The Effect of Twitter User's Commenting Behavior on the Propagation of COVID-19 Misinformation

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Abstract We investigate how including comments when sharing (accountable or false) news on social media would affect its propagation on social media. When sharing external news, users may directly share without comment, copy-paste contents from the news, or posting their own opinions. We hypothesize posting comments would boost the chance of the post to propagate on social media. With a dataset of 170K COVID-19 news-sharing Tweets, we use regression models to test our hypothesis on sharing of news of different qualities. Our results show that the users' commenting behavior when sharing external news on social media significantly boost its propagation across both trustworthy and false news. The effect of such commenting behavior is much larger than any content factors such as emotions in the comments themselves. This finding calls for awareness on this factor before study the effect of contents in future studies on the propagation of misinformation.

1 Introduction

Social media has become a significant news source amid the heated debate over the concerns regarding the pervasiveness of misinformation propagating online [1, 9, 24]. A variety of works dedicated to detect and identify rumors and false information from language [25], network patterns [23], or user profiling [26]. Meanwhile, it is equally important to understand how those harmful messages propagate and potentially go viral on social media platforms, from which we may measure the consequences of the online misinformation.

Users' re-posting (including those with comments) and likes are the evidences commonly used to quantify the popularity of social media posts [12, 13]. Despite the factors from social media post creators such as audience size, social media usage history [25], and social network structure [10], content features are most studied as the individual-level factors affecting the popularity those posts. Emotions, especially negative emotions such as anger, anxiety, and sadness, are reported by many researchers to be positively correlated with the popularity of social media posts [4, 12, 16]. Other than emotions, usage of social functions, including mentions and hashtags [20], is also positively related to the posts' popularity. In these works individual social media post is treated as the unit of analysis; however, the condition is more complicated in sharing external news on social media. There are two steps in this propagation, where in the first step, the viewers of the news articles act as "initial-sharers" bringing the external information into social media platforms. In the second step, the audiences of the sharers see and spread the posts. Are the initial-sharers altering (i.e. posting additional contents other than the to-be-shared information) the information when bringing the external information to social media? If so, are their altered messages influencing the information to propagate?

We hypothesize the user-generated comments when sharing news on social media would boost the popularity, for two reasons. Firstly, the posted comment would add additional contents to the post. This newly injected text may or may not change the linguistic attributes, such as emotions, of the original post; however, it includes the sharer's opinion into the post. At the close-range of the social network, the echo-chamber effect [9, 31] would increase the acceptability of the injected opinions and consequently increase the chance that the post to be agreed upon and shared by others [8, 30]. Additionally, as argued by researchers in consumer and marketing studies, the comments also create a Word of Mouth on the electrical materials (articles) to be spread in social media [15]. Typically a WoM with positive sentiment would increase the chance of spread [14], and people would be more likely to share positive sentimental WoMs rather than negative ones [22]. Secondly, the action of comment on social media acts as the initiation of discussions [29]. As reported by surveys, "participating in a discussion" is identified as one psychological motivation of people retweeting others [6, 27]. This motivation is more likely to be affected by user comments, and thus an increased chance of getting propagated is expected. We make the hypothesis on the effect of commenting behaviors on whether social media would get propagated:

H1: Posting commenting contents would increase the chance for the post get propagated on social media.

In addition to the influence of commenting behavior on popularity, we further investigate the factors affecting this behavior. The initial-sharing (with a comment or not) itself is potentially affected by the articles' emotional contents similar to other sharing processes; however, the effect of different emotions would affect, in particular, the commenting behavior differently. Studies in emotional psychology argued that emotions have different levels of arousal (regarding the most studied emotions in propagation: anger - high arousal, anxiety - moderate arousal, and sadness - low arousal) [2]. Experiencing high arousal would trigger the "achievement motive" of people [21], affected by which individuals would likely to act actively rather than passively. Additionally, Bradley et al. argue that anger emotion would increase activation level, while sadness does the reverse [3]. Compared to sharing without original opinions on social media, leaving a comment would be an active behavior. Consequently, the tendency to comment at high activation level (such as experienced anger) would be higher, while it would be lower at low activation level (experienced sadness). From the theories on arousal we make our second hypothesis explaining why people would comment when sharing as:

H2: The commenting behavior can be positively affected by anger in article contents and depressed by sadness.

