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Character of COVID-19 Prevention Information of CDC and its Impact on Online Engagement

Fanbin Zeng[1]

Abstract

This study investigated the character of COVID-19 prevention information of Centers for Disease Control and Prevention (CDC) Twitter account and its impact on online engagement based on Framing theory, Extended Parallel Process Model (EPPM), and Reactance theory. The current study analyzed the content of tweets from the CDC Twitter account quantitatively and qualitatively. A census of the tweets from CDC (N1=201) and comments on the sample of these tweets (N2=100) were collected and subsequently coded. Results showed that COVID-19 prevention information was more gain-framed appeals than loss-framed. The number of comments, retweets, and likes were found to be highly and positively related to each other. Messages of more efficacy elements, rather than messages originality, in the tweets led to more online engagement. However, even the efficacy elements of the tweets of CDC account instigated online engagement, almost half of the comments from these tweets showed reactance. The theoretical implications were discussed, as well as limitations and suggestions for future research.

Keyword: *Framing theory; EPPM; Originality; Online Engagement; Reactance*

Introduction

COVID-19 has a great impact on Americans in 2020. It is caused by a new virus popularly referred to as coronavirus, which came from China in December, 2019. As of August, 8, 2020, there are 4,920,369 cases of COVID-19 with 160,220 deaths in the United States where the virus was confirmed to have outreached in January 2020, according to the notification of Centers for Disease

[1] Department of Communication, Western Illinois University, United States

Control and Prevention (CDC), one of the most prestigious representatives of public health authorities in America (CDC, 2020).

Although CDC, like other public health agencies, still employs print media, TV and radio to disseminate information to the citizens in risk intensification and attenuation, it also utilizes social media, such as Facebook and Twitter, to share real-time information through large population networks. This is because a social media platform can quickly air information to the public (White, 2011; Yates & Paquette, 2011). On 2nd of October, 2014, it is a topical Twitter conversation with the population that CDC initiated in an endeavor to assuage concerns and bestow correct information about the disease and transmission of Ebola (Crook et al., 2016).

Research on the social media usage by the CDC is beneficial for our understanding of messages in these social media platforms of state public health departments and how these messages influence individuals' online engagement of health information, such as COVID-19. According to Thackeray et al. (2012), there are more than 60% of state public health departments that utilized at least one social media platform to disseminate their information. The duty of the public health departments is to protect the people's health, advocate their well-being, and inform the threats to both their health and safety (Gostin, 2000). It is only understanding the online interaction between individuals and state public health departments that engenders us to improve the quality of health messages of public health departments.

There are already a range of research exploring the character of health information of social media and its impact on online engagement (Crook et al., 2016; Jiang & Beaudoin, 2016; Shi & Chen, 2014; Vos & Buckner, 2016). In terms of the character, some argued the health information of people who lived with HIV/AIDS group of Microblog, one of social media platforms in China, was predominantly encompassed emotional, informational, and instrumental support（Shi & Chen，2014). Others pointed out the element of perceived risk, subjective norms and self-efficacy exited in the articles of antismoking information on Microblog (Jiang & Beaudoin, 2016). With regard to the impact, Vos and Buckner (2016) found that there were few tweets about the H7N9 virus that transmitted efficacy information which could assist the public in sharp contrast the crisis suitably. In addition, Chen, Yang, Fu et al.(2019) noticed the major bodies of the articles that contained low extents of efficacy but high extents of threat resulted in the failure of generating public engagement, yet those with high levels of threat and efficacy acquired the largest number of likes. However, most studies about health messages using social media are major descriptive research (Chou et al. 2013) even though some of them employed one or two theories to analyze the issue (Jiang & Beaudoin, 2016; Chen, Yang, Fu et al., 2019). There is lack of combining different theoretical frames to explore the character of health messages of social media and its impact on online engagement in the past research, which is a major gap the present research hopes to fill.

The present study intends to investigate the character of COVID-19 prevention information of CDC Twitter account and its impact on online engagement based on incorporating Framing theory, Extended Parallel Process Model (EPPM), and Reactance theory, as well as exploring more audiences' online engagement with social media content. The current study further analyzes the content of tweets from CDC official account. A census of COVID-19 tweets (N1=201) and comments on the sample of these tweets (N2=100) were collected and subsequently coded into a standardized and impartial manner.

There study firstly, examines different theoretical aspects and proposes questions and hypotheses accordingly. It then reveals the detail and comprehensive methods that are used how to collect and analyze the data of this study. Finally, results are discussed and conclusions compared with other literature for the sake of appreciating the contributions and limitations of this research.

Framing Theory

Framing theory includes gain-framed and loss-framed appeals. A gain-framed appeal accentuates the benefits of adopting advocated activities or perspectives and a loss-framed appeal highlights the detriments of abandoning activities or perspectives. The persuasive effects of gain-framed and loss-framed appeals possess two different psychological approaches----the former derived from prospect theory and the latter from the phenomena of negativity bias and loss aversion. The negativity bias and loss aversion appears to argue that loss-framed appeals will generally be more persuasive than gain-framed appeals. The prospect theory seems to suggest that the comparative persuasiveness of gain-framed and loss-framed appeals would alter based on whether the advocated action is a disease detection behavior or a disease prevention behavior because prospective costs (loss-framed) or benefits (gain-framed) could have outstandingly dissimilar influences on individuals' decision making (Tversky & Kahneman, 1981).

