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Emotion Makes Rumor Viral? The Effects of Discrete Emotions on Rumor-Mongering on Social Media During a Social Crisis

Yuhao Wu
School of Management, Huazhong University of Science and Technology

Chuxin Zou
School of Management, Huazhong University of Science and Technology

Ling Wang
School of Management, Huazhong University of Science and Technology

Zhao Pan
School of Management, Huazhong University of Science and Technology, victola.pz@gmail.com

Full Research Paper

Emotion Makes Rumor Viral? The Effects of Discrete Emotions on Rumor-Mongering on Social Media During a Social Crisis

Yuhao Wu, Chuxin Zou, Ling Wang, Zhao Pan *

School of Management, Huazhong University of Science and Technology

Abstract: The rapid development of social media services has broadened the way people share emergency information during a social crisis. However, this also raised an issue of unverified and emotional rumors mongering. This paper extracted discrete emotions based on the Pleasure-Arousal-Dominance (PAD) emotional state model, and examined the differential effects of eight discrete emotions (sadness, disgust, fear, anger, gratitude, joy, surprise, like) on rumor-mongering during the COVID-19 crisis. We empirically tested the hypotheses by analyzing data collected from online citizens' engagement of rumor events on Sina Weibo. The findings show that emotions such as fear, anger, disgust, and surprise significantly affect rumor-mongering. In addition, the impact of sadness, like, joy and gratitude on rumor-mongering, is not significant. These findings contribute to a better understanding of the vital role of emotions in rumor-mongering during a social crisis.

Keywords: COVID-19, Rumor Theory, Discrete Emotion, PAD emotional state model, Social Crisis

1. INTRODUCTION

The rapid development of social media services and mobile devices has drastically changed the way people create, distribute, and share emergency information during a social crisis [14]. Social media is superior to mainstream media in the convenience, speed, and breadth of information dissemination during social crises. For example, when coronavirus disease 2019 (COVID-19) broke out, many people shared their emergency information on their mobile devices, which spread quickly and gained wide attention on social media. However, this raised another issue: the uneven quality of information generated by online citizens on social media may contain many emotional unverified rumors. For example, on January 31, 2020, some media reported a rumor that the Shuanghuanglian oral liquid has an inhibition effect on the novel coronavirus. This rumor evokes public emotions (e.g., anger, disgust, and fear), leading to a wide range of rumor spreading. Subsequently, Shuanghuanglian-related products in domestic pharmacies were quickly sold out online and offline. The spread of emotional rumors caused public panic and market chaos, disturbed the normal life order, and even affected the stability of society [6]. Therefore, it is essential to explore how emotions impact rumors mongering on social media services during a social crisis.

The majority of literature examining the factors of rumors diffusion on social media focus on the following three aspects: user-based factors (e.g., verified identity, numbers of followers and followees, and registration time), propagation-based factors (e.g., number of comments, retransmission, network, and temporal feature of information diffusion), and content-based factors (e.g., embedded URLs, videos, pictures, hashtags) [8][10]. Recently, sentiment in the message is also considered an essential factor that may affect the transmission process[15]. Several studies have utilized sentiment factors of posts (positive and negative) to investigate rumors diffusion on social media.

However, the transmission of emotional content may not be driven solely by polarity; apart from being positive or negative, emotions also differ on the level of physiological arousal or activation they evoke. According to Berger and Milkman, even two emotions with the same valence may have different effects on

* Corresponding author. Email: victola.pz@gmail.com (Zhao Pan)

sharing if they induce different arousal levels [2]. Take anger and sadness for example, although the valance of both emotions is negative, anger might increase diffusion (because it is featured by high arousal), while sadness might actually decrease diffusion (because it is featured by low arousal). During a social crisis, a variety of public emotions may lead to widespread rumors. Therefore, it is meaningful and important to explore whether the effects of different discrete emotions on rumor-mongering exist subtle differences.

For these reasons, the current work attempts to fill this research gap by addressing the following research question:

RQ: How do discrete emotions affect rumor-mongering on social media during a social crisis?

