

# Emotions, Risk and Misinformation Sharing on Social Media during a Health Crisis

*Completed paper*

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## ABSTRACT

During complex health crises, social media has become a primary outlet to circulate harmful misinformation. Facing risky contexts like health crisis misinformation, understanding people's reactions, including their expressed emotions and subsequent behaviors such as sharing misinformation on a social media platform (Twitter (now X)), are crucial in safeguarding a possibly affected community. Utilizing the COVID-19 pandemic as a use case, we investigate how people's emotions in the context of risk, together with platform-specific features, relate to online misinformation sharing behaviors (reflected by Twitter's retweets). In addition, we investigate how risk (measured as estimated risk by healthcare experts) moderates the relationship. We collect a dataset of social media conversations on Twitter platform related to 30 COVID-19 misinformation scenarios. Findings from the analysis contribute to theoretical understanding about (mis) information diffusion and crisis communication and can also have practical implications for mitigation of online harmful misinformation flows.

## Keywords

Health Misinformation, Social Media, Sentiment, Risk Perception, Information Sharing

## **INTRODUCTION**

A crisis, such as the COVID-19 pandemic, exposes various communities to risks that impact their life and well-being. This drives people to consume unverified yet fast circulating messages on social media (Beydoun et al., 2018). Traditional or mainstream sources of information are often unable to relay relevant and timely information to the affected people (Oh et al, 2015) and as a result, various social media platforms have become the go-to source for timely, albeit often incorrect information (Tran et al., 2022; Valecha et al., 2020). Prior studies have found that misinformation is far more likely than verified true information to be shared on social media. For example, in the context of the Zika virus, one study found that half of the leading news stories were based on misinformation, and these were three times more likely to be shared in social media than fact-based news stories (Sommariva et al., 2018). Especially, prior studies have shown that during COVID-19 pandemic, misinformation about COVID-19 spread much faster and wider than true information, (Himelein-Wachowiak et al., 2021). Such a context calls for serious efforts to confront widespread health misinformation on social media (Rai, 2020).

Prior research has shown that in a health crisis, people's reactions can be shaped by their emotions (Chew and Eysenbach, 2010; Li et al., 2014; Son et al., 2020). Affective emotions, such as fear and anger, that are pervasive during a crisis, increase the desire for information seeking and sharing (So et al., 2019). While information seeking and sharing during a crisis through social media can help speed up the spread of critical information in crisis responses, it can produce significant risk when there is misinformation. Risk of harm from misinformation can be recognized by people in this context for many reasons – for instance, they may have heard about evidence of hundreds of deaths and thousands of hospitalizations due to belief in misinformation and rumors (Islam et al., 2020). Various scholars have also argued that during health crises, perceptions regarding risks can

trigger information sharing behavior (Bode and Vraga, 2018; Reiss and Diamond, 2019). However, in much of the literature, the presence of misinformation and the resultant risks of negative consequences has not received sufficient attention, especially in the context of social sharing of emotions. In the context of this paper, the term “risk” refers to the risk of harm from misinformation messages that can result in incorrect decisions by the readers rather than the risk of associated COVID-19 health crisis. In the following sections, we measure the term risk by specifically asking several doctors as health experts to estimate the risk of harm to the readers (concerned persons) when they read the misinformation messages.

This research aims to address two key areas: first, understand how emotions in the context of misinformation risk influence (mis) information sharing by the public on social media. Second, it seeks to understand how risk (estimated by contextual experts, i.e., medical doctors in this case), moderates information sharing. By providing these insights, the study aims to equip those involved in fighting misinformation with better strategies to improve social well-being (Tran et al., 2023). Specifically, this paper focuses on the following research questions (RQ) on X (formerly Twitter) social media platform:

*(RQ1) How do emotions that arise in a risky situation impact social sharing of information in a health crisis?*

*(RQ2) How does the (expert’s assessment of) risk moderate the relationship between the emotions and the social sharing of information?*

Using X data, this study investigates the relationship between expressed emotions and information sharing (retweets) in the context of the risk of harm from COVID-19 misinformation. By building on social sharing of emotions (SSE) theory, we examine how emotions influence information sharing in various risk scenarios. This research aims to inform social media platforms,

governments, and policymakers in developing strategies to combat misinformation's negative impacts during health crises. For example Facebook implemented a strategy called remove, reduce, and inform to address misinformation harm content. This approach involves removing content that violates their policies, limiting the visibility of problematic content that doesn't explicitly break the rules, and providing users with additional information to help them make informed decisions about what to click, read, or share (Rosen, 2019).

The following sections of our paper reviews relevant literature, detail the methodology (scenario selection, data collection, analysis), presents results, and offer conclusions and future research suggestions.

