The Public Needs More: the Informational and Emotional Support of Public Communication amidst the Covid-19 in China

Abstract

Public communication is critical for responding to disasters. However, most research on public communication is largely focused on its informational support function, overlooking the emotional support that could equally offer. This study takes the lead to investigate their separate impacts. In particular, the variable public engagement, which is a function of the number of Shares, Likes, and Comments in a particular post, is introduced to benchmark the effect of public communication. Besides, considering the evolving nature of the crisis, their dynamic impacts across different COVID-19 pandemic stages are examined. Data from Dec 2019 to Jul 2020 were collected from 17 provincial government-owned social media (Weibo) accounts across COVID-19 in China with a Natural Language Processing-based method to compute the strengths of informational support and emotional support strength. An econometric model is then proposed to explore the impacts of two supports. The findings are twofold: the impact of emotional support on public engagement is empirically confirmed in the study, which is not in lockstep with the informational support; and their impacts on public communication are dynamic rather than static across stages throughout the crisis. We highlighted the importance of emotional support in public engagement by deriving its impact separately from informational support. The findings suggest incorporating both social supports to create stronger public communication tactics during crises.

Keywords: COVID-19; Emotional Support; Government-owned Social Media; social Support Theory; Public Communication

1 Introduction

Government agencies have become unprecedentedly relied on social media for public communication (Reuter & Kaufhold, 2018), especially during emergent situations (Palen, *et al.*, 2009). Its impelling advantage for this role is genuine and deeply ingrained communication

amongst users given that social media entails the systemic capacity to the public information and warning approaches (Tagliacozzo & Magni, 2018). Comparatively, the information on social media is updated in a highly prompt manlner (Al-Saggaf & Simmons, 2015) and its flat networked structure transmits the information timely to a wider range of audiences (Dabner, 2012). Those affordances together ensure that social media can efficiently and effectively disseminate situational awareness information, which is of utmost importance in a crisis context (O'Brien, *et al.*, 2020; Zhang, *et al.*, 2019). Particularly, the restrictive measures involving self-isolation, quarantine, and city lockdown at the height of Covid-19 have largely reduced mobility, resulting in social media as a prominent channel for the government authorities to broadcast and disseminate information (Chen, *et al.*, 2020; Islam, *et al.*, 2020).

In addition to its information influences, there is an increasing understanding that social media can be leveraged to impose psychological impacts on social communities (Hu, *et al.*, 2022a; Hu, *et al.*, 2022b). Specifically, social media can create a mutual aid environment, providing an outlet for social interaction and voicing fear, and offering a voluntary reciprocal exchange of resources and services for mutual benefit (Marzouki, *et al.*, 2021). Nevertheless, most extant studies emphases on mutual aid amongst the public, overlooking the situation between the government (the sender) and the public (the receivers), where psychological influence is transposed through public communication as the public are seeking psychological support in addition to information through social media (Jin, 2010). Indeed, the public communication posts released by government-owned social media play a prominent role not only in publishing pandemic information but also in providing emotional support (e.g., encouragement, and sympathy) during the COVID-19 pandemic(Hu, *et al.*, 2022a). As a result, while a multitude of studies have posited that emotional support can be conveyed through public communication (Langford, *et al.*, 1997; Liang, *et al.*, 2011), empirical evidence on how the government can exploit social media to transpose emotional support to the online community remains scant.

Furthermore, the devastating pandemic has gripped the globe for more than two years as of February 9, 2022, when Sweden first set to lift all coronavirus restrictions. Given this prolonged

duration of the pandemic, the impacts of both informational and emotional support are prone to be rather complex than fixed. According to McKinney, *et al.* (2002), the impact of web service is affected by public expectations and possible disconfirmation between such expectations and web performance. Waves of Covid-19 compounded by rounds of lockdowns have altered the public's expectations for public communication with the government (Chen, *et al.*, 2020), giving rise to changes in their expectations for social media (Huang, *et al.*, 2020). In such a sense, the impact of social media is prone to be dynamic throughout the emergency rather than static. Further, amidst the emergency, reasonable caution has been allocated to the "infodemic" or information overload (Zarocostas, 2020). It is identified as a pressing issue as it hinders the effective dissemination of information on social media, and may further impose negative impacts on an individual's mental well-being by triggering stress, frustration, dissatisfaction, and feeling of loss of control (Bucher, *et al.*, 2013). In addition, the interim public policies formulated in the first place during crises are not often fully supported by sufficient scientific evidence when being disseminated via social media (Moore & MacKenzie, 2020), which may lead to confusion and/or uncertainty (Erku, *et al.*, 2021). Likely, the information provided through social media may not always stay in line with the public's expectations (Coombs, 2007, 2010). To this end, instead of assuming social media's support are constantly positive, we must accept that the impact of information support and emotional support can be negative. It thus highlights the need of making the best use of social media between the government and the public for desirable outcomes.

Considering the above, we aim to examine two research questions in this study:

(1) What is the empirical evidence for emotional support along with informational support on Weibo amidst COVID-19 in China?
(2) How did the impacts and dynamic changes of informational support and emotional support present during the emergency?

To answer these questions, we utilized Natural Language Processing (NLP) techniques to investigate and quantify the information support and emotional support from the government

to the public by analyzing the social media data from 17 government-owned Weibo in China. We then deployed public engagement as the proxy for the effect of public communication and an econometric model is then proposed to explore the impacts of two supports. Then, we deployed COVID-19 as the context because it is an ongoing global event, which offers us long enough time and sufficient data to empirically collect and analyze data.

2 Literature Review

2.1 Public communication

It has been well documented that public communication has a significant impact in emergent situations to limit the scope and mitigate the impacts of adverse events through disseminating timely and verified information to wide public audiences (Seeger, 2006; Wirtz & Zimbres, 2018). According to Perry and Nigg (1985), the role of public communication in crisis is three-fold, it improves situational informing, facilitates information exchange, and supports government reputation restoration.

The importance of early warning and risk information cannot be overstated during disasters. Public communication address this need by reaching the public timely and informing them of the nature, magnitude, and significance of the disaster, its associated risk, and possible coping strategies through the production of the public message (Reynolds & W. Seeger, 2005). This process seeks to alert individuals, provide protective action guidance and induce a public behavioral change in alleviating the threat (Reynolds & W. Seeger, 2005; Sutton, *et al.*, 2014). Particularly during the Covid-19 pandemic, an absence of verified information has caused "panic buying" in many parts of the world (Torero, 2020; Zhu, *et al.*, 2021). Such behavior not only impairs the government's central effort in mobilizing the resource but also stressing to the psychological distress among the citizens (Hu, *et al.*, 2022a).