This study has several contributions to both theory and practice. First, we enrich the literature on emotion and rumor by highlighting the vital role of discrete emotions based on the Pleasure-Arousal-Dominance(PAD) emotional state model in rumor-mongering on social media during a social crisis. Second, the findings provide insights into discrepancies in the effects of discrete emotions on rumor-mongering around pleasure, arousal, and dominance dimensions of emotional states. Third, our findings can also provide guidelines for the platform supervisor to identify and control rumor diffusion on social media.

The rest of this work is organized as follows. Section 2 provides a literature review, including misinformation sharing and the existing emotion research. Section 3 presents the research model and proposes our research hypotheses. Section 4 depicts our methodology, including data collection, data coding, and data analysis. Section 5 describes the discussion. Section 6 discusses the conclusion and future work.

2. LITERATURE REVIEW

2.1 Rumor theory and social crisis

Rumor-mongering is a collective and impromptu behavior of seeking and exchanging information among citizens to control social tension and solve crises. It represents a collective, cooperative action by community members to provide, evaluate and interpret information to reach a consensus on uncertain situations, reduce social tensions, and solve collective crisis problems. In the early literature on social psychology, Allport and Postman defined a rumor as a specific (or topical) proposition for belief, passed along from person to person, usually by word of mouth, without confirmation or certainty with respect to their facticity [1]. According to Rosnow, rumors are public communications that reflect private assumptions about how the world works and an effective way to help us cope with our anxieties and uncertainties. In this paper, we rigorously define a rumor as the unverified information during circulation that is officially confirmed to be false after a period of time. Since its birth, rumors have included the dynamics of communication around common issues in the community; In practice, the generation and dissemination of rumors are inseparable. Therefore, this paper uses rumor, rumoring, and rumor-mongering interchangeably to highlight the relevance and dynamic nature of rumor.

The early study about rumor-mongering can be traced back to the World War II period. In their seminal work on rumor transmission from mouth to mouth, Allport and Postman formulate the number of rumors in circulation as the importance of the subject to the person concerned times the ambiguity of the proof with respect to the topic at issue, in other words, importance and ambiguity are the two main drivers of rumor transmission. Later, many studies focus on the improvement of this rumor transmission formula[1]. For example, Chorus showed that individual characteristics are also an important factor in disseminating rumors, so critical sense is added to the formula. Rosnow systematically summarizes the four main factors that affect the generation and spread of rumors: general uncertainty, personal anxiety, outcome-related involvement, and credulity, which further promote the development of rumor theory.

By analyzing Twitter data from three different crisis events, Oh O et al. introduce anxiety, source ambiguity, content ambiguity, personal involvement, and directed messages to explain rumor-mongering on Twitter during social crises [10]. Clearly, anxiety and personal involvement reflect the level of importance, source ambiguity, and content ambiguity reflect the level of ambiguity, while directed messages are regarded as a proxy for social influence, it further emphasizes that these two factors play an important role in rumor transmission. Based on this work, Liu et al. modified the model slightly, kept anxiety, personal involvement, content ambiguity unchanged, increased two extra variables sender's credibility and attractiveness in the new model, to interpret rumors retransmission on tweets [8]. Kwon et al. investigated the propagation of the rumors on Twitter from the perspective of the user, linguistic, network, and temporal feature, specially, they found that linguistic features are powerful and stable predictors of rumor.

However, these studies mainly focus on the cognitive factors of rumor-mongering. Although a few studies have found that some emotions, such as anxiety, have an important impact on rumor-mongering, there is a lack of systematic research on the relationship between discrete emotions and rumors mongering on social media during a social crisis. Thus, the present work aims to provide new insight into rumor-mongering by examining the effects of discrete emotions.

2.2 Emotion literatures on social media

Emotion represents a number of psychological states that contain subjective experience, expressive behavior (e.g., facial, bodily, and verbal), and peripheral physiological responses (e.g., heart rate and respiration). Emotion can refer to not only a feeling or mood, but also an attitude or viewpoint. There are two main research streams proposed to classify various emotions. One regards emotions as distinct states, such as Ekman's six basic emotions, such as joy, surprise, anger, fear, disgust, sadness [5]. The other conceptualizes emotions as different dimensions, such as pleasure (also called valance), arousal (also called activation), and dominance, like the Pleasure-Arousal-Dominance emotional state model [9] or Russell's circumplex model of emotion [11]. Specially, eight basic emotions were defined in Plutchik's wheel of emotions model, and their relationship was described. Last but not least, based on the previous studies [13], Ekkekakis defined an integrated framework called emotion's hierarchical structure model by combining the state-based and dimension-based classification methods of emotions.