Riskier actions are more motivated by loss-framed appeals, such as disease detection behavior, while less-risky behaviors are more encouraged by gain-framed appeals like disease prevention behaviors. In terms of COVID-19 prevention information, gain-framed appeals are more persuasive than loss-framed appeals because prevention behaviors are viewed as low-risk behaviors. There are almost 100 studies that recommends gain-framed appeals have significantly more persuasive power than loss framed appeals in disease prevention information, but not other preventive actions such as safer-sex behaviors, skin cancer prevention deportments, or diet and nutrition practices (O'Keefe, & Jensen, 2007). As an official account, CDC Twitter account might harness more gain-framed appeals in message designing so as to be more persuasive. Consequently, the following hypothesis 1 is proposed:

H1: COVID-19 prevention information of CDC Twitter account is more gain-framed appeals than loss-framed appeals.

Online Engagement

In social media environment, online engagement is defined to contain an audience's feelings when he/she perceive a movement, and manner of reaction to media messaging (Stavrakantonakis et al., 2013). Social media offer great opportunities for individuals' online engagement, so Twitter, Facebook and other social media platforms encourage frequent users expressions of their thought, perceptions and opinions. Online engagement is measured by audiences' actions on existing posts, including commenting on, indicating interest in or liking of, and sharing with others on social media. Online engagement with social media, or social media engagement, means to be liked, shared, or commented on, which represents its power to engage its audiences on social media (Helene, 2012; Jiang & Beaudoin, 2016). Audiences are more responsive to and more influenced by the movement as they are higher engaged in a media campaign (Bronner & Neijen, 2006).

Since engagement is an important step in the persuasion process that leads to behavior change, creating engaging messages has been a major focus in health research (Crutzen et al., 2011; Strecher et al., 2008). An article's online engagement was measured by the sum of shares, reactions, and comments on social media in previous studies (Jiang & Beaudoin, 2016; Rus & Cameron, 2016). Platt et al. (2016) evaluated online engagement with Facebook by frequency of posts per users, length of discussion threads, and the number of participants in discussion thread based on conducting content analysis. However, different health communication campaigns yield different engagements on account of divergent audiences and channels. This research focuses on audience's online engagement with COVID-19 prevention information of CDC Twitter account, so we propose the following research question:

RQ1: What are the characteristics of an audience's online engagement with COVID-19 prevention information of CDC Twitter account?

Extended Parallel Process Model (EPPM)

The extended parallel process model (EPPM) predict how persons would react when confronted with fear inducing stimuli (Witte, 1992) and it defines four key factors: susceptibility, severity, self-efficacy, and response efficacy. First, susceptibility is the perception that an individual feels the possibility of the threat impacting him/her. Second, severity is the perception an individual has of the immensity of the threat. Third, self-efficacy is information about how the target individual is able to accomplish the recommended response. Fourth, response efficacy is the message features that stress the potency of an individual's response in avoiding the threat.

The EPPM conceptually distinguishes between threat as a message component and perceived threat. Threat as a message component comprises message features that provide factual or visual information about the severity of the threat and the target population's susceptibility to the threat; perceived threat is the subjective evaluation of the threat contained in the message. Both severity and susceptibility of the threat as messages features are often manipulated in experimental studies (Witte, 1994).

The EPPM also conceptually distinguishes between efficacy as a message characteristic and perceived efficacy (Witte, 1994).Efficacy as a message features comprises response efficacy and self-efficacy; perceived efficacy is defined as cognitions about the effectiveness, feasibility, and ease with which a recommend response alleviates or help in avoiding a threat. Efficacy is also manipulated in the EPPM experiments (McKay et al., 2004).

Based on the inputs of susceptibility, severity, self-efficacy, and response efficacy, the EPPM predicts three possible outcomes. The first is danger control. The EPPM proposes that individuals will engage in danger control that involves making efforts to lower their risk when there are both high perceived threat and high perceived efficacy. The second is fear control. While the perceived threat is high but perceived efficacy is low, individuals find ways to control their fear. The third is no response. There is no response from people when the severity or susceptibility of the danger is perceived as low. For example, Witte (1991) found no response, the least amount of attitude, intention, and behavior change in the low threat situation, disregarding efficacy level.

Most of the time, the overall goal of EPPM messages design is to encourage the danger control process. As a state public health department, CDC should design messages to encourage danger control, such as increasing the threat and efficacy of messages to improve online engagement which can help for danger control. Wakefield et al. (2010) argued discussions and engagement in the China Tobacco Control Media Campaign could assist advantageous changes in people's smoking behavior. In terms of the relationship between the threat and efficacy of messages and online engagement, Jiang and Beaudoin (2016) argued the characteristics of content, including subjective norms, perceived risk (i.e. threat), and self-efficacy (i.e. efficacy) can stimulate audience engagement in the health campaign. Based on these mentioned research, we propose the following hypothesis 2a and 2b:

H2a: Threat (susceptibility and severity) of COVID-19 prevention information positively predicts an audience's online engagement with social media.

H2b: Efficacy (self-efficacy and response efficacy) of COVID-19 prevention information positively predicts an audience's online engagement with social media.

