Fake News Sharing: An Investigation of Threat and Coping Cues in the Context of the Zika Virus

ROHIT VALECHA, University of Texas at San Antonio

SRIKRISHNA KRISHNARAO SRINIVASAN, University of South Florida

TEJASWI VOLETY, University of Texas at San Antonio

K. HAZEL KWON, Arizona State University

MANISH AGRAWAL, University of South Florida

H. RAGHAV RAO, University of Texas at San Antonio

Fake news has become a growing problem for societies, spreading virally and transforming into harmful impacts in social networks. The problem of fake news is even more troubling in the healthcare context. In the healthcare literature, it has been well established that threat situations and coping responses facilitate information sharing and seeking among the public. Along a similar vein, we argue that threat and coping related cues are important indicators of shareworthiness of fake news in social media. We address the following research questions associated with fake news sharing in the context of Zika virus: How do threat- and coping-related cues influence fake news sharing? We characterize threat situations that have threat and severity cues and coping responses that are based on reaction to protection and fear cues. The results indicate the significant positive effect of threat cues and protection cues on fake news sharing. Such an investigation can allow the monitoring of viral fake messages in a timely manner.

CCS Concepts: • **Human-centered computing** → *Collaborative and social computing*; • **Computing methodologies** → *Natural language processing*; *Machine learning*; • **Security and privacy** → *Social network security and privacy*; • **Applied computing** → *Sociology*;

Additional Key Words and Phrases: Fake news, fake news sharing, threat cues, protection cues, fear cues, neural network, Twitter, Zika

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Authors' addresses: R. Valecha, T. Volety, and H. R. Rao, Information Systems and Cyber Security Department, University of Texas at San Antonio, TX 78249; emails: rohit.valecha@utsa.edu, {mgmtrao, teja.volety}@gmail.com; S. K. Srinivasan and M. Agrawal, Information Systems and Management, University of South Florida, Tampa, FL 33620; emails: srikrishnak@mail.usf.edu, magrawal@usf.edu; K. H. Kwon, Journalism and Mass Communication, Arizona State University, Tempe, AZ 85281; email: k.hazel.kwon@gmail.com.

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1 INTRODUCTION

Fake news can become rapidly viral and transform into more harmful impacts in social networks [77], just like a wildfire. Fake news sharing is a social as well as a psychological phenomenon, which “indirectly acknowledges the [various] contexts in which they arise” [8] (p. 589). Some crisis-related fake news could cause unrest in society and could adversely impact the effectiveness of response to the crisis [35]. The effects of fake news in healthcare sector are troubling. *The Atlantic* has stated, “of all the categories of [misinformation], health news is the worst.”¹ This is because reputable sources and organizations such as medical journals, medical societies, WHO, CDC, and the like take an understandably significant time to release their statements. These delays encourage health-related fake news through its sharing [72].

Fake news (or rumor) sharing is the sharing of health-related fake messages within a larger landscape of cyberspace. In order to manage health-related fake news, it is important to understand what makes citizens prone to engaging in health-related fake news sharing. The prior literature has focused on fake news sharing as a way to collectively manage fear associated with the threat situation [24]. In the healthcare literature, it has been well established that threat situations and coping responses facilitate citizens’ information seeking and sharing behavior [11, 49, 50, 78]. Further, Laibson [25] points to the importance of cues in shaping behavior. Therefore, to examine the behavior of fake news sharing, we explore the threat situations that have threat cues and severity cues as well as coping responses that result from reaction to protection cues and fear cues [5], in the context of the Zika virus health crisis on Twitter social media platform.

In summary, this article proposes to investigate the material conditions that “lead audiences to provisional acceptance of a preferred claim (of fake news) and the possibility of further transmission or action” [10] (p. 186). It extends traditional theories to consider the effect of fake news characteristics for investigating fake news sharing. The primary research method is an analysis of tweet data through content analysis.

This research will help social media channels flag messages so that users are better informed about the “fakeness” of messages they receive over information channels in cyberspace. This research is a step towards “bright ICTs”² that counter the negative effects of technologies and help establish a secure and trustworthy society [27, 28].

