real-life messages without researchers’ intervention.

Our findings were exploratory in nature. First, although Facebook users are a large and diverse population, people who leave Facebook comments on official risk messages are not representative of social media users who have access to the messages. A small number of relevant comments and the latent content of comments also inhibit us from conducting confirmatory analyses. Second, the diverse needs identified in the study are preliminary needs for message improvement. Researchers and practitioners need to prioritize the preliminary needs even before confirming them. For example, for some needs (such as meeting the information need of “When relief”), if they are met, the messages may be more attractive. For some needs (such as dealing with distrust in Heat Index), if they are met, the messages may reduce heat vulnerability. Third, although we checked the intercoder reliability of the specified and residual categories, we did not check the intercoder reliability for comments categorized as relevant versus irrelevant. Given the exploratory nature of this study, we chose not to do so since we did not aim to exhaustively identify all possible needs for risk messaging.

This study contributes to risk communication research in three ways. First, our findings about people’s needs for heat risk messages provide directions for researchers and practitioners to follow up in order to design and test more effective heat risk messages. For example, future studies should investigate how generalizable the need and three more-detailed needs suggested by the “Normalization” category are. Practitioners should also collaborate with researchers to craft solutions to fulfill the needs and address potential psychological barriers to protective actions. In addition, the public’s needs identified in the present study could have implications for needs identification in the context of other hazards. For example, when people lack relief measures such as

electricity and transportation in other types of hazards such as winter storms, official risk messages that providing alternative coping strategies might also be needs of the public. Assessment of people's needs in previous hazardous events is important to design effective risk messages for future events which are responsive to people's needs and help protect public health. Second, this study demonstrates a promising method to collect public feedback and inform message improvement: analyzing Facebook comments on official risk messages through the lens of consumer feedback. This novel method may become a complementary method to other techniques used to elicit public feedback related to risk communication. This is because the method enables needs identification with high ecological validity and low research cost. Third, to our knowledge, this study, for the first time, uses the word "*consumers*" to acknowledge the role of the public for risk communication in social media who consume products (e.g., official risk messages and emergency services) and may also provide feedback. When considering risk messages to be products and online comments to be the form of feedback, this study also empirically shows how recognition of the role of the public as *consumers* can help improve risk communication in social media.

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CHAPTER VI

CONCLUSIONS

This dissertation aims to improve heat risk messaging and motivate protective actions. Drawing on fear appeal theories in health communication literature, Study 1 (Chapter 2) identified several types of persuasive message content that are theoretically persuasive. Using heat risk messages posted on Twitter, Study 1 also content-analyzed the usage of the persuasive message content in the messages and Study 2 (Chapter 3) examined how the persuasive message content influence message diffusion. Using an online survey experiment (N=1, 386), Study 3 (Chapter 4) compared the effectiveness of different statements about who are susceptible to heat-health impacts. Study 4 (Chapter 5) explored the public needs for heat risk messaging by inductively coding online comments on heat warning messages posted on Facebook.

Two overarching themes emerge from the four studies. First, descriptions of hazard intensity (e.g., temperature and/or Heat Index) are important but insufficient for risk messages. Heat warning messages disseminated on social media usually include descriptions of the temperature and/or Heat Index (Study 1, Study 2, and Study 4). The presence of such descriptions predicted increased retweet counts, a measure of message diffusion (Study 2). However, to maximize message diffusion, descriptions of the temperature and/or Heat Index should be accompanied by other descriptions including heat-safety tips, who or which behavior is vulnerable, and the severity of health consequences of maladaptation (Study 2). Mentioning the temperature and/or Heat Index,

by itself, appears to be insufficient to convince some people of the necessity of taking the heat seriously (Study 4).