Message Originality

It is original content that health campaigners always rely on to push their messages to listeners (Nyilasy & Reid, 2009) because original content exerts more significant influence on audiences than non-original content. In the context of social media, previous study has operationally defined original and non-original message in terms of tweets and retweets respectively (Neiger et al., 2013). What CDC Twitter account tweets and retweets constitutes different information. As an important health organization, the original tweets information from CDC Twitter account should comprise more susceptibility, severity, self-efficacy and self-efficacy character than its retweets non-original information. At the same time, compared with retweets, Neiger et al. (2013) showed that the original tweets were more effective in developing social relationships and engaging followers than non-original retweets. Based on previous literatures, we propose the following hypothesis:

H3: Original COVID-19 prevention tweets have more online engagement with social media than non-original COVID-19 prevention information retweets.

Reactance

Although according to the EPPM, threatening messages leads to danger control when both perceived threat and efficacy are high, it also posits reactance to threatening messages (Witte & Allen, 2000) when people feel their freedom is threatened (Brehm & Brehm, 1981; Rains & Turner, 2007), and even leads individuals to reject persuasive messages with intense reactance responses. Reactance, the motivation to regain a freedom after it has been lost or threatened, leads people to resist the social influence of others. There are four components to reactance theory: freedom, threats to freedom, reactance, and restoration of freedom. Freedoms are beliefs about the ways in which one can have. Psychological reactance is the motivational state that is hypothesized to occur when a freedom is eliminated or threatened with elimination.

The scholars who proposed the reactance theory showed that this theory was not able to be measured (Brehm, 1966; Brehm & Brehm, 1981). However, Dillard & Shen (2005) argued that there is a possibility to use a combination of self-report cognitive and emotional measures to create a more or less direct index of reactance. So, this research also desires to utilize combinations of cognition and affect to measure reactance. As no more research on what is the reactance of individuals on health messages before, this study proposes the following research question 2:

RQ2: What is reactance of the public replied to the COVID-19 prevention information of CDC Twitter account?

Methodology

The data includes tweet of CDC and comments on these tweets. A content analysis of COVID-19 prevention information of CDC Twitter account from Mar 12, 2020 to April 20, 2000 with total 201 tweets was conducted and the unit of analysis for this study was a single article. Utilizing the random function in excel, the coders randomly selected 20 tweets (approximately 10% of the corpus) from the complete dataset samples of CDC official account. Among these 20 tweets, 5 comments following these tweets were randomly selected with total 100 tweets in comments as analysis sample for this research. Coding scheme was created to reflect how the tweet comments expressed sentiments. Statistical Product and Service Solutions (SPSS) software was used for all statistical analyses.

Manual content analysis was used in the procedure of the current study. Specifically, two research coders received two days of training in the coding task. Both coders encrypted the same 10 tweets or retweets by reading each messages and the noting the code discussed previously. The beginning reliability score was less than 0.7, so the two coders met to discuss discrepancies, revised the codebook, and then coded all the tweets with the refined codebook. Inter-coder reliability scores on this set of the pilot coding data was again calculated using Krippendorff's (1970) alpha and the scores was more than 0.9, representing high reliability.

Measurement

Gain-framed appeals and Loss-framed appeals

Loss-framed message focused on how not using prevention activity may lead to negative consequence and gain-framed messages focused on how adopting prevention activity may lead to positive outcomes. All the tweets according to each of the gain-loss frame were coded in level of loss-framed (0) and gain-framed

Severity

Severity means the perception the individual has of the magnitude of the threat. It appears to be a multifaceted concept, including somatic manifestations of fear, permanent consequences, financial/career issues, mortality, and even mental consequences (Milne et al., 2000). In the present study, severity was coded when tweets or retweets included message about the seriousness of COVID-19 when addressing numerical figures or statistic related to COVID-19 mortality. All the tweets according to severity were coded in level of absent (0) and present (1).

Susceptibility

Susceptibility refers to the perception the individual has of how likely the threat is to be impactful. Witte (1992) stated susceptibility as the faith about an individual's probability of experiencing a threat. For instance, individuals who perceives they are susceptible to HIV infection discerns themselves as being 'at-risk'. In the present study, susceptibility was coded when tweets include messages about the likelihood of developing COVID-19, when addressing morbidity rates of COVID-19, and when addressing specific or other potential risk factors. All the tweets according to susceptibility were coded in level of absent (0) and present (1).

Self-efficacy

Self-efficacy entails people's belief in their capability to implement a special activity in order to attain a consequence. In the research of self-efficacy, Bandura (1977) designated self-efficacy was anticipations of personal efficacy deciding whether behavior will be inaugurated, how much effort will be enlarged, and how long it will be carried. Witte (1994) pointed out self-efficacy is a person's beliefs about his or her ability to perform the advocated response to avert the threat. In the present study, self-efficacy was coded when tweets or retweets include messages about individuals' ability to perform the recommended behavior to control threat. This incorporates addressing the way people deal with nervousness associated with getting vaccinations, addressing alternative ways people can reduce the risks of COVID-19, and addressing the ways people can select a doctor or a clinic. All the tweets according to perceived self-efficacy were coded in level of absent (0) and present (1).