Its next role is surrounding information exchange, where public feedback is sought on specific procedures and/or policies to further address public concern (Covello, 1992). This process emphasizes developing communication strategies that respond to and anticipate the public's

needs (Lachlan, *et al.*, 2016; Reynolds, *et al.*, 2014; Reynolds & W. Seeger, 2005; Veil, *et al.*, 2008). It is widely argued that public service needs to account for the demand sides (Andrews & Entwistle, 2013; Andrews & Van de Walle, 2013). An absence of communication between the government and the public, especially during disasters, may consequence in mismatching demand. As stated above, rumors or unverified information may lead to the public's psychological distress, distrust in the government, and non-compliance behaviors during the disaster response, which imposes significant challenges to the ability of society in coping with the disasters. The imbalance of demand-supply relationships is prone to further result in a waste of public resources and improving the effectiveness of public communication.

In addition, good public communication can also be exploited to restore public trust in government and minimalizes the potential reputation loss caused by rumors or misinformation (Coombs, 2007). When a crisis occurs, rumors may distort the truth, further reinforcing the public's distrust of the government authorities (Cheng, *et al.*, 2020). If it is not properly managed, such a miscommunication would erode public trust in the government (Schmelz, 2021). Good public communication can not only facilitate the clarification of rumors, misunderstandings, and distorted facts but also signify the government's responsibility and accountability to manage disasters (Goldfinch, *et al.*, 2021), which are drivers for the public's trust in the government. Further, Rosenberg (2021) argued that the level of citizens' compliance with policy reflects their level of trust in government, whereas a low level of trust may result in non-compliance behaviors and even social chaos (Bargain & Aminjonov, 2020).

2.2 Social media based public communication

Compared to traditional medium (e.g., radio, television), online medium, such as social media, has quickly evolved into a new impetus for public communication during a crisis because they can greatly address the public's needs (Lachlan, *et al.*, 2016; Ma & Zhan, 2016). As an alternative to traditional media, social media is considered a reliable channel for situational informing, information exchange, and reputation restoration (Hu, *et al.*, 2022a; Liao, *et al.*, 2020; Marzouki, *et al.*, 2021; Mori, *et al.*, 2021).

Its remarkable benefit in public communication is ingrained in its disperse networked structure. Such structure, as opposed to the conventional top-down hierarchical public communication paradigm, enables government information to communicate directly and promptly to a wider range of people (Dabner, 2012). This benefit has been empirically observed in scenarios such as the Haitian earthquake (Yates & Paquette, 2011), Hurricane Sandy (Hughes, *et al.*, 2014), and the Covid-19 pandemic (Liao, *et al.*, 2020; Marzouki, *et al.*, 2021; Mori, *et al.*, 2021). Particularly during Covid-19 when strict quarantine and city lockdown measures are taken, social media has become an indispensable tool for public communication (Marzouki, *et al.*, 2021). Such rapid information and warning delivery facilitate the public to prepare for the coming risk and adverse impact, which is foremost in the public's response to the crisis.

Second, with the increasing adoption of social media amongst government agencies, such as the U.S. Federal Emergency Management Agency (Hughes, *et al.*, 2014; Yates & Paquette, 2011), the National Health Commission of China (Liao, *et al.*, 2020), in promoting public communication during crises, the information posted is carefully scrutinized and validated (Li, *et al.*, 2020), further enhancing the credibility. The timely and trustworthy information from the government in the online medium is most likely to exert positive impacts on bundles of multiple and heterogeneous aspirations, values, and perspectives between governments and the public (Li, 2020; Wu, *et al.*, 2021).

In addition, online mediums have radically revolted public communication during crises by bringing forward two-way communications (Panagiotopoulos, *et al.*, 2016). Indeed, one-way asymmetrical communication might be efficient in terms of speed (Bertot, *et al.*, 2012), but two-way dialogical interaction is more effective in information exchange because it enables the public to voice their needs and concerns while also making it easier for government to collect of first-hand information (ibid). These information exchange activities will serve as a bottom-up channel to inform the government of better disaster situational awareness, which is critical for policy-forming and policy development amid a crisis (Brombal, *et al.*, 2017). Moreover, recent studies have implied that social media shift the role of the public in public

communication from a passive recipient to an active information seeker (Oh, *et al.*, 2013) or even an information service co-providers (Mori, *et al.*, 2021).

Nevertheless, most of the existing studies on the possible influence of public communication during disasters are revolving around the information service provision, sporadic evidence also implies that beyond information, online public communication can also convey positive emotions, perception of support, and companionship (Hu, *et al.*, 2022a).

2.3 Social support in social media based public communication during the crisis

Social support theory (Langford, *et al.*, 1997) provides a theoretical foundation to reveal the impact of both informational and emotional support through social media based public communication amidst an emergency Broadly, social support has been defined in the literature as the assistance and protection given to others, especially to individuals (Wortman & Dunkel-Schetter, 1987), shielding them from precarious events and adverse effects. Shumaker and Brownell (1984) describe social support as a process of resource exchange between individuals, giving rise to the notion that social support is reciprocal in nature (Cohen & Syme, 1985). Indeed, social support is a complex concept and researchers have put forth various taxonomies (Cohen & Syme, 1985; Coulson, *et al.*, 2007; House, 1983) to categorize it, including the classic four-dimensional framework by House (1983), namely informational, emotional, instrumental, and appraisal support. Notwithstanding the diversity of taxonomies, more recent studies classified different social support constructs into two main types (Hu, *et al.*, 2022a; Kort-Butler, 2017; Yan & Tan, 2014). Specifically, informational support comes in the form of the transmission of information during a time of stress while emotional support in the form of provisioning caring, concern, empathy, love, and trust (Kort-Butler, 2017).

In social media, social support theory is also a popular theoretical framework for understanding the use of impact of the online community on individuals (Reblin & Uchino, 2008; Stephens & Berner, 2011; Yan & Pedraza-Martinez, 2019a). One of the most noticeable practices is social support reinforces two-way interactions in the online community, as the public perceives

supportive resources by collectively interacting with the posts through embedded functions, such as like, share, and comment (Yan & Pedraza-Martinez, 2019a). This further motivates their engagement in resource exchange in social media, contributing to the decision-making process for fast-evolving situations (Lovari & Bowen, 2019). Particularly, the influence of social support in social media can be understood through two influence mechanisms, namely emotional and informational support (Carr, *et al.*, 2016; Liang, *et al.*, 2011; Rains & Keating, 2011). While the compelling advantages of social media in delivering timely information update to a wider audience is extensively acknowledged in literature (Al-Saggaf & Simmons, 2015; Dabner, 2012), recants studies have shifted the focus to social media's role in providing emotional support. For instance, Marzouki, *et al.* (2021) posited that social media can create a mutual aid environment, providing an outlet for social interaction and voicing fear, and offering a voluntary reciprocal exchange of resources and services for mutual benefit. Similar findings are evidenced in the work by Yan and Pedraza-Martinez (2019a) that online communities via social media can construct different social relationships, by which to exchange emotional support.

