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User Engagement and Uncertainty from COVID-19 Misinformation on Social Media: An Examination of Emotions and Harms

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ABSTRACT

During the COVID-19 pandemic, people were often exposed to harmful social media misinformation. Prior studies have devoted their efforts to detecting misinformation and understanding the psychological features related to misinformation. This paper contributes to the literature of handling crisis misinformation by connecting psychological characteristics to people's actual actions. Anchoring on social media user engagement reflected in the numbers of retweets, we examine the effects of expressed uncertainty and emotions as well as various platform-specific aspects (hashtags and URLs) by extracting features from captured conversations on Twitter social media platform. Subsequently, we quantify expected harms from the chosen COVID-19 misinformation scenarios from the judgements of several healthcare experts, which were then utilized to classify scenarios into different categories for further analyses. With much of the hypotheses supported in both main effects and interaction effects, the study has theoretical contributions in establishing a mechanism to measure expressed uncertainty and emotions from captured Twitter conversations, measuring misinformation harms from professional experts and examining causal relationships between social media behaviour and uncertainty, emotions, harms and several platform specific features. It also has practical contributions of deriving insights to help involved stakeholders in crisis communications

understand the role of misinformation harms, and to reduce misinformation diffusion and minimize possible harms.

Keywords: Misinformation, COVID-19, User Engagement, Uncertainty, Emotion, Harms.

INTRODUCTION

A health crisis like the COVID-19 pandemic exposes various communities to threats whose mitigation requires a large amount of quick information for making critical decisions, driving people to consume unverified yet fast circulating messages on social media (Beydoun et al., 2018). Consequently, numerous social media platforms have been the source of intentional or unintentional misinformation that misleads people (Wardle and Derakhsan, 2017), causing various types of harms such as life threatening, financial or emotional harms (Tran et al., 2020).

However, research on the connection between psychological (including uncertainty), misinformation harms and online behaviour is scarce. This is particularly true in the context of a widespread health crisis like the COVID-19 pandemic with high levels of unknown elements such as its origin, spread, proper preventions and treatments (Lytvynenko, 2020). In this paper, adopting insights from existing literature, we propose an examination of social media user engagement captured from Twitter conversations and multiple antecedents such as expressed uncertainty, emotions and misinformation harms. This study is expected to contribute to the understanding of not only the mechanisms of misinformation spreading but also the relationship between psychological features and perceptions and actual actions.

Anchoring on the roles of social media engagement (measured by retweets), uncertainty, and potential harms from COVID-19 misinformation, this research answers the following questions: (1) How can we capture and quantify uncertainty expressed in online social media conversations in the presence of misinformation? (2) Besides expressed uncertainty, what are the antecedents of user engagement in terms of core drivers such as emotions and social media platform characteristics? (3) How is social media behaviour affected by the potential harm from a misinformation scenario and what are its interactions with the core drivers? Answering such questions will contribute to an understanding of how to reduce users' engagement and diffusion of crisis misinformation, particularly the systematic quantification of uncertainties and expressed emotions from online conversations. In addition, utilizing the context of captured Twitter conversation, this research also has practical implications by extracting valuable insights to support involved stakeholders such as social media companies, governmental officials or policy makers to improve the effectiveness of their decision-making processes that aim to minimize or mitigate possible harms from misinformation during health crises similar to this pandemic.

In order to address these questions, we first 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 from social media text and platform specific features such as numbers of hashtags, embedded hyperlinks (or URLs) used within the tweets. In a subsequent task, we engaged the services of three healthcare experts (two doctors and one registered nurse) with extensive experience in the field to estimate possible harms from the chosen scenarios. Finally, we investigate the causal relationships between expected antecedents and the social media behaviour of retweeting before summarizing and discussing the findings.

The paper is structured as follows. At first, we review the prior studies to form our theoretical research background. Subsequently, we present the methodology involving in our study, including choosing scenarios and data collection and analysis approach. Finally, we discuss the analyses' results and draw conclusion before giving suggestions for future research.

LITERATURE REVIEW

In this section, we provide a review of prior efforts in addressing misinformation, user engagement, uncertainties, as well as the role of potential antecedents of user engagement.

