Conversational Uncertainty from Misinformation in Social Media during COVID-19: An Examination of Emotions

Thi Tran[1], Pranali Mandaokar[1], Naga Vemprala[1],

Rohit Valecha[1], Govind Hariharan[2], and H. Raghav Rao[1]

[1]Department of Information Systems and Cyber Security, The University of Texas at San Antonio, USA
[2]Department of Economics, Finance and Quantitative Analysis, Kennesaw State University, USA
thi.tran@my.utsa.edu, pranali.mandaokar@utsa.edu, naga.vemprala@gmail.com, rvalecha6446@gmail.com, gharihar@kennesaw.edu, mgmtrao@gmail.com

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Abstract. The current COVID-19 pandemic has generated ideal conditions for widespread harmful misinformation on social media. To contribute to the efforts of social media networks and public health agencies to build community resilience and to effectively counter health misinformation, this research investigates the role of uncertainty and answers the question: Which emotions are drivers of uncertainty. From a large corpus of tweets captured from the Twitter platform, we examine the relationships between expected antecedents and quantified uncertainty extracted from social media conversations circulating around 30 chosen COVID-19 misinformation scenarios. All considered negative and positive emotions (anger, fear, surprise, sadness, joy and disgust) were found to have significant effects on Uncertainty. Detailed results are discussed.

Keywords: Misinformation, Uncertainty, Social Media, COVID-19, Emotion, Belief.

1 Introduction

The current COVID-19 pandemic has generated an ideal condition for widespread misinformation, especially in conversations on social network platforms such as Facebook and Twitter (Taylor, 2020). Defined as false or misleading information or claims, which can be either intentional or unintentional (Scheufele and Krause 2019), misinformation can lead to various types of harms such as life harm, financial harm, emotional harm or confusion harm (Tran et al., 2020). The misinformation has generated high levels of uncertainty among the public about what to follow or not. As a result, an extensive amount of information is exchanged among the general public in an attempt to reduce uncertainty. Prior studies have examined how uncertainty of information can be linked to misinformation that "confuse and mislead publics" (p. 471), especially in such a widespread and severe health crisis as the COVID pandemic (Dunwoody, 2020). In order for social media networks and public health agencies to build community resilience and effectively counter health misinformation, there is a critical need to understand the role that uncertainty plays (Politi et al., 2007).

This research asks the following question: Which emotions are the drivers of uncertainty? Answering the question will contribute to the theoretical understanding of how to build community resilience by reducing uncertainty caused by misinformation during a crisis, particularly the systematic quantification of uncertainties and expressed emotions from online conversations. Measuring uncertainty in social media data has often been a challenge in the past but recent research has shown that uncertainty measured through text analysis or twitter conversations correlate well with uncertainty measured in the stock market, providing some support for the importance of using the large social media data sets to measure uncertainty (Baker et al., 2016; 2020; 2021)

In order to address these questions, we capture online social media conversations on Twitter platform related to several chosen COVID-19 misinformation scenarios. Through data filtering and feature extraction, we obtain variables from millions of captured tweets, and extract both the expressed emotions and social media platform features such as number of hashtags and embedded hyperlinks (or URLs) used within the tweets. We then investigate the relationships between antecedents and the uncertainties from tweets related to the Misinformation scenarios before summarizing and discussing the findings.

The paper is structured as follows. We first review prior literature on misinformation during crises and uncertainty from misinformation to form the theoretical research background. We then present the methodology, including choosing misinformation scenarios, collecting and filtering data, extracting features and performing analyses. Finally, we discuss the results and conclusions, followed by outlining the future research efforts.

2 Prior Research

In this section, we provide a review of prior efforts in addressing the uncertainties from misinformation, and the antecedents of uncertainty.

2.1 Misinformation Context

Despite several existing efforts addressing technical solutions to detect and eliminate Misinformation or behavioral solutions to understand harms from misinformation, to the best of our knowledge, there is no research specifically addressing uncertainty arising from misinformation during large scale crises like the COVID pandemic. Our research aims to fill the literature gap and to practically support efforts by identifying and quantifying misinformation uncertainty as well as possible antecedents of uncertainty.

2.2 Research Hypotheses: Uncertainty and Antecedents

The spread of misinformation on social media has become common during a crisis situation, owing to the extreme uncertainty as well as the absence of the correct information that each individual in such a situation pursues (Starbird et al., 2016). Their study focused on "expressed uncertainty" in social media messages characterizing clear, linguistic expression of uncertainty about the truth of information covered. Starbird et al. (2016) finds that expressed uncertainty is an early indicator of rumouring and hence could be used as an early warning sign to build community resilience.

In our current study, we argue that emotions are significant antecedents of uncertainty. Within social networks and social media, people express their opinions and feelings related to social issues. People demonstrate emotions when misinformation may inflict physical or psychological harm on themselves or on the people and things they hold dear (Smith & Pain, 2012).