Particularly in times of crisis, the need for informational and emotional support is highlighted in the literature. For instance, it is repeatedly identified that fast information and warning delivery helps the public prepare for potential danger and negative effects, which is crucial in the public's response to the crisis (Dabner, 2012; Hughes, *et al.*, 2014; Marzouki, *et al.*, 2021). On the other hand, recent COVID-19 pandemic related studies have stressed the importance to address the prevailing mental health issues among the general public and suggested that social support in social media may provide a potential solution to address when professional treatment is not readily available to the massive public (Cohen & McKay, 2020; Hu, *et al.*, 2022a; Li & Peng, 2021; Liao, *et al.*, 2020; Yan & Pedraza-Martinez, 2019b).

In line with Hu, *et al.* (2022a), we argued that facilitated by the interactive function of social media, public communication can exert a positive impact on the massive public through social

support provision. Indeed, evidence from China during the COVID-19 pandemic demonstrated that social media postings did play a crucial role in establishing the truth (e.g., sharing pandemic information, refuting rumors, fostering public self-protect measures) (Shen, *et al.*, 2022) and boosting the social morale (e.g., encouraging messages, voices from top scientists and the COVID-19 fighters) (Hu, *et al.*, 2022a). Nevertheless, several research gaps remain unaddressed. First, while the impacts of both emotional and informational support have been well studied independently, they have not been compared. Second, much of the study treats the effects of social support as static, omitting to look at their dynamic effects at various stages. Last but not least, despite all the attempts, there is a dearth of empirical evidence on how government can leverage social support for better public communication.

3. Methodology

3.1 Research Setting

To investigate the dynamic of informational support and emotional support strategies, we phased the timeliness of the pandemic into five stages according to the White Paper released by China's State Council Information Office (SCIO, 2020) as depicted in Appendix 1. In addition, according to the National Health Commission, after nearly two months of no new local Covid-19 transmissions, Beijing reported 79 fresh cases since June 12, 2020, where the public fell into fear of the second wave in Beijing after the Xinfadi market outbreak (Tan, *et al.*, 2020). Therefore, we further separate Stage 5 into Stage 5a and Stage 5b (Figure 1).

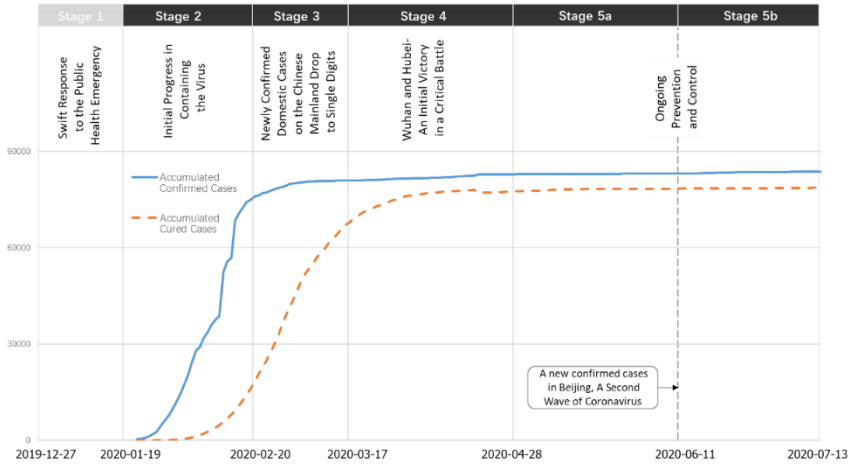

Figure 1 Division of Pandemic Stage

3.2 Data

We took extra efforts in mitigating the data collection challenges in social science research (Starr and Van Wassenhove (2014) by collecting time-series *Weibo data* (including id, post time, post content, like, share, comment, etc.) and *pandemic data* that both cover all five pandemic stages. First, applying the inter-rater policy, each author had a preliminary search independently on the scope of Weibo data. We then reached the conclusion that 23 out of the 34 provincial administrative units in China so far have operated social media accounts (by Information Officer) at Weibo, the most influential social media in China with 550 million monthly active users (WeiboCorporation, 2020), and 17 provincial administrative units (Table 1) released posts that covered all above five stages. For selected provincial administrative units' Weibo accounts, Sina Weibo Application Processing Interface (API) is employed to collect relevant such as daily activity (e.g., daily information released frequency, the content of each post) and its corresponding feedback (like share, and comment) from the public. In addition, we used daily pandemic data from the health commission office as a proxy for the severity of the pandemic (provincial level). The pandemic data includes both newly and accumulated cases (confirmed, suspicious, cured, and dead) data.

Table 1 The sample scope of this study

Total Numbers	Sample Scope * （17）	Out-of-Sample Scope（17）
Provincial Administrative Unit	Beijing, Tianjin, Shanghai, Chongqing, Henan, Hubei, Jiangsu, Jiangxi, Jilin, Heilongjiang, Shanxi, Shandong, Qinghai, Guangdong, Guizhou, Zhejiang, Xinjiang	Hebei**, Hunan**, Liaoning, Shaanxi, Anhui, Hainan, Fujian, Taiwan, Gansu, Yunnan, Sichuan**, Tibet, Ningxia, Guangxi, Inner Mongolia, Hong Kong, Macau

Note: * The social media account selected for analysis in this study are Weibo accounts that are officially operated by the Information Office of the government of each provincial administrative unit respectively.

**Hebei, Hunan, and Sichuan do have official Weibo accounts, but neither of them posts information that covers the entire epidemic period, and therefore not included in this study.

3.3 Variables

The definition and description of all the variables are depicted in Appendix 3.

3.3.1 Dependent variables

The public engagement level in social media is set as the dependent variable. We deduced the measuring metric from Agostino and Arnaboldi (2016), Bonsón and Ratkai (2013), and many other scholars that daily public engagement is computed as a function of the feedback from the public (like share, and comment) and the characteristics of the e-government platform (number of followers, number of daily posts). In particular, the public engagement level $Engagement_{i,t}$ of all posts in province i at date t is computed as the equation below:

$$\boldsymbol{Engagement_{i,t} = \frac{Likes_{i,t} + Shares_{i,t} + Comments_{i,t}}{Followers_i \times Post_{i,t}}}$$

Where $Likes_{i,t}$, $Shares_{i,t}$, $Comments_{i,t}$, $Post_{i,t}$ denotes the total number of likes, shares, comments, and posts in province i at date t. $Followers_i$ represents the total number of followers of province i. It should be noted that consistent with previous work (e.g., Agostino and Arnaboldi (2016), Bonsón and Ratkai (2013)), we treat $Followers_i$ as a time-independent variable, since it is assumed that changes in followers are relatively small compared to changes in other variables.

3.3.2 Independent variables

We considered daily public communication frequency, informational support, and emotional support strength as three independent variables for this study. Specifically, the daily public communication frequency is computed as the number of posts released from a particular social media account on a particular date. The variable is introduced to verify whether the frequency of public communication activity (e.g., too many, or too less) would influence public engagement.