The rest of the article is organized as follows: The next section introduces the background for the context of Zika virus, literature for social media, including Twitter, and shareworthiness of social content. Subsequently, we discuss the theoretical foundation and introduce the conceptual model and discuss the set of research hypotheses. Then, we explain the research methodology and present the analysis and results. We conclude the article with discussion and conclusion.

2 BACKGROUND AND LITERATURE REVIEW

In this section, we provide a background on the Zika epidemic, an overview of social media and Twitter platform. Subsequently, we discuss the literature review of information sharing in Twitter platform.

2.1 Social Media, Twitter and Sharing in Zika Context

Social media are the most important platforms for risk communication during public health crises [66, 69]. Social media have become important information centers, where individuals and organizations create and disseminate real-time content beyond their personal social networks and physical location [35]. As people become more reliant on social media for emergency information, public officials and government agencies are increasingly utilizing these technologies to communicate with citizenry during times of crisis [30]. Public expectations have

¹<https://www.theatlantic.com/health/archive/2017/06/of-all-the-categories-of-fake-news-health-news-is-the-worst/531540/>.

²Bright ICT is an initiative that encompasses development of relevant technologies, business models and public policies for addressing the side effects of information and communications technology (ICT) platforms across borders [27, 28].

also increased, resulting in heightened pressure on government agencies to more efficiently and comprehensively integrate social media into their crisis communication strategies [64, 67].

Twitter is one of the largest and most productive social media networks and sharing information and has been a popular means of disseminating news and updates in emergent situations, such as public health crises. People use Twitter because they feel it enables them to communicate more effectively and disseminate information using multimedia [70]. Sharing of Twitter data has increased, especially on communication platforms. During public health crises, Twitter has been used much more to communicate information in an efficient and effective way [48].

Zika is caused by a virus transmitted primarily by *Aedes* mosquitoes that bite during the day. Zika infection during pregnancy can cause birth defects in the brain called microcephaly. It is also linked to other problems, such as miscarriage, stillbirth, and other birth defects. Given that many people view social media outlets like Twitter as a source of reliable health information, it is important to consider how topics like the Zika virus are addressed.

There have been several studies that have investigated sharing of tweet messages in the context of Zika virus. Table 1 discusses several studies that have investigated sharing of messages, but very few studies have investigated sharing of fake messages within healthcare crisis context. In order to address these gaps, we investigate fake news sharing on Twitter in the context of the Zika virus. This investigation can help health professionals better understand misinformation about viral outbreaks. It can help public health authorities improve risk communication by addressing the problem of fake news. It can help governments build their social media communication strategies in order to effectively target fake news that results in chaos during emergent health situations.

2.2 Fake News and Fake News Sharing

Fake news is defined as fabricated news articles that are intentionally and verifiably false, in order to mislead readers [4, 21, 43, 44]. In this way, it is similar to false rumors (ambiguous and unverified information that is false) [68–70]. Recently, there has been a proliferation of fake news on social media [7, 18], which has the potential for serious negative impacts [60–62] on individuals and society, ranging from distrust to chaos [53, 54]. Fake news intentionally deceives consumers to accept biased or false beliefs. Fake news is usually manipulated to influence certain viewpoints [53].

The majority of research in the arena of fake news has focused on detection of fake news using textual content and social context [53]. Some studies have utilized crowdsourcing [45], while some have employed third-party fact-checking organizations like Snopes and PolitiFact to flag fake content [6, 16]. Yet other studies have investigated patterns of fake/false information propagation [73]. Merchant and Asch [34] have mentioned three factors that contribute to misplaced trust in social media: the rapid decrease in the cost of publishing information, the increasing ability to select what information is heard, and the tools to perpetuate information. Then they have mentioned countermeasures to respond to the threat of misplaced trust in social media through management of provenance, engagement, transparency, narrative, and reputation.

Parikh and his colleagues have conducted several studies in the area of fake news detection [37–40]. In one of their initial studies, they performed a literature review focusing on characterization of fake news stories, listing of fake news datasets and content data types, and their prevalence on various platforms. In their subsequent studies, they have identified an existing gap within the fake news literature in understanding how fake news originates and spreads. Based on their hypotheses testing, they conclude that fake news are more often published by lesser known media outlets, more likely to be proliferated by unverified users and majority are written in a specific linguistic tone. They have also noted that not much attention has been paid to the impact of fake news. In order to address this gap, they developed a model incorporating the scope of the news, the reputation of the source, and the popularity of the proliferator to analyze the impact of fake news. They have created a framework to detect tampered and impersonated tweets based on a screen capture of the tweet, containing name, username, tweet text content, and timestamp attributes, resulting in 83% accuracy.