## **THEORETICAL BACKGROUND**

In this section, we provide a review of prior research in addressing misinformation, emotion and risk in health crises.

### **Misinformation on Social Media**

Wang et al (2019) performed research on misinformation about health with the primarily focus on vaccine and infectious diseases. The results of their study indicate that misinformation is very common in social media. Along similar lines Suarez-Lledo and Alvarez-Galvez (2021) found that the most common places to find misinformation about health was Twitter, for significant public health topics like vaccines and diseases. To study misinformation, prior studies have mainly focused their efforts in two areas: detecting misinformation and controlling the spread of misinformation. In the first research stream, various studies have built misinformation detection systems by using extracted patterns from text data such as messages circulating online through various channels like YouTube (Li et al., 2020) or Twitter (now X) (Kouzy et al., 2020). In the second research stream, several studies have examined behavioral or psychological features

influencing the spread of online misinformation (Valecha et al., 2020) such as trust and risk perceptions (Krause et al., 2020).

Yet, there is a paucity of research specifically on risks of harm from misinformation, emotions and information sharing during large-scale health crises. This study fills this literature gap and helps address how emotions under risk of harm from misinformation affect its sharing.

## **Emotion and Risk in Health Crisis**

Prior literature has explored the impact of emotions on public behavior (Chew and Eysenbach, 2010; Marquis et al., 2018) such as during the 2003 SARS Epidemic (Yin et al., 2015), the 2012 Fukushima Nuclear Radiation disaster (Li et al., 2014), the 2011 Egyptian Revolution (Oh et al., 2015) amongst others. Regarding the COVID-19 pandemic, the study by Ning et al. (2020) showed that different types of people's emotions shaped their protective actions facing the health crisis. Wang et al. (2021) studied public reaction to risk message characteristics by examining the articles related to 2018 romaine E. coli outbreak. They concluded that the emotional tone of the food safety communication message was associated with greater virality of those articles on social media. Much of the prior literature has found that emotions play a key role in social media behavior and has explored the impact of emotions on the public (Chew and Eysenbach, 2010; Li et al., 2014; Oh et al., 2015; Yin et al., 2015).

The effect of risk on information sharing has also been investigated within the IS literature. For example, Wang et al. (2015) have investigated the effect of perceived risk of computer security threats on its sharing and searching. We also note that in the literature of health crisis communication, the concept of risk plays a vital role in defining people's fear, which then triggers subsequent emotional reactions and behavioral decisions (Malecki et al., 2021). In this paper, since the background of all concerned misinformation contexts are within such a large-scale health crisis

as COVID-19 pandemic, we rely on the domain expert judgements from medical doctors to identify the risk from misinformation messages for our analyses.

Particularly, in our chosen context of health crisis misinformation, while the health crisis like COVID-19 pandemic itself has widely recognized risks, since the main concern is the potentially harmful misinformation, in this paper, we identify the concept of interest related to risk as the risk of harm from the misinformation messages.

In the risky context, according to Kim (2021), the themes that media messages transmit have the ability to elicit a variety of distinct emotions. For instance, one is prone to become angry over a certain problem if media information implies undue offense to oneself. Similarly, one might experience fear if the message suggests an undesirable outcome that could endanger oneself. Thus, based on the distinctive themes presented in media messaging, people may have differing feelings regarding risky contexts. In a similar vein, studies have revealed that people's emotional responses vary based on their assessment of risk facing possible impactful concerns such as stressful lifestyles (Lazarus, 1991). People experience emotions like anger and sadness when they believe a situation is risky and uncontrollable, which influences their decisions and actions. Fear is a feeling that is highly correlated with situational control and great uncertainty. The inability to escape the imminent risk connects fear to an increased perception of how disastrous the risk could be. Numerous empirical research has also revealed that a person who is afraid tends to view risk more negatively and may advocate preventative measures or give up on the battle altogether (Lerner and Keltner, 2001). When a person is surrounded by risky atmosphere they are more prone to get overwhelmed by anger, fear, disgust and sadness emotions associated with the loss and overestimated risks that they see (Yang and Chu, 2018). Yıldırım and Güler (2021), findings point to the importance of positivity in a risky COVID-19 situation which can help people in the

development of strength-based therapies and preventions that aim to lessen psychological distress and increase happiness. Peng and Huang (2020) suggest that emotion surprise can also be found in a risky health situation. Therefore, in this paper we consider 6 specific emotions that have strong ties to risky contexts: anger, fear, sadness, disgust, joy and surprise.

## **Social Sharing of Emotions**

During crises like the COVID-19 pandemic, understanding the factors influencing information sharing behavior is critical, as misinformation can rapidly propagate and disrupt social order. Misinformation often evokes emotional responses in social media users, who then share content within online conversations. This study employs the Social Sharing of Emotion (SSE) theory to investigate the relationship between emotions and information sharing behavior on social media in a risky context.