To quantify the informational and support strength of the post, a supervised machine learning approach is adopted. The complex post content was first tokenized into simple unit tokens. A

Part of Speech (POS) tagger is then applied to identify the parts of speech (e.g., noun, verb, adjective, adverb, preposition, and conjunction) of each token. For the informational support strength study, we only kept nouns and verbs, however for the emotional support analysis, we kept nouns, verbs, adjectives, and adverbs. The frequency of each token is then determined using the Frequency-Inverse Document Frequency (TF-IDF) vectorizer. To save effort, only tokens with a frequency of more than 50 times (7,123 tokens) are chosen for the manual annotation.

In the annotation process, three domain experts are asked to annotate the score for emotional support and informational support independently using a 5 points Likert scale measurement (1: not at all, 2: slightly, 3: somewhat, 4: very, 5: extremely). The strength is computed as the mean score from the three experts. To ensure internal consistency, the three experts are asked to reach a consensus on the annotation standard before labeling. The internal consistency test achieved a Cronbach alpha value of 0.93, indicating excellent internal consistency. The strength for emotional support and informational support are respectively computed as the maximum emotional support and informational support strength of all tokens in a post.

Using a training dataset of 3,104 posts, we then trained the model using Naive Bayes classification in "SnowNLP", a popular NLP toolkit (Wang, 2020). The whole set of test data (61,297 posts) is then applied to the model. It is noted that all the informational support strength and emotional support strength are normalized to [0,1], where 0 indicates no support and 1 is extremely strong support. Sample texts in the data set are depicted in appendix 2

3.3.3 Control variables

We controlled for a set of other factors that could potentially influence the level of public engagement in social media amid a crisis including provincial characteristics and pandemic development tally. In addition to Gross domestic product (GDP), and population (POP), we also controlled for the number of 3A hospitals (Hospital), distance to Wuhan, adjacency with Wuhan, number of followers in the Weibo account, etc. It should be noted that we adopted the

number of 3A hospitals as the control variable because it is argued that the number of 3A hospitals mirrors a province's medical capability. In addition, among all the pandemic tally, we adopted accumulative confirmed cases, accumulative cured cases, newly confirmed cases, and newly cured cases as control variables.

3.3.4 Model specification

We developed the research model by drawing on the Social Reciprocity Theory (SRT). SRT suggests that positive reciprocity occurs when an action committed by one individual that has a positive effect on someone else is returned with an action that has an approximately equal positive effect (Falk & Fischbacher, 2006). When social media is deemed as a social community, members consider exchange behaviors based on positive interactions, which impacts their intention to engage in the social community in the future (Wu, *et al.*, 2019). In social media, there are two primary participants – the sender (post agencies) and the receiver (the public); reciprocity will be established by positive interactions when agencies provide social support through releasing information and the public engages in the information and provides feedback through functions such as like, share and comment (Yan & Pedraza-Martinez, 2019a). It is thus understandable that the more social support offered, the higher the public engagement would be on social media. We conjectured accordingly that (1) social support provided by government agencies in social media has impacts on public engagement, and (2) the effect of social support strategies on public engagement may vary across different pandemic stages.

3.3.5 Analysis procedure

Our main interest lies in how social support strategies, particularly informational support and emotional support as proposed by (Kort-Butler, 2017; Liang, *et al.*, 2011; Yan & Pedraza-Martinez, 2019a), may influence public engagement in social media-based public communication. The analysis procedure is described as follows. First, the normality for all the variables is checked using the Q-Q plot in R. For those variables (engagement, emotional

support, information support, accumulated confirmed cases, accumulated cured cases, newly confirmed cases, newly cured cases) that do not follow the normal distribution, a log-transformation is applied. Then the multicollinearity of all variables is checked using the variance inflation factor (VIF) value. The VIF values for all variables are less than 5, suggesting moderate multicollinearity problems among these variables are not likely to exist (Shrestha, 2020). Besides, the descriptive statistic and the correlation matrix of all the variables are displayed in Appendix 4 and Appendix 5, respectively. After validating the assumption testing for the model, we conducted ordinary least squares (OLS) regression analysis on the whole dataset and at different stages, respectively.

4. Results

We analyzed the Weibo based social media data in regard to public communication amidst the pandemic from all accounts of 17 provincial governments in China and several illuminating findings arise.

4.1 Descriptive statistics results

In this section, the quantity of the post, the strength of both social support, and the corresponding public engagement (e.g., Likes, Shares, Comments) outcome across different stages of the pandemic will be presented.

The number of posts or government engagement on social media, according to Zhu, *et al.* (2021) reflects a government's attentiveness toward the COVID-19 pandemic. The accumulated number of post across different stages are depicted in Figure 2. In general, two findings, in particular, are noteworthy. First of all, as the pandemic has progressed, the overall tendency for government activity shows an upward trend, indicating an intention on the part of the government to improve public communication, at least in terms of quantity, on social media. Particularly, there are more than three times as many posts in Stage 5B (16411) than there are in Stage 2. (5389). Second, the overall tendency of the number of posts is fluctuating rather than constantly increase, suggesting the government's response (in terms of public

communication activity) to the pandemic is dynamic rather than static. Particularly, the uncertainty in the COVID-19 pandemic and restrictive measures (e.g., social distancing, city lockdown) may have boosted the need for government to communicate with the public in Stage 3, while Stage 4 may have seen a decrease in the number of posts as the need for communication with the public decreases.

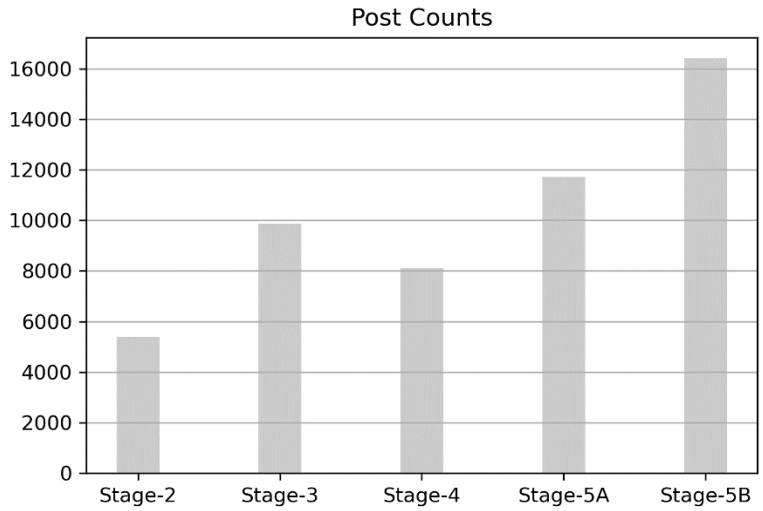

Figure 2 The accumulated public communication counts at different stages

Figure 3 shows the mean and standard deviation of social support, including both informational and emotional support, as determined by the NLP-based content analysis. Surprisingly, compared to the aforementioned post quantity, the average social support strength encompassed in public communication is also fluctuating, however, demonstrated a different hump-shaped pattern from Stage 2 to Stage 5B. This implies that the responsibility of public communication may extend beyond simple posting to include more intricate social support provision functions, which confirms the necessity of the present study. Further, while the strength of both informational and emotional support peaks at mid-stages (Stage 3 and Stage 3, respectively), there are not identical. Particularly, the overall strength of emotional support is weaker than that of informational support, and it peaks later. All of these findings imply that public communication should not be conducted without strategies and that revisiting its outcomes is necessary in order to provide nuanced insights into its impacts.