Chen et al. (2020) investigated the association between negative emotions (such as fear) in COVID-19 context and market uncertainty and found that such emotions are positively associated with uncertainty. Fink et al. (2018) conducted an experiment where emotional images showing disgust were investigated, and it was found that such emotional stimuli aroused stronger uncertainty.

Sometimes misinformation can result in positive emotions such as joy if it has good news. Such emotions are an outcome of a future event and since the future is uncertain (JohnsonHanks et al., 2005), these emotions are related to uncertainty. In addition, Meyer et al. (1997) note that some positive emotions such as surprise act as interruption tools, which are elicited by unpredicted events, breaking ongoing activities and thoughts, and encourages individuals to take note of the unpredicted stimulus. Unpredicted events frustrate people's requirement of structure and predictability (Abelson et al., 1968; Gawronski & Strack, 2012) and lead to uncertain outcomes (Elliot & Devine, 1994; Mendes et al., 2007).

These emotions are expected to have a positive effect on uncertainty since heightened emotions whether positive or negative exacerbate the level of uncertainty (Anderson et al., 2019). So we hypothesize that in the context of social media, misinformation messages that convey negative or positive emotions in the text are likely to demonstrate higher uncertainty. This gives the hypothesis:

***H1**. Negative emotions will be positively related to misinformation related uncertainty*

***H2**. Positive emotions will be positively related to misinformation related uncertainty*

Following Ekman (1992), this study opens the black-box of emotions by exploring six specific types of emotions: anger, fear, surprise, sadness, joy and disgust. Anger is an emotion that includes an uncomfortable response to a perceived (or real) grievance (Frisch & Frisch, 2006). Fear is an emotional state, which is induced by a perceived threat of pain or some form of distress. Sadness is a basic emotional pain which is related with, or described by feelings of disadvantage, despair, sorrow, and loss (Ekman & Keltner, 1997). Watkins et al. (2018) defines joy as an emotional state that is typically about good news for an individual. Meyer et al. (1997), define surprise as an interruption tool, which is elicited by unpredicted events, breaking ongoing activities and thoughts, and encourages individuals to take note of the unpredicted stimulus. Fink et al. (2018), find that people react to disgust with either avoidance or extended exploration. To explore this behaviour, they conducted an experiment where disgust images were investigated, and it was found that disgust stimuli aroused stronger uncertainty and few accurate responses. Through this research, we attempt to study how these positive and negative emotions expressed in social media misinformation messages are related to uncertainty.

3 Methodology

This section details the methodology of the study, including misinformation scenarios, data collection, pre-processing and variable conceptualization.

3.1 COVID-19 Misinformation Scenarios

We begin by outlining the various COVID-19 misinformation scenarios. The misinformation scenarios were chosen based on the following criteria: (1) The scenarios must be popular so that people have sufficient understanding; (2) The scenarios should have the potential to cause harms for readers, and (3) They should cover a wide range of topics within the context of COVID-19 pandemic. These scenarios were debunked by various sources such as factcheckers employed by social media companies (like Facebook or Twitter), factcheckers from media sources (like CNN, BBC, etc.), professional factchecking organizations (like Snopes.com, Politifact.com, Factcheck.org), or several governmental organizations (such as CDC – Center for Diseases Control or WHO – World Health Organization).

3.2 Twitter Data Collection and Data Pre-processing

Our dataset comprises of six months of tweets collected from Twitter beginning in January 20, 2020, when it was officially declared by China that cases had spread beyond Hubei province using the Twitter REST search APIs using the search keyword #covid and #coronavirus. In addition, factcheck statements were also collected from official sources and fact checker websites. These claims were used to segregate the tweets into the list of all 30 Misinformation scenarios falling within 15-days before and after the debunk date.

The collected data was then cleaned by removing '@' symbol that convey replies to twitter posts, special characters, emojis, hashtags and stop words (words such as 'a', 'an', 'the'…). Then the pre-processing of the data was done by performing stemming and lemmatization to reach singular levels of words in tweets.

After pre-processing, we segregated the tweets based on the scenario. To objectively classify the tweets into each of the scenarios, we have captured the Jaccard similarity between the tweets and the corresponding scenario text. To test the accuracy of our classification technique, we randomly selected tweets with varying Jaccard similarity. Two independent graduate researchers manually read the tweets and found that a Jaccard similarity of 0.20 provides optimal classification, and tweets with a Jaccard similarity greater than or equal to 0.20 were identified as relevant to the scenarios.

