An Investigation of Cyber-rumor Sharing: The Case of Zika Virus

Extended Abstract

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Introduction: Bright ICT faces a big challenge from cyber-rumors (Oh et al., 2013; Rao, 2016) (of which other related forms are fake information or misinformation). Cyber-rumors can become rapidly viral and transform into more harmful impacts in social networks (Webb et al., 2016). In a health crisis context, the more citizens accept cyber-rumors, the greater is the misunderstanding between healthcare experts and civil society, which can weaken the effectiveness of health crisis response.

The health sector cannot rely on public opinion to infer true information. In fact, much of the population is inadequately equipped to evaluate health-related information provided on the social media and healthcare communities. Reliable information would be from reputable sources such as medical journals, medical societies, WHO, CDC, etc. Typically, such organizations take a significant time to release statements. These delays encourage health-related cyber-rumors. This is the reason why, The Atlantic stated, "of all the categories of [misinformation], health news is the worst."[1]

A key element for successful health-related cyber-rumor management is "to understand what makes citizens prone to engaging in [health-related] cyber-rumor sharing" (Kwon & Rao, 2017; p. 307). We focus on citizens' cyber-rumor sharing tendency that arises within the larger context of a Zika virus health crisis on Twitter social media platform.

In the healthcare literature (though not related to cyber-space), it has been well established that threat situations and threat response facilitate citizens' behavior (Folkman, 2013; Rogers, 1975; Witte, 1992). Specifically, we build on existing rumor studies to explore whether citizens' cyber-rumor sharing is influenced by threat and severity (threat appeal), and strategies and expertise (response appeal). This research is a step towards "bright ICTs" that counter the negative effects of technologies and help establish a safe and secure society (Lee, 2015; Lee, 2016).

Theoretical Background: Threat situation is a contextual force that facilitates cyber-rumor sharing by invoking a sense of fear in public minds (Pezzo & Beckstead, 2006). For example, in the context of Zika virus, stories related to newborn brain defect may result in fear amongst pregnant women. In the fear appeals literature, it has been suggested that individuals manage their feeling of fear by engaging in various social behaviors, such as religious activities (Solomon et al., 1991). Kwon & Rao (2017), state that cyber-rumor sharing is one way to collectively manage fear associated with the threat situation.

Although Kwon & Rao (2017) have found that the threat situation is one of the important antecedents of cyber-rumor sharing, there has not yet been systematic research that examines the ways in which fear appeals (consisting of both threat appeals and response appeals) induced from a rumor message influence citizens' cyber-rumor sharing. In fact, Kwon & Rao (2017) also state that "studies that investigate the threat situational effect in the real-world context are very rare" (p. 309). In order to address this gap, this study examines the fear appeal effect on citizens' cyber-rumor sharing.

H1: Cyber-rumor sharing will be positively influenced by (a) threat appeal and (b) severity appeal in a rumor message.

H2: Cyber-rumor sharing will be positively influenced by (a) response appeal and (b) expertise appeal in a rumor message.

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 (Stieglitz & Dang-Xuan, 2013). We include these variables as controls.

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

Methodology: In this paper, we collected data for Zika outbreak from Twitter about the epidemic by recording the date, content, user, retweet count, Follower count, URL of web content, location from September 2015 to May 2017. We collected 161,463 tweets using #zika, #zikavirus and other Zika related hashtags. From this corpus of Twitter data, we extracted 50,929 unique English tweets related to known rumors in the Zika context. For the dependent variable, cyber rumor-sharing, we chose retweet count that denotes the number of times the rumor tweet has been shared. For coding the threat and response appeals, we utilized content of the tweet. We resorted to unsupervised machine learning using Neural Networks. Our aim was to find the keywords used in similar context as threat, severity, solutions and expertise within the rumor tweets.

This was accomplished in 3 steps: 1) From the 50,929 extracted rumor tweet samples, we created an overall dataset of 129,873 sentences. 2) We cleaned, lemmatized and stemmed the rumored tweets. This ensured that there are no special characters except line break tweets within the list of sentences. 3) We trained a word2vec model to identify similar words in a text (where similarity is based on the distance between the keywords). This trained neural network model understood the context of each word in the dataset, which was then utilized to find words most like the threat and response appeals – "virus" for threat, "disabled" for severity, "engineering" for strategies and "doctor" for expertise. Table 1 shows some of the words derived from the neural network, which are used to create the coding scheme.