Second, depicting people's susceptibility (the likelihood of experiencing negative consequences of a threat) is important, and *how* to depict people's susceptibility seems more important for risk messages. Past studies have acknowledged that underestimation of personal risks from extreme heat is a psychological barrier to warning compliance (Mayrhuber et al., 2018; Sampson et al., 2013). In response to this barrier, Study 1 and Study 2 learned from a related domain, health communication, and identified depicted susceptibility as one type of promising message content to deal with the barrier. Study 1 further identified several variations or subtypes of depicted susceptibility in real-life heat risk messages. A lack of recognition of the subtypes may contribute to the statistically insignificant effects of depicted susceptibility—the inclusive type—on message diffusion for heat warning messages (Study 2). When Study 3 compared the effectiveness of some subtypes, we found that the “anyone can be at risk” statement was more effective than the “certain subgroups are at more risk” statement in making heat warning messages personally relevant to the general public (Study 3). The relative effectiveness of this pair of statements, as well as the other pairs of subtypes examined in Study 3, has rarely been examined in the context of health communication. In other words, although health communication has widely investigated depicted susceptibility, some subtypes and the relative effectiveness of some pairs of subtypes have been under-examined (Ref. Study 3). One possible reason is that, unlike in natural hazard communication, the intended audience in health communication is usually subpopulations, instead of the general public. The second overarching theme and specific findings in Study 3 could have implications

on health communication especially during times of the coronavirus disease 2019 (COVID-19) pandemic when the intended audience needs to be the general public in many cases.

With respect to the overarching contribution, the studies in this dissertation show how recognition of persuasion can improve understanding and inform practices about risk communication in the field of natural hazards. Traditionally risk communication in the context of natural hazards has focused largely on informing the public, often with an implicit assumption that informing, by itself, will lead to behavioral adaptation and risk reduction (Demeritt & Nobert, 2014; Reynolds & Seeger, 2005). Using heat hazards as a case study, the dissertation work contributes to the persuasion aspect of risk communication in the field of natural hazards in two ways. First, this work shows how established persuasive strategies—such as fear appeals—in other domains can be adapted to the natural hazard domain and inform weather risk messaging. Second, this work shows how available data in social media platforms can be used as a complementary data source to investigate risk communication between government agencies and the public.

While this dissertation improves understanding about message persuasion, this work did not successfully identify a risk messaging strategy that is empirically persuasive, which means a strategy that positively influences people's attitudes, behavioral intentions, or behaviors. With respect to future research, it would be particularly interesting to conduct another survey experiment to compare the persuasive effects between the “certain subgroups are at more risk” statement and the “anyone can be at risk” statement among the elderly, which would help identify persuasive messaging strategies for the subgroup with elevated heat vulnerability. In addition, future research

that deepens the understanding of the perception about “Normalization” (Study 4) would have both theoretical and practical implications for weather risk messaging. Finally, with respect to risk communication in the broader domain of natural hazards, future research should pay more attention to transforming findings from perception studies into communication strategies. Understanding how people perceive risks is essential, but insufficient, to know how to effectively communicate these risks with people. A large number of perception studies have stated implications for risk communication in the discussion sections. However, a low proportion of these implications draw subsequent research attention, and thus little is known about whether and how these perception findings can be transformed into evidence-based communication strategies. This dissertation research showcases and contributes to the perception-communication collaboration, and more future studies about the collaboration would be beneficial for both intellectual and practical understanding.

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APPENDICES

APPENDIX A

DESCRIPTIVE STATISTICS OF PREDICTORS

TABLE 13. Descriptive Statistics of Predictors

	Heat-related tweets (N=904)	Heat warning tweets (N=223)	Non-warning tweets (N=436)
<i>Individual-level Predictor</i>	Count (Percentage)	Count (Percentage)	Count (Percentage)
<i>Hazard intensity</i>			
0: absence	144 (15.9%)	66 (29.6%)	44 (10.1%)
1: presence	760 (84.1%)	157 (70.4%)	392 (89.9%)
<i>Health risk susceptibility</i>			
0: absence	725 (80.2%)	158 (70.9%)	375 (86.0%)
1: presence	179 (19.8%)	65 (29.1%)	61 (14.0%)
<i>Health impact</i>			
0: absence	805 (89.0%)	186 (83.4%)	407 (93.3%)
1: presence	99 (11.0%)	37 (16.6%)	29 (6.7%)
<i>Response instruction</i>			
0: absence	569 (62.9%)	120 (53.8%)	308 (70.6%)
1: presence	335 (37.1%)	103 (46.2%)	128 (29.4%)
<i>PMF count</i>			
0	77 (8.5%)	53 (23.8%)	19 (4.4%)
1	504 (55.8%)	67 (30.0%)	295 (67.7%)
2	132 (14.6%)	26 (11.7%)	61 (14.0%)
3	159 (17.6%)	65 (29.1%)	51 (11.7%)
4	32 (3.5%)	12 (5.4%)	10 (2.3%)
<i>Grouping variable</i>	Count (Percentage)	Count (Percentage)	Count (Percentage)
<i>Created time of day</i>			
0am - 6am	242 (26.8%)	72 (32.3%)	129 (29.6%)
6am - 12pm	224 (24.8%)	65 (29.1%)	103 (23.6%)
12pm - 6pm	280 (31.0%)	58 (26.0%)	121 (27.8%)
6pm - 12am	158 (17.5%)	28 (12.6%)	83 (19.0%)
<i>Created day of week</i>			
Monday	104 (11.5%)	19 (8.5%)	67 (15.4%)
Tuesday	128 (14.2%)	26 (11.7%)	73 (16.7%)
Wednesday	148 (16.4%)	44 (19.7%)	59 (13.5%)
Thursday	146 (16.2%)	40 (17.9%)	53 (12.2%)
Friday	157 (17.4%)	47 (21.1%)	59 (13.5%)
Saturday	104 (11.5%)	27 (12.1%)	58 (13.3%)