2 Method

We test both of our hypotheses on a Twitter dataset related to the COVID-19 pandemic. Using two regression models, we test the significance of commenting behaviors on propagation and factors affecting it. This section is organized as an introduction of the dataset, the extraction of variables, followed by the models we used.

Data We run our analysis on the dataset published by Chen et al. [7]. This dataset is tracked with COVID-19 related keywords during Jan. 2020 and May. 2020. We identify news article sharing activities from this dataset with a predefined list of news outlets reported by Grinberg et al. [11]. The list split the outlets into categories of green (accountable journalism), yellow (low-quality journalism), orange (negligent or deceptive), and red (little regard for the truth). We filter with the list in the Twitter dataset, and get 170K (64K, 36K, 28K, and 12K for Green, Yellow, Orange, Red domains, respectively) original Tweets sharing URLs from the listed domains.

Dependent Variable. We use the sum of #retweet and #like to measure the *popularity* of a Tweet post. We treat zero popularity (no retweets and likes) as not getting propagated and popularity above zero as getting propagated. In this dataset, we have 78044 (45%) of the posts that have zero popularity.

Independent Variables and Controlling Variables. We parse the Tweet collection with Myers' difference algorithm [18] to identify repeated article titles or first sentences in the Tweet messages to identify non-article contents as the user's comments. For instance, a Tweet reads: "*Bill Gertz <mention> is one of the top National Security journalists in the world. This is his latest piece on the bio warfare labs in Wuhan. - Virus-hit Wuhan has two laboratories linked to Chinese bio-warfare program #coronaviruschina #outbreak*". With the string difference algorithm, we extract "*Virus-hit Wuhan has two laboratories linked to Chinese bio-warfare program*" because it is identical to the sentence that appeared in the article. The remaining part is then counted as user comments. We identify 127K Tweets that contain the user's comment with this method in total and create a binary variable. We also include other variables reported as factors of the propagation of social media posts for the controlling purpose, including: *Audience Size* of the sharer measured by his/her number of followers; *Emotion in article* which is from the LIWC [19] word count of emotional words in the news article normalized by the number of sentences; *Emotion in Tweet* which is existence of LIWC emotional words in the comments; and other metadata including *length of the article*, *#hashtags.* and *#mentions* in Tweet.

Models. We use logistic regression (with robust standard errors to account for hetero-scedasticity) to model the relationships between variables and the chance of getting propagated to test **H1**. A Structural Equation Model (SEM) [28] is used to exam the effect of article emotions on commenting behaviors for **H2**. As shown in Figure 2.1, we draw paths from article emotions variables to both the variable "whether a tweet contains comments" and the dependent variable of the chance getting propagated. We include anxiety in the hypothesized effective emotion group as one with a moderate arousal level for comparison.