Table 1. Comparison of Existing Techniques

Article	Purpose	Source of data	Techniques	Findings
[13]	To determine original tweets from the public and responses from Centres for Disease Control (CDC)	Twitter messages which included #CDCchat	Text analysis	Ten mutually exclusive topics from public-generated tweets included information about the virology of Zika virus and how it spreads, consequences for babies, promotion of the chat, prevention, and travel precautions, education and testing for the virus, consequences for pregnant women trying to conceive, insect repellent, sexual transmission, encouragement to join the chat, and symptoms.
[32]	To analyze the sentiments of tweets concerning Zika and classify them mainly into three categories: positive, neutral, and negative tweets	5303 random tweets	Supervised classification algorithms, namely logistic regression, support vector machines, and random forest	Random tweets were accurately classified into three categories: positive, negative, and neutral
[14]	To investigate Zika virus-related information circulated on Twitter, identifying the patterns of dissemination of popular tweets and tweets from public health authorities	10% of entire Twitter data stream	Mixed-method approaches (i.e., qualitative and the quantitative approaches) and machine learning	The results revealed possible discrepancies between what the public were interested in, and what public health authorities provided during the Zika outbreak.
[80]	To investigate influences of multimedia tweets on retweetability during public health crises, for facilitating effective use of Twitter for health communication.	358,613 tweets collected between August 25, 2016 and September 5, 2016	Quantitative analysis including descriptive statistics and chi-squared tests	The text tweets were sent out more frequently than multimedia tweets, but multimedia tweets reported more retweetability. The tweets by government, mainstream news media and online news media were frequently retweeted
[46]	To explore main disseminators of information, the tone and type of message being shared.	201,143 tweets from February 23 to April 6, 2016	Exploratory analysis	The results of this study showed that public responded to positives messages about Zika relief efforts, as demonstrated in the analysis of the most retweeted messages in the data.
[15]	To examine the use of Twitter by federal, state, and local government actors in times of emergencies	Twitter data from August 25, 2016 to September 21, 2016	Content analysis and coding	The key findings identified the number of twitter handles in each category (level of government) and multimedia types (URL, Images).
This article	To explore threat situations that have threat cues and severity cues and response mechanisms that react to protection cues and fear cues.	45,498 tweets related to the fake news between September 2015 to May 2017	Empirical analysis	The results indicate that tweets that utilize threat cues and protection cues are positively associated with the likelihood of fake news sharing.

There have also been several studies that have investigated fake news in the context of health information. Waszak et al. [76] investigated top shared health misinformation stories in the Polish language social media. Utilizing keywords related to the most common diseases and causes of death, such as cancer, neoplasm, heart attack, stroke, hypertension, diabetes, vaccinations, HIV, and AIDS, they checked for the presence of fake news. They found out that 40% of the most frequently shared links contained fake content, which was shared more than 450,000 times. Despite the growing literature on fake news in recent years, the following gaps exist: there are no studies, to our knowledge, that have (1) investigated antecedents of fake news sharing, (2) explored theoretical models for understanding fake news sharing, (3) examined fake news sharing in the healthcare context, and (4) suggested countermeasures to respond to fake news sharing.

Studies of fake news have suggested a dual nature of fake news propagation. First, fake news is an unsubstantiated claim, and the propagation of a fake news does not necessarily correlate with its veracity. Accordingly, fake news sharing may be understood as a networked sensemaking process that can potentially create a misinformed collective [56, 59, 63]. Second, despite the risk to contribute to breeding misinformed knowledge, individuals may still engage in fake news sharing because an act of information exchange—whether it is true or not—helps individuals relieve anxiety and regain a sense of control over the uncertain situation. From this view, fake news sharing is understood as a form of threat-coping mechanism [24].