Social sharing of emotions (SSE) theory examines the sharing of emotion as an interactive process, wherein people start to engage in interactive behavior by talking and sharing their emotional experience about the event with others (Rimé et al., 1991). SSE theory suggests that people are motivated to share their emotions during an event. SSE identifies two distinct features namely emotion and sharing in the context of the usage of an IS artifact. User emotion reflects users' affect or attitudes and the other feature represents users' sharing action.

## **RESEARCH MODEL**

Social sharing of emotion theory suggests that emotions play a vital role in influencing individuals to search and share information (Rimé, 2009). When confronted with an ambiguous, complex, unpredictable, and risky event such as the pandemic, the lack of verified information can lead to emotions about the issue (Lundgren and McMakin, 2009; Palenchar and Heath, 2002). Looking at the emotion in posts on social media, people have a tendency to share the posts to regulate their

emotional status (Rimé et al., 2020). These posts also engage other social media users via sharing, liking, and commenting (Ji et al., 2019). A few studies have considered two broad categories of emotions, i.e. negative emotions (such as anger, fear or sadness) and positive emotions (such as joy, happiness or surprise) as antecedents triggering people's associated behaviors, such as information sharing online (Rimé et al., 1991; Rimé et al., 2020). However, in order to consider the nuances of the negative and positive emotions in the risky context, when applying SSE to our context of health misinformation during COVID-19 pandemic, we follow the approach of separately considering specific emotions rather than the two groups of positive or negative emotions in examining the effects on risk of harm from misinformation sharing.

In the context of misinformation, Starbird et al. (2014) studied the 2013 Boston Marathon bombing event to examine the use of X for the spread of misinformation and rumors. They observed that tweets containing negative emotions, such as anger, and disgust tend to be retweeted more than tweets containing positive emotions. Hasell and Weeks (2016) examined data from the 2012 U.S. presidential election and found posts that showed the presence of more anger were shared more on social networking platforms. In a similar vein, Han et al. (2023) discovered that misinformation about COVID-19 was more likely to be spread by citizens that reflected anger in their messages. Berger and Milkman (2013) state that "Content that evokes high-arousal emotions like anger is more viral." Social media posts with emotions thus result in different effects on information sharing (Lwin et al., 2020). As a result, we hypothesize that anger would play a crucial role in triggering the spread of information. Therefore, we hypothesize:

*H1: Social media misinformation messages that convey anger are positively associated with their sharing.*



Fear is defined by the uncertainty about one's ability to get away or prevent an undesirable outcome (Smith and Ellsworth, 1985). Ruiter et al. (2001) have suggested that the state of fear is an emotional state that involves physiological arousal and motivates behavioral reactions directed towards mitigating the threat. When fear is concerned, it drives people to engage in different protective measure (Yang and Chu, 2018). During COVID-19, the amount of misinformation found on social media was overwhelming and made people fearful about the situation and the protective measure one needs to take, which creates a widely concerned “infodemic” (Rai, 2020). In the context of misinformation sharing (Zhang and Zhou 2020) suggests that fear arousal greatly increased the intention to explicitly communicate risk warnings. Therefore, we hypothesize:

*H2: Social media misinformation messages that convey fear are positively associated with their sharing.*

As an emotional reaction to an unpleasant stimulus, disgust is a sense of revulsion that prompts withdrawal from the stimulus (Rozin et al., 2000). It is believed that the definition of disgust is basically "something offensive to the taste" (Darwin, 1872) and, based on the flavor that is offended, has been divided into many disgust subtypes (Haidt et al., 1997; Tybur et al., 2009). One category, for instance, is core disgust, also known as pathogen disgust, and it has to do with consuming potentially hazardous food (drinking bleach). Other side to this would be, people who were more sensitive to disgust exhibited more concern of catching COVID-19 (McKay et al., 2020) and were also more inclined to practice preventive health measures including washing their hands often and donning face masks (Shook et al., 2020). To understand the sharing behavior, experiments by Peters et al. (2009) revealed that individuals were more likely to share social events that disgusted them to an unidentified audience. When used in the context of COVID-19, misinformation disgust will lead to more sharing of such information. Therefore, we hypothesize:

*H3: Social media misinformation messages that convey disgust are positively associated with their sharing.*