Response Efficacy

Response efficacy is defined as the perception the individual has that the action will result in successful avoidance of the threat if implemented. Thrasher et al.(2016) measured perceived response efficacy as the benefit of quitting smoking by asking, "How much do you think you would benefit from health and other gains if you were to quit smoking permanently in the next 6 months?", with a 1-to 9-point scale. So in the present study, response efficacy was gauged the benefit from carrying out preventing COVID-19 suggestions. It was coded when a tweet or retweet includes messages about effective and feasible ways to avoid the threat by addressing either effectiveness of the vaccination in preventing. All the tweets relating to response efficacy were coded in level of absent (0) and present (1).

Threat

Threat including severity and susceptibility was added up by these two values. The scores of perceive threat comprises from 0 to 2 which represents 'No threat element', 'one threat element' and 'two threat elements' respectively.

Efficacy

Efficacy involving self-efficacy and response efficacy was added up by these two values. The scores of efficacy comprises from 0 to 2 which represents 'no efficacy element', 'one efficacy element' and 'two efficacy elements' respectively.

Message Originality

Following previous research (Jiang & Beaudoin, 2016; Neiger et al., 2013), the present study considered tweets created by CDC official account regarding COVID-19 prevention information to be original whereas retweets from other accounts about this aspect to be non-original. All the tweets relating to message originality were coded in level of non-original retweets (0) and original tweets (1).

Online Engagement with social media

Online Engagement with social media was measured as the sum of numbers of likes, retweet, and comments because liking, retweet, or commenting on a particular message represents responsive online behavior to the message. Park et al. (2015) operationalized engagement as the sum of number of likes and retweets. Kim and Kim (2020) measured engagement as the sum of amount of likes and comments. Based on the above, the sum of number of likes, retweets and comments were adapted into the scale of online engagement.

Reactance

Previous measurement of reactance involves two procedures (Dillard & Shen, 2005): One used Likert scales to assess anger; another asked respondents to list any thoughts that they had while reading the messages. The results were coded by researchers in a four-step process that unitized the data, then screened out self-reports of emotions as well as cognitions that were unrelated to the messages or topic. According to the research of Dillard & Shen (2005), reactance measurement combined two major components: Anger and negative cognition so that these two aspects were also used to measure reactance in this research. Anger, skepticism, and humor or sarcasm, the three latter of which were regarded as negative cognitions, were specifically involved into the reaction measurement of this study.

Results

The Character of COVID-19 Prevention information from CDC **Twitter Account**

First, with regard to 'H1: COVID-19 prevention information from CDC Twitter account is more gain-framed appeals than loss-framed appeals', the results show that 30.8% (62) articles involve gain frame appeal but no articles implies loss frame appeal. The remaining 69.2% (139) articles have no gain or loss frame appeal. Therefore, H1 that COVID-19 prevention information from CDC Twitter account is more gain-framed appeals than loss-framed appeals was supported.

In terms of "RQ1: What are the characteristics of audience's engagement with COVID-19 prevention information from CDC Twitter account?" the current article initial examined it with quantitative analysis. Among all the 201 tweets, the means of the number of comments is 168.73(SD=311.323, range 10-3000), the means of the number of retweets is 1139.04 (SD=2061, range 57-15000), and the means of number of likes is 2038.87(SD=4369.97, range 82-29900). When examining the relationships between the number of comments, retweets and likes, three Pearson product-moment correlations were conducted. The number of comments was found to be significantly and positively correlated to the number of retweets, r (200) = 0.879, p<0.001, which was considered a high relationship. The number of comments was found to be significantly and positively related to the number of likes, r (200) = 0.851, p<0.001, which was considered a high relationship. The number of retweets was found to be significantly and positively related to the number of likes, r (200) = 0.946, p<0.001, which was considered the highest relationship of the three examined.

The outcome of this research showed that 8.0% (16) articles involved 'severity', 14.4% (29) articles involved 'susceptibility', 63.2% (127) articles involved 'self-efficacy', and 30.8% (62) articles involved 'response efficacy'. Consequently, the tweets in CDC official account mostly involved 'self-efficacy' messages

Adding up these numbers, the results showed that 82.1% (165) articles involved one of the EPPM components: threat or efficacy. To be specific, 17.9% (36) articles contained 'No threat element and no efficacy element', 10.0% (20) carried 'One threat element and no efficacy element', and 0.5% (1) accommodated 'Two threat elements and no efficacy element'.39.3% (79) articles contained 'No threat element and one efficacy element', 9.0% (18)

held 'One threat element and one efficacy element', and 1.0% (2) seated 'Two threat elements and one efficacy element'. It is also found that 21.9% (44) articles carried 'No threat element and two efficacy elements', 0.5% (1) accommodated 'One threat element and two efficacy elements', and 0 % (0) seated 'Two threat elements and two efficacy elements' (Please see table 1):

Table 1: *Distribution of article involved Threat and efficacy*

	Article	
	Frequency(N)	Percent (%)
No threat element and no efficacy element	36	17.9
One threat element and no efficacy element	20	10
Two threat elements and no efficacy element	1	0.5
No threat element and one efficacy element	79	39.3
One threat element and one efficacy element	18	9
Two threat elements and one efficacy element	2	1
No threat element and two efficacy elements	44	21.9
One threat element and two efficacy elements	1	0.5
Total	201	100

In addition, more descriptions and examples of article categories emerged from the data (Please see table 2).