Social Media Misinformation

To study misinformation, prior studies mainly focused their efforts on two aspects: detecting misinformation and controlling misinformation diffusions. In the first research stream, various studies have built misinformation detection systems or algorithms by using extracted patterns from past data of messages circulating online through various channels like YouTube (Li et al., 2020) or Twitter (Kouzy et al., 2020). In the second research stream, several studies have examined behavioural or psychological features influencing the spread of online misinformation (Valecha et al., 2020) such as trust, risk perceptions (Krause et al., 2020).

Despite several existing efforts addressing technical solutions to detect and eliminate misinformation or to reduce its spread, to the best of our knowledge, there is no current research specifically incorporating user engagement, uncertainties and other antecedents during large scale crises like the COVID pandemic. Our research aims to fill this literature gap and to practically support efforts facing misinformation by identifying and quantifying misinformation uncertainty as well as possible antecedents of user engagement (Retweets) such as Affect and Harms. In order to fulfil this objective, we obtain the data from two separate sources, one from Twitter conversations and one from a panel of healthcare experts, as described in detail later.

User engagement on social media and the role of Retweets

In the context of crisis misinformation, especially during COVID-19 pandemic, it is crucial to understand the mechanism affecting people's behaviors facing the threats from misinformation. In turn, behavior can not only reflect the consequences of misinformation but also indicate the potential resulting diffusion of misinformation. Anchoring on misinformation spread on social media, we propose that examining social media users' engagement to the misinformation context can reveal various insights from COVID-19 misinformation.

Twitter is one of the most popular social media platforms that capture various aspects of user perceptions, emotions, opinions and reactions. Information spread not only by originally posting the messages (called as 'tweets') but by sharing such messages (via 'retweets'). By sharing the tweets as original or modifying the messages to show supports or critiques, retweets reflect various features regarding the involved topic or original messages (Boyd et al. 2010) such as expressed personal feelings, agreement and disagreement, or the intention to influence viewers' attitudes (Papacharissi and Oliveira, 2012). Accordingly, we propose that user engagement can be captured by the numbers of retweets, which indicates public interests on specific messages. Therefore, numbers of retweets are utilized as our study's dependent variable.

The role of Uncertainty and COVID-19 misinformation

When confronted with an ambiguous, complex, unpredictable, and concerning event such as the pandemic, uncertainty about what to do or not do prevails, thereby resulting in information seeking to reduce that uncertainty. Uncertainty has become a central focus in crisis communication and policy. Understanding uncertainty and its role is critical for social media networks and public health agencies to effectively counter health misinformation during a pandemic and mitigate the harms associated with it (Politi et al., 2007).

Starbird et al. (2016) stated that the spread of misinformation on social media has become common during a crisis situation due to the extreme uncertainty and due to the absence of the correct information which is what each individual in such a situation is looking for. Their study focused on “expressed uncertainty” on social media messages meaning clear, linguistic expression of uncertainty about the truth of information covered. They made an effort to understand uncertainty at both post level and at different stages of rumour lifecycle. Starbird et al. (2016) in measuring expressed uncertainty (linguistic expression of uncertainty in tweets) utilize a detailed comprehensive measure of expressed uncertainty that includes doubt about source and content of tweet. In our paper, we likewise utilize a broad measure of uncertainty leaving measurement of type of uncertainty to future work. Our measure of uncertainty as distinct from Son et al. (2020) measures uncertainty using the Starbird approach of expressed uncertainty in tweets but we deviate from Starbird et al. (2016) in measuring expressed uncertainty only in the presence of misinformation. In this study, we extract uncertainty scores from social media user tweets that discuss specific COVID-19 misinformation scenarios. Hence, besides the main concern about user engagement reflected by the number of retweets, we focus on the examination of the uncertainty that specifically refers to the misinformation claims when a Twitter user is exposed to the claims rather than other types of uncertainties in the COVID-19 pandemic context.