3 CONCEPTUAL MODEL

Understanding fake news sharing as a form of threat-coping mechanism helps elaborate psychological conditions prone to the spread of fake news. Laibson [25] has argued that behavior is characterized by cues, pointing to the importance of cues in shaping behavior. In accordance, we describe the conceptual model that investigates the relationship of threat situations using threat cues (H1), and severity cues (H2), as well as coping responses that are a result of reaction to protection cues (H3), and fear cues (H4) on fake news sharing.

Threat can be broadly defined as “a relationship between the person and the environment that is appraised by the person as relevant to his or her well-being and in which the person’s resources are taxed or exceeded” [12] (p. 152). This definition points out two essential characteristics: having an impact on one’s wellbeing and demanding additional resources. These characteristics closely resonate with the conditions for fake news sharing that researchers have commonly agreed: anxiety and uncertainty [1, 22, 51, 52]. In other words, if a given situation is threatening to one’s well-being, the situation may prompt “state anxiety” [74] (p. 353). The state anxiety would be relieved quickly if the situation is readily interpretable and resolved by using existing knowledge and resources. However, if the existing knowledge and resources are insufficient to reduce the uncertainty, anxiety will last longer and may evolve into a collective fear, as a result of which fake news spreads.

In other words, fake news sharing is an informational behavior that aims to cope with state of anxiety caused by perceived threat to the wellbeing of an individual or a community. The perception of threat is thus an important precondition for fake news belief [47]. For example, Liberman and Chaiken [31] found that coffee drinkers were more susceptible to believe a high-threatening message about coffee’s negative health impact than non-drinkers because the conceivable outcome of the message, if it turned out to be true, would matter to coffee drinkers’ well-being more than to non-drinkers. Rosnow [51] similarly suggests that an individual’s relatedness to an outcome affects the strength of fake news belief and circulation.

Such personal relevance may be an important factor for fake news sharing as well. For example, geographical, cultural, or social proximity to an event may prompt social media users to engage in informational searching and sharing more proactively, including not only facts but also fake news [24, 72]. While the current study cannot address each Twitter user’s personal relevance with a Zika outbreak, we instead examine whether fake news that recognizes a Zika event as a threat (referred to as “threat cues” hereafter) is more likely to be shared via online network than fake news without threat cues.

H1: Threat cues in fake news will be positively associated with its sharing.

From the psychology perspective, the threat cues described above pertains to anxiety induced from a situation [55], also known as the “state anxiety” [74]. The state anxiety is distinguished from the anxiety invoked by fake news [47]. While Walker and Beckerle [74] showed that the state anxiety influences the likelihood of fake news transmission regardless whether fake news is anxiety-enhancing or -alleviating, Pezzo and Beckstead [47] conversely highlighted the importance of anxiety driven by the message itself, finding it to be the most explanatory antecedent of fake news sharing.

In fake news (rumor) sharing context, Kwon and Rao [24] found positive effects of both state anxiety and message anxiety on fake news sharing. While prior research has measured message anxiety as individuals’ cognitive response to preselected fake news, the current study highlights threat situations in terms of severity cues embedded in the message, in accordance with health campaign research. Studies on health campaign messages have shown that threat severity cues in the campaign materials (narratives, images, etc.) are among the most persuasive strategies for behavioral change [79]. In Twitter, for example, a health campaign called the Tips Campaign showed that the vast majority of Twitter users (87%) engaged in the spreading of the campaign by accepting the message, while only 7% rejected the message [9].

Based on the discussion above, we contend that fake news emphasizing the severity of the Zika outbreak (referred to as “severity cues” hereafter) may invoke anxiety in users’ mind and more likely to be shared than those that do not indicate the severity of the issue.

H2: Severity cues in fake news will be positively associated with its sharing.

While threat and anxiety are commonly discussed in stress literature, coping responses have not yet been emphasized in fake news research. Coping response broadly refers to “cognitive and behavioral efforts to prevent, manage, or alleviate stress” [42] (p. 1216). Coping response is viewed as a function of cognition as well as emotion: On the one hand, it engages strategic effort to improve the threat situation by taking a protective action, which is referred to as “problem-focused coping” and on the other hand, it is required to regulate distressing emotions, referred to as “emotion-focused coping” [12] (p. 152).