Table 2: *Descriptions and Examples of Article Categories*

Content	Description	Example tweets or retweets
No threat element and no efficacy element	Article that has No threat elements and no efficacy elements	CDC thanks all the healthcare workers who are fighting #COVID19. For detailed resources to guide you as you keep our communities safe, see: https://bit.ly/33UUNA2
One threat element and no efficacy element	Article that has one threat element and no efficacy elements	CDC report shows the percentage of deaths due to pneumonia not associated with flu has increased sharply since the end of February. This could be caused by #COVID19. https://bit.ly/2X9KpDc
Two threat elements and no efficacy element	Article that has two threat elements and no efficacy elements	The CDC network that tracks #COVID19 hospitalization rates shows overall hospitalization rate increasing, w/ rates increasing w/ age. Rates in ppl 65+ are highest at 39 per 100,000 people. Ppl 65+ should take special precautions to prevent COVID-19. https://bit.ly/2WdYQ8I
No threat element and one efficacy element	Article that has No threat elements and one efficacy element	Parents: Help your child stay connected with loved ones during #COVID19. Encourage them to call or video chat with friends and family. They can also send pictures, emails, or letters. See more: https://bit.ly/3e8hWUq. #PhysicalDistance
One threat element and one efficacy element	Article that has one threat element and one efficacy element	As of April 1, 46 U.S. states and 1 US territory report some community spread of #coronavirus (COVID-19). Of those, 25 states report #COVID19 cases are "widespread." Stay at home and practice social distancing. For info on your state, see https://bit.ly/39gqyEH.
Two threat elements and one efficacy element	Article that has two threat elements and one efficacy element	People over 65 and people with underlying medical conditions are at higher risk for getting seriously ill from #coronavirus. Together, we can help slow the spread. Learn ways to protect yourself and others at http://coronavirus.gov. #COVID19
No threat element and two efficacy elements	Article that has No threat elements and two efficacy elements	Wearing a cloth face covering CORRECTLY can help prevent the spread of #COVID19 to others. When you go out on essential trips, follow these "do's". If you have a child, remember those under age 2 should not wear a face covering. See https://bit.ly/2R9av5m.
One threat element and two efficacy elements	Article that has one threat element and two efficacy elements	A new report in @CDCMMWR shows serious disease & death from COVID-19 in US is higher in older age groups, similar to other countries. Communities should encourage hand hygiene & social distancing to help slow the spread of COVID-19 & protect older adults. http://bit.ly/2xP3EaF
Two threat elements and two efficacy elements	Article that has two threat elements and two efficacy elements	No Examples

Finally, the results showed that 85.6% (172) articles contained original COVID-19 tweets and 14.4% (29) articles involved non-original COVID-19 retweets.

The Impact of COVID-19 Prevention information on Online Engagement

The impact of EPPM elements

In terms of H2a and H2b, this research first wanted to determine whether there was a significant difference in the threat and efficacy messages and the number of comments. A one-way ANOVA was calculated using the threat and efficacy messages as the independent variable and the number of comments as the dependent variable. A significant difference was noted: F (4, 192) = 7.672, $p<0.001$, $\eta 2=0.138$.

In a following-up to this question, a Turkey HSD post hoc was conducted. The Turkey HSD post indicated that there was a significant different(Please see table 3) between 'No threat element and no efficacy element'(M=90.06, SD=101.333) and 'No threat element and two efficacy elements'(M=385.75, SD=566.875), between ' One threat element and no efficacy element' (M=119.00, SD=161.611) and ' No threat element and two efficacy elements(M=385.75, SD=566.875)', between 'No threat element and one efficacy element' (M=107.20, SD=147.407) and ' No threat element and two efficacy elements '(M=385.75, SD=566.875), and between 'One threat element and one efficacy element' (M=132.44, SD=136.773) and ' No threat element and two efficacy elements' (M=385.75, SD=566.875). However, the Turkey HSD post hoc test did not find the significant difference between other relationships.

Table 3: *Distribution of perceived threat and efficacy when dependent variable is the number of Comment*

Perceived threat and efficacy	Mean	Std. Deviation	N
No threat element and no efficacy element	90.06	101.333	36
One threat element and no efficacy element	119	161.611	20
No threat element and one efficacy element	107.2	147.407	79
One threat element and one efficacy element	132.44	136.773	18
No threat element and two efficacy elements	385.75	566.875	44
Total	169.79	314.233	197

Second, this research question wanted to determine whether there was a significant difference in the threat and efficacy messages and the number of retweets. A one-way ANOVA was calculated using the threat and efficacy messages as the independent variable and the number of retweets as the dependent variable. A significant difference was noted: F (4, 192) = 7.480, $p<0.001$, $\eta2=0.135$.