With its theme of irreversible loss, sadness is the emotion that assumes the highest unpleasantness and situational control. It seems that a key component of sadness is the conviction that the unfavorable circumstances are beyond one's control and that there is nothing that can be done to change them (Smith and Ellsworth, 1985). Sadness, is accompanied by helplessness (Roseman et al., 1994). During COVID there were many situations that let people to feel sad as they were stuck at their home and did not know what should be done. To understand the effect of sadness with the misinformation sharing Hancock et al. (2008) investigated emotional communication in computer-mediated communications (CMC) by eliciting negative affect in one condition and neutral affect in another. The findings showed that those with negative emotion exchanged messages more slowly and used more sad terms. Berger and Milkman (2013) also found a similar finding and suggests that sadness-inducing content is less viral. Therefore, we hypothesize:

*H4: Social media misinformation messages that convey sadness are negatively associated with their sharing.*

In the same vein, positive emotions (e.g., joy or happiness) also play an important role in helping individuals obtain support and build rapport during uncertain times (Li et al., 2014). Such positive content shared can help others improve their feelings and give them the strength to handle the disaster situation better (Chen et al., 2020). If true or helpful information sharing can be triggered by happiness or joy, in our context of possibly harmful misinformation, we expect the reverse effect where the expressed joy emotions can lower people's decision to share misinformation messages. Similarly, Peters et al., 2009 also conducted experiments to show that participants were more inclined to share information related to happiness or joy. Therefore, we hypothesize:

*H5: Social media misinformation messages that convey joy are positively associated with their sharing.*

Finally, surprise is also recognized for its impact on individual behaviors. In their Surprise-Interruption-Reorientation model, Wessel and Aron (2017) suggested that the feeling of surprise will interrupt decision makers' ongoing actions, direct their attention to the emerging situation, and start corrective actions aiming at resolving the unexpected situation. When applied in the misinformation context, it means that the surprise feeling may divert citizens' attention to the misinformation messages and motivate social actions, such as sharing OEM messages, that restore the normal life in a neighborhood. Scholars have even conjectured that the reason misleading information provided on Twitter spreads more than accurate information is because the incorrect information tended to be more inventive and likely to surprise people (Vosoughi et al., 2018). Therefore, we hypothesize that:

*H6: Social media misinformation messages that convey surprise are positively associated with their sharing.*

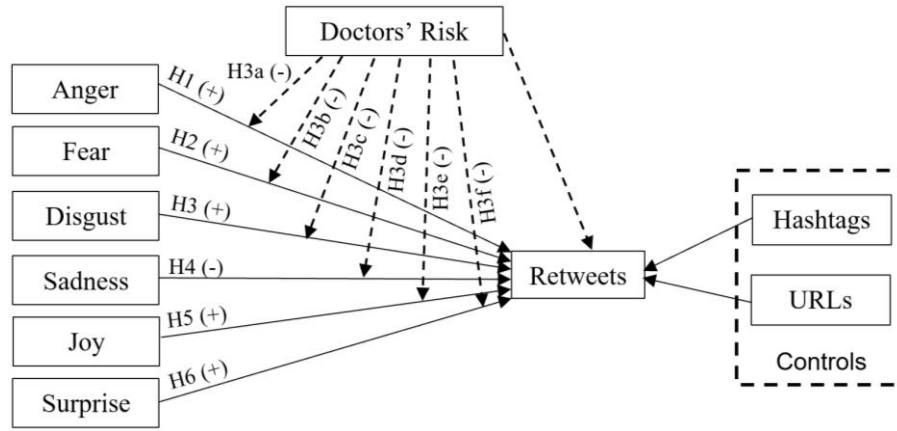
Risk has become a central focus in crisis communication and policy. Understanding risk and its role is important for public health agencies to effectively counter health misinformation during a pandemic and mitigate the risks of harms associated with it (Politi et al., 2007). Risk (of harm from misinformation) can be an umbrella for many emotions. For example, a controversial subject that depicts a higher level of risk may increase the relationship between emotions and sharing. People's emotions are frequently accompanied by their feelings of uncertainty about the accuracy of the information related to COVID-19 (Mohammed et al., 2021). As such, people are less likely to share risky information because it drives their feelings of anxiety. Lee and Ho (2018) concluded that texts and images portraying risk and emotion drastically reduced the support from the public

for nuclear energy. During the COVID-19 pandemic, tweets containing information on the number of death cases or lockdowns commonly provoked negative emotions among the public (Abd-Alrazaq et al., 2020; Lwin et al., 2020). More specifically, risk (from misinformation) can have significant moderating effects on social sharing of emotions. Social media users' likeliness to share may decrease when they observe risk indicators in the shared message on social media. We collected risk scores that we refer to as Doctor's risk. Due to hesitation facing risk of harm from misinformation, we argue that interaction between risk (as estimated by doctors, as health experts) and emotions (expressed by the public, represented by Twitter users) may weaken subsequent behavioral reactions. Therefore, in our context, we expect the risk of harm from misinformation scenarios to have negative moderation effects on the emotions (including anger, sadness, fear, disgust, joy and surprise) in shaping people's misinformation sharing behaviors. In accordance, we propose the following hypotheses:

*H7a,b,c,d,e,f: Doctors' risk negatively moderates the relationship between anger/fear/disgust/ sadness/joy/ surprise emotions and the sharing of the misinformation messages.*

In addition to the above, we also consider control variables, the number of hashtags and the number of URLs in the tweet which has been shown to influence its sharing (Suh et al., 2010; Tsur and Rappoport, 2012).