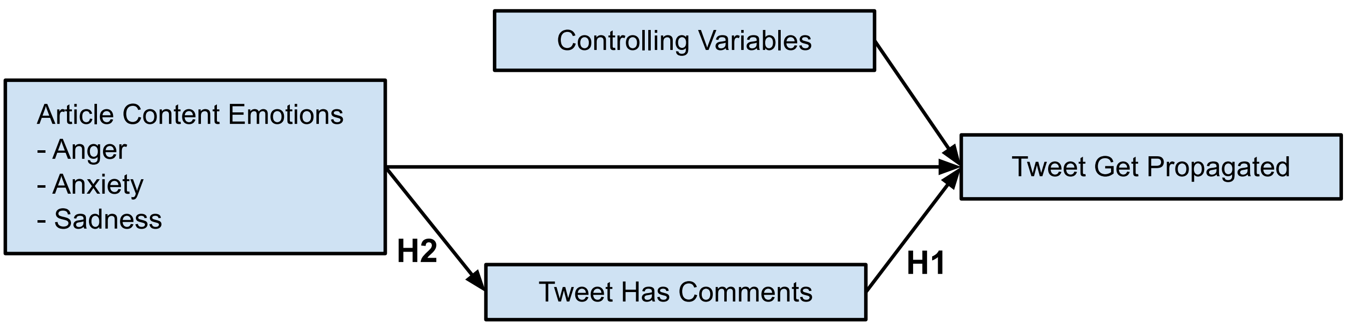

Figure 2.1: **SEM Structure.** The hypothesized emotions has effect on both the commenting behaviors and the dependent variable. The commenting behavior has effect on the propagation. Controlling variables include other content features in article/comments, and the audience size of sharers.

3 Results

Table 3.1 reports the results of the Logistic Regression for each data subsets. As shown in the table, the commenting behavior is persistently a significant indicator to whether a news-sharing post would get propagated (0.17***, 0.21***, 0.17***, 0.08***, 0.13*** for each model, all $p < 0.001$). Moreover, the loadings on emotions in the comments (Twt.Anger, for instance) are mostly not significant to the dependent variable, suggesting that the injected emotional contents is not responsible for the major effect on the propagation, regarding the commenting behavior itself. This evidence confirms the hypothesis **H1** that the action of commenting would increase the chance of a social media post getting propagated. Previous research emphasized the effect of emotional contents in social media posts affecting the propagation of those posts; however, our data shows the existence of users' comment is a more significant factor than the emotional signals appeared anywhere in the posts. The effect from the commenting behavior itself is consistent across news-sharing posts on social media articles of different qualities. This finding calls attention in future studies to separate the effect from commenting behavior (which is pervasive on any one of the social media platforms) before investigating further factors from the contents.

Table 3.2 report the results of SEM models. Root Mean Square Error of Approximation (RMSEA) of all models are below .08, suggesting they are good fits. Like the Logistic Regression Result, the commenting behavior still plays a major role in determining whether a Tweet would get propagated (0.10, 0.12, 0.10, 0.05, 0.08, with all $p < 0.001$). As hypothesized, instead of directly having effects on the chance of getting propagated, the anger emotion is associated with the behavior of commenting in all but yellow article sharing posts (with coefficients: all case 0.02 ($p < 0.001$), green articles 0.02 ($p < 0.001$), orange articles 0.05 ($p < 0.001$), and red articles 0.03 ($p < 0.001$)), and sadness emotion affect negatively to this "active sharing actions" due to its low arousal (all articles -0.006 ($p < 0.01$), yellow articles -0.02 ($p < 0.001$), red articles -0.02 ($p < 0.01$)). However, the negative effect of sadness reversed in "Green" article posts (0.015 ($p < 0.001$)), which rejects part of the hypothesis **H2**. This exception may be due to some factors that are not captured by the model, for instance, the trust of viewers in the legit "Green" article sources. As reported by multiple studies [17, 5], the trust in news sources may positively drive people's behavior of sharing. Consequently, viewers of these articles may actively share and comment regardless of the arousal in the article contents. Our data shows that emotional content in news articles indeed is associated to more active sharing behaviors. Although such emotional content's direct effects are not significant, they have indirect influences on the propagation of messages on social media. For instance, we see that anger is more likely to be associated with the commenting behaviors, and the later one would further increase the chance of social media posts to propagate. By exploring the behavior of commenting, we propose an alternative explanation in addition to previous works on why the emotional content would be positively associated with social media propagation.

