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Understanding the impact of emotional support on mental health resilience of the community in the social media in Covid-19 pandemic

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ABSTRACT

Background: Emotional support in social media can act as a buffer against the negative impact of affective disorders. However, empirical evidence relating to emotional support in social media and how it influences the wider public remains scanty. The objective of this study is therefore to conduct a prototype investigation into the translation mechanism of emotional support in social media, providing empirical evidence for practitioners to use to tackle mental health issues for the wider public.
Methods: A regression model is proposed to examine the relationship between perceived and received emotional support. Received emotional support is set as the dependent variable and measured using public activity. Perceived emotional support is derived using Natural Language Processing (NLP)-based content analysis. The model is then analyzed using a panel date with a total number of 61,297 posts from 17 Weibo accounts in 17 provincial administrative units in China.
Results: The relationship between perceived and received emotional support is not linear but complex, suggesting that translation of emotional support is not automatic. Further, our empirical evidence suggests that the translation of emotional support in social media is affected by frequency and pandemic stage.
Limitations: The study does not examine the direct relationship between perceived and received emotional support, instead adopting public activity as a proxy for the latter construct. In addition, the relationship between perceived and received emotional support is more complex than linear, requiring further model and theory development.

1. Introduction

The devastating Covid-19 pandemic has caused affective disorders such as fear, anxiety, and depression (Yao et al., 2020), mental health issues that have garnered global attention. Affective disorders have significantly affected both individual mental conditions and disaster management agencies leading the response to Covid-19 (Bargain and Aminjonov, 2020; Harper et al., 2021). At individual level, such disorders cause symptoms such as confusion and emotional isolation, which can further translate into a range of emotional reactions such as distress, depression, anxiety, and panic (Pfefferbaum and North, 2020), leading to non-compliance behavior with the Covid-19 response and relevant directives (e.g. home confinement, vaccination), thus impairing pandemic containment responses at community level. As such, addressing the issue of affective disorders is fundamental to the mental health resilience of the public and the effectiveness of Covid-19 crisis management (Cullen et al., 2020; Kumar and Nayar, 2021; Usher et al., 2020; Yao et al., 2020).

Usually, symptoms of affective disorders can be relieved through clinical treatment, when individuals attend regular outpatient visits for diagnosis and prescriptions. However, restrictive measures imposed amidst the pandemic, such as home confinement and social distancing, have made such direct intervention inconvenient and even impractical (Shensa et al., 2020). Furthermore, during the pandemic, about four in ten adults in the U.S. have reported symptoms of affective disorders, a largely consistent percentage, up from one in ten adults from January to

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June 2020 (Panchal et al., 2020). This raises concern over the depletion of medical resources, which have already been stretched to the limit (Usher et al., 2020; Yao et al., 2020). A need therefore emerges to seek alternative approaches to counter the negative impact of affective disorders and provide protection for the wider population.

Admittedly, social media is traditionally considered to have an adverse effect on mental health, with numerous studies (Lin et al., 2016; Vannucci et al., 2017; Yoon et al., 2019) arguing that use of social media can lead to social isolation, anxiety, and depression, resulting in increased mental health issues rather than a reduction. However, it is possible that the impact of social media also has an alternative effect, enabling us to protect the wider population from mental health issues. As a result, an increasing number of studies (Marzouki et al., 2021; Shensa et al., 2020; Yan and Pedraza-Martinez, 2019) have sought social media solutions to address affective disorder issues. Specifically, they have advocated that social media can form an environment of mutual aid for social interactions, in which members can exchange emotional support by, for example, voicing fears, expressing feelings, and providing psychological support (Zhu et al., 2021), with a potentially positive effect, providing a buffer against anxiety and other affective disorder issues (Marzouki et al., 2021). Despite the appealing potential of social media in providing emotional support, from the perspective of information producers, practical usage remains inaccessible because translation of emotional support to the public through the spread of information is far from well known. From the perspective of supply and demand, the relationship between perceived and received emotional support is not linear: emotional support provided by information producers may or may not lead to public receipt, and abuse of it could lead to an infodemic (Depoux et al., 2020) that could accelerate the spread of fear and anxiety (Ahmad and Murad, 2020). Understanding the mechanism of emotional support is therefore the premise of using it against affective disorders. Further, the public's attitudes toward social media could be influenced by other factors such as development of the pandemic or infodemic levels (Zhu et al, n.d.; Zhu et al., 2021), potentially further imposing a parallel influence on the emotional support translation mechanism. It is therefore also necessary to identify how these factors influence the translation of emotional support. In view of the gaps identified, the paper addresses the following two overarching research questions:

RQ1: What is the relationship between perceived and received emotional support in social media?

RQ2: Will this relationship change over time according to the frequency of information release?