Nowadays, sentiment analysis methods are increasingly applied to social media content analysis to analyze emotions. According to Pang and Lee, sentiment analysis is also called opinion mining, which copes with the computational treatment of opinion, sentiment, and subjectivity, especially in text. So far, most studies about sentiment analysis mainly focus on a bipolar level, namely, computing the emotional polarity (e.g., positive, negative, and neutral) in the text. For example, Bollen et al. studied whether the collective mood states derived from the large-scale Twitter feed are related to the value of the Dow Jones Industrial Average (DJIA) over time by using two mood trace tools, namely OpinionFinder that measures positive vs. negative mood and Google-Profile of Mood States (GPOMS) that measures mood's six dimensions (calm, alert, sure, vital, kind, and happy). Stieglitz and DangXuan examined whether sentiment in social media content correlates with users' information sharing online behavior under the background of political communication. Likewise, by estimating a dynamic panel data model[15], Rui et al. found that the positive Twitter WOM is associated with higher movie sales, whereas the negative Twitter WOM is correlated with lower movie sales. Although the bipolar analysis (positive or negative) method is likely sufficient for some studies. However, treating emotions in more fine-grained way provides us with a more nuanced perspective to increase our understanding of the phenomena to be studied. Recently, there have been several literature based on the discrete emotions method, such as online content virality[2]; perceived helpfulness of online review[18][3]; but it is relatively limited.

In conclusion, existing studies have proposed some systematic classification frameworks for emotions, but the empirical research on emotions on social media mainly focuses on the dimension of pleasure (positive and negative), and there is less research on the dimensions of arousal and dominance. Furthermore, during a social crisis, a variety of public emotions may lead to widespread rumors. However, limited research utilizes different discrete emotions to examine rumors spread on social media during a social crisis. So this paper aims to fill this gap by examining how discrete emotions based on the PAD emotional state model affect rumor-mongering on social media.

3. RESEARCH MODEL AND HYPOTHESIS

3.1 Identifying discrete emotions during social crisis

The Pleasure-Arousal-Dominance(PAD) emotional state model, proposed by Mehrabian and Russell [9], is a model to express diversification emotions. It has three dimensions, including pleasure (Pleasure-unpleasure, representing the positive and negative states of emotions), arousal (Arousal-non-arousal, representing the level of physiological activation), and dominance (Dominance-non-dominance, representing the dominance of the environment). Using the PAD emotional state model can effectively measure and explain people's emotional states [12].

Based on the basic emotional model of Ekman and Plutchik, we selected eight basic discrete emotions (sadness, disgust, fear, anger, gratitude, joy, surprise, like) during social crises, which correspond to eight different emotional states in the three-dimensional emotional space of the PAD emotional state model. For instance, fear includes low pleasure, high arousal, and low dominance; surprise includes high pleasure, high arousal, and low dominance; anger includes low pleasure, high arousal, and high dominance. Table 1 shows our selected independent variables.

Table 1. Independent Variables of Discrete Emotions

Pleasure/Arousal/Dominance	P (Low)	P (High)
A (Low)	Sadness (P-A-D-)	Gratitude (P+A-D-)
	Disgust (P-A-D+)	Joy (P+A-D+)
A (High)	Fear (P-A+D-)	Surprise (P+A+D-)
	Anger (P-A+D+)	Like (P+A+D+)

Notes: +, - represents the high or low levels of the dimension. For example, P-A+D- means that fear is an emotion with low pleasure, high arousal, and low dominance.