Article Set	All	Green	Yellow	Orange	Red
Aud.Size	1.241***	1.331***	1.198***	1.150***	1.271***
Art.Anger	-0.007	-0.017	-0.009	0.061***	-0.028
Art.Anx	0.006	-0.001	0.022*	-0.018	-0.039
Art.Sad	0.021***	0.031**	-0.002	0.045**	-0.005
Art.PosEmo	0.008	0.051***	0.004	-0.040**	0.029
Art.Negate	-0.027***	0.001	-0.068***	-0.005	-0.032
Art.Length	0.027***	-0.067***	0.071***	0.053***	0.048*
Twt.Anger	-0.014*	-0.026**	-0.004	-0.002	-0.011
Twt.Anx	0.012*	0.015	0.020*	-0.009	-0.018
Twt.Sad	0.021***	0.016	0.035***	-0.007	0.026
Twt.PosEmo	0.046***	0.052***	0.051***	0.023	0.045
Twt.Negate	0.031***	0.011	0.043***	0.050***	0.041
#hash	0.122***	0.105***	0.077***	0.272***	0.119***
#mention	0.147***	0.146***	0.140***	0.177***	0.167***
Twt.HasCmt	**0.171*** **	**0.205*** **	**0.168*** **	**0.082*** **	**0.132*** **
const	0.200	0.113	0.243	0.371	0.049
Pseudo R^2	0.180	0.202	0.173	0.157	0.195

Table 3.1: **Logistic Regression Results.** From left to right we report results of All data (N=170,026), Tweets sharing Green (N=64,778), Yellow (N=65,281), Orange (N=28,039), and Red (N=11,895) articles. (*: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$)

Dataset	All	Green	Yellow	Orange	Red
Popularity~					
Aud.Size	0.736***	0.787***	0.713***	0.685***	0.753***
Twt.Anger	0.002	0.006	0.007	0.003	0.003
Twt.Anx	0.013***	0.015**	0.018**	-0.003	-0.008
Twt.Sad	0.017***	0.015**	0.026***	-0.002	0.019
Twt.PosEmo	0.045***	0.053***	0.049***	0.019*	0.042**
Twt.Negate	0.028***	0.021***	0.034***	0.033***	0.033*
#hash	0.094***	0.089***	0.066***	0.169***	0.092***
#mention	0.088***	0.089***	0.083***	0.105***	0.096***
Twt.HasCmt	0.101***	0.120***	0.100***	0.045***	0.078***
Art.Anger	-0.004	-0.009*	-0.004	0.035***	-0.017
Art.Anx	0.001	0.001	0.008	-0.012	-0.024
Art.Sad	0.012***	0.018***	-0.002	-0.027**	-0.007
Art.PosEmo	-0.001	0.026***	-0.009	-0.026**	0.018
Art.Length	0.018***	-0.036***	0.040***	0.036***	0.028*
Twt.HasCmt~					
Art.Anger	0.026***	0.022***	0.012**	0.055***	0.033***
Art.Anx	0.005*	0.009*	0.008*	0.016***	-0.041***
Art.Sad	-0.006*	0.014***	-0.017***	-0.009	-0.026**
RMSEA	0.049	0.047	0.048	0.079	0.048

Table 3.2: **Structural Equation Modelling Results** We report the coefficients of the SEM model. The effect of variables on propagation is reported on the top of the table followed by the effect of trigger emotions on the commenting behavior.

4 CONCLUSION

We propose our hypotheses on the positive effect of commenting behavior on the propagation of social media news-sharing posts. Also, we discuss how previously found factors of content emotions trigger this behavior. By analyzing a dataset of COVID-19 news sharing on Twitter, we confirm our hypothesis and call attention to this users' commenting factor in future studies on social media propagation. Moreover, with our data, we provide an alternative explanation of why news articles' emotional contents would influence their social media propagation through the positive association with the commenting behavior. This explanation deepens the understanding on the direct factors of misinformation propagation on social media, and creates additional space for studying the intervention of misinformation through manipulations on users' comments in sharing. From our data, some of the emotional contents show exceptions in cases of different categories of articles, and the exceptions could be caused by the distinct nature of the articles. More research is needed to reveal whether various news media sources would drive viewers differently sharing their content on social media.

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