2. Research background

2.1. Emotional support

Emotional support is a concept derived from social support and refers to the provision of care, concern, empathy, love, and trust (Kort-Butler, 2017). Numerous studies (Kort-Butler, 2017; Liang et al., 2011; van der Velden et al., 2020; Yan and Pedraza-Martinez, 2019) have highlighted that online emotional support can have a buffering effect on mental health and its absence can lead to adverse effects. First, and most obviously, health research implies that emotional support can provide potential recipients with a safe space where they can feel heard, express feelings, and voice fear, reducing feelings of distress and loneliness (Yan, 2020). This is especially important in times of stress and sadness as it stabilizes the mental conditions of recipients against affective disorders, further shaping individual resilience in the face of mental health issues (Marzouki et al., 2021). Second, and perhaps less obviously, exchange of emotional support can strengthen member solidarity, enhancing a collectivist culture (Kim et al., 2008). Collectivism during public health events such as the Covid-19 pandemic can further enhance the effectiveness of people's psychological protection, thus acting as a buffer against the impact of negative emotions (Kim et al., 2016). Nevertheless, despite repeated emphasis on the importance of emotional support, empirical evidence on how it can be translated from providers to recipients remains scanty, undermining its value in practical usage.

2.2. Social reciprocity

To better understand translation of emotional support in social media, the construct of emotional support can be separated into two subconstructs – namely perceived and received emotional support (Uchino, 2009; Wethington and Kessler, 1986). The former refers to the amount of emotional support provided by post agencies releasing information that encompasses emotional support. The latter, on the other hand, refers to the amount of emotional support that the public or the audience of the post actually feels. Thus, translation of emotional support can be understood through investigating the relationship between perceived and received emotional support. Nevertheless, while perceived emotional support can be directly measured through content analysis in social media, direct measurement of received emotional support is difficult without involving human respondents.

Social Reciprocity Theory (SRT) offers a solution to understanding the relationship between perceived and received emotional support. SRT posits that receiving social support from social interactions motivates the support recipient's intention to return an action that has a positive effect (Falk and Fischbacher, 2006). In the context of social media, when an individual receives emotional support, this increases the likelihood that they will engage with social media to return emotional support by providing feedback in the form of likes, shares, or comments (Yan and Pedraza-Martinez, 2019). Thus, levels of public activity in social actions can be understood as a proxy for received emotional support in social media. Greater availability of received emotional support is likely to encourage greater intention to engage in social interactions, returning emotional support (Wu et al., 2019). We conjectured accordingly that perceived emotional support is positively related to public engagement levels.

2.3. Measurement

Measurement of emotional support is extensively investigated in the literature. For instance, Weber and Patterson (1996) measure emotional support as the degree to which participants agree or disagree with statements about their partners' ability to communicate emotional support using a 20-item instrument. As emotional support is often characterized by perceptions of trust within a relationship (Buunk and Schaufeli, 1999), later studies formulate scale of emotional support based on the extent to which people have confided in one another (Cella et al., 2010; Lebel et al., 2020). Nevertheless, these studies are designed for a face-to-face context, which is not always readily borrowed for the social media environment. Meanwhile, there are a few studies (Meng et al., 2017; Shensa et al., 2020; Shensa et al., 2016) extending the measurement scale to the social media context. For instance, Shensa et al. (2020) translated the scale of emotional support from face to face to social media to understand depression risk among young adults on social media. However, the above-mentioned measurement scale is impractical for extension into this study because of the huge number of posts involved and the absence of human respondents. For this reason, a content analysis methodology is adopted in this study for the purposes of measurement.

3. Methodology

3.1. Research context

Covid-19 has ravaged the globe on an unprecedented scale. With other countries affected by the pandemic, China has been working around the clock in a resolute battle to curb the spread and prevent the virus from re-surging. In a White Paper released by China's State Council

Information Office (SCIO) (SCIO, 2020), the SCIO divided the countermeasure efforts put in place so far into five stages (Fig. 1). Given that the research is based on a case study of China, we followed its timeframe in organizing the data. It is worth mentioning that (1) Stage 1 was removed from the study as it relates to the sporadic outbreak of Covid-19 and the relevant post rate on social media is below 1%; and (2) Stage 5 is broken down into two sub-stages – before and after 11th June 2020, when a new confirmed case was reported in Beijing, indicating a second wave.

We made extra efforts to mitigate challenges involved in data collection in social science research (Starr and Van Wassenhove, 2014), collecting time-series *Weibo data* and *pandemic data*. While Facebook, Twitter, and others are popular leading social media platforms in China, Weibo is one of the most influential social media in the country, with 550 million active monthly users (WeiboCorporation, 2020), making it an appropriate focus for a study aiming to understand the impact of social media on risk communication, specifically in the Chinese context. Weibo data was collected from the Sina Weibo Application Programming Interface (API). Using the API, we were able to collect Weibo posts from users' timelines and produce a list of Weibo posts from specific users. For each post on Weibo, attributes such as ID, Text, URL, Location, Date, Like, Comment, Share, Topic, and @User were retrieved and saved.