Problem-focused coping should be especially important in the health fake news context, given that informational seeking behavior is intertwined with one’s ability to control the health risk [29]. Problem-focused coping is a reaction to protection cues that can be considered as a message characteristic that affects the likelihood of fake news sharing. Accordingly, this study posits the following hypothesis:

H3: Protection cues in fake news will be positively associated with its sharing.

“Emotion-focused coping” is often alluded to in fake news and rumor research. Online users’ emotional reaction to fake news has been in the form of apprehension (e.g., [3]). Emotion-focused coping is commonly seen in response to fear.

In the context of social media messages, fear messages are a persuasive attempt to arouse fear through impending danger or harm. These messages have fear cues embedded in them. Such cues have message characteristics that are reflective of sharing. Kanavos et al. [17] has investigated the effect of fear on retweet diffusion and found a significant rate of retweeting fearful messages. Steiglitz and Dang-Xuan [57, 58] have reported a positive relationship between tweets indicating affective dimensions, including negative emotions and its retweet rate. Social media users are likely to share fear-related messages to warn their followers of health-related dangers. Therefore:

H4: Fear cues in fake news will be positively associated with its sharing.

Studies have also shown that there are a number of other factors that also have an impact on information sharing behavior in social media, such as hashtags, URLs and followers [58]. Therefore, we include these variables as controls.

Fig. 1. Fake News Distribution.

4 METHODOLOGY

In this section, we describe the methodology consisting of data collection, followed by extracting fake news stories. Subsequently, we elaborate on the measures (dependent variable and control variables), and discuss the neural network coding used for creating the independent variables. Then, we validate the neural network-based measures by comparing with human-coded measures. Finally, we provide the descriptive statistics and analysis for testing the hypotheses.

4.1 Data Collection

We collected data for the Zika outbreak from Twitter in the time period September 2015 to May 2017 (see Figure 1). Twitter provides three APIs to enable researchers and developers to collect data, namely STREAMING, REST, and SEARCH APIs. Satisfying user-specified filtering criteria (based on keywords, location, language, etc.), STREAMING API is used to get tweets and their corresponding user's data in real time, REST API is used to get the data in select historical time period, and SEARCH API provides data on relevant searches on Twitter [70]. We collected 161,463 tweets using #zika, #zika virus, and other Zika-related hashtags [65, 71, 72] using SEARCH API. For each tweet, we collected its date, time, tweet text, retweet count, and follower count.

4.2 Fake News Stories

We also collected known Zika virus fake news from various sources. The sources and the fake news are identified in Tables 2 and 3. These fake news stories (1) misinformed health symptoms and effects, (2) targeted vulnerable population, including infants and pregnant women, and (3) in many countries such as US, Brazil, India, etc. Many of these Zika fake news stories are also reported in the literature [33].

Based on the identified fake news, we extracted 45,498 tweets related to the fake news. For associating a specific tweet to a specific fake news, we used text matching based on the tweet text. We assigned tweets related to fake news based on topical relevance, and referents of the statement (that is, an object, person, or situation rather than an idea or theory).

Table 2. Extracted Fake News

<p>Known fake news in the context of Zika virus were obtained from:</p> <ul style="list-style-type: none"> a) https://www.nytimes.com/interactive/2016/02/18/health/what-causes-zika-virus-theories-rumors.html?mcubz=0 b) https://www.elsevier.com/about/press-releases/research-and-journals/zika-conspiracy-theories-on-social-media-putting-vulnerable-people-at-risk c) https://undark.org/2016/06/01/zika-conspiracy-theories-twitter/ d) http://www.snopes.com/americans-immune-zika-virus/ <p>These known fake news messages were identified as follows:</p> <ul style="list-style-type: none"> a) Genetically modified mosquitoes are the real cause of the birth defects b) Larvicide in drinking water causes microcephaly (Zika virus symptom) c) News have blamed both a “bad batch of rubella vaccine” and the introduction of a new pertussis vaccine in Brazil, or aluminum in that vaccine d) Brazil has been undercounting Microcephaly (A symptom where baby’s head is significantly smaller than expected, could be due to Zika) e) Most pregnant women who have Zika have normal babies f) Microcephaly is caused by the MMR vaccine and pharmaceutical companies are blaming Zika virus in order to profit from selling Zika vaccines. g) Americans are immune to the Zika virus

4.3 Measures

We utilized the number of times a fake tweet was retweeted (shared) as the measure of fake news sharing, the dependent variable. For the control variables, we counted the number of ‘#’ in the fake tweet to create a hashtag count, and we used the number of followers of the user posting the fake tweet as a follower count. For creating the independent variables, threat cues, severity cues, protection cues, and fear cues, we utilized neural network coding as discussed in the next section.