3.3 Variable Conceptualization

We calculated the uncertainty score for each tweet using the "tentative" words in the LIWC (Linguistic Inquiry and Word Count) dictionary (Pennebaker et al., 2015). Additionally, we also calculated the number of hashtags and number of URLs that were present in the unprocessed tweet text. Next, emotion tagging was performed on each of the tweets to find the emotions associated with the tweets. For this we used the NRC emotion-lexicon, aka Emolex (Mohammad and Turney, 2010) and considered the six basic emotions proposed by Ekman (1992), which are anger, fear, surprise, sadness, joy, and disgust. Misinformation scenarios are shown in Table 1.

Table 1. 30 COVID-19 Misinformation Scenarios.

ID	Scenario	ID	Scenario	ID	Scenario	ID	Scenario
S1	Wearing masks	S9	Drinking garlic water	S16	Hand sanitizer	S24	Contaminated toilet paper
S2	Microwave masks	S10	Homeopathy	S17	Vodka sanitizer	S25	Pets
S3	Vitamin C / Lemon juice	S11	Gargling salt water	S18	Self-test – holding breath	S26	Immune children
S4	Eating banana	S12	Heat	S19	Air purifier	S27	Old people
S5	Oregano oil	S13	Drinking bleach	S20	Eating cold food	S28	Receiving Chinese packages

S6	Moist throat	S14	Fish tank cleaner	S21	Flu shot	S29	Eating at Chinese restaurants
S7	Drinking water	S15	Chloroquine	S22	Runny nose	S30	Compare to flu
S8	Eating garlic			S23	Antibiotics		

3.4 Data Analysis Approach

We identified the dependent variable of the analysis as the uncertainty obtained from tweets (using LIWC), and the independent variables obtained from tweets that show emotion (using NRC Lexicon). We also capture the number of hashtags and URLs within the tweets. We employed a mixed model using STATA15 with 'Uncertainty' as the dependent variable. The data was analyzed as follows:

$$Uncertainty = \beta_0 + \beta_1 * Anger + \beta_2 * Fear + \beta_3 * Surprise + \beta_4 * Sadness + \beta_5 * Joy + \beta_6 * Disgust + \beta_7 * Hashtag + \beta_8 * URL + \varepsilon$$

Where: β_i are the coefficients of the variables in the regression, and ε is the error term of the analysis.

4 Data Analyses' Results and Discussion

The results of the regression on dependent variable Uncertainty are summarized in Table 2.

Table 2. Effect of Emotions on Uncertainty.

Independent variable	**Coefficient (β_i)**	**Standard Error**
Anger	-0.0007863***	0.0000975
Fear	-0.0003211***	0.0000479
Surprise	0.001928***	0.0000853
Sadness	0.0001702*	0.0000821
Joy	0.0003464***	0.0000474
Disgust	0.0001803*	0.0000904
Hashtag	-8.60e-06**	2.78e-06
URL	-0.0000993***	9.95e-06
[Constant]	0.0003792***	0.0000344

*Note: *: p-value≤0.05; **: p-value≤0.01; ***: p-value≤0.001;*

From the results, we can see that the effects from various emotions considered as antecedents are significant toward the misinformation related uncertainty. As hypothesized, positive emotions (such as joy and surprise) have a positive effect on uncertainty, as well as the negative emotions (such as sadness and disgust) have a positive effect on uncertainty. However, some of the negative emotions (such as anger and fear) have a negative effect on uncertainty. This is probably because public fear about the pandemic and the potential negative impact may have reduced the opportunity for Twitterati to spread misinformation. These findings call for future research on uncertainty about misinformation scenarios.

5 Conclusion

Uncertainty exists during crisis events such as the COVID-19 pandemic due to a lack of understanding about what works and what does not. Uncertainty encourages people to seek information through social media. The presence of misinformation in social media networks has the potential to wreak havoc on efforts to build community resilience during a crisis. While there is research on misinformation, the issue of uncertainty in the presence of misinformation has received limited attention. This study makes several contributions to fill this research gap: (1) identifying and examining antecedents that affect misinformation uncertainty; and (2) quantifying the effects of such antecedents on uncertainty using regression analysis. The findings not only contribute to the existing literature on uncertainty related to misinformation during crises, but also provide an early window into the development of effective interventions and communications by social media companies and governments to build community resilience by reducing uncertainty and panic caused by misinformation. It extracts practical insights to assist individuals or organizations dealing with misinformation in developing systematic methods for capturing, quantifying, or evaluating the causal relationships between variables surrounding uncertainty, as well as predicting the values of such variables in similar future contexts of healthcare crises.

Future investigation into the reasons for why extreme negative emotions of anger and fear have a negative effect on uncertainty (unlike the other positive and negative emotions) is warranted. It would be useful to open the black box of anger and fear in the aftermath of health crises. Finally, from the findings, we shall examine the role of different social media features (such as hashtags or URLs) in curbing misinformation related uncertainty.

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