Sunday	117 (12.9%)	20 (9.0%)	67 (15.4%)
Created month			
June	290 (32.1%)	61 (27.4%)	142 (32.6%)
July	403 (44.6%)	105 (47.1%)	196 (45.0%)
August	211 (23.3%)	57 (25.6%)	98 (22.5%)
Sending WFO			
NWS Phoenix	98 (10.8%)	20 (9.0%)	36 (8.3%)
NWS Chicago	97 (10.7%)	41 (18.4%)	45 (10.3%)
NWS Fort Worth	89 (9.8%)	25 (11.2%)	46 (10.6%)
NWS Wichita	88 (9.7%)	6 (2.7%)	28 (6.4%)
NWS New Orleans	79 (8.7%)	11 (4.9%)	56 (12.8%)
NWS Tulsa	75 (8.3%)	47 (21.1%)	14 (3.2%)
NWS Louisville	66 (7.3%)	10 (4.5%)	47 (10.8%)
NWS Columbia	49 (5.4%)	2 (0.9%)	46 (10.6%)
NWS Las Vegas	43 (4.8%)	14 (6.3%)	18 (4.1%)
NWS Seattle	40 (4.4%)	3 (1.3%)	11 (2.5%)
NWS Mount Holly	32 (3.5%)	11 (4.9%)	10 (2.3%)
NWS Flagstaff	27 (3.0%)	16 (7.2%)	2 (0.5%)
NWS Bismarck	25 (2.8%)	0 (0.0%)	17 (3.9%)
NWS San Angelo	24 (2.7%)	6 (2.7%)	13 (3.0%)
NWS New York NY	24 (2.7%)	10 (4.5%)	3 (0.7%)
NWS Miami	21 (2.3%)	1 (0.4%)	18 (4.1%)
NWS Atlanta	14 (1.5%)	0 (0.0%)	13 (3.0%)
NWS Burlington	13 (1.4%)	0 (0.0%)	13 (3.0%)
NWS region			
Southern Region	302 (33.4%)	90 (40.4%)	160 (36.7%)
Central Region	276 (30.5%)	57 (25.6%)	137 (31.4%)
Western Region	208 (23.0%)	53 (23.8%)	67 (15.4%)
Eastern Region	118 (13.1%)	23 (10.3%)	72 (16.5%)
<i>Group-level predictor</i> ¹	Mean (SD)	Mean (SD)	Mean (SD)
Monthly normal temperature (in °C)	24.51 (4.11)	25.37 (4.02)	24.54 (4.15)
Monthly temperature anomaly (in °C)	1.01 (0.85)	1.08 (0.91)	1.02 (0.85)
Follower count (in thousand)	17.90 (13.75)	19.73 (14.35)	17.90 (13.75)
Population size (in million)	5.84 (6.79)	6.38 (7.16)	5.84 (6.79)

¹ The descriptive statistics of group-level predictors were calculated across groups, instead of across individual tweets. For example, follower count was a group-level predictor for the grouping variable of sending WFO, and there were 15 sending WFOs which posted heat warning tweets. Then the mean of follower count for heat warning tweets was the average of these 15 follower counts responding to each of the 15 sending WFOs.