This research specifically focused on Weibo accounts officially operated by the Information Offices of each provincial administrative unit, with a particular interest in investigating perceived emotional support from the government to the public and its impact, thus using the government-owned Weibo account as a proxy. We believe that their information release strategy differs significantly from those making up the focus of this study as they are professional media outlets.

For selected Weibo accounts, we recorded daily activity (e.g., frequency of daily information released, content of each post) and corresponding feedback (likes, shares, and comments) from the public. In addition, pandemic data was collected from the health commission of each province. The pandemic tally is updated daily, and we use this as a control variable that serves as a proxy for the severity of the pandemic. The pandemic data includes both new and accumulated cases (confirmed, suspicious, cured, and dead).

In this study, a total of 61,297 posts from 17 provinces across five pandemics stages were analyzed. To do this, applying inter-rater policy, each author first completed an independent preliminary search of the scope of Weibo data. We then reached the conclusion that 23 of the 34 provincial administrative units in China so far operate social media accounts (through information officers) on Weibo, the most influential social media platform in China (WeiboCorporation, 2020). We removed three accounts from the scope of our study because these accounts were considered inactive with less than one daily post released. We also removed an additional three accounts that did not incorporate information release covering all five pandemic stages (Fig. 1), resulting in 17 provincial administrative units (Table 1).

3.2. Content analysis

Strength of emotional support is computed using NLP. Particularly useful for sentiment analysis in the Chinese context, SnowNLP is a well-established kit built upon the naïve Bayes classifier, widely deployed for estimation of public emotions (Chen et al., 2016) and emotions in organizational Weibo (Feng and Jiang, 2019). It is therefore deemed an appropriate method for the purposes of this study. Three main steps are required to extract emotional strength from the content of Weibo posts.

First, after the data is collected, we applied SnowNLP for each post to tokenize the content into smaller words, or tokens. Complex sentence structure was therefore broken down into smaller pieces for further analysis. All the tokens were saved into a text corpus.

The text corpus was then filtered through part of speech (POS) tagging and term frequency and inverse document frequency (TFIDF) to reduce the size of the text corpus and eliminate abundant tokens. To further determine the weight of each token and remove those less important, TFIDF weighting was deployed. For the POS filtering, we

Table 1
Data scope.

	Sample scope[a]	Out-of-sample
Total number	17	17
Provincial administrative unit	Beijing, Tianjin, Shanghai, Chongqing, Henan, Hubei, Jiangsu, Jiangxi, Jilin, Heilongjiang, Shanxi, Shandong, Qinghai, Guangdong, Guizhou, Zhejiang, Xinjiang	Hebei[b], Hunan[b], Liaoning, Shaanxi, Anhui, Hainan, Fujian, Taiwan, Gansu, Yunnan, Sichuan[b], Tibet, Ningxia, Guangxi, Inner Mongolia, Hong Kong, Macau

[a] The social media accounts selected for analysis in this study are Weibo accounts officially operated by the Information Offices of the governments of each provincial administrative unit.
[b] Hebei, Hunan, and Sichuan do have official Weibo accounts, but none posts information that covers all five pandemic stages, meaning that they are not included in this study.

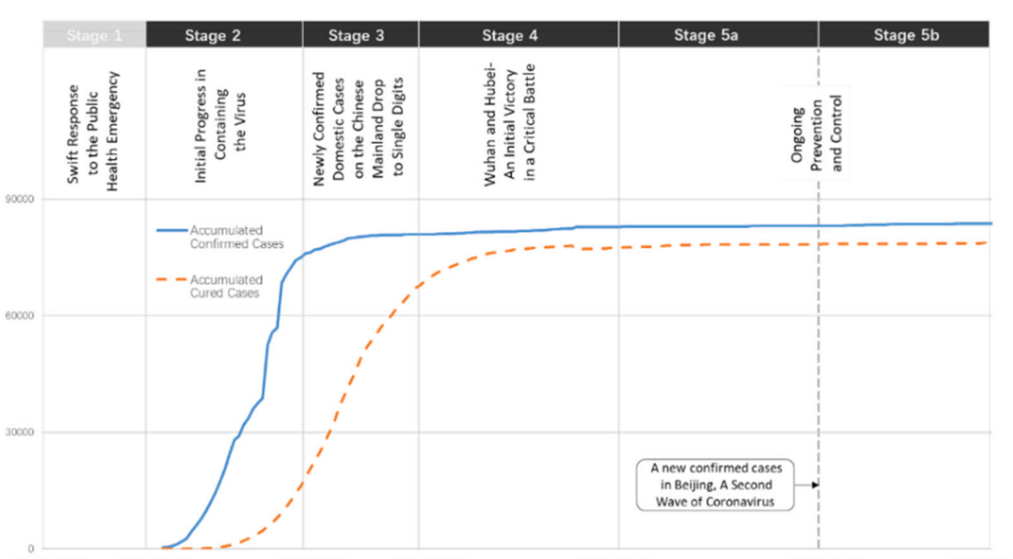

Fig. 1. Stages of the pandemic.

kept note of nouns, verbs, adjectives, and adverbs for emotional support analysis.