In a following-up to this question, a Turkey HSD post hoc was conducted. The Turkey HSD post indicated that there was a significant different between(Please see table 4) 'No threat element and no efficacy element'(M=448.50, SD=456.669) and 'No threat element and two efficacy elements'(M=2541.80, SD=3457.315), between ‘One threat element and no efficacy element’ (M=797.40, SD=1421.829) and ' No threat element and two efficacy elements’(M=2541.80, SD=3457.315) ', between ‘No threat element and one efficacy element’ (M=873.28, SD=1470.755) and ' No threat element and two efficacy elements'(M=2541.80, SD=3457.315), and between 'One threat element and one efficacy element' (M=749.94, SD=568.548) and '' No threat element and two efficacy elements(M=2541.80, SD=3457.315). However, the Turkey HSD post hoc test did not find the significant difference between other relationships.

Table 4: *Distribution of perceived threat and efficacy when dependent variable is the number of retweets*

Perceived threat and efficacy	Mean	Std. Deviation	N
No threat element and no efficacy element	448.5	456.669	36
One threat element and no efficacy element	797.4	1421.829	20
No threat element and one efficacy element	873.28	1470.755	79
One threat element and one efficacy element	749.94	568.548	18
No threat element and two efficacy elements	2541.8	3457.315	44
Total	1149.35	2080.366	197

Third, this research question wanted to determine whether there was a significant difference in the threat and efficacy messages and the number of likes. A one-way ANOVA was calculated using the threat and efficacy messages as the independent variable and the number of likes as the dependent variable. A significant difference was noted: $F(4, 192) = 7.602$, $p<0.001$, $\eta 2=0.137$.

In a following-up to this question, a Turkey HSD post hoc was conducted. The Turkey HSD post indicated that there was a significant different(Please see table 5) between 'No threat element and no efficacy element'(M=951.75, SD=1442.598) and 'No threat element and two efficacy elements'(M=5077.48, SD=8045.096), between 'One threat element and no efficacy element' (M=1252.55, SD=2571.038) and 'No threat element and two efficacy elements'(M=5077.48, SD=8045.096) , between 'No threat element and one efficacy element' (M=1313.97, SD=1971.433) and ' No threat element and two efficacy elements '(M=5077.48, SD=8045.096), and between 'One threat element and one efficacy element' (M=1013.22, SD=717.330) and ''No threat element and two efficacy elements'(M=5077.48, SD=8045.096). However, the Turkey HSD post hoc test did not find the significant difference between other relationships.

Table 5: *Distribution of perceived threat and efficacy when dependent variable is the number of likes*

Perceived threat and efficacy	Mean	Std. Deviation	N
No threat element and no efficacy element	951.75	1442.598	36
One threat element and no efficacy element	1252.55	2571.038	20
No threat element and one efficacy element	1313.97	1971.433	79
One threat element and one efficacy element	1013.22	717.33	18
No threat element and two efficacy elements	5077.48	8045.096	44
Total	2054.64	4411.842	197

Therefore, H2a that predicted threat (susceptibility and severity) on COVID-19 prevention information positively influences engagement with social media was not supported because there is no difference between the number of comments, retweets, and likes of the tweets that involved 'One threat element and no efficacy element' and 'One threat element and one efficacy element' with other tweets. However, H2b that predicted that efficacy (self-efficacy and response efficacy) on COVID-19 prevention information positively influences engagement with social media was supported because the number of comments, retweets, and likes of the tweets that involved "No threat element and two efficacy elements" are more than other tweets.

The impact of originality

With regards to 'H3: Original COVID-19 prevention tweets have more engagement with social media than Non-original COVID-19 prevention information retweets', an independent t test was first conducted to determine whether original tweets (M=140.23, SD=274.93) and non-original retweets (M=337.72, SD=442.835) affected the number of comments. Levene's test for equality of variances was significant (F=17.772, p<0.001), so equality of variances cannot be assumed, t (31.736) =2.327, p=0.026. There is a significant difference in the number of comments between original tweets and non-original retweets.

Second, an independent t test was conducted to determine whether original tweets (M= 1033.77, SD= 1877.722) and non-original retweets (M= 1763.41, SD= 2887.294) affected the number of retweets in the comment. Levene's test for equality of variances was significant (F=10.019, p=0.002), so equality of variances cannot be assumed, t (32.109) =1.315, p=0.198. There is no significant difference in the number of retweets in the comment between original tweets and non-original retweets of CDC official account.

Third, an independent t test was conducted to determine whether original tweets (M= 1616.81, SD= 3283.318) and non-original retweets (M= 4542.07, SD= 7936.268) affected the number of likes. Levene's test for equality of variances was significant

($F=28.825$, $p<0.001$), so equality of variances cannot be assumed, t (29.635) =1.957, p=0.06. There is no significant difference in the number of likes between original tweets and non-original retweets.

Therefore, hypothesis 3 that original COVID-19 prevention tweets have more engagement with social media than non-original COVID-19 prevention information retweets was not supported. A following up analysis on 29 non-original retweets shows that 37.9% (11) articles from Dr. Robert R. Redfield who is CDC director, 10.34% (3) from Surgeon General, and 20.68(6) from the White House. These signified CDC, as an official account, always retweeted other authoritative information to audiences, instead of unreliable messages, which also attracted its audience's online engagement.