APPENDIX B

CHECKS ABOUT THE VALIDITY OF CUMULATIVE EFFECTS

We checked whether the effects of the number of PMFs were dependent on a single influential PMF by conducting 12 additional models (for each PMF and tweet type) dropping tweets mentioning one of the four PMFs from one of three message types. The effects of the number of PMFs remained statistically significant, positive predictors for eight models, and the other four models were overfitted and not found to have statistically significant, cumulative effects. One of the four models used heat warning tweets removing those containing the PMF of *response instruction*, in which the cumulative effect approached significance, $IRR=1.25$ [95% CI: 0.97-1.60], $p = 0.08$. The other three models that did not pass the check used data sets dropping tweets containing the PMF of *hazard intensity*. Because tweets containing mentions of *hazard intensity* were disproportionately high in each original data set, the remaining data sets after removing tweets mentioning *hazard intensity* did not have enough cases to check the cumulative effects. As an alternative, we modeled the number of PMFs for each original data set without dropping any tweets and controlled for the variable of *hazard intensity* in addition to other control variables. For each of the alternative models, the number of PMFs was a statistically significant and positive predictor of retweet counts. Overall, we concluded that the effects of the number of PMFs were not driven by a single PMF across message types.

APPENDIX C

MESSAGES AND CHARACTERISTICS OF SAMPLE BY EXPERIMENTAL CONDITIONS

As an introduction, all participants were presented with same text as follows that described a hypothetical situation.

“Imagine that one day during the past summer you saw the following message from your local office of the U.S. National Weather Service. This is a message about an Excessive Heat Warning, which is issued when extreme heat conditions will happen soon. This message was issued on the same day when you saw it.

Please read this message carefully. If necessary, **zoom in** on your device so you can take a closer look at this message.”

Full graphic messages assigned to the four treatment groups are as follows.



Figure 8. Graphic message containing the subgroup statement



Figure 9. Graphic message containing the anyone statement



Figure 10. Graphic message containing the anyone+subgroup statement



Figure 11. Graphic message containing the no depicted susceptibility statement

The characteristics of sample by experimental conditions are shown in Table 14.

Table 14. Characteristics of sample by experimental conditions

	Subgroup statement N (%)	Anyone statement N (%)	Anyone+ subgroup statement N (%)	No depicted susceptibility N (%)	<i>p</i> value in chi- square test
Sex					0.53
Male	155 (43.4%)	150 (45.3%)	169 (47.7%)	166 (48.4%)	
Female	202 (56.6%)	181 (54.7%)	185 (52.3%)	177 (51.6%)	
Missing data	0	0	0	1	
Age (years)					0.90
18-29	94 (26.3%)	85 (25.7%)	99 (28.0%)	87 (25.4%)	
30-44	85 (23.8%)	74 (22.4%)	79 (22.3%)	75 (21.9%)	
45-60	97 (27.2%)	99 (29.9%)	106 (29.9%)	114 (33.2%)	
Over 60	81 (22.7%)	73 (22.1%)	70 (19.8%)	67 (19.5%)	
Missing data	0	0	0	1	
Race/ethnicity					0.80
White, non-Hispanic	264 (76.3%)	240 (76.2%)	260 (75.8%)	251 (75.8%)	
Black, non-Hispanic	16 (4.6%)	21 (6.7%)	24 (7.0%)	16 (4.8%)	
Hispanic	29 (8.4%)	20 (6.3%)	29 (8.5%)	25 (7.6%)	

Other or 2+ races, non-Hispanic	37 (10.7%)	34 (10.8%)	30 (8.7%)	39 (11.8%)	
Missing data	11	16	11	13	
Education					0.61
High school or less	44 (12.6%)	36 (10.9%)	55 (15.6%)	53 (15.5%)	
Some college	87 (24.9%)	91 (27.6%)	88 (25.0%)	89 (26.0%)	
College graduate	142 (40.6%)	135 (40.9%)	148 (42.0%)	131 (38.3%)	
Graduate degree	77 (22.0%)	68 (20.6%)	61 (17.3%)	69 (20.2%)	
Missing data	7	1	2	2	
Household income					0.39
Less than \$25,000	66 (20.6%)	53 (17.5%)	56 (17.6%)	62 (19.9%)	
\$25,000-\$49,999	73 (22.7%)	63 (20.9%)	80 (25.2%)	71 (22.8%)	
\$50,000-\$74,999	54 (16.8%)	73 (24.2%)	66 (20.8%)	65 (20.9%)	
\$75,000-\$99,999	52 (16.2%)	50 (16.6%)	39 (12.3%)	35 (11.3%)	
\$100,000 or more	76 (23.7%)	63 (20.9%)	77 (24.2%)	78 (25.1%)	
Missing data	36	29	36	33	
Region					0.69
Northeast	66 (18.6%)	63 (19.1%)	62 (17.8%)	56 (16.6%)	
Midwest	67 (18.9%)	68 (20.7%)	91 (26.1%)	79 (23.4%)	
South	129 (36.4%)	116 (35.3%)	114 (32.7%)	118 (34.9%)	
West	92 (26.0%)	82 (24.9%)	82 (23.5%)	85 (25.1%)	
Missing data	3	2	5	6	
Device used to take the survey					0.27 ¹
Desktop or Laptop	138 (38.7%)	124 (37.5%)	120 (33.9%)	112 (32.7%)	
Phone or Tablet	216 (60.5%)	204 (61.6%)	232 (65.5%)	224 (65.3%)	
Other devices	3 (0.8%)	3 (0.9%)	2 (0.6%)	7 (2.0%)	
Missing data	0	0	0	1	
Total observations	357	331	354	344	