Lastly, a naïve Bayes classifier supported by the widely used NLP toolkit named “SnowNLP” (Wang, 2020) was applied to measure strength of public emotions (Chen et al., 2016; Feng and Jiang, 2019). As a supervised learning method, naive Bayes classification required labels to guide model training. Domain experts manually annotated the strength of informational support and emotional support for a total of 7123 samples using a five-point Likert scale measurement (1: Strongly Disagree, 2: Disagree, 3: Neutral, 4: Agree, 5: Strongly Agree). Annotators adhered to rules and annotation standards that we created for the project. Each sample was assigned to at least three experts. It applied the mode of the annotated labels as the final label of the sample, which might be further verified by one additional annotator to ensure the consistency and accuracy of labels. Trained models were evaluated on test data (61,297 posts), with all emotional support strength normalized to [0,1] based on min-max feature scaling, where 0 indicates little support and 1 indicates strong support. A sample text from the data set is displayed in Appendix 1.

3.3. Variables

The definition and decryption of all variables are shown in Table 2. Based on the model, public involvement activity level is employed as the dependent variable. Notably, for the public activity level $Activity_{i,\ t}$ of all posts in province i at the date, t is computed as:

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

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.

For the dependent variable, the strength of emotional support in each post is set. A detailed description of the method is given in the content analysis section.

In addition, we controlled for a set of other factors that could potentially influence levels of public activity in social media during the Covid-19 pandemic. These control variables include (1) provincial characteristics such as gross domestic product (GDP), population (POP), E-government development index (EDGI), number of 3A hospitals (Hospital), distance to Wuhan, adjacency with Wuhan, number of Weibo account followers, etc.; (2) control for pandemic development, incorporating, for example, accumulative confirmed cases, accumulative cured cases, newly confirmed cases, and newly cured cases.

Before applying all the data to the model, the parametric test for each variable was checked. In this study, the normality of perceived emotional support, as well as the four control variables (Conf_Accu, Cure_Accu, Conf_delta, Cure_delta) for pandemic development, were not met, meaning that we applied the logarithm function to each variable instead of using the original value.

Table 2
Definition and description of variables.

Variable	Description
Dependent variable	
Activity	Computed as a function of (share, like, comment), denoted the engagement level of province i in time t
Independent variable	
Perceived_Sup	Perceived emotional support strength from Weibo in province i on day t
Provincial characteristics	
Freq	Information release frequency from Weibo in province i on day t
Followers	Number of followers on Weibo in province i (in tens of thousands)
Adjacency	Adjacency of province i to pandemic center, where 0 indicates the pandemic center, 1 indicates direct adjacency, 2 indicates indirect adjacency, and 3 indicates remote
Distance	Travel distance between province i and pandemic center (in km)
GDP	GDP of province i (in hundreds of millions RMB)
Pop	Population of province i (in tens of thousands)
EGDI	E-government development index of province i, developed by National School of Administration, where 1 refers to lowest and 100 refers to the highest
Hospital	Number of 3A hospitals in province i, an indicator for benchmarking medical care levels
Control for pandemic development	
Conf_Accu	Number of accumulative confirmed cases in province i in time t
Cure_ Accu	Number of accumulative cured cases in province i in time t
Conf_delta	Number of newly confirmed cases in province i in time t
Cure_delta	Number of newly cured cases in province i in time t

Note: i denotes provincial administrative unit ID; t denotes index for the day; k denotes index for the pandemic stage.

3.4. The model

We developed the research model by drawing on 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 and Fischbacher, 2006). When social media is deemed to be a social community, government can provide emotional support through posts, impacting public intention to become involved in posting behavior (Wu et al., 2019). Emotional support between the government and the public is established if members of the public perceive emotional support in the post content and become actively involved in providing feedback through functions such as like, share, and comment (Yan and Pedraza-Martinez, 2019). It is thus understandable that the more emotional support is received, the higher public involvement is on social media. We conjectured accordingly that (1) emotional support provided by government agencies on social media impacts on public involvement in social media, and (2) the effects of emotional support strategies on public engagement vary across different stages of the pandemic. We therefore construct panel data with open data in Weibo to investigate the influence of social support on public engagement, considering the heterogeneity issue at province and day level and introducing controls for (1) the variation effect of a different province X_i; and (2) the variation effect of a daily pandemic situation $Y_{i,\ t}$. Hence, the activity level is a function of the amount of emotional support, information support, provincial characteristics, and the characteristics of the daily pandemic situation:

$$Activity_{i,t} = \alpha_0 + \beta_1 Emo\_Sup_{i,t} + \beta_2 Freq_{i,t} + \beta_3 X_i + \beta_4 Y_{i,t} + \xi_i + \varepsilon_{i,t}$$

Our primary motivation is in the estimation and comparison of parameters β that indicate how emotional support affects public activity across different stages of the pandemic.