4.4 Neural Network Coding

We employed unsupervised machine learning using Neural Networks. We coded the threat situation and coping responses using the content of the tweet. The objective was to find the keywords used in similar context as threat, severity, protection and fear in the fake tweets. This was accomplished in three steps: (1) we created an overall dataset of 45,498 extracted fake tweet samples, (2) we removed special characters by cleaning, lemmatizing, and stemming the fake tweets, and (3) we identified similar words in a text (where the similarity was based on the distance between the keywords) by training a word2vec model [70]. We trained our own word2vec model using the collected Twitter data (fake tweets data). The threshold used to identify neighboring words was set to 7. This trained neural network model understood the context of each word in the dataset, which was then utilized to find words most similar to threat and coping cues—e.g. “menace” for threat and “suffering” for severity cues. Similarly, words associated with “defend” were used for protection cues, and “panic” for fear cues. Table 4 shows some of the words derived from the neural network, which are used to create the coding scheme.

Quantitative content analysis was performed on the output received from the neural network. The importance or emphasis, referred to as a “hit”, was derived based on the frequency of occurrence for each keyword. Then the “hit-density” was calculated using the number of hits per fake tweet and the total number of words contained in

Table 3. Evidence of Fake News

Fake News	Evidence of Fake News
a) Genetically modified mosquitoes are the real cause of the birth defects	This statement is not true, because generally mosquitoes travel less distance flying, when released, and they do not bite humans or spread disease. Moreover, the genetically programmed mosquitoes die quickly.
b) Larvicide in drinking water causes microcephaly (Zika virus symptom)	Larvicide called pyriproxyfen, it is a chemical mimic of an insect hormone that signals larvae to stop growing, and insect hormones do not endanger humans. Moreover, Pyriproxyfen has been approved by the United States and there are places where brain damages had occurred when the larvicide hasn't been used.
c) News have blamed both a “bad batch of rubella vaccine” and the introduction of a new pertussis vaccine in Brazil, or aluminum in that vaccine	There was no news of rubella outbreak among pregnant women and no evidence of bad batch. Pertussis was used in many countries including the United States, and it caused no harm of microcephaly.
d) Brazil has been undercounting Microcephaly (A symptom where baby's head is significantly smaller than expected, could be due to Zika)	Cases about Zika were being reported in seven states in tropical northeast Brazil, 40 cases a year in the start but, were being increased by the end of the year reaching 600 by December.
e) Most pregnant women who have Zika have normal babies	Only 5% of U.S. pregnant women with Zika had baby with a birth defect, one in 10 pregnant women with Zika have babies with birth defects.
f) Microcephaly is caused by the MMR vaccine and pharmaceutical companies are blaming Zika virus in order to profit from selling Zika vaccines	The uncertainty about the source of origin of Zika virus led to the conspiracy theories such as the above statement. Such theories can have lasting effect on people's health-related decisions. They can avoid vaccination and distrust health authorities.
g) Americans are immune to the Zika virus	The statement is not true. There are already hundreds of cases registered in the US. This is the misinformation on the Internet could prove to be a significant health hazard.

Table 4. Neural Network-based Coding Scheme

Variable	Words
Threat cues	threat, terror, menace, medical, scourge
Severity cues	pain, sting, suffering, ache, burn, hurt, anguish, distress, plague
Protection cues	protect, screen, cover, guard, avoid, defend, prevent, safeguard, shield
Fear cues	fear, chill, hysteria, alarm, panic, horror, concern, scare

Table 5. Sample Tweets

Sample tweets	Description
... the impact of zika virus on fetuses must be seen as full spectrum syndrome ... zika virus outbreak now an international public health emergency	Tweets showing examples of threat cues
the main ones of zika are fever conjunctivitis red eyes rash muscular pain zika threat to babies may be greater than thought after virus found in stillborn girl ...	Tweets showing examples of severity cues
the best way to prevent zika is to prevent mosquito ... millions of modified mosquitoes to be released in brazil colombia zika fight	Tweets showing examples of protection cues
officials fear of zika cases following brazils rainy season fear scientists are bewildered by zikas path across latin america ...	Tweets showing examples of fear cues