¹A Fisher's exact test was also performed for the variable of "Device used to take the survey" to check the random assignment of treatment groups, because some counts in this variable were less than five. The *p*-value in the Fisher's exact test was 0.32.

APPENDIX D

POST HOC ANALYSIS IN EACH AGE GROUP

We conducted a preliminary analysis about treatment effect heterogeneity by age group in order to better interpret our main findings. Using the same data collected in this study, we performed unadjusted pairwise t tests (pooled standard deviation and two-sided tests) to compare the differences in mean outcomes between all pairs of treatments for each age group. The results are shown in Table 15 and visualized in Figure 12.

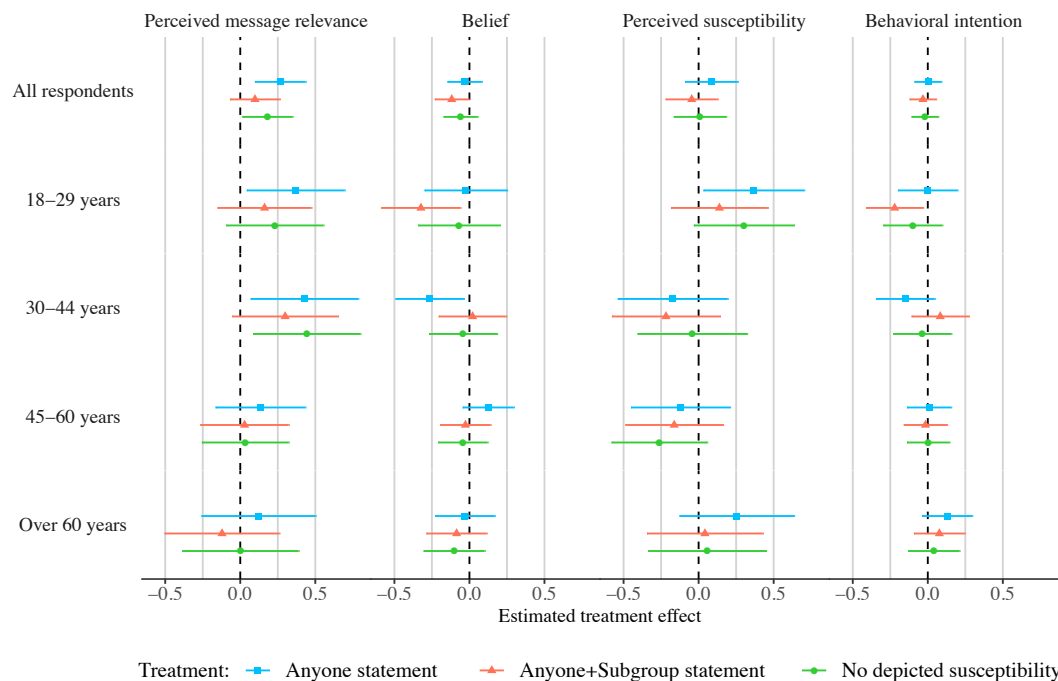


Figure 12. Estimated average treatment effects and heterogeneous treatment effects by age group (subgroup statement as the control group). Squares, triangles, and points indicate the estimated effect, and lines represent 95% confidence intervals.