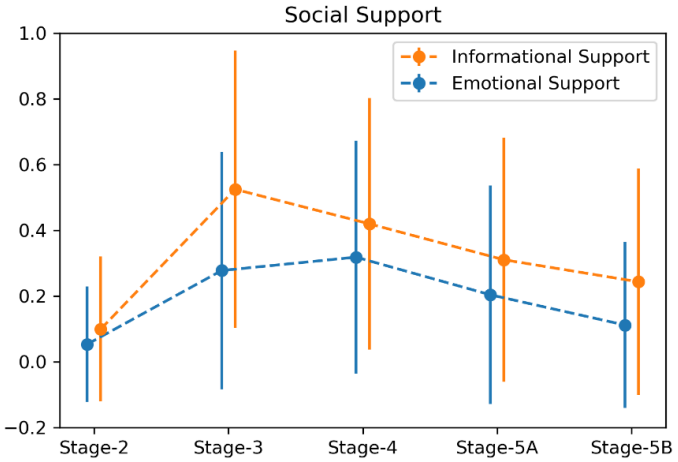

Figure 3 The strength of informational and emotional support at different stages

In this study, we used public engagement level (measured by a function of shares, likes, and comments) (as depicted in Table 2) to proxy the outcome of public communication. Two findings are worth noting. First, compared to the average number of followers (272 thousand Appendix 4), the average daily Likes, Shares, and Comments start at a low level. In addition, the large standard deviation implies that the distribution of Likes, Shares, and Comments is highly dispersed. This indicates that the strategy for enhanced public engagement in social media is shy of systematic. Second, the distribution of likes, shares, and comments (Table 2) has a similar hump-shaped pattern to the strength of social support (Figure 3), raising the possibility that public engagement and social support from the government are related. However, the relationship between social support and public engagement has not yet been established, necessitating additional research on the interactions between the public and the government in order to offer more insightful conclusions.

Table 2 Descriptive statistics of likes, shares, and comments across stages

Stages	Likes		Shares		Comments	
	Mean	S.D	Mean	S.D	Mean	S.D
STAGE-2	70.76	565.13	4.33	15.97	8.39	32.98
STAGE-3	371.47	2874.80	60.67	263.28	32.32	282.63
STAGE-4	89.70	724.76	20.14	104.09	12.54	51.95
STAGE-5A	49.20	275.35	13.46	65.86	9.86	45.61
STAGE-5B	57.86	2727.58	7.57	159.38	7.72	52.09

4.2 Regression analysis results

Figure 4 summarizes the regression analysis result. Both social supports (emotional support and information support) are testified to positively and significantly with the public engagement level in the full model, however, demonstrate a subtle difference in the staged model. Regarding the effect of emotional support, the significant correlation is only identified in later stages (Stage 4, Stage 5A, and Stage 5B), but not in earlier stages (Stage 2, Stage 4). Specifically, the effect reaches a peak at Stage 4 ($\beta = 0.577$) when phased success in controlling Covid-19 is witnessed, however, drops at stage 5A ($\beta = -0.268$), when a new wave of the Pandemic strikes, and then bounces back at Stage 5B, when the pandemic is properly handled ($\beta = 0.794$). Regarding the effect of informational support, in contrast to the effect of emotional support, the significant correlation is only witnessed in earlier stages (Stage 2, Stage 3, Stage 4), not in the later stages (Stage 5A, Stage 5B). Particularly, the trend of the effect is on the decline from Stage 2 (0.709) when mitigation and Containment of COVID-19 are observed to Stage 4 (0.327) when phased success in controlling Covid-19 is witnessed. It is also intriguing to point out that the effect of both support is not entirely positive. For instance, the effect of emotional support at Stage 5A is significant and negative ($\beta = -0.268$). This implies that the impact mechanism of social support is more complex than previously thought.

Regarding the effect of public communication frequency, the negative effect is confirmed in both the full model ($\beta = -0.008$). Particularly the effect of public communication frequency on public engagement is consistently negative and significant in all staged models, except for stage 5B. This is in line with the concern over information overload or “infodemic” that has

been widely seen on social media amidst the pandemic (Erku, *et al.*, 2021; Zarocostas, 2020), which could eventually stifle communication between the government and the public. Surprisingly, the number of followers is found a minor predictor of public engagement. In all staged models except Stage 3 (Daily tally dropped to a single digit), the effect of the follower on public engagement is insignificant.

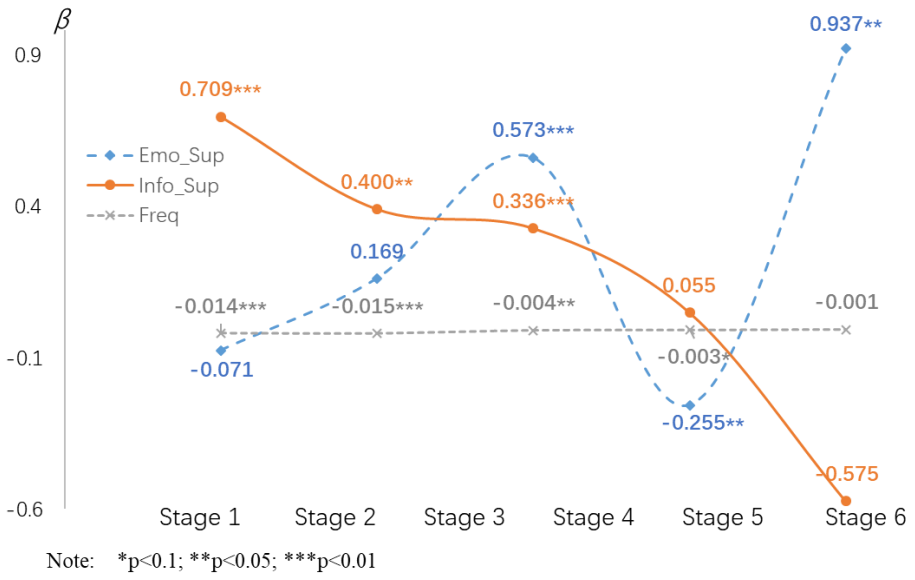

Figure 4 Dynamic impacts of informational support and emotional support

In terms of control variables, all provincial strength characteristics (e.g., GDP, EGDI, followers, 3A hospitals, etc.,) are found significantly related to public engagement in the full model, however, the effect is comparably small compared to the effect of emotional support, informational support, or public communication frequency. This gives rise to the thought that provincial strength may not be directly linked to the public communication between the government and the public, reinforcing the notion that social support is complex and dynamic. Regarding the control variables for the daily pandemic, it is identified that while the daily pandemic tally is generally significantly related to public engagement in the full model, but not necessarily significant in the staged model. This means that public engagement may not be strongly linked to the development of the pandemic. Besides, the adjacency of the province to Wuhan is found an insignificant predictor of public engagement.