Research Hypotheses: Retweets and Antecedents

When twitterers come across any information about which they feel uncertain, they dive deep in search of correct information and then commune together with others to exchange this verified and confirmed information (Oh et al., 2015). Twitterers with correct information may be more confident to retweet. We state that when a tweet’s uncertainty is less, the level of misinformation is considered clear, accurate and more significant, thus increasing its retweet count. Son et al. (2020) stated that as the uncertainty in crisis tweets as measured by entropy increases, the retweet count decreases meaning due to presence of uncertainty in tweets they are not exchanged more (Bergeron & Friedman, 2015) also the information content is not very significant (Mileti & Sorensen, 1990), all these reasons together contribute to show how uncertainty can be expected to have a negative influence on the retweet count.

***H1**. Uncertainty is expected to be negatively related to Retweets.*

Prior literature has explored the impact of emotions on the public (Chew & Eysenbach, 2010) such as the 2003 SARS Epidemic (Yin et al., 2015), the 2012 Fukushima Nuclear Radiation disaster (Li et al., 2014), or the 2011 Egyptian Revolution (Oh et al., 2015). Much of the prior literature has found that emotions play a key role in social media behaviour and has explored the impact of emotions on the public (Chew & Eysenbach, 2010) such as the 2003 SARS Epidemic (Yin et al., 2015), the 2012 Fukushima Nuclear Radiation disaster (Li et al., 2014), or the 2011 Egyptian Revolution (Oh et al., 2015). Anderson et al. (2019), explains "affect" as a broader term that suggests feelings of discomfort or pleasure, emotions, stress, mood and arousal. More precisely, affect is believed to signify an aspect of mental states that consists of two factors: one is the valence that varies from pleasant to unpleasant, and another is arousal which varies from activated to deactivated (Russell and Barrett, 1999). We, therefore, use Affect in our study as a variable that aggregates emotions. To understand the relationship between affect and the retweeting behaviour of Twitterers, Stieglitz and Linh (2012) in their study investigate this relationship and showed tweets that contain the words reflecting affective processes have a tendency to be retweeted more in comparison to tweets that are missing such words. They further go deeper to specify that both negative as well as positive emotions expressed in the tweets increases their likelihood to spread over the Twitter network. This gives us our second hypothesis on the affect variable (as the overall emotion) and retweet count captured from Twitter conversations is therefore stated as:

***H2**. Affect is expected to be positively related with the number of retweets.*

In addition to Uncertainty and Affect, we identify another possible antecedent of retweets as the number of URLs appearing in each record from Twitter conversations. By considering the number of URLs present in a twitter message we argue that this is an indication of the proven or factual information providing the user with verifiable and concrete confirmation of the claim made in the message. Son et al., (2020) finds that the number of URLs in a tweet also play an important role in contributing supplementary enriching information during a crisis. Therefore, our third hypothesis is as follows:

***H3.** Number of URLs is expected to be positively related with the number of retweets.*

Besides these variables that can be extracted from captured tweets, we consider an additional antecedent that can influence retweets: the estimated harms from misinformation. Such estimated harms are captured with the participation of several health experts. As a trusted source their evaluation of the harms from misinformation can be expected to be a key element in social media behaviour. While estimated harms are at the scenario-level all of the other variables are at the individual tweet-level. Keeping that in mind, we postulate that estimated harms will have a moderating effect on the relationships between Retweeting behaviour and its antecedents. The more the potential harms from the topic, the more people tend to engage in sharing and discussing the message. Thus, we state our fourth hypotheses as:

H4: *Estimated harms positively moderate the relationships between the antecedents and retweets.*

In addition to the above, we also consider one possible control variable that might have effects on retweets: the number of hashtags of the tweets.

METHODOLOGY

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

Choosing COVID-19 misinformation scenarios

We first identify various COVID-19 misinformation scenarios considered. 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 are the false claims that 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). (Details of the claims as well as proofs of debunked messages can be provided upon request.)

Based on these, we chose a list of 30 scenarios that reflect the main aspects of the COVID-19 pandemic such as prevention methods, treatments or different ways to prevent the spread of the virus. These were subsequently filtered and finally 20 scenarios were chosen.

Data Collection and Data Processing

We analyzed the data from January 20, 2020, when it was officially declared by China that the COVID-19 cases were seen outside Hubei province. Our dataset comprises of six-months of tweets collected from Twitter using the Twitter REST search APIs using the search keyword #covid and #coronavirus. Along with these factcheck statements were also collected from official sources and fact checkers. These claims were used to segregate the tweets into the list of all 20 misinformation scenarios falling within 15-days before and after the debunk date amounting to a total of 94,551.