The research model with all the aforementioned hypotheses is illustrated as shown in Figure 1.



**Figure 1.** Research model and hypotheses.

## METHODOLOGY

In this section, details about the methodology of the study are presented.

### Choosing COVID-19 Misinformation Scenarios

We first identify various COVID-19 misinformation scenarios. The misinformation scenarios are chosen based on the following criteria. The scenarios must: (1) be significant or widely known so that people have sufficient understanding; (2) any action based on the scenarios should have the risks of harm from misinformation, and (3) must cover a wide range of topics within the context of COVID-19 pandemic. These scenarios are the many false claims that were debunked by various factcheckers employed by social media companies (like Facebook or X), from media sources (like CNN, BBC, etc.), professional factchecking organizations (like Snopes.com, Politifact.com, Factcheck.org), or governmental organizations (such as CDC – Centre for Diseases Control or WHO – World Health Organization). Based on these, we chose a list of 30 scenarios that reflected the main themes of the COVID-19 pandemic such as prevention methods, treatments, or different ways to prevent the spread of the virus (see Table 1). Listed debunked dates were later used for defining the time frame of data collection, which will be further discussed.

Scenarios	Summary of misinformation messages	Debunked dates	Fact checker
S1: Wearing masks	People should not wear masks in public and masks can only be used when having proper symptoms.	04/03/2020	CDC
S2: Microwaved masks	After each wear, masks should be placed in a Ziplock bag and microwaved in 2 to 3 minutes to sanitize.	04/10/2020	Snopes
S3: Lemon juice	Drinking lemon juice or consuming vitamin C will boost immune systems and prevent or cure COVID 19.	01/30/2020	BuzzFeed News
S4: Banana	Eating bananas will boost immune systems and prevent or cure COVID-19.	03/22/2020	Snopes
S5: Oregano oil	Oregano oil effectively fights COVID 19.	01/27/2020	Washington Post
S6: Most throat	Keeping your throats moist by constantly drinking warm water is effective to prevent COVID-19.	01/28/2020	Snopes
S7: Drink water	Drinking water every 15 minutes will prevent COVID.	03/11/2020	Snopes
S8: Eating garlic	Eating many garlic to prevent COVID-19.	02/11/2020	BBC, WHO
S9: Garlic water	Drinking boiled garlic water will cure COVID-19.	03/10/2020	Snopes
S10: Homeopathy	Homeopathy and medicine can help prevent and manage COVID-19 symptoms.	01/29/2020	BuzzFeed News
S11: Bleach	Drinking bleach will kill COVID-19.	01/28/2020	FDA, BBC
S12: Chloroquine	Chloroquine can kill 100% COVID-19 and is safe for the public to use.	03/23/2020; 06/15/2020	PolitiFact, Facebook
S13: Hand sanitizer	Hand sanitizer can only kill bacteria and not the virus.	03/03/2020	BuzzFeed News
S14: Vodka sanitizer	Vodka can be used to make hand sanitizer that is effective enough to prevent COVID-19.	03/05/2020	Snopes
S15: Self-test	Holding breaths for more than 10 seconds can be used to self-test for COVID 19 infection.	03/11/2020	Snopes
S16: Immune children	Children are immune to COVID 19 and should not be worried about being infected.	03/19/2020	BuzzFeed News
S17: Flu shots	People can get COVID-19 from the flu shot.	05/14/2020	Snopes
S18: Antibiotics	Antibiotics will fight and kill COVID 19.	5/19/2020	WHO

S19: Chinese packages	It is not safe to receive a package from China because the package can be contaminated by COVID-19.	07/14/2020	Live Science
S20: Compare to flu	COVID 19 is less deadly than the flu.	07/14/2020	Live Science
S21: Salt water	Gargling warm and salt water will kill COVID-19 and prevent infection.	03/28/2020	Reuters
S22: Heat	COVID-19 is not heat-resistant and will be killed by a temperature of just 26 to 27oC (79 to 81oF).	03/12/2020	FactCheck
S23: Fish tank cleaner	Fish tank cleaner has chloroquine and can treat COVID 19.	03/24/2020	Politifact
S24: Air purifier	Air purifier can kill COVID 19 within a single air pass.	01/27/2020	BuzzFeed News
S25: Cold food	People should stay away from ice cream and eating cold to avoid contracting COVID-19.	03/25/2020	UNICEF, WHO
S26: Runny nose	If you have runny nose, you are not infected by COVID 19. COVID has dry cough with no running nose.	03/12/2020	Factcheck.org
S27: Toilet paper	COVID 19 had been found in packages of contaminated toilet paper, and people should start using a wet washcloth to clean themselves instead.	03/11/2020	Snopes
S28: Pets	Pets can spread COVID 19.	07/14/2020	Live Science
S29: Chinese restaurants	You can get COVID if eating at Chinese restaurants.	07/14/2020	Live Science
S30: Old people	COVID 19 only affects the old people.	03/25/2020	WHO