4. Results

4.1. Preliminary results

Average post-release frequency, emotional support strength, and public feedback activity across the five stages are depicted in Fig. 2. The average frequency of posts released *Freq* for each province is 18.43, 18.18, 16,84, 15,64, and 17.91 respectively. From Stage 2 to Stage 5A, the average daily post released by each province is shown to be on a slowly decreasing trend. When a new *confirmed case* was reported in Beijing, indicating the second wave in stage 5B, the average number of posts released daily jumped to 17.91. In relation to emotional support, the logarithm of emotional support strength: $log(Perceived\_Sup + 1)$ demonstrates a hump-shaped pattern across the five stages, with a mean value of 0.178 and a median of 0.153. Specifically, mean emotional

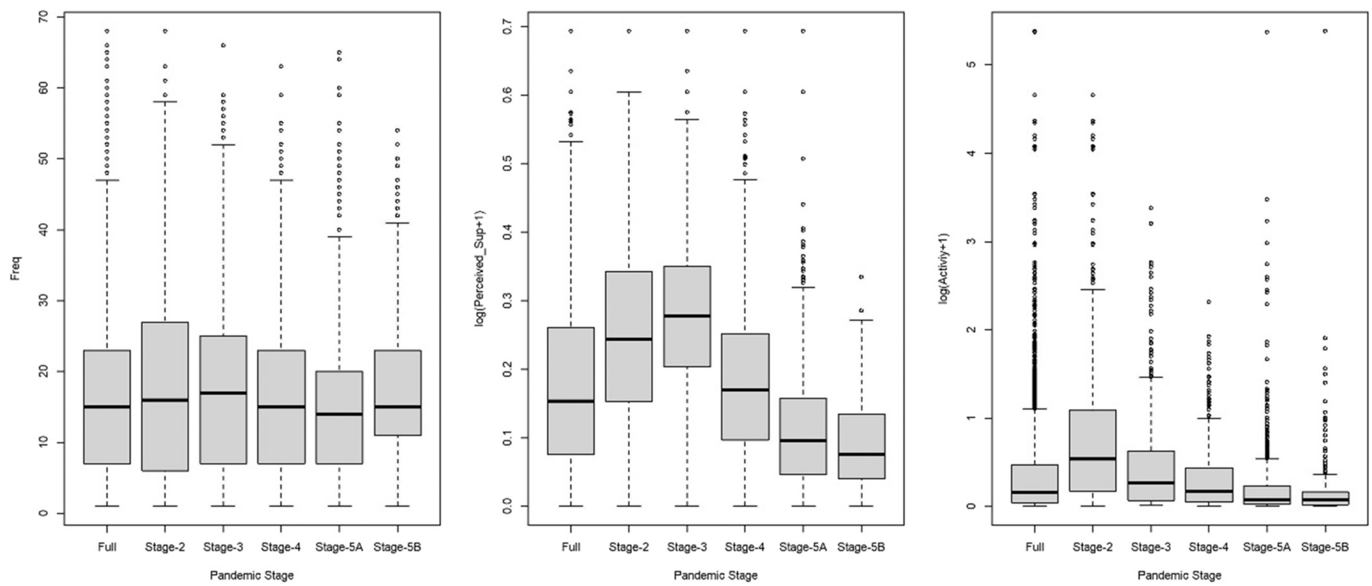

Fig. 2. Preliminary results.

Table 3
Regression analysis results.

	Dependent variable					
	Log(Activity +1)					
	OLS	*Panel*				
		Linear				
	Full model	Stage 2	Stage 3	Stage 4	Stage 5A	Stage 5B
log(Perceived_Sup + 1)	0.643***	0.111	0.336**	0.634***	−0.259**	0.790*
	−0.074	−0.262	−0.167	−0.085	−0.116	−0.427
Freq	−0.008***	−0.016***	−0.016***	−0.005***	−0.003*	−0.0002
	−0.001	−0.003	−0.003	−0.002	−0.002	−0.005
log(Conf_Acu + 1)	0.094***	0.208***	−0.095	−0.076	0.420*	0.225
	−0.019	−0.047	−0.16	−0.114	−0.219	−0.929
log(Cure_Acu + 1)	−0.169***	−0.270***	−0.043	0.031	−0.577***	−0.378
	−0.016	−0.055	−0.087	−0.13	−0.216	−0.926
log(Conf_delta +1)	−0.008	−0.077*	0.098***	0.085***	0.070***	−0.018
	−0.012	−0.042	−0.029	−0.014	−0.027	−0.109
log(Cure_delta +1)	0.025***	0.078	0.029	−0.005	0.048**	0.005
	−0.008	−0.054	−0.023	−0.013	−0.021	−0.077
Adjacency	0.046**	0.201	0.128	−0.019	−0.202	−0.171
	−0.02	−0.264	−0.233	−0.134	−0.175	−0.223
Distance	−0.0001***	−0.0004	−0.0001	0.00003	−0.0001	−0.0001
	−0.00002	−0.0003	−0.0002	−0.0001	−0.0001	−0.0002
Pop	0.0001***	0.0001	0.0002*	0.00004	0.0001	0.0002*
	−0.00001	−0.0002	−0.0001	−0.0001	−0.0001	−0.0001
GDP	−0.00001***	−0.00002	−0.00002**	−0.00001*	−0.00001*	−0.00002*
	0	−0.00001	−0.00001	0	−0.00001	−0.00001
Followers	−0.0004***	−0.001	−0.001**	−0.0004	0.0004	0.0003
	−0.0001	−0.001	−0.0005	−0.0004	−0.001	−0.001
EGDI	0.020***	0.041**	0.049***	0.013*	0.002	0.013
	−0.001	−0.02	−0.014	−0.008	−0.011	−0.013
Hospital	−0.003***	−0.018	−0.013	0.001	0.007	−0.004
	−0.001	−0.016	−0.011	−0.006	−0.008	−0.01
Constant	−0.181*	−0.728	−1.146	−0.112	1.328	0.632
	−0.092	−1.257	−1.045	−0.643	−0.836	−1.031
Observations	2939	535	445	696	1049	214
R^2	0.308	0.139	0.131	0.17	0.046	0.06
Adjusted R^2	0.305	0.117	0.105	0.154	0.034	−0.001
Residual std. error	0.470 (df = 2925)					
F statistic	100.349*** (df = 13; 2925)	83.888***	65.854***	139.207***	49.322***	12.687