The collected data was then cleaned of '@' symbol, special characters, emojis, hashtags and stop words (not meaningfully important words such as 'a', 'an', 'the'…). Then the pre-processing of the data was done by performing stemming and lemmatization to reach singularity levels of words in tweets. After pre-processing, we segregated the tweets according to the scenario. To get tweets belonging to each of the scenarios a Jaccard match was made between the processed data and processed claim. A threshold level of the Jaccard score = 0.20 was considered to be optimal and 37,474 tweets meeting the criteria of Jaccard score greater than or equal to this threshold value were sorted into each of the scenarios.

Extracting and measuring Uncertainty and other tweet-level antecedents of retweets

After processing, we had all the tweets that belonged to their respective scenarios. We calculated the uncertainty score for each tweet. The uncertainty score was calculated using the Jaccard similarity of the tweets with words that correspond to "tentative" in the NRC dictionary. Additionally, we also calculated the number of hashtags and number of URLs that were present in the unprocessed tweet text. Finally, sentiment analysis was performed on each of the tweets to find the emotions associated with the tweets. Since Affect is a much broader umbrella term depicting all emotions, we used Affect as a composite of emotions using the LIWC dictionary to extract Affect. We now had all the necessary tweet level variables for our study.

Estimated Harms from Healthcare Experts

A critical element of our study is the evaluation of the harms from each misinformation scenario. To capture this, we obtain estimated harms from 3 healthcare experts (2 doctors and 1 registered nurse, with healthcare experience ranging from 8 to 40 years). We asked the experts to rate the health harms from the actual claims of the COVID-19 misinformation scenarios on a scale from 1 to 10. We filtered out the scenarios that had much disagreement among experts. Finally, from the original 30 scenarios, we obtain a list of 20 misinformation scenarios with high level of agreements on estimated harms (66.66%), as shown in Table 1. From the estimated harm scores, we calculate the average scores for 20 scenarios. We then classify the scenarios into 2 distinct groups: Group 1 of the ten scenarios with high harm scores (equal to or higher than 5.0) and Group 2 of the ten scenarios with low harm scores (less than 5.0).

Table 1. Final List of 20 COVID-19 Misinformation Scenarios

High perceived health harms (≥5.0)				**Low perceived health harms (<5.0)**			
ID	**Scenario**	**ID**	**Scenario**	**ID**	**Scenario**	**ID**	**Scenario**
S1	Antibiotics	S6	Compare to flu	S11	Pets	S16	Eating banana
S2	Chloroquine	S7	Old people	S12	Eating garlic	S17	Eating cold food
S3	Bleach	S8	Hand sanitizer	S13	Drinking water	S18	Moist throat
S4	Fish tank cleaner	S9	Detection by runny nose	S14	Drinking garlic water	S19	Receiving Chinese packages
S5	Wearing masks	S10	Vodka sanitizer	S15	Gargling salt water	S20	Eating at Chinese restaurants

Data Analysis Approach

We identified the outcome (dependent variable) of our analysis as the captured numbers of retweets from each captured tweets. Antecedents of the outcome (independent variables) include the uncertainty obtained from tweets (using LIWC), the Affect obtained from tweets that show emotion (using LIWC), number of URLs in the tweet, and estimated harm scores from healthcare experts, and URL numbers. For the estimated harm scores obtained from healthcare experts, we considered whether the scenarios were in group 1- high harm (1) or group 2 – low harm (0), which is named as 'HarmGroup' variable. In addition to the independent variables, we examine one control variable that might have effects on retweets: the tweets' hashtags. Finally, we examined both the main effect and the interaction effects between HarmGroup and all other independent variables. We employed a mixed model using STATA15 with 'Retweets' as the dependent variable. The mixed model involves both fixed effects and random effects that considers both overall records and nested groups of records based on the 20 chosen COVID-19 misinformation scenarios. Our chosen grouping variable for the mixed model (the 'identity" in Stata) are the values of estimated harm (0 and 1) of scenarios that are listed in Table 1.