Table 15. Means of outcome variables by experimental conditions for each age group

Age group	Outcome variable ¹	Subgroup statement		Anyone statement		Anyone+ subgroup statement		No depicted susceptibility	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
18-29 years	Relevance	3.52 ^a	1.15	3.89 ^b	1.09	3.68 ^{ab}	1.19	3.75 ^{ab}	0.92
	Belief	3.33 ^a	0.88	3.31 ^a	0.84	3.01 ^b	1.01	3.26 ^{ab}	0.98
	Susceptibility	2.76 ^a	1.14	3.12 ^b	1.09	2.89 ^{ab}	1.18	3.06 ^{ab}	1.16
	Intention	3.45 ^a	0.67	3.45 ^a	0.59	3.23 ^b	0.75	3.35 ^{ab}	0.65
30-44 years	Relevance	3.41 ^a	1.18	3.84 ^b	1.05	3.71 ^{ab}	1.22	3.85 ^b	1.11
	Belief	3.60 ^a	0.54	3.34 ^b	0.95	3.62 ^a	0.63	3.56 ^{ab}	0.74
	Susceptibility	2.89	1.14	2.72	1.24	2.67	1.19	2.85	1.13
	Intention	3.51 ^{ab}	0.54	3.36 ^a	0.73	3.59 ^b	0.51	3.48 ^{ab}	0.71
45-60 years	Relevance	3.91	1.01	4.04	1.14	3.93	1.05	3.94	1.05
	Belief	3.68 ^{ab}	0.55	3.81 ^a	0.42	3.65 ^{ab}	0.73	3.64 ^b	0.66
	Susceptibility	3.20	1.11	3.08	1.19	3.03	1.17	2.93	1.23
	Intention	3.61	0.55	3.62	0.47	3.59	0.53	3.61	0.55
Over 60 years	Relevance	3.86	1.15	3.99	1.16	3.74	1.28	3.87	1.20
	Belief	3.73	0.57	3.70	0.54	3.64	0.72	3.63	0.67
	Susceptibility	2.95	1.24	3.21	1.22	2.99	1.12	3.01	1.24
	Intention	3.55	0.65	3.68	0.47	3.63	0.43	3.59	0.52

Notes: Statistically significant differences determined by unadjusted p -values are reported using superscripts. In the same row, means without common superscripts are statistically significantly different from each other (pairwise t tests with pooled SD, $p < 0.05$). The Hedges' g values of these differences were all above 0.3, which indicate small to medium magnitudes of differences. In the same row, means with shared superscripts are not statistically significantly different from each other (pairwise t tests with pooled SD, $p < 0.05$). In rows, means having no superscripts are not statistically significantly different from each other (pairwise t tests with pooled SD, $p \geq 0.05$).

¹ For outcome variables, "relevance" represents "perceived message relevance", "susceptibility" represents "perceived susceptibility", and "intention" represents "behavioral intention".

APPENDIX E

SAMPLED FACEBOOK PAGES

Table 16. Facebook pages included in the data set

Facebook page name	No. of heat warnings w/comments	No. of comments
National Accounts		
U.S. National Weather Service	24	279
NOAA NWS Weather Prediction Center	16	117
Regional Accounts		
US National Weather Service Eastern Region HQ	2	5
US National Weather Service Western Region HQ	1	1
US National Weather Service Southern Region HQ	0	0
US National Weather Service Central Region Headquarters	0	0
Field Accounts		
US National Weather Service Phoenix Arizona	102	943
US National Weather Service Austin-San Antonio Texas	23	328
US National Weather Service Boston MA	28	275
US National Weather Service Binghamton NY	15	222
US National Weather Service San Francisco Bay Area/Monterey California	32	178
US National Weather Service Omaha/Valley Nebraska	6	162
US National Weather Service Springfield Missouri	10	112
US National Weather Service Amarillo Texas	11	88
US National Weather Service Baltimore/Washington	11	86
US National Weather Service Sioux Falls South Dakota	12	80
US National Weather Service Shreveport Louisiana	18	66
US National Weather Service Hastings Nebraska	8	63
US National Weather Service Huntsville Alabama	15	54
US National Weather Service Detroit / Pontiac Michigan	3	44
US National Weather Service Marquette Michigan	1	23
US National Weather Service Dodge City Kansas	2	22
US National Weather Service Midland Texas	10	18
US National Weather Service San Juan Puerto Rico	2	12
US National Weather Service Indianapolis Indiana	2	4
US National Weather Service Louisville Kentucky	0	0
US National Weather Service Cheyenne Wyoming	0	0
US National Weather Service Glasgow Montana	0	0