Table 6. Results of Inter-Coder Reliability

	Round 1 (N = 39)	Round 2 (N = 40)	Total (N = 79)
Total	82%	83%	82%
Threat cues	90%	70%	80%
Severity cues	44%	90%	68%
Protection cues	90%	90%	90%
Fear cues	100%	80%	90%

Table 7. Results of Preliminary Validation

	Round 1 (N = 39)	Round 2 (N = 40)	Total (N = 79)
Total	95%	85%	90%
Threat cues	90%	60%	75%
Severity cues	89%	100%	95%
Protection cues	100%	100%	100%
Fear cues	100%	80%	90%

that fake tweet, which represents how densely the keywords are populated in the fake tweet [19, 41]. The next step was to dichotomize the hit-density to denote the presence or absence of each antecedent, namely threat, severity, protection and fear in the tweets (these are shown in Table 5).

4.5 Validation of Neural Network Coding

Based on [75], we performed a preliminary validation of the measurements of threat cues, severity cues, protection cues and fear cues in two-steps: (1) having human (student) coders manually code some randomly selected tweets, and (2) correlating human coding with neural measures for the random sample.

In the first step, we provided 40 random tweets to the two students, who helped us with content coding in two rounds. Both the students were pursuing graduate studies in the field of Information Technology at a southern university in the United States. Without providing any training, we asked them to code threat cues, severity cues,

Table 8. Correlation Table

	1	2	3	4	5	6
1	1.000	0.651***	0.002	0.032***	0.010*	0.013**
2		1.000	0.021***	0.030***	0.013**	0.020***
3			1.000	-0.017***	-0.015***	-0.001
4				1.000	0.378***	0.174***
5					1.000	0.552***
6						1.000

1: Hashtag count, 2: Follower count, 3: Protection cues, 4: Threat cues, 5: Fear cues, 6: Severity cues.

Table 9. Negative Binomial Results

	Estimate	Std. Error	Support
Intercept	-1.572***	0.011	
Hashtags	3.639***	0.014	
Followers	0.347***	0.004	
Threat cues	0.061**	0.021	H1 supported
Severity cues	-0.002	0.042	H2 not significant
Protection cues	0.053**	0.020	H3 supported
Fear cues	-0.044	0.035	H4 not significant

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

protection cues and fear cues as follows: '0' in the absence of information about that concept, and '1' otherwise. The coding sample provided to the students did not contain the neural measures. One tweet in the first round was duplicated so we removed it from the analyses.

Our goal was to repeat the coding process until the kappa value reached greater than 0.7 threshold. Higher kappa values indicate an agreed understanding between the coders [23, 26]. Both rounds of pilot coding resulted in a kappa value greater than 0.7 (see Table 6), thereby confirming that our coding was robust.

In the second step, we compared the inter-coded and the neural-based measurements of threat cues, severity cues, protection cues and fear cues (see Table 7). Results of the preliminary validation show that there were about 90% matches overall, indicating validity of the neural-based measurements. For protection cues and fear cues, there were 100% and 90% matches respectively, while for threat cues and severity cues, there were 75% and 95% matches, respectively.

4.6 Descriptive Statistics

As shown in Table 8, the Spearman correlation test indicates that all correlations are less than 0.7, indicating that no significant multi-collinearity problems exist [20].

4.7 Analysis

In order to test the hypotheses, we followed prior studies [24, 35]. Due to violation of normality in residuals, Ordinary Least Square (OLS) regression cannot estimate the appropriate statistics when the dependent variable is a count variable, as in our case of retweet counts. Negative binomial regression has been suggested as a possible method to deal with count-dependent variables [36]. So each of the four hypotheses were tested using negative

Table 10. Results for High Follower Count Users

	Estimate	Std. Error	z value
Intercept	− 0.17***	0.02	− 7.42
Hashtags	0.39***	0.00	90.47
Followers	0.04***	0.00	115.07
Threat cues	0.00	0.04	− 0.10
Severity cues	− 0.05	0.05	− 0.88
Protection cues	0.11**	0.04	3.01
Fear cues	− 0.03	0.06	− 0.57

* p < 0.05; ** p < 0.01; *** p < 0.001.