Table 3 Ordinary least square regression results

Dependent variable: log(Engagement + 1)						
	OLS	panel linear				
	Full Model	Stage 2	Stage 3	Stage 4	Stage 5A	Stage 5B
log(Emo_Sup + 1)	0.499***	-0.043	0.230	0.577***	-0.268**	0.794*
	(0.079)	(0.263)	(0.181)	(0.086)	(0.120)	(0.426)
log(Info_Sup + 1)	0.376***	0.709***	0.356*	0.327***	0.021	-0.709
	(0.076)	(0.222)	(0.183)	(0.097)	(0.096)	(0.483)
Freq	-0.008***	-0.014***	-0.015***	-0.005***	-0.003*	-0.002
	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)	(0.005)
Followers	-0.0004***	-0.0005	-0.001***	-0.0003	0.0005	0.0002
	(0.0001)	(0.001)	(0.0003)	(0.0003)	(0.001)	(0.001)
Adjacency	0.027	0.14	0.116	-0.052	-0.262	-0.066
	(0.020)	(0.291)	(0.152)	(0.115)	(0.209)	(0.257)
Distance	-0.0001***,.	-0.0003	-0.0001	0.00003	-0.0001	-0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP	-0.00001***	-0.00002	-0.00002***	-0.00001**	-0.00001	-0.00001*
	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00001)	(0.00001)
Pop	0.0001***	0.0002	0.0002***	0.00004	0.0001	0.0002*
	(0.00001)	(0.00002)	(0.0001)	(0.00005)	(0.0001)	(0.0001)
EGDI	0.018***	0.035	0.046***	0.010	0.002	0.017
	(0.001)	(0.022)	(0.009)	(0.007)	(0.013)	(0.014)
Hospital	-0.003**	-0.017	-0.013*	0.003	0.008	-0.008
	(0.001)	(0.017)	(0.007)	(0.005)	(0.009)	(0.011)
log(Conf_Acu + 1)	0.064***	0.158***	-0.087	-0.079	0.388*	0.389
	(0.020)	(0.049)	(0.130)	(0.113)	(0.223)	(0.992)
log(Cure_Acu + 1)	-0.141***	-0.226***	-0.039	0.021	-0.584***	-0.488
	(0.017)	(0.056)	(0.088)	(0.126)	(0.217)	(0.982)
log(Conf_delta + 1)	-0.007	-0.082*	0.088***	0.078***	0.070***	-0.022
	(0.012)	(0.042)	(0.029)	(0.014)	(0.027)	(0.108)
log(Cure_delta + 1)	0.018**	0.074	0.021	-0.008	0.047**	0.012
	(0.008)	(0.053)	(0.023)	(0.013)	(0.021)	(0.078)
Constant	-0.091	-0.627	-1.089	0.064	1.595	0.216
	(0.094)	(1.380)	(0.683)	(0.55)	(1.001)	(1.180)
Observations	2,939	535	445	696	1,049	214
R2	0.314	0.154	0.173	0.191	0.045	0.063
Adjusted R2	0.311	0.131	0.146	0.174	0.032	-0.003
Residual Std. Error	0.468 (df = 2924)					
F Statistic	95.669*** (df = 14; 2924)	94.296***	89.860***	160.346***	48.612***	13.443

Note: *p<0.1; **p<0.05; ***p<0.01

5. Discussion

Our primary goal is to analyze the impact mechanisms of public communication. The findings confirm the significant correlation between both social support and public engagement,

suggesting that the social support theory can be a well-founded framework to explain the impact of public communication. Our findings also suggest that the effect of public communication (both emotional support and informational support) are dynamically evolving rather than static during a crisis. This means that public communication is less likely to be a "one-size-fits-all" government-oriented process, but rather should be handled with strategic adjustments.

5.1 Impacts of emotional support cannot be underestimated

While most of the extant studies emphasized the importance of public communication on information dissemination and exchange (O'Brien, *et al.*, 2020; Zhang, *et al.*, 2019), drawing upon social support theory, we argued that the power of public communication should go beyond informational support, but encompass emotional support that is equally if not more important. Specifically, the value of social support theory in dissecting the effects of public communication has been demonstrated by the different impact patterns of the two dimensions of support. First, the two aspects of social support have distinctive coefficients and levels of significance. Specifically, the emotional support coefficient has shown fluctuation, but the informational support coefficient is monotonously declining. This implies that the impact mechanism of emotional support and informational support on public engagement may be inconsistent. In light of this, the social support theory offers a theoretical framework to treat emotional support as a separate dimension of information support, and in turn, make it easier to comprehend how public communication exerts positive psychological or emotional influence on the public (Ko, *et al.*, 2013; Liang, *et al.*, 2011).

Second, as discussed earlier, the outcome of public communication is prone to be stage-based because the demand for informational and emotional support is likely to be stage-depend across different stages of a crisis. Further, we can identify the distinct demand pattern for public communication across stages with the aid of our incorporation of social support theory. Based on the significant level (Figure 4), the demand for informational support is substantial in the early stages (Stage 2, Stage 3, Stage 4) whereas the demand for emotional support may be lagged (Stage 4, Stage 5A, Stage 5b) but cannot be overlooked. Information-focused research

can therefore undervalue or underestimate the necessity of offering emotional support through public communication. In sum, it is evidenced that emotional support differs from informational support regarding support strength, and stage-based variations. Our incorporation of social support theory provides a more comprehensive understanding of both the influence of public communication and the dynamic demand of the public across different stages. Underestimating the influence of emotional support would otherwise result in an incomplete perception of the impact of public communication, and further, restrain the rationality and effectiveness of public communication strategies.