**Table 1.** Descriptions, details, and sources of misinformation scenarios.

## Measures

Sentiment analysis (Ho et al. 2019) is applied on the tweets to find the emotions associated with the tweets. We extract the scores for anger, fear, disgust, sadness, joy and surprise expressed in each of the tweets' texts using the word-emotion lexicon of the National Research Council (NRC) sentiment and emotion lexicon (Mohammad and Turney, 2010). The NRC lexicon has been widely utilized in prior research for the classification of emotions in different contexts and varied domains,

such as disaster responses and sentiment classification for social media data on Twitter platform (Ragini et al., 2018; Bravo-Marquez et al., 2013). Emotion scores are calculated from each tweet based on emotional terms presented in the considered texts. By default, the NRC lexicon extracts eight emotions (anger, anticipation, disgust, fear, joy, sadness, surprise, and trust) as the texts' emotional scores. As mentioned in section 2.2 about different types of emotions, we specifically focus on the specific types of emotions that have strong ties to such a risky context as the COVID-19 health crisis, which resulted the list of six out of aforementioned eight NRC emotions, including anger, fear, sadness, disgust, joy and surprise. These six emotions were also the building blocks of our main and interaction effects in our research model.

In addition to the scores of six extracted NRC emotions, the estimated risks from misinformation were captured for each scenario based on input from 3 doctors. The doctors had extensive experience ranging from 15 to 45 years. The doctors were also infected by the COVID-19 virus, along with their family members. Hence being the victim and the expert in the field we asked the doctors to estimate (1) the potential health harms; (2) morbidity and mortality harms; (3) likelihood of getting health harms; and (4) likelihood of getting morbidity and mortality harms for each of the COVID-19 misinformation scenarios on a scale from 1 to 10. Then, we calculated the average values of the two estimated severity and two estimated likelihood scores. Finally, we computed the estimated risk scores as the product of the average severity scores and average likelihood scores. While estimated risk scores were calculated at the scenario-level, the other measures were computed at the individual tweet-level.

Additionally, we also capture the actual retweet counts as the dependent variable and calculate the numbers of hashtags and URLs in the unprocessed tweet texts as the control variables in the model.



## Data Collection and Data Processing

We obtained a dataset comprising six-months of tweets collected from X using the REST search APIs (Twitter provides a RESTful API that enables developers to programmatically access Twitter's features) using the search keyword #covid and #coronavirus, resulting in more than 400 million tweets. Along with these, factcheck statements were also collected from official sources and factcheckers. These claims were used to segregate the tweets into the groups of misinformation scenarios falling within the time frame of 15-days before and after the debunk date. The collected data was pre-processed by deleting '@' symbol, special characters, emojis, hashtags and stop words (not meaningfully important words such as 'a', 'an', 'the', etc.). Then we performed stemming and lemmatization to reach singularity levels of words in tweets. After pre-processing, we segregated the tweets according to the scenarios. A Jaccard similarity index match was used to segregate the tweets into respective scenarios. Finally, employing human coder for labelling at different cutoff points of Jaccard similarity scores when matching the contents of the tweets and scenario descriptions, preferably from 10% to 40%, we identified a threshold level of the Jaccard score that is optimal in classifying relevant and irrelevant tweets for further analyses.

## Descriptive Statistics and Correlations

We checked for correlation and descriptive statistics among the variables using the Pearson correlation test (see Table 2). The Pearson correlation test showed that most of the correlations were less than 0.5 indicating that there were no serious concerns related to multicollinearity (Kishore et al., 2004).