Therefore, the research equation can be summarized as:

$$Retweets = \beta_0 + \beta_1{*}Uncertainty + \beta 2{*}Affect + \beta_3{*}URL + \beta_4{*}HarmGroup + \beta 5{*}Hashtag + \beta_6{*}HarmGroup{*}Uncertainty + \beta_7{*}HarmGroup{*}Affect + \beta_8{*}HarmGroup{*}URL + \varepsilon$$

Where: β_i, i.e., coefficients of the variables in the regression, and ε the error term of the analysis. In general, a variable will be concluded to have significant effects on the dependent variable (Retweets') if it has resulted p-value associated with the coefficient β_i equals to or less than 0.05 (equal to or more than 95% confident that the variable has significant effects).

DATA ANALYSES' RESULTS AND DISCUSSION

Table 2 shows the descriptive statistics of captured and matched 37,474 tweets.

Table 2. Descriptive statistics

Variable name	Mean	Standard deviation	Range

Retweets	89.88	2271.095	0 - 83092
Uncertainty	0.00021	0.00117	0.00000 – 0.01899
Affect	0.07349	0.16646	0.00000 – 1.00000
URL	0.63	0.59	0 - 11
Hashtag	0.77	2.096	0 - 32
HarmGroup	0.45	0.498	0 - 1

The results of the mixed model regression on dependent variable Retweets are summarized in Table 3.

Table 3. Results from Mixed Model Regression of Retweets

Main Effect			**Interaction Effect**		
Independent variable	**Coefficient (β_i)**	**Standard error**	**Independent variable**	**Coefficient (β_i)**	**Standard error**
Uncertainty	-266.4547	79.192**	HarmGroup*Uncertainty	261.1167	88.957**
Affect	-5.713621	0.903***	HarmGroup*Affect	3.235554	1.042**
URL	1.033827	0.238***	HarmGroup*URL	-1.430337	0.263***
Hashtag	-0.1851096	0.019***			
HarmGroup	7.926927	2.429**			
[Constant]	-5.735255	1.585***			

*Note: *: significant (p-value≤0.05); **: highly significant (p-value≤0.01); ***: very significant (p-value≤0.001); [NS]: not significant (p-value>0.10).*

From the results, we can see that all of the relationships between the considered antecedents and retweets are significant, including: Uncertainty, Affect emotion, URL, HarmGroup, all interaction effects and the effect of the control variable. With respect to our proposed hypotheses, there are several key results: Consistent with our expectation retweets, the independent variables such as 'uncertainty' and the control variable 'hashtag' have significant negative effects and URL has a positive effect, meaning H1 and H3 are supported. The negative relationship between uncertainty and retweet is consistent with the findings of Son et al. (2020) who used entropy as a measure of uncertainty while we use expressed uncertainty in tweets to measure it. On the other hand, Affect has a significant negative effect on retweets, which is opposite to our expectation in H2 of a positive effect, Further analysis may be needed in future work to explain this.. It is of interest that one of our novel hypothesis, H4, about the moderating effect of HarmGroup is supported indicating that scenarios which have a higher harm level evoke a larger level of retweets. It is also of interest that two out of three interactions with HarmGroup significantly increase retweets (interactions with uncertainty and affect) while the other interaction (with URL) significantly lowers retweets. This could be interpreted as providing strong support to the role that the level of harm in an information scenario plays in retweeting behaviour and search for information. While others have attempted to measure harm, our approach is unique, to our best knowledge, in using health professional's evaluation of harm. To summarize, our study finds that our key measures of uncertainty expressed in tweets, and professionally evaluated harms of misinformation scenarios play an important role in retweeting behaviour and the search for information during a crisis.

CONCLUSION

Misinformation and uncertainty are prevalent and influence social media engagement behaviour during widespread and severe health crises such as the COVID-19 pandemic with significant implications for the effectiveness of interventions. The impact of uncertainty and the harms associated with misinformation on social media engagement as captured in their retweeting behaviour is the focal point of this paper. We contribute to the literature on misinformation through unique variables such as uncertainty expressed in tweets and professional estimation of harms in misinformation scenarios along with a rigorous approach to capturing variables from tweets.

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