3.2 Discrete emotions on rumor-mongering

Sadness is viewed as a negative emotion that evokes uncertainty about the situation and perceives no control over the consequences. It reflects an extremely unpleasant state of being, such as the feeling of loss, despair, grief, helplessness, and sorrow. According to Berger and Milkman, although sadness and anger are all negative emotions, anger may increase spread (because anger is characterized by a high-arousal emotion), while sadness may actually decrease spread (because sadness is characterized by a low-arousal emotion)[2]. In the context of the COVID-19 crisis, one may reveal sadness when his friends or relatives suffer from the epidemic. The more sadness a message contains, the less likely it is transmitted. This leads to the following hypothesize:

H1: The level of sadness contains in messages during a social crisis has a negative effect on rumors (mongering).

Disgust is an emotional response of revulsion to something considered offensive, distasteful, or unpleasant. It is experienced primarily in relation to the sense of taste (either perceived or imagined), and secondarily to anything which causes a similar feeling by sense of smell, touch, or vision. Based on the literature on rumor, Bell and Sternberg found that urban legends are more likely to be spread if they evoke great disgust. Vosoughi et al. indicated that false information that evokes fear, disgust, and surprise spread significantly farther, faster, deeper, and more broadly than actual stories that reflected sadness, joy, and anticipation [16]. The more disgusted a message is, the more likely it is shared. Consequently, we hypothesize:

H2: The level of disgust contains in messages during a social crisis has a positive effect on rumors (mongering).

From the point of emotional dimension, Allport and Postman suggested that rumor is a justification process to alleviate one's emotional tension by telling a story to gain acceptance from the audience. Therefore, the more fear a person is, the more likely he/she is to spread rumors. The conclusion is consistent with the pioneer rumor study on the social crisis, after the great earthquake, fear was aroused to an intense degree, which further caused people's emotional instability, when this emotional instability reached a certain degree, a large variety of rumors grew with remarkable rapidity and spread widely. This is also the case with the situation of the COVID-19 crisis. Based on these findings, and considering the uncertain and apprehensive nature of the COVID-19 crisis, we hypothesize the following:

H3: The level of fear contains in messages during a social crisis has a positive effect on rumors (mongering).

Anger is often seen as an emotion that triggers engagement. For example, by analyzing the data set of all online New York Times's most emailed articles over a three-month period, Berger and Milkman find that articles that evoke high-arousal positive (awe) and negative (anger, anxiety) emotions are more likely to be shared than low-arousal (sadness) emotion. In another study about the emotion sharing of the cancer community on Twitter, the authors find that the presence of anger increased the likelihood of retweeting. Following these findings, we hypothesize that:

H4: The level of anger contains in messages during a social crisis has a positive effect on rumors (mongering).

Finally, we expect the emotion of gratitude is also associated with information sharing. Gratitude is featured by a feeling of thankfulness, gratefulness, and appreciation for life in response to either someone helping you or simply toward the positive things in your life. Septianto et al. show that the emotional appeals of pride and gratitude increase consumers' willingness to spread word-of-mouth about sustainable luxury brands on social media. During the COVID-19 crisis, the messages that express gratitude can promote the self-enhancement of an individual and behave prosocially in the future. The more gratitude a message contains, the more likely it is shared, thus, we suggest the following hypothesize:

H5: The level of gratitude contains in messages during a social crisis has a positive effect on rumors (mongering).

Joy usually refers to happiness, a general positive emotion, and emerges from cheerful situations (Fredrickson 2009). The studies conducted by [2]; Eckler and Bolls indicate that, in a more concrete way, content that conveys pleasant emotion (e.g., joy) increases the chance of virality. More recently, Wang and Wei found that joy is positively related to retweeting about the emotional content of the cancer community. In the context of the COVID-19 crisis, the share of joyful messages can effectively alleviate the psychological tensions of people. The more joyful a message is, the more likely it is retweeted. Thus, we suggest the following hypothesize:

H6: The level of joy contains in messages during a social crisis has a positive effect on rumors (mongering).