Reaction analysis of COVID-19 Prevention information of CDC Twitter Account

This study used the tweets of comments from CDC official account, which was similar to user self-reports, to analyze the original content. Concerning 'RQ2: What is reactance on the public replied to the COVID-19 prevention information from CDC Twitter account', this study randomly selected 20 tweets from CDC official account as a sample. These 20 tweets or retweets involved recommendations on wearing a cloth face mask, geographical differences in COVID-19 cases and death statistics within the United States cases and deaths in the U.S, treatment of members' sick with #COVID19, strategies aimed at helping our most critical workers, household tips, ongoing investigations on COVID19, using #telemedicine for routine medical visits, guidance on protecting a jobsite's essential workers, incarcerated persons, and potential visitors from coronavirus, SARS-CoV-2 RNA found on surfaces in cruise ship cabins, defer any travel on cruise ships, and using '#askCDC'.

Previous research have demonstrated that classified tweets by sentiment had been shown to track public opinion (Barbosa & Feng, 2010; O'Connor et al., 2010; Tumasjan et al., 2010).The 100 comments following these Tweets were coded with a qualifier if present. These tweets were categorized the following items: Anger, skepticism, humor or sarcasm, frustration, fear, happiness, question, and no emotions or unrecognizable sentiments. More detail information is as bellows:

First, tweets express anger. The following are examples: "CDC should allow N95 Masks to be distributed to the public as well. Amazon refuses 2 sell masks to the public. It's the public spreading the virus for crying out loud". "If you want to stop the crush on med workers, mask the citizens! TESTING!!! IDIOTS..... TESTING is the only safe way out of all this. MASSIVE testing of as many Americans as POSSIBLE..... Massive testing. Jesus you are DUMB". "You (CDC) need a good clean out and update—TOP TO BOTTOM!!!!!! Your numbers are misleading and false. Hiding the healthy is irresponsible. You are causing a worse #pandemic all to push unnecessary and unwanted #vaccinations". "Why didn't CDC recommend wearing masks earlier? CDC is a part of the problem, not the solution. Asian countries provide their people with free n95 masks. The richest country in the world is telling its people to wear homemade masks instead of proper ones."

Second, tweets express skepticism. The following are examples: ‘Masks are only useful if they are waterproof’; ‘There are individuals who’ve tested positive for COVID-19 yet never experienced ANY symptoms, so what’s your point?” “If an asymptomatic carrier coughing and sneezing next to you or in your face, I bet “washing hands” will do you no help at all ”;”” Preventing spreading of the disease is not just one thing.... It should be a comprehensive approach, including but not “just” washing your hands”.

Third, tweets are comedic or sarcastic. The following are examples: ‘ReallyKnox County isn’t low infection rate. We don’t have tests so we don’t know. Now, we’re just all waiting to be set loose on Tuesday so we can keep spreading the viruses’. ‘Ridicule; Hard to stay 6 feet away. My arms are too short! Avoid peak hours?’ ‘What a luxury majority of people don’t have! This is the first pandemic caused by social media* Fixed it for you’.

Fourth, tweets express annoyance, scorn, or volatile contempt. The following are examples: ‘for hospital switchboard operator?’ ‘Makes “us all” feel like cannon fodder? In case you haven’t heard, the majority who are dying like flies in NYC are the homeless.’

Fifth, tweets express COVID-19 related fear, anxiety, worry, or sadness for self to others. The following are examples: ‘fears dogs and cats could be coronavirus 'super spreaders' as virologist questions safety. A CORONAVIRUS expert has warned pet owners they could be at risk of not only infecting their animals but also having the virus transmitted to them through contact with their pets, with the science...’;’It killed even the Flu virus !

People spreading long before 1st symptoms. That's what made it so difficult to track & recognize as capable of community spread per most writings.'; 'I'm pretty sure I will never set foot on another cruise ship in my life, so my doctors from Wuhan was saying, that it could take UP to 28 days !!!!'.

Sixth, tweets express joy, happiness, gratitude or sense of peace. The following are examples: 'Surgeon General, super smart AND can make a mask!! I am impressed!!' 'What's good bro @Surgeon General; this would also be great for patients with disabilities. We can cover our nose/mouth with anything!! A tee shirt! A scarf! Just do it already!!'

Seventh, tweets asked questions or contained a question mark. The following are examples: 'you realize that you have lost credibility by bending to what trump wants right?'' Do you have scientific evidence showing homemade face covering is effective to prevent spreading the coronavirus? ''DMV in California, a B.MERINO , wants me in a letter dated 3.27.2020to drive 1 hour to have a doctor's appointment for notice of reexamination. What does CDC and CA SAY I SHOULD DO' 'Does this mean it is not classified as other viruses according to the NxHx system?'

Eighth, tweets express no emotions or unrecognizable sentiments. The following are examples: 'Also true; I don't even know what that means'; 'Please help us spread the word to put our FREE app in the hands of patients who need it'. 'We offer secure remote symptom and vital signs tracking'. 'Providers can set alerts and chat with patients'.

In all, among these tweets, there are 16% articles reflecting anger, 18% incorporating skepticism, 12% comprising humor or sarcasm, 2% containing frustration, 6% involving fear, 7% including happiness, 15% encompassing question, and 24% no emotions or unrecognizable sentiments. According to the measurement of reactance in this present research, there are 46% tweets(16% articles reflecting anger+18% incorporating skepticism+12% comprising humor or sarcasm) encompassing reactance.