[*] $p < 0.1$.
[**] $p < 0.05$.
[***] $p < 0.01$.

support starts from 0.253 in Stage 2, climbs to 0.278 in Stage 3, and gradually declines from 0.182 to 0.090, from Stage 4 to Stage 5B. For public feedback activity, the activity $log(Activity + 1)$ logarithm is on a similarly decreasing trend to post-release frequency, but more dramatically from 0.778 at Stage 2 to 0.205 at Stage 5B.

Several findings from the preliminary results are worth noting. First, the average daily post-release frequency is largely overlapped by developments in the pandemic. Before Stage 2, number amounted to fewer than five – however, this jumped to 16.99 in Stage 2, a process that continued into Stage 5B. This implies that the intention of provincial governments to release information through social media is positively related to developments in the pandemic. Further, fluctuations in perceived strength of emotional support on social media is prone to overlaps with pandemic development. Specifically, the outbreak of the pandemic in Stage 2 prompted the government move toward emotional support provision and this intention weakened in Stage 5A, with the pandemic gradually being brought under control. This implies that the amount of emotional support provided by governments through social media is positively related to pandemic developments. In all, the government's provision of emotional support, particularly related to frequency and strength, is not without strategies. Post frequency and perceived strength of emotional support cannot provide nuanced insights into the effectiveness of such strategies, which require further investigation, particularly of feedback from the public side.

4.2. Perceived emotional support and public activity

The regression analysis results in Table 3 further establish the relationship between perceived strength of emotional support and public activity on social media. Based on the model, the relationship between perceived emotional support and public activity in the early stages (Stage 2) of the pandemic is insignificant, while, in the later stages (Stage 3 to Stage 5B.), the relationship becomes significant. In sum, the co-efficient demonstrates a volatility pattern in the latter stages. Specifically, the co-efficient starts positive at Stage 3 ($\beta_1 = 0.336$), then reaches a peak at Stage 4 ($\beta_1 = 0.634$), descending in Stage 5A ($\beta_1 = -0.259$) prior to climbing to another peak at Stage 5B ($\beta_1 = 0.790$). It is also worth mentioning that the association (co-efficient) is not entirely positive. For instance, in Stage 4, which saw phased success in controlling Covid-19, co-efficiency turned negative, suggesting that an increase in the quantity of perceived emotional support alone does not necessarily lead to an increase in public activity. The relationship between perceived emotional support and public activity is mixed rather than linear, and thus requires investigation of the influence of other potential influencers.

4.3. Emotional support frequency and public activity

The regression analysis results depicted in Table 3 demonstrate a significant and negative relationship between emotional support frequency and public activity. For instance, the co-efficiency is consistently negative in all models. In particular, the co-efficient is −0.008 for the full model and −0.016, −0.016, −0.005, −0.003 for the Stage 2 to Stage 5A models, respectively. The negative relationship partially aligns with concerns over information overload or an “infodemic”, widely apparent on social media amidst the pandemic (Erku et al., 2021; Zarocostas, 2020). It is reasonable to assume that abuse of emotional support in terms of frequency can lead to a negative rather than a positive influence on public activity, potentially even stifling the positive influence of emotional support provided by the government to the public.