5.2 The stage-based pattern of social support influence

Our findings show that public communication outcome (as benchmarked by public engagement in this study) is closely related to the strength of staged-dependent social support rather than being anticipated by a province's strength (e.g., GDP, Pop, EDGI). This means, in order to achieve substantial rather than symbolic public communication, government agencies may need to play a more active role in communication by tailoring their communication strategies to the public's staged-dependent demand in crisis (Zhu, *et al.*, 2021), rather than treating it solely as the government-led process of information dissemination. Indeed, since the Government Performance and Results Act of 1993, outcome-based performance evaluations are made formal for measuring the service provision by the governments (Heinrich, 2002). Particularly for public communication, numerous scholars are investigating the metrics to quantify the performance from public feedback such as public satisfaction (Ho & Cho, 2017), public engagement (Agostino & Arnaboldi, 2016; Bonsón & Ratkai, 2013), etc.

Despite the differences, these works are all built upon an underlying assumption that there is a major causality between public communication and the positivity of public activities: the better the public communication becomes, the more positive the public's activities would be. This is justifiable in a static situation where the public's demand for the communication service remains almost the same. However, in a real-life setting, which is dynamic and fast-evolving, such as Covid-19, the rapid change of public demand in public communication may alter their

evaluation because social support may fail to satisfy the changing demand. Given that the expectations of informational demands and emotional demands from the public are evolving across stages (Ozamiz-Etxebarria, *et al.*, 2020; Zhao, *et al.*, 2020), leading to the possible disconfirmation between the demands of the public and support provision from the government. For instance, in the early stages (Stage 2 and Stage 3) when the pandemic unsettled the public, the informational support provided through Weibo posts greatly addressed the public's concern for situational awareness, resulting in a high significance of the correlation between informational support and public engagement. When the pandemic was taken under control (Stage 4, Stage 5A, Stage 5B), the demand for informational support dropped, resulting in a low significance level. In contrast, the full model, which treats the entire stages as a whole (Table 3), failed to identify such insights at the granular level. As a result, the impact of public communication on public engagement amid a crisis should be better understood and further assessed by identifying the pandemic stages and evaluating them correspondingly.

5.3 Information fatigue inhibits the impact of social support

Infodemic, a term used frequently in relation to social media during COVID-19, refers to the experience of information fatigue brought on by exposure to excessive amounts of information (Zarocostas, 2020). In this study, we introduced daily public communication frequency as an independent variable to see if such phenomena might be present in public communication. The negative and significant association between public communication frequency and public engagement confirms that too much public information may exert a negative effect on public communication outcomes. In line with other works (Islam, *et al.*, 2020; Zarocostas, 2020), this research confirms that the overwhelming volume of posts could dampen the intended social support. According to the full model in Table 3, the daily public communication frequency is reported to have a significant and negative ($\beta = -0.008, p < 0.05$) impact on public engagement. This means excessive government communication may not only fail to bring about good outcomes but also cause information fatigue among the public. This phenomenon is echoed by the observation of Farooq, *et al.* (2020), who noted that excessive use of public

communication via social media may backfire as it can cause information overload or over-thinking amongst individuals, negating public motivation to positively engage in public communication or even crisis response.

Additionally, it is also necessary to provide social support that caters to the demand of the public at different stages to prevent the detrimental effects of infodemic on public communication (McKinney, *et al.*, 2002). Indeed, the public's demand for both emotional support and information could vary along with the development of the pandemic. If the type or the amount of social support encompassed in public communication does not adjust accordingly, the excessive provision of social support may overwhelm the public's demand, leading to the feeling of exhaustion and lower levels of engagement level (Maier, *et al.*, 2015). For instance, the expectation for informational support may drop when the pandemic was progressively brought under control and the situation grew less worrisome and unclear. The effect may diminish as seen from Stage 2 to Stage 5A if the amount of information support remains constant (Table 3). In other words, the change in stage-based need for emotional and informational support may have *also* resulted in an abundance of social support that creates information fatigue and further reduces the impact of information support.

5.4 Implications

Theoretically, drawing upon the social support theory, we proposed a prototype attempt to comprehend the impact of social media based public communication amid a crisis. Regarding public communication amid a crisis, the incorporation of social support theory provides nuanced insights into how emotional support encompassed in public communication can exert a positive influence on the public. Besides, we additionally introduced the variable daily public communication frequency to conceptualize the commonly related "infodemic" phenomena in COVID-19-related literature and unravel its potential impact. Regarding social support theory, this study enhances its context by expanding it to public communication, urging further research to better understand the interaction between the public and the government, which would, in turn, support the theory's development and empirical examination.

Practically, the findings of this study can be extended to developing better public communication strategies amid a crisis. Through identifying the distinctive impact patterns of the two supports, we highlight that while informational support is crucial in the earlier stages of a crisis, emotional support could be of great help in the later stages of the crisis to comfort the emotions of the public. This means that when developing tactics for public communication amid a crisis, the pivot role of emotional support cannot be overlooked. Second, our analysis demonstrates that the influence of social support on public communication in times of crisis varies depending on the stage. Governments must, therefore, adapt and tailor their public communication strategy as the crisis develops rather than creating a strategy that is "one-size-fits-all". Finally, we empirically validated that the “infodemic” could also occur in public communication amid a crisis. We, therefore, argued that improving the quantity of public communication would not help promote the public communication outcome. Rather, public communication that accounts for the public’s demand and tailors to the evolving of the crisis is more effective.

6. Conclusion

The present studies investigate the impact of public communication amid crisis through the theoretical lens of social support theory. Particularly, we utilized public engagement as a proxy for the outcome of public communication amid the crisis and the dynamic impacts of two facets of social support are examined. Using the 17 Chinese provincial government-owned social media (Weibo) accounts, the separate impact of emotional support and informational support on public engagement is examined Based on the findings, this study recommends that government organizations take into account emotional support as a strategy for public communication, dynamically adapt their strategies to the people's demands as the crisis develops, and exercise prudence when it comes to the "infodemic" phenomenon. Despite being undertaken in a COVID-19 pandemic context, it is argued that all these findings are focused on public communication strategies, which can extend beyond the scope of the pandemic to general crises. The results of this study are preliminary overall, but they can be used as a starting

point and encourage more research into the role that emotional support plays in public communication.

The present study is not without limitations. We adopted the public engagement metrics from existing literature (Agostino & Arnaboldi, 2016) to benchmark the outcome of public communication, which is a function of share, like, and comment. However, it should be also noted that the three facets (like, share, and comment) of engagement may reflect different attitudes, which might be a consequence of different influences. For instance, a "like" in the communication post may imply that the influence of the post on the citizens is positive, but does not necessarily enact citizens to actively disaster preparation. On the other hand, a "comment" in the post reflects citizens' active involvement in the response, however, it may be motivated by negative rather than positive affections. Thus, it is necessary to separately investigate the mechanisms of how social support encompassed in public communication can lead to three engagement activities and how three engagement activities connect to the public's better physical and mental readiness for disasters.

Two potential changes to the research methodology should be mentioned. First, it takes a lot of time to annotate the work done by the domain experts for the supervised training model that we used to extract both social support strengths. Future research on creating a more practical strategy to address timeliness during a crisis is acknowledged as being necessary. Second, we include daily public communication frequency as an independent variable in the regression model to confirm the impact of social support overload. However, the post frequency may have a moderation effect on emotional support and informational support, which needs to be addressed in our future research.