Surprise occurs when a startle response is experienced by people as a result of an unexpected event. In a study of identification and emotions experienced after a celebrity cancer death, the authors found that if an individual reported a high degree of identification, surprise, or anger, they are more likely to participate in social sharing than those who did not. In another study, the authors indicated that, in the Benign dataset, for every increase in the emotion surprise, the tweets were more likely to be shared than tweets without surprise, while in the Malicious dataset, the tweets that contain surprise were less likely to be retweeted than tweets without surprise. In the context of the COVID-19 crisis, surprise can motivate people to explore the situation, this could usually take the form of seeking relevant information that can help them have a better understanding of the situation and the epidemic through various channels (e.g., TV, broadcast, social media, etc.). The more surprise a message contains, the more likely it is to spread. Consequently, we hypothesize:

H7: The level of surprise contains in messages during a social crisis is positively associated with rumors (mongering).

The literal meaning of like is a fondness for something or someone. In this paper, the emotion of like is defined as the set of other common positive emotions except for joy and gratitude, such as like, love, hope, etc. Take hope for example, in a work on cancer information diffusion on Sina Weibo, the authors showed that the effect of hope emotion on virality was significant, besides, the emotion of fear, hope, personal experience-relevant content, and the number of followers were positive and significantly associated with the number of comments received. Myrick et al. applied a content analysis method to examine the relationship between emotional expression and online social support in tweets about cancer. They showed that hope had a positive effect on information giving. Under the background of the COVID-19 crisis, despite the epidemic has caused a heavy psychological blow to the public, they also hope and believe that the fight against the epidemic will be successful and everything will get better in the end. This is also the case with other positive emotions that are classified as like. The more like a message contains, the more likely it is shared. Based on these findings, we hypothesize:

H8: The level of like contains in messages during a social crisis is positively associated with rumors (mongering).

3.3 Control variables

To make the estimation more convincing, we added control variables that may affect the dependent variable. We include the following three categories:

(1) user features, including gender, verified identity, Weibo number of followers and followees', member level, Weibo level, social ties, and personal involvement [10];

(2) propagation features, including retransmission, equipment, time span (Stieglitz and Dang-Xuan 2013);

(3) content features, including hyperlink [14], plaintext, hashtags, quote, source ambiguity, and content ambiguity [10].

The research model of our study on rumor-mongering is represented in Figure 1.