US National Weather Service Aberdeen South Dakota	0	0
US National Weather Service Guam	0	0
US National Weather Service Pago Pago American Samoa	0	0

CURRICULUM VITAE

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EDUCATION

Ph.D. in Environment and Society (Expected: May 2021)
 Presidential Doctoral Research Fellow
 Utah State University, The United States of America
 Dissertation: *Investigating Heat Risk Messaging Using Social Media Studies and a Survey Experiment*

B.E. in Environmental Engineering (2013)
 Yantai University, China
 Thesis: *Designing a Feasible Plan to Carry Out Domestic Waste Sorting in Yantai University (in Chinese)*

PUBLICATIONS

REFEREED JOURNAL ARTICLES

- 2021 **Li, Yajie**, Amanda Lee Hughes, and Peter D. Howe. 2021. "Toward Win-Win Message Strategies: The Effects of Persuasive Message Content on Retweet Counts During Natural Hazard Events". *Weather, Climate, and Society*. Early online release. <https://doi.org/10.1175/WCAS-D-20-0039.1>

ARTICLES UNDER REVIEW

Li, Yajie, and Peter D. Howe. "Moving Beyond Listing Vulnerable Populations: An Exploratory Experiment About Heat Risk Messaging". *Environmental Communication* (under review, resubmitted after revisions).

REFEREED CONFERENCE PAPERS

- 2018 **Li, Yajie**, Amanda Lee Hughes, Peter D. Howe. 2018. "Communicating Crisis With Persuasion: Examining Official Twitter Messages on Heat Hazards". *Proceedings of the 15th International Conference on Information Systems for Crisis Response and Management ISCRAM2018*, 469-479.

NON-REFEREED PUBLICATIONS

- 2020 Howe, Peter D., Brittany S. Shield, and **Yajie Li**. June, 2020. “Public opinion on climate change adaptation, 2019-2020: results from a four-wave U.S. national survey.” Utah State University: Logan, UT.
- 2013 **Li, Yajie**, Danqing Wang, Xiaoyan Liu, Feng Liu, Jianguo Song and Wei Liu. 2013. “Investigation on Optimal Allocation of Domestic Waste Collection Facilities in the University Campus —Taking Yantai University as an Example”. *Environment and Sustainable Development* 3: 101-102 (in Chinese).
- Wang, Danqing, **Yajie Li**, Changming Wang, Chuan Wang and Jianguo Song. 2013. “Study on Domestic Waste Source Sorting in University —A Case Study of Yantai University”. *Environmental Science and Management* 3: 9-11 (in Chinese).

TEACHING

Lab teaching assistant, GEOG/WILD 1800: Introduction to Geographic Information Sciences (Fall 2018, Utah State University)

GRANTS

GRANTS RECEIVED

- “Designing a Feasible Plan to Facilitate the Implementation of Domestic Waste Sorting in Yantai University” (PI). Faculty Mentor: Jianguo Song, Yantai University: Scientific and Technological Innovation Project for University Students, Oct. 2011- Nov. 2012 (¥1,200)
- “Study on Domestic Waste Source Sorting Behaviors in Yantai University” (Co-PI). Faculty Mentor: Jianguo Song, Yantai University: Scientific and Technological Innovation Project for University Students, Oct. 2011- Nov. 2012 (¥1,200)

PRESENTATIONS

CONFERENCE PRESENTATIONS

- 2018 Li, Yajie, Amanda Lee Hughes, Peter D. Howe. 2018. “Communicating Crisis with Persuasion: Examining Official Twitter Messages on Heat Hazards” Paper, May 2018, The 15th International Conference on Information Systems for Crisis Response and Management. Rochester, New York, USA
- 2017 Li, Yajie, Forrest Schoessow, Emily Esplin, and Peter D. Howe “Beat the Heat: Content Analysis of Communication Strategies on Twitter” Paper, April 2017, Association of American Geographers (AAG) Annual Meeting. Boston, Massachusetts, USA.