5. Discussion

5.1. The relationship between perceived and received emotional support in social media

Our study provides empirical evidence on the relationship between perceived and received emotional support in social media during the Covid-19 pandemic. Previous health research suggests that perceived and received emotional support are two separate constructs, with the former emphasizing the availability of emotional support and the latter emphasizing receipt of such support (Wethington and Kessler, 1986). The results empirically confirm that, in the context of online emotional support, the two constructs are also different. Specifically, in the full model, perceived emotional support is found to be significantly and positively related to received emotional support ($\beta = 0.634$, $p < 0.01$). However, this significant and positive relationship does not cover all models, suggesting that the correlation represents the essence of complex interconnectivity. In relation to the complexity of the relationship between the two constructs, two findings are worth noting. First, the association is insignificant in the early stages (Stage 2). This implies that the translation of perceived emotional support to received emotional support does not happen automatically. Otherwise, at the beginning of the pandemic (Stage 2), the association would have been significant and positive in the first place. Second, the association turns significant and negative in Stage 5A ($\beta = -0.259$, $p < 0.05$), suggesting that perceived emotional support is not always positively related to received emotional support. Both findings have suggested a mixed rather than a linear relationship between the two constructs.

Further, in relation to practical implications, health research has highlighted the importance of receiving emotional support, as this is consistently related to beneficial health outcomes (Barrera, 2000; Uchino, 2009). On the other hand, perceived emotional support sometimes fails to have positive effects on health (Uchida et al., 2008). However, measuring perceived emotional support and investigating how it can be translated into received emotional support cannot be overlooked. This is particularly important for government agencies or healthcare providers, which have attempted to enhance received support through manipulation of supportive behaviors provision because an effective intervention to enhance received emotional support requires cognition of how emotional support is translated from provider to recipient (Haber et al., 2007).

5.2. The impact of developments in the pandemic

Analytical results in this study suggest that the pandemic may have influenced the translation of emotional support. Specifically, the significant level and co-efficient between perceived emotional support and public activity relates to pandemic development. Two findings are worth noting. First, the relationship between perceived and received emotional support tends to align with stages of pandemic development. For instance, when the pandemic evolves rapidly (Stage 3, Stage 4, Stage 5B), the relationship becomes positive. However, when the pandemic is gradually coming under control (Stage 5A), the relationship decreases and even becomes negative. Second, and surprisingly, the relationship is insignificant in Stage 2 when the pandemic is most serious in terms of newly confirmed cases. One possible explanation behind this may lie with the supply–demand relationship. In the initial outbreak (Stage 2), uncertainty relating to the pandemic may have resulted in the public demanding information support – Wang et al. (2019) posited that informational and emotional support-seeking are two motivations for the public to engage online and the former comes first. In later stages (Stage 3 and Stage 4), when the uncertainty of the pandemic decreased and anxiety, as well as other affective disorders, increased, demand for emotional support increased (Aslam et al., 2020; van der Velden et al., 2020; Zhu et al, n.d.), thus enabling easier translation of emotional support. In times when the pandemic has been under control, reduced demand for emotional support makes translation of such support less efficient. It is therefore reasonable to assume that the influence of pandemic development on the translation of emotional support cannot be overlooked. Further, from a practical perspective, both findings advocate that government agencies attempting to enhance public health through emotional support provision need to match their emotional interventions with pandemic development. This aligns with the key concept of situational crisis communication theory (Coombs, 2007) that crisis managers should match crisis response strategies to the level of crisis.

5.3. Impact of emotional support release frequency

Our empirical results from social media during the Covid-19 pandemic also confirm that emotional support frequency can influence received emotional support. In particular, our study found that daily post-release frequency had a significant negative impact on the public's received emotional support. This means post-release frequency inhibited public reception of emotional support. The findings partially overlap with concern for the "infodemic" on social media during the Covid-19 pandemic (Buchanan, 2020; Orso et al., 2020; Zarocostas, 2020) – that information overload could harm an individual's mental well-being and further inhibit their engagement with social media (Aslam et al., 2020; Bucher et al., 2013). While the above-mentioned studies primarily emphasize information provision, the empirical evidence in this study confirms that similar phenomena could exist in the emotional support provision. Specifically, cognitive load theory (Sweller, 2011) explains that abuse of emotional support provision may strengthen anxiety and other affective disorders requiring more mental effort to cope with, resulting in lower availability of mental effort to embrace emotional support, thus negatively influencing received emotional support. This further implies that practitioners should be cautious when providing emotional support because emotional support provision is also likely to be subjected to "infodemic" treatment.

5.4. Implications

Theoretically, this study provides a prototype study integrating content analysis and SRT to investigate the impact of emotional support in social media. First, this study revisits perceived and received emotional support in social media from the perspective of SRT, providing a theoretical foundation for translation of emotional support. It further contributes to literature on mental health, highlighting the need to influence the translation of emotional support and the influence of emotional support on mental health. Second, in contrast to the previous method, which is based on self-report questionnaires (Fang et al., 2020; Shensa et al., 2016), this study provides an objective measurement of perceived and received emotional support: perceived emotional support is derived from content analysis, while received emotional support is measured through public activity and use of shares, likes, and comments. While the measuring metrics require further refinement and validation, the metrics introduced are beneficial for understanding provision of emotional support and other behaviors of the wider public on social media.