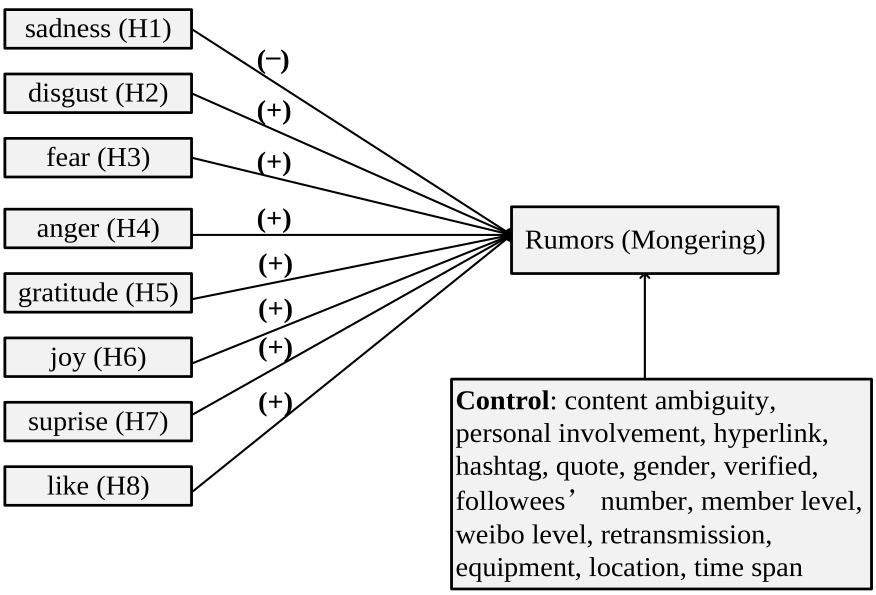

Figure 1. Research Model

4. Research Methodology

4.1 Data collection

Since we focus on rumor-related messages engaged by online citizens on Sina Weibo during the COVID-19 crisis, it is necessary to select an influential rumor. We selected one of the most influential rumors "Does drinking alcohol protect you against COVID-19? (喝酒能预防新型冠状病毒？)", because it was refuted by the following four major Rumor Verification Platform at home and abroad: China internet rumor refuting platform[1]; Myth busters of world health organization[2]; Tencent's jiaozhen platform[3]; Dingxiangyuan[4]. We apply python web crawler to collect Weibo messages by using the keyword "New coronavirus (新型冠状病毒)" and "alcohol (酒)" from January 21, 2020, to September 1, 2020. We collected a total of 24927 Weibo messages and removed the unrelated data. Finally, 1487 Weibo messages were left for subsequent analysis.

4.2 Coding scheme

The manual coding method was a mainstream method for measuring emotions and rumors [2]. Given we needed to measure the more fine-grained discrete emotions, the accuracy of manual identification is higher than that of machine identification [4]. Thus, we used the manual coding method in this paper. We invited two native Chinese-speaking, well-trained coders to encode each Weibo message (N=1487) independently to examine the effects of sadness, disgust, fear, anger, gratitude, joy, surprise, and like on rumor-mongering.

According to Oh O et al.[10], we coded the dependent variable rumors mongering. If the meaning of Weibo messages backed the rumor "Does drinking alcohol protect you against COVID-19", we coded supported as "1" (rumor-mongering occurred), while if the meaning of Weibo messages refuted the rumor, we coded supported as "0" (rumor-mongering did not occur). We also coded the independent and control variables according to our coding scheme. Two well-trained coders who are native Chinese speakers independently coded all Weibo messages to examine the intercoder reliability. Cohen’s kappa Values was reported as 0.92 (rumor-mongering), 0.89 (sadness), 0.74 (disgust), 0.99 (fear), 0.80 (anger), 0.92 (gratitude), 0.73 (joy), 0.76 (surprise), 0.82 (like), 0.70 (source ambiguity), 0.83 (content ambiguity), 0.89 (personal involvement), 0.91 (hyperlink), 0.80 (plaintext), which were acceptable.

4.3 Data analysis and results

Due to the dichotomous nature of most variables, we used logistic regression to test our model. Firstly, we performed the Spearman rank test on all independent and control variables. The results showed that the coefficients between some variables were more than 0.7, indicating collinearity that may severely distort model estimation and subsequent prediction. We gradually removed the redundant variables until the coefficient between any two variables was less than 0.7. We then formulated the logistic regression equation as follows; as shown in this equation, we compared those Weibo messages that supported rumor with that messages that did not monger the rumor. Among the control variables, followees' number, member level, Weibo level, retransmission, and time span are continuous variables, other variables are all binary variables. We finally run logistic regression to test our hypothesis. The results are presented in Table 2.

$$
\begin{aligned}
Prob(Rumors(mongering))& \\
\approx\ & \beta_0 + \beta_1 sadness + \beta_2 disgust + \beta_3\, fear + \beta_4 anger + \beta_5 gratitude + \beta_6 joy \\
& + \beta_7 surprise + \beta_8 like + \beta_9 content\ ambiguity + \beta_{10} personal\ involvement \\
& + \beta_{11} hyperlink + \beta_{12} hashtag + \beta_{13} quote + \beta_{14} gender + \beta_{15} verified \\
& + \beta_{16} followees'\ number + \beta_{17} member\ level + \beta_{18} weibo\ level + \beta_{19} retransmission \\
& + \beta_{20} equipment + \beta_{21} location + \beta_{22}\ time\ span + e
\end{aligned}
$$

[1] http://www.piyao.org.cn/
[2] https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public/myth-busters
[3] https://vp.fact.qq.com/home
[4] https://ncov.dxy.cn/ncovh5/view/pneumonia_rumors

As shown in Table 2, the results of the regression analysis indicate a good model fit, as $\chi^2(22)$ = 740.01 ($p < .001$), the hypotheses related to disgust (H2), fear (H3), anger (H4), and surprise (H7) are supported. A comparison of the regression coefficients shows that disgust is the most important factor, anger is the next most important factor. However, the effects of sadness, gratitude, joy and like on rumor-mongering are insignificant (H1, H5, H6, H8).