Regarding the data, this study used 17 Chinese provincial government-owned social media as the study cope and covered the period from the initial outbreak (Dec 2019) to the successful control of Covid-19 (Jul 2020) in China. However, However, Covid-19 is a global crisis rather than a regional incidence, and a dataset covering a longer duration would be favorable.

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Appendix 1 Phased China's COVID-19 action timeline (SCIO, 2020)

Stage	Description	Duration
Stage 1	Initial Response to Covid-19	27/12/2019 – 19/01/2020
Stage 2	Mitigation and Containment of Covid-19	20/01/2020 – 20/02/2020
Stage 3	The daily tally dropped to single digit	21/02/2020 – 17/03/2020
Stage 4	Phased success in controlling Covid-19	18/03/2020 – 28/04/2020
Stage 5	Ongoing prevention and control	29/04/2020 onwards

Appendix 2 Sample texts in the data set

ID	Sample Content	Sample Content(in English)	Emotional Support Strength	Information Support Strength
1	截至 1 月 29 日 24 时，国家卫生健康委收到 31 个省（自治区、直辖市）和新疆生产建设兵团累计报告确诊病例 7711 例，现有重症病例…	As of 24:00 on January 29, the National Health Commission has received a total of 7711 confirmed cases from 31 provinces (autonomous regions and municipalities) and the Xinjiang Production and Construction Corps: severe cases …	0.12	0.89
2	…0-6 岁儿童日常如何做好新型冠状病毒的预防？外出时可采取哪些预防措施？当孩子的照护者出现可疑症状时有哪些建议？孩子生病时又该如何应对？来看中国疾控中心的一图解读。详见↓ #上海战疫##上海加油# 0-6 岁儿童如何预防新型冠状病毒？一图解读	… How do children aged 0-6 prevent the new coronavirus? What precautions can be taken when going out? What advice do you have when your child's caregiver has suspicious symptoms? What should I do when my child is sick? Take a look at a picture interpretation of the China Centers for Disease Control and Prevention. For details, see ↓ #Fight! Shanghai# #Coming Shanghai# …	0.47	0.71
3	…近日，湖南疫情防控一线再传好消息。截至 2 月 6 日 16 时，湖南已有 75 例新型冠状病毒感染的肺炎患者治愈出院。走出隔离医院，他们会说什么？	… Recently, good news has spread on the front line of Hunan epidemic prevention and control. As of 16:00 on February 6, 75 cases of pneumonia patients infected by the new coronavirus in Hunan have been cured and discharged. What would they say when they walked out of the isolation hospital?	0.74	0.74
4	【为奋战在“战疫”一线的白衣天使而歌】抗疫歌曲《托起生命的风采》致敬逆行者，呼唤众志成城！加油中国！加油武汉！	[Eulogy for the angels in white who are fighting on the front line of the epidemic] The anti-epidemic song "The Demeanor of Life" pays tribute to retrogrades and calls for unity! Come on China! Come on Wuhan!	0.91	0.09

Appendix 3 Definition and Description of Variables

Variable	Description
	Dependent Variable
Engagement	Computed as a function of (share, like, comment), denoted the daily engagement level
	Independent Variable
Emo_Sup	Emotional Support Strength
Info_Sup	Information Support Strength
Freq	Daily public communication frequency
	Control for Provincial Characteristics
Followers	Number of followers (in thousands)
Adjacency	The adjacency of the province to the pandemic center
Distance	The travel distance between the province and the pandemic center (in km)
GDP	GDP of the province (in billion yuan)
Pop	The population of the province (in thousands)
EGDI	The e-government development index of the province developed by the National School of Administration
Hospital	No of 3A hospitals in the province an indicator for benchmarking the medical care level
	Control for Pandemic Development
Conf_Accu	Daily accumulative confirmed cases of the province
Cure_ Accu	Daily accumulative Cured cases of the province
Conf_Newly	Daily newly confirmed cases of the province
Cure_Newly	Daily newly Cured cases of the province

Appendix 4 Descriptive Statistics

Variable	Mean	S.D.	Min	Max
log(Engagement + 1) (1)	0.37	0.56	0	5.38
log(Emo_Sup + 1) (2)	0.18	0.14	0	0.69
log(Info_Sup + 1) (3)	0.28	0.16	0	0.69
Freq(4)	16.99	12.83	1	68
Followers(5)	274.27	255.48	10.31	933.2
Distance(6)	1130.7	793.67	0	3268
GDP (7)	36542.45	28963.69	2966	107671
Pop(8)	4565.05	2849.83	608	11521
EGDI(9)	64.71	12.73	41.35	94.88
Hospital(10)	40.22	19.94	9	102
log(Conf_Acu + 1) (11)	5.89	1.94	0	11.13
log(Cure_Acu + 1)	5.45	2.26	0	11.07
log(Conf_delta + 1)	0.66	1.3	0	9.61
log(Cure_delta + 1) (14)	0.82	1.39	0	8.01

Note: To avoid multi-collinearity and skewness, engagement, emotional support, information support, accumulated confirmed cases, accumulated cured cases, newly confirmed cases, and newly cured cases are log-transformed.

Appendix 5 Correlation Matrix of the variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
log(Engagement + 1) (1)	1													
log(Emo_Sup + 1) (2)	0.27	1												
log(Info_Sup + 1) (3)	0.34	0.52	1											
Freq(4)	-0.15	-0.02	0.02	1										
Followers(5)	-0.16	0.03	0.13	0.25	1									
Distance(6)	-0.03	-0.12	-0.11	0.06	0.07	1								
GDP(7)	-0.13	0.1	0.08	-0.19	0.2	-0.47	1							
Pop(8)	-0.02	0.13	0.06	-0.3	-0.12	-0.43	0.87	1						
EGDI(9)	0.02	0.15	0.31	0	0.47	-0.45	0.67	0.5	1					
Hospital(10)	-0.02	0.06	0.13	-0.25	0.1	-0.35	0.77	0.81	0.68	1				
log(Conf_Acu + 1) (11)	-0.14	0.15	0.1	-0.06	0.06	-0.53	0.41	0.44	0.52	0.44	1			
log(Cure_Acu + 1) (12)	-0.26	0.01	-0.12	-0.09	0.03	-0.45	0.33	0.36	0.41	0.36	0.92	1		
log(Conf_delta + 1) (13)	0.23	0.3	0.47	0.07	0.14	-0.15	0.16	0.13	0.25	0.21	0.14	-0.18	1	
log(Cure_delta + 1) (14)	0.09	0.4	0.36	0.04	0.12	-0.24	0.2	0.2	0.27	0.26	0.41	0.26	0.47	1