Table 11. Results for Low Follower Count Users

	Estimate	Std. Error	z value
Intercept	− 1.94***	0.01	− 136.08
Hashtags	0.86***	0.00	179.66
Followers	0.47***	0.02	22.73
Threat cues	0.08*	0.04	2.16
Severity cues	− 0.05	0.05	− 0.97
Protection cues	− 0.05	0.04	− 1.39
Fear cues	− 0.03	0.06	− 0.53

* p < 0.05; ** p < 0.01; *** p < 0.001.

binomial regression. The model was tested using negative binomial regression as follows:

$$\begin{aligned}
 \text{Log}(\text{Retweet_count}) = & \beta_0 + \beta_1 \text{Hashtag_count} \\
 & + \beta_2 \text{Follower_count} + \beta_3 \text{Threat_cues} \\
 & + \beta_4 \text{Severity_cues} + \beta_5 \text{Protection_cues} \\
 & + \beta_6 \text{Fear_cues} + e
 \end{aligned}$$

5 RESULTS

The results of the negative binomial regression analysis are summarized in Table 9. The results show significant positive effects of threat cues and protection cues and insignificant negative effect of severity and fear cues on propagation of tweets, at $p < 0.05$. This implies that threatening tweets as well as protection tweets are more likely to be shared in the network. However, we do not find significance to indicate that severity cues and fear cues in tweets are less likely to be shared in the network. Furthermore, the effects of hashtags and followers on cyber-rumor sharing are positive and significant at $p < 0.05$.

6 POST HOC ANALYSIS

In this section, we investigate how less or more followed users engage in fake news sharing. Twitter allows users with high follower count the power to influence opinion-making and agenda-setting processes. In order to gain a deeper insight into the effect of follower count on fake news sharing in Twitter, we investigate how sharing differs between different types of online users, particularly focusing on more vs. less influential users. [2] state that influential users were the ones who already had more number of followers. So, based on the follower counts in the sample, we focus on roughly the top and bottom half users.

Using negative binomial estimator for both groups, more and less influential users, we test the effect of threat, severity, protect and fear cues on fake news sharing. Results of the post-hoc analysis are presented in Table 10 and Table 11. Interestingly, a key difference in the results for these two groups is that, for the less influential users,

the results show a positive and significant effect of threat cues on fake news sharing, while for more influential users, we see a significant positive effect of protection cues (problem-focused coping) on fake news sharing. This means that the users that have fewer followers in Twitter focus on threat aspect of fake news, while the users that have more followers in Twitter focus on protection from the threat within fake news.

7 DISCUSSION AND CONCLUSION

The results of overall negative binomial regression indicate that Zika tweets that utilize threat cues and protection cues are positively associated with the likelihood of fake news sharing. This needs contextual interpretation. Fake news that report higher levels of threat are more likely to be shared in the network. One reason for the positive effect is that it may provoke large-scale anxiety due to the collective stress reaction about immediately threatening circumstances to large populations. Similarly, fake news reporting protection cues are also more likely to be shared in the network. However, we did not find significance for the effect of severity cues and fear cues on sharing in the network. The findings on threat and coping cues are in line with previous findings of offline misinformation studies.

As a contribution, (1) we have investigated the threat effect in the real-world context of a health crisis, (2) we have examined coping response in investigation of fake news sharing in the context of health crisis within large-scale social networks. This study has some limitations. Some of the Twitter messages were in Spanish and Portuguese. We dropped them from the analysis, due to research team's lack of proficiency in these languages. Furthermore, the selection of fake news stories is relatively small,³ however, this is a limitation of our data collection from Twitter. Future work could consider these non-English languages such as Portuguese (which is used by Brazilians). In order to extend the research further, we plan to investigate if specific types of coping measures, affect fake news sharing. Furthermore, instead of using dummy variables (presence/absence), future research can use the density measures in the regression for providing richer interpretations. Moreover, future research needs to "validate" the coding approach by collecting crowdsourcing data (e.g., Amazon Mechanical Turk).

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