Table 2. Results for hypothesize testing

	Variables	B	Std. Error	Sig.	Exp(B)	Hypothesis
IVs	sadness	1.005	1.669	.547	2.732	H1 Not Supported
	disgust	3.838	.351	0	46.413	**H2 Supported**
	fear	1.318	.535	.014	3.734	**H3 Supported**
	anger	3.632	1.218	.003	37.797	**H4 Supported**
	gratitude	.947	1.151	.41	2.579	H5 Not Supported
	joy	-.985	.53	.063	.374	H6 Not Supported
	surprise	1.373	.459	.003	3.947	**H7 Supported**
	like	.228	.293	.436	1.256	H8 Not Supported
CVs	content ambiguity	-.535	.534	.316	.585	
	personal involvement	-2.232	.348	0	.107	
	hyperlink	1.364	.364	0	3.911	
	hashtag	.281	.208	.178	1.324	
	quote	1.221	.213	0	3.39	
	gender	-.209	.173	.227	.811	
	verified	1.333	.243	0	3.794	
	followees’ number	0	0	.541	1	
	member level	.137	.041	.001	1.147	
	weibo level	.012	.006	.046	1.012	
	retransmission	0	.002	.983	1	
	equipment	-.868	.244	0	.42	
	location	-.797	.357	.026	.451	
	time span	-.027	.005	0	.974	
	constant	-11.522	2.602	0	0	
Model Fit	=740.01, df = 22 (p < .001)					

Notes: IVs = Independent Variables; CVs = Control Variables; O = Opposite.

5. DISCUSSION

5.1 Key findings

Our results support four of our hypotheses. Specially, the emotions of disgust, anger, fear, surprise are all the vital contributing factors that caused rumors (mongering). This implies that, during a social crisis, Weibo messages filled with high-arousal emotions such as fear, anger and surprise are more likely to be rumor-mongering. The results are consistent with the previous research [2][16]. From the three dimensions of the PAD emotional state model, individuals with low pleasure and high arousal emotion are more likely to rumor-mongering, which is also consistent with previous studies [2]. However, the effects of emotions with high dominance on rumor-mongering are uncertain.

5.2 Theoretical and practical contributions

This study mainly develops a discrete emotional model to explain the driving factors of rumor-mongering on social media during the COVID-19 crisis, which has important implications for research. Existing research on rumor seldom considers emotional factors, while this study enriches previous rumor-mongering literature by illuminating the importance of discrete emotions. Our model explains how different discrete emotions based on the PAD emotional state model affect rumor-mongering within social media during the COVID-19 crisis. Our empirical tests show different emotions have differential effects on rumors (mongering) across pleasure, arousal, and dominant dimensions. Our study also provides a novel insight for future studies to examine rumor-mongering.

After the COVID-19 crisis, the propagation of various rumors on social media may generate many negative effects on our society. For example, it may quickly spark people's panic, change public opinion, weaken public trust in governments, so it is meaningful and necessary to figure out why rumors monger. Our study results provide a novel perspective for platform supervisors to control rumors during a social crisis, that is, to identify the emotional content embedded in messages. If a message is charged with low pleasure and high arousal, especially for disgust, anger, fear, and surprise, it is more likely to be a rumor-mongering. This result provides guidelines for the platform supervisor to identify and control rumor diffusion on social media.

6. CONCLUSION & FUTURE WORK

Based on the theory of rumor spread and the PAD emotional state model, we developed and empirically tested a model of rumor-mongering on social media during the COVID-19 crisis. From the discrete emotional perspective, we found subtle differences between the effects of different discrete emotions on rumor-mongering, which further deepened our understanding of the critical role of emotions on information diffusion.

To improve the generalization of our study, it makes more sense to verify whether our research results can be replicated in other social media platforms, such as Twitter, Facebook, etc. In addition, we only study the emotional expression of a type of rumor event; future work can focus on the relationship between different discrete emotions and rumor-mongering across various rumor events. Finally, we mainly employ a manual coding method to measure our variables, machine learning methods can also be adopted to verify the results in the future.

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