The output of the neural network was used as the input for quantitative content analysis. The frequency of occurrence for each keyword was used as an indicator of the importance or emphasis, referred to as a "hit". We used the number of hits per rumor tweet and the total number of words contained in that rumor tweet to calculate "hit-density," which represents how densely the keywords are populated in the rumor tweet (Kim et al., 2005; Park et al., 2007). Finally, we dichotomize hit-density to denote the presence or absence of each antecedent, namely threat, severity, solutions and expertise, within the rumor tweet.

In order to examine the effect of threat appeal and response appeal on cyber-rumor sharing, we ran negative binomial regression.

$$Log(Retweets) = \beta_0 + \beta_1 Hashtags + \beta_2 URL + \beta_3 Followers + \beta_4 Threat + \beta_5 Severity + \beta_6 Response + \beta_7 Expertise + e$$

Table 1. Neural Network-based Coding Scheme

Variable	Words	Examples
Threat	vector, bacteriophage, virus, arbovirus	As summer travel season begins, we're reminding New Yorkers about the risks of traveling to areas with #Zika virus
Severity	handicapped, disabled, sick, dead, blind, doomed, lost, deformed, wounded, defeated	There is no longer any doubt that the #Zika virus can cause babies to be born with damaged brains, including microcephaly, says @CDCgov.
Strategies	evidence, engineering, design, inspect, science, technology, survey, review, practice, draft, examine, follow, investigate	Center director speaks on #zika at national roundtable; faculty finding ways to battle virus The prevalence of #microcephaly was not higher in the areas in which #pyriproxyfen was used
Expertise	doctors, scientists, physician, surgeon, specialist	Scientists have confirmed that the Zika virus does cause birth defects

Results: The results of the regression analysis are summarized in Table 2. The results show significant negative effects of threat ($p < 0.05$) and positive effects of severity ($p < 0.01$) on cyber-rumor sharing,

implying that the rumor tweets that state threat of Zika virus are less likely to result in cyber-rumor sharing, while the rumor tweets that identify the severity of Zika virus are more likely to produce a higher level of cyber-rumor sharing. The results also show significant positive effect of response ($p < 0.001$) and negative effects of expertise ($p < 0.01$) on cyber-rumor sharing. This means that the rumor tweets that identify strategies to respond to Zika virus are more likely to result in cyber-rumor sharing, while the rumor tweets that make claims to expert opinions to respond to Zika virus are less likely to produce a higher level of cyber-rumor sharing. Furthermore, the results also show significant positive effects of URLs ($p < 0.05$) and significant negative effects of followers ($p < 0.01$) on cyber-rumor sharing.

Table 2. Negative Binomial Results

	Estimate	**Std. Err.**	**Z Value**	**Exp(β)**
Intercept	0.711	0.116	6.092	2.035***
Hashtag	0.111	0.941	0.117	1.117
URL	0.109	0.043	2.500	1.115*
Followers	-0.065	0.023	-2.754	0.937**
Threat	-0.028	0.013	-2.121	0.972*
Severity	0.057	0.017	3.257	1.058**
Response	0.084	0.016	5.250	1.087***
Expertise	-0.117	0.043	-2.677	0.889**

Conclusion: The result of overall negative binomial regression indicates that rumor tweets that utilize fear appeals, including severity appeals and response appeals are likely to be shared more. The findings show that severity of the threat as well as response to the threat drives people into cyber-rumor sharing behavior.

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Appendix

Known rumors in the context of Zika virus were obtained from:

https://www.nytimes.com/interactive/2016/02/18/health/what-causes-zika-virus-theories-rumors.html?mcubz=0

https://www.elsevier.com/about/press-releases/research-and-journals/zika-conspiracy-theories-on-social-media-putting-vulnerable-people-at-risk

https://undark.org/2016/06/01/zika-conspiracy-theories-twitter/

http://www.snopes.com/americans-immune-zika-virus/

These known rumors are identified as follows:

1. Genetically modified mosquitoes are the real cause of the birth defects

2. Larvicide in drinking water causes microcephaly (Zika virus symptom)

3. Rumors have blamed both a "bad batch of rubella vaccine" and the introduction of a new pertussis vaccine in Brazil, or aluminum in that vaccine

4. Brazil has been undercounting Microcephaly (A symptom where baby's head is significantly smaller than expected, could be due to Zika)

5. Most pregnant women who have Zika have normal babies

6. Microcephaly is caused by the MMR vaccine and pharmaceutical companies are blaming Zika virus in order to profit from selling Zika vaccines.

7. Americans are immune to the Zika virus