Practically, the contribution of this study is two-fold. First, and most importantly, our work highlights that the social media community can form a mutual aid community (Andalibi et al., 2018; Lewis, 2015) where emotional support can be translated from providers to the public. It provides an alternative solution to address mental disorder issues, which is especially important when professional treatment and medical resources are not available to the wider public. Second, the empirical evidence in this study provides nuanced insights into the translation of emotional support on social media, beneficial for practitioners looking to take advantage of emotional support to improve community mental health issues. Specifically, we highlighted that the translation of emotional support online is not without strategies and practitioners should match emotional support provision with pandemic development and be cautious about frequency.

6. Conclusion

This study aims to identify the translation mechanism of emotional support on social media to provide nuanced insights enabling government agencies to make full use of it against affective disorders. Specifically, we introduced two sub-constructs – perceived emotional support measured using content analysis and received emotional support measured through activity levels. Drawing upon SRT, we established a positive relationship between perceived emotional support and activity levels on social media. A regression model was then built based on empirical data from Weibo accounts in 17 provincial administrative units in China during the Covid-19 pandemic to address two research questions: (1) What is the relationship between perceived and received emotional support in social media? (2) Does this relationship and the frequency of information release change over time? Several findings are worth noting. First, the relationship between received emotional support and public activity is not entirely consistent, suggesting that translation of emotional support is not automatic. Further, our empirical evidence suggests that the translation of emotional support in social media is affected by the frequency of the support. These findings advocate that researchers should further investigate the complex emotional support translation mechanism to provide better empirical evidence and emotional support strategies while practitioners should take advantage of translation of emotional support in social media to provide a buffer for the public against affective disorders.

This study had several limitations. First, the study investigates the translation mechanism from perceived to received emotional support in social media. However, because of the absence of human respondents and the impracticality of using larger amounts of data drawing upon SRT, we used public activity levels to measure perceived emotional support. Admittedly, the difference between public activity and received support. emotional support is non-negligible. The results and findings in this study should therefore be interpreted with caution. Future research is encouraged to provide a direct measurement metric for received emotional support and better examine the translation mechanism. Second, in relation to the translation mechanism, this study assumes a linear relationship between perceived and received emotional support. However, the relationship can be more complex. A potential avenue for future research may introduce other constructs (e.g., expected emotional support) or theory (e.g., expectation disconfirmation theory) to enable better explanation. In all, the study is not intended to present an all-in-one solution to address the above-mentioned challenges, but rather establish a starting point to develop a broader repertoire of strategies and exploit the benefits of social media for improving community mental health resilience.

CRediT authorship contribution statement

Category 1

Conception and design of study: Hu, Xuan; Shen, Shan; Liu, Bingsheng,

acquisition of data: Song, Yanqing; Zhou, Bowen; Li, Xuelian; Bao, Han.

analysis and/or interpretation of data: Shen, Shan; Zhou, Bowen; Hu, Xuan;

Category 2

Drafting the manuscript: Hu, Xuan; Zhu, Ruilin; He Shuang.

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Category 3 Approval of the version of the manuscript to be published (the names of all authors must be listed): Hu, Xuan; Song, Yanqing; Zhu, Ruilin; He, Shuang; Zhou, Bowen; Li, Xuelian; Bao, Han; Shen, Shan; Liu, Bingsheng.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Appendix 1
Sample texts in the data set

ID	Sample content	Sample content (in English)	Emotional 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 29th January, 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
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 from the China Center for Disease Control and Prevention. For details, see ↓ #Fight!Shanghai# #Coming Shanghai# …	0.47
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 human epidemic prevention and control. As of 16:00 on 6th February, 75 cases of human pneumonia patients infected by the new coronavirus have been cured and discharged. What would they say when they walked out of the isolation hospital?	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

Appendix 2
Descriptive statistics of the variables

Statistic	N	Mean	St. Dev.	Min	Max
Like	2932	129.58	640.93	0	15,089.78
Share	2932	25.69	93.21	0	2326.33
Comment	2932	14.03	40.54	0	1030.28
Activity	2932	1.13	7.15	0.002	216.53
Perceived_Sup	2932	0.21	0.17	0	1
Freq	2932	17.02	12.83	1	68
Followers	2932	274.74	255.61	10.306	933.20
Adjacency	2932	2.18	0.93	0	3.00
Distance	2932	1129.73	794.31	0	3268
GDP	2932	36,617.90	28,956.03	2966	107,671
Pop	2932	4573.47	2847.54	608	11,521
EGDI	2932	64.77	12.70	41.35	94.88
Hospital	2932	40.28	19.91	9	102
Conf_Acu	2932	4061.16	14,851.40	0	68,135
Cure_Acu	2932	3314.63	12,827.12	0	64,452
Conf_delta	2932	26.71	333.97	0	14,840
Cure_delta	2932	25.64	184.26	0	3020

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