Variable	Mean (SD)	Correlations							
		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Retweets	108.67 (2468.56 8)	1							

Anger	0.021 (0.083)	0.025**	1						
Disgust	0.023 (0.0801)	0.030**	0.505**	1					
Fear	0.082 (0.174)	0.012*	0.362**	0.187**	1				
Joy	0.0392 (0.131)	-0.010*	-0.006	-0.027**	-0.086*	1			
Sadness	0.027 (0.093)	0.027**	0.561**	0.416**	0.435**	-0.013**	1		
Surprise	0.018 (0.078)	0.024**	0.450**	0.173**	0.231**	0.154**	0.359**	1	
DrRisk	21.908 (23.949)	0.024**	0.101**	0.035**	0.417**	-0.157**	0.128**	0.105**	1

*Note: SD: Standard deviation.*

**Table 2.** Descriptive Statistics and Correlations among Variables in Main Research Model

## Analysis

For the proposed analyses the following steps after data collection was performed. We identify the outcome (dependent variable) of our analysis as the number of retweets from each captured tweet. In the social media context, especially on Twitter retweeting is considered as one of the very effective methods for disseminating information widely (Majmundar et al., 2018). Two recent updates from Twitter may increase the effectiveness of retweeting. One modification, for instance, concerns the algorithmic timeline, which presents users with trending subjects at the front of their feed and speeds up the spread of viral tweets (Oremus, 2017).

Antecedents of the outcome include anger, fear, disgust, sadness, joy and surprise emotions obtained from tweets. In addition to these independent variables, we include two control variables, the number of hashtags and hyperlinks (URLs) in the tweets. We employ a mixed model using STATA15. The mixed model involves both fixed effects and random effects based on the COVID-19 misinformation scenarios. Since the estimated risk from doctors is expected to moderate the relationships between emotions and retweets, its direct effect on retweets is also examined. The equation for the full proposed research model is:

$$Retweets_{ij} = \beta_0 + \beta_1*Anger_{ij} + \beta_2*Fear_{ij} + \beta_3*Disgust_{ij} + \beta_4*Sadness_{ij} + \beta_5*Joy_{ij} + \beta_6*Surprise_{ij} + \beta_7*DrRisk_{ij} + \beta_8*Hashtag_{ij} + \beta_9*URLs_{ij} + \beta_{10}*Anger*DrRisk_{ij} + \beta_{11}*Fear*DrRisk_{ij} + \beta_{12}*Disgust*DrRisk_{ij} + \beta_{13}*Sadness*DrRisk_{ij} + \beta_{14}*Joy*DrRisk_{ij} + \beta_{15}*Surprise*DrRisk_{ij} + \varepsilon$$

Where:  $\beta$  represents coefficients of the variables,  $\varepsilon$  the error term,  $i$  is the tweet level and  $j$  is the scenario level.

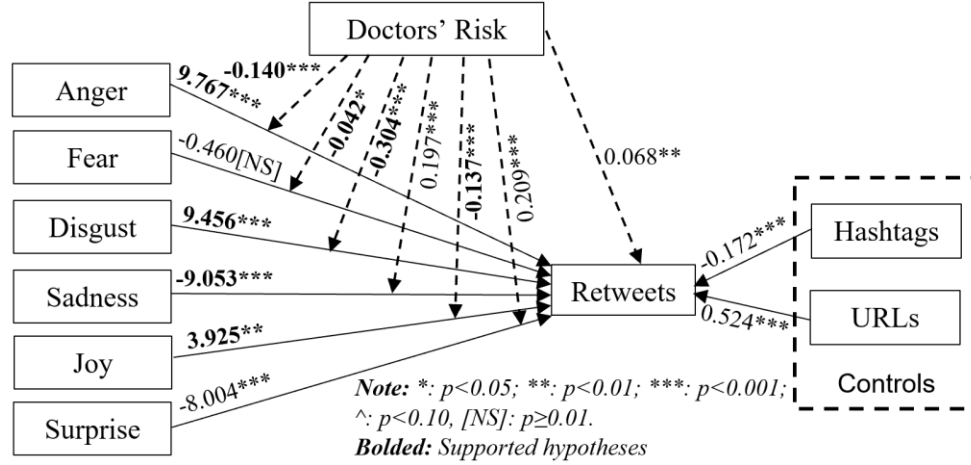
## Results

The final analysis and hypothesis testing results for both main effects and interaction effects from STATA mixed effect regressions are shown in Table 2 and Figure 2.

To Retweets	Variable	Coef.	SD	p-value	Hypotheses
Main effects	Anger	9.767	1.826	0.000	H1: Supported
	Fear	-0.460	1.163	0.692	H2: Not supported
	Disgust	9.456	1.583	0.000	H3: Supported
	Sadness	-9.053	1.296	0.000	H4: Supported
	Joy	3.925	1.220	0.001	H5: Supported
	Surprise	-8.004	1.920	0.000	H6: Not supported, significant, CI
Interactions	Drs' Risk	0.068	0.024	0.004	NA
	Anger* Drs' Risk	-0.140	0.042	0.001	H7a: Supported
	Fear* Drs' Risk	-0.042	0.021	0.048	H7b: Supported
	Disgust* Drs' Risk	-0.304	0.029	0.000	H7c: Supported
	Sadness* Drs' Risk	0.197	0.030	0.000	H7d: Not supported but significant, CI
	Joy* Drs' Risk	-0.137	0.030	0.000	H7e: Supported
	Surprise* Drs' Risk	0.209	0.043	0.000	H7f: Not supported but significant, CI
Control	Hashtag	-0.172	0.015	0.000	NA
	URLs	0.524	0.074	0.000	NA
Const		0.193	0.878	0.826	NA

**Note:** Coef.: coefficient of the effect; SD: Standard deviation; CI: counter-intuitive result; NA: Not applicable (no hypothesis).