- 2016 Li, Yajie, Forrest Schoessow, and Peter D. Howe “The relationship between land cover and risk perceptions of heat waves across the U.S.” Illustrated Paper, March 2016, Association of American Geographers (AAG) Annual Meeting. San Francisco, California, USA.
- Schoessow, Forrest S., Yajie Li, and Peter D. Howe “Defining Vulnerable Population & Exploring Socio-Environmental Predictors of Heat Wave Risk Perceptions.” Illustrated Paper, March 2016, Association of American Geographers (AAG) Annual Meeting. San Francisco, California, USA.
- Howe, Peter D., Yajie Li, Forrest Schoessow, Jennifer Marlon, and Anthony Leiserowitz. “Geographic variation in risk perceptions and vulnerability to extreme heat hazards in the U.S.” Paper, March 2016, Association of American Geographers (AAG) Annual Meeting. San Francisco, California, USA.

RESEARCH ACTIVITIES

Graduate Research Assistant, “Collaborative Research: Multi-Scale Modeling of Public Perceptions of Heat Wave Risk.” Sponsored by the National Science Foundation: Decision Risk and Management Sciences Program, Advisor: Peter D. Howe (2015 – 2019)

Graduate Research Assistant, “CAREER: Location-aware social science for adaptation: modeling dynamic patterns in public perceptions and behavior.” Sponsored by the National Science Foundation: Geography and Spatial Sciences Program & Decision, Risk, and Management Sciences Program, Advisor: Peter D. Howe (Spring, 2020)

Second Coder for a mental model interview conducted by Emily D. Esplin to check intercoder reliability, “It’s a Dry Heat: Shifting Professional Perspectives on Extreme Heat Risk in Utah” (Spring, 2018)

AWARDS

FELLOWSHIPS AND HONORS

Jeanne X. Kasperson Student Paper Award, American Association of Geographers Hazard, Risks, and Disasters Specialty Group (2017)

Excellent Communicator Badge for Poster in Student Research Symposium, Office of Research and Graduate Studies (RGS), Utah State University (2016)

Presidential Doctoral Research Fellowship, RGS, Utah State University (2015-2019)

Provincial Excellent Graduate, Human Resources and Social Security Department of Shandong Province (2013)

Excellent Paper in Social Practice, Yantai University (2011)

Second Prize in the Yantai University Poetry Recitation Contest, Yantai University (2009)

Excellent Debater, College of Environmental and Materials Engineering (2009)

TRAVEL GRANTS

Graduate Student Travel Award, RGS, Utah State University (2016, 2017, 2018)

PROFESSIONAL MEMBERSHIPS

Association of American Geographers (2016, 2017)

The Information Systems for Crisis Response and Management Association (2018)

SPECIAL TRAINING

International Teaching Assistant Workshop and Certification, Attendee and was recommended for a Teaching Assistantship as a classroom instructor or lab instructor based on the workshop evaluation, The Intensive English Language Institute at Utah State University, Utah, USA (August 16-23 2018)

ADVISING

MENTORING UNDERGRADUATE RESEARCHERS

- 2017 Stewart, Jared, “[Risk Communication on Social Media to Spanish-Speaking Populations](#)”. Peter D. Howe is the faculty mentor, and I worked as a near-peer mentor. For ten weeks, the undergraduate in University of Utah conducted an independent summer research project titled above, and he also worked as a second coder helping the intercoder reliability check for part of my dissertation research. Funding was provided by the National Science Foundation, award OIA-1208732 “iUTAH-innovative Urban Transitions and Aridregion Hydro-sustainability.” May-July, 2017
- 2012 Liu, Xiaoyan, (PI) “Building Multi-Indicator Evaluation System for Domestic
Fall Waste Collection Facilities in the University”. Faculty Mentor: Jianguo Song, Yantai University: Scientific and Technological Innovation Project for University Students, Nov. 2012-unknown
- Yang, Yang, (PI) “Study on the Management System for the Students’ Waste Sorting Behavior in the University”. Faculty Mentor: Jianguo Song, Yantai University: Scientific and Technological Innovation Project for University Students, Nov. 2012-unknown

ACADEMIC SERVICE

PROFESSIONAL SERVICE

Manuscript reviewer:

Utah State University Extension Fact Sheet (1)

Proposals for the Undergraduate Research and Creative Opportunities Grant Program, Utah State University (1)

CERTIFICATES OF COMPLETION

Desert Mountain Medicine's 16-hour Wilderness First Aid curriculum (2016-2018)

Desert Mountain Medicine's urban and wilderness CPR curriculum (2016-2018)