Discussion

This study examined the character of COVID-19 prevention information of CDC twitter account and its impact on online engagement with social media, providing a new approach to examine the effects of social media–based health campaigns. The content of social media might stimulate people's online engagement (i.e., liking, retweets, and commenting) (Wakefield et al., 2010; Chen, Guo, & Shi, 2019), which promotes actual behaviors (Alhabash et al., 2015).The principal findings are as bellows:

First, the hypothesis that COVID-19 prevention information of CDC Twitter account is more gain-framed appeals than loss-framed appeals was tested. This finding conformed to previous research. For example, Salovery, Schneider and Apanovitch (2002) argued that gain-framed information might have more possibility to expedite performing prevention behaviors that might not be discerned as risky in any degree. Although this research failed to indicate that a gain-framed appeal was more significantly persuasive than a loss-framed appeal, it showed all the tweets of COVID-19 prevention information from CDC Twitter account are gain-framed appeals and no loss-framed appeals.

Second, the number of comments, retweets, and likes were found to be highly and positively related to each other in CDC official account; 'self-efficacy' messages in the tweets in CDC official account are more than other EPPM elements. These findings contradict Vos & Buckner (2016)'s research, which found less than 2% of the tweets about the H7N9 virus collected contained efficacy information in Twitter. This is maybe our research focus on the tweets of CDC official account while Vos & Buckner (2016) centered on all the related tweets. The number of comments, retweets, and likes of the tweets that involved "No threat element and two efficacy elements" are more than other tweets, so messages of efficacy elements (self-efficacy and response efficacy) on COVID-19 prevention information positively predicted online engagement with social media. In addition, the tweets with more efficacy components had a greater number of online engagements than others. Therefore, more efficacy elements in the tweets lead to more online engagement with social media, but more threat elements in the tweets did not cause more online engagement.

Third, there was no significant difference in online engagement with social media (i.e. the number of comments, retweets, and likes) between original tweets and non-original retweets. This shows originality in the tweets cannot lead to more engagement with social media. Although campaigners depended on original information to propel their messages to individuals (Nyilasy & Reid, 2009), every so often some retweets also make a significant contribution on health campaigns. For instance, in this study, most of retweets sent by CDC official account are authoritative data that also draws attention from its viewers.

Fourth, even the efficacy elements of the tweets from CDC account instigated social media engagement, almost half of tweets in the comments from CDC official accounts showed reactance, which included 16% articles reflecting anger, 18% incorporating skepticism, 12% comprising humor or sarcasm.

In all, this research investigated the information produced about health messages on social media and whether these information contain content allowing audiences to respond effectively. Despite lack of analysis of responsive behavior for COVID-19 prevention messages, this study utilized the number of comments and retweets as online engagement with social media regarded as responding health messages, which enlarged the scope of previous research (Chen, Yang, Fu et al., 2019). The result of present study differ from some research on the similar topic. For example, Jiang and Beaudoin (2016) demonstrated the importance of original content in promoting audience engagement and argued that perceived threat was a significant predictor of online audience engagement. However, the present study never found any differences in engagement with social media between original tweets and non-original retweets. It was also shown that perceived efficacy, rather than perceived threat, predicted online audience engagement. This may be due to discrepancy between western countries and China, thus more research should be conducted to reveal why that happened.

Limitations

Despite its significant contributions, we faced several limitations in conducting this research: First, the limitation of our study is the lack of a well-defined study population. While our data allows us to link a user with any given tweet, it was beyond the scope of this study to retrieve every user profile in order to determine the demographics of our sample. It is estimated that in the United States, Twitter users are much younger than the average U.S adult and are also more likely than the general public to have a college degree. For example, the median age of Twitter users is 40 years old, while that of U.S. adult is 47; 42% of adult Twitter users have at least a bachelor's degree, while 31% of the public have this level of education (Wojcik & Hughes, 2019). Therefore, those who tweet about COVID-19 from CDC official account may not necessarily be representative of the Twitter population, and the Twitter population is also never representative of the whole population.

Second, the quality and quantitative of the sample needs to be improved. Only COVID-19 prevention–related articles were examined in this study, which may limit generalization of the findings to other pandemic conditions. Additionally, this study only analyzed one official twitter account in one country. Finally, the sample is very small, with only 200 CDC official account tweets and 100 tweets of comment. Future studies should examine social media content regarding other pandemics, expand more social media platforms or accounts, and analyze more tweets.

Third, the content analysis of comment in this study is limited by our difficulty in interpreting some messages, especially given their variety and informality of language and potential for sarcasm. Furthermore, the content and valence of comments are likely to influence how information is interpreted, but it is still unknown what fraction of readers consults comments. In the future, the classification of sentiment analysis should be more divided and content analysis combined with survey research.

Fourth, this study examined the effects of social media only on individuals' engagement with the information rather than their actual behaviors. Although previous studies have indicated the link between engagement with information and genuine behavior (Wakefield et al., 2010), future research should examine whether and how online engagement with information affects actual preventive behavior.

Conclusion

This study has illustrated the potential and feasibility of using social media to conduct research for health information. COVID-19 tweets of CDC account have been primarily used to disseminate information from credible sources to the public, but also a rich source of opinions and experiences expressed by its audiences. This research has involved manual classifications, as well as preliminary automated analyses and more advanced processing tools should be used in the future to classify tweets with more precision and accuracy.

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