**Table 2.** Analysis and hypothesis testing results.



**Figure 2.** Analysis and hypothesis testing results.

The final results indicated that most of our tested hypotheses were statistically supported, with some varied details. First, out of six main tested effects from six extracted NRC emotions to the DV (retweets), we had four supported hypotheses (H1, H3, H4, H5), associated with anger, disgust, sadness and joy emotions. Second, in two unsupported main hypotheses, while fear has insignificant result, surprise has significant but counter-intuitive results with a negative instead of expectedly positive effects toward retweets. While the majority of prior studies have stated that surprise triggers information sharing like retweeting behavior (Wessel and Aron, 2017; Vosoughi et al., 2018), some studies (Luo et al., 2021) stated that for the specific context of misinformation on social media, misinformation messages containing surprise factors are harder to be discussed and circulated online, which is in line with our seemingly unexpected result. This finding shed lights for future research to replicate and confirm the actual effects of surprise on (mis)information diffusion regarding conflicting suggestions from the current literature. Third, out of six interaction effects between doctors' estimated risks and six emotions, we found four significant effects associated with hypotheses H7a, H7b, H7c, and H7e. The two unsupported hypotheses H7d and H7f (related to the interactions of risk – sadness and risk – surprise) are all extremely statistically significant ( $p$ -values = 0.000), but counter-intuitive (positive instead of expectedly negative

effects). Interestingly, both the main effect and the interaction effect related to surprise are very statistically significant but are all counter-intuitive, which strongly suggests future research to replicate and expand on our study to unbox the underlying mechanisms surrounding surprise emotion in shaping (mis)information sharing behaviors. On the other hand, it is a surprise that while fear has insignificant effect, its interaction with the estimated risk yielded very significant and desired result toward retweets, indicating the role of different risky contexts (as judged by medical experts) in triggering fear's effects on information sharing behaviors. Finally, although not hypothesized, the two control variables (URLs and hashtags) also have very significant effects in shaping retweeting behaviors.

## **DISCUSSION AND CONCLUSION**

Risks from misinformation are prevalent in social media and influence social sharing of emotions during crises situations such as the COVID-19 pandemic with significant implications for the effectiveness of interventions. This study is expected to contribute to the literature on managing information during a health crisis by explicitly considering social sharing of emotions in health crisis and misinformation scenarios. It also takes a rigorous approach to capturing variables from tweets. Our study can therefore provide guidance on the need to identify and manage social sharing of emotions for misinformation messages in health crises.

This study examines the possible effects that the six distinct emotions and risks from a misinformation tweet could directly or indirectly play important roles in sharing behaviors during a crisis. It also examines if the contextual risky level (as judged by the domain experts, i.e. medical doctors) moderates the effects of emotional content on sharing behavior, reflected by retweets. Lastly, our study suggests that social media strategies to ensure speedy and reliable information

spread during crises need to consider the distinct characteristics of information such as the veracity of the information, and its risks of causing harms from misinformation.

From our supported and unsupported hypothesis testing results, we have outlined several insights for future research. First, as our study anchors on 30 misinformation scenarios of the early stage of COVID-19 pandemic, future studies can replicate our research model in more phases of the pandemic, or in other health crises to investigate and confirm our findings. Second, as we detected the very significant but counter intuitive findings from both main effect (surprise to retweets) and two interaction effects (risk-sadness and risk-surprise to retweets), future research can extend our work to explore more about the underlying reasons leading to these results, especially about the main and interacting effects surrounding one emotions: surprise. Third, future research expansion can consider other platform-based behaviors from social media users beyond retweets, such as favorites or quotes, in replicating our research model. Fourth, in future we would like to extend this study by collecting and examining data from platforms like Reddit, Instagram or TikTok. Fifth, for our future research we plan to collect and examine vaccine misinformation related hashtags (#VaccineHoax, #VaccineScam, #DoNotVaxx, #VaxxKills, #BigPharmaLies). Sixth we plan to examine disinformation, which involves the malicious intent behind sharing false information. All of these can be valuable in enlightening theoretical and practical contributions facing harmful misinformation.

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