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## Can people hear others' crying?: A computational analysis of help-seeking on Weibo during COVID-19 outbreak in China

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### ABSTRACT

Social media like Weibo has become an important platform for people to ask for help during COVID-19 pandemic. Using a complete dataset of help-seeking posts on Weibo during the COVID-19 outbreak in China ( $N = 3,705,188$ ), this study mapped their characteristics and analyzed their relationship with the epidemic development at the aggregate level, and examined the influential factors to determine whether and the extent the help-seeking crying could be heard at the individual level using computational methods for the first time. It finds that the number of help-seeking posts on Weibo has a Granger causality relationship with the number of confirmed COVID-19 cases with a time lag of eight days. This study then proposes a 3C framework to examine the direct influence of content, context, and connection on the responses (measured by retweets and comments) and assistance that help-seekers might receive as well as their indirect effects on assistance through the mediation of both retweets and comments. The differential influences of content (theme and negative sentiment), context (Super topic community, spatial location of posting, and the period of sending time), and connection (the number of followers, whether mentioning others, and verified status of authors and sharers) have been reported and discussed.

### 1. Introduction

The beginning of 2020 witnessed a sudden outbreak of COVID-19 in Wuhan, which became a major public event affecting the whole country, and even the world. In the early stages of the outbreak, a lack of knowledge of the virus and inadequate preparation of relevant medical resources, along with psychological panic, confusion, and helplessness, brought about severe social crisis. Many people turned to social media to cry for help. Social media has played an important role in spreading these help-seeking messages and facilitating possible problem-solving, which deserves a systematic analysis.

What are the basic characteristics of help-seeking messages spreading on major social media platforms such as Weibo and do they reflect the development of the pandemic? Can people hear others' crying for help during the public health and social crisis? Which factors influence the diffusion and effectiveness of help-seeking messages? In this paper, we focus on the help-seeking in the COVID-19 pandemic and use computational methods to analyze the large-scale dataset of help-seeking messages on Weibo, hoping to better understand the help-seeking and assistance behaviors online.

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Specifically, we propose a 3C framework to explain the main factors influencing the responses received by help-seeking posts and problem-solving reported at last. 3C refers to Content, Context, and Connection. To be more specific, "Content" is composed of the theme and emotional attributes of help-seeking posts; "Context" denotes the spatial and temporal characteristics of the posts; "Connection" refers to the ability of the posts to reach out to other people (e.g. mentioning behavior using "@"). We thus contribute to the study of shared experiences during the COVID-19 pandemic by focusing on the help-seeking on social media and understanding this issue with the content-context-connection framework.

The world is still suffering from the COVID-19 pandemic, with the infected number keeps growing up. Besides the physical health damage, the pandemic could trigger mental health problems (Abbas et al., 2021; Moreno et al., 2020; Saltzman et al., 2020). Global recovery involves the improvement in both the physical and mental health status of people around the world and requires not only control over the infected number but also more sophisticated ways of coordination, collaboration, and caring with each other, empowered by social media as an important social connection and mobilization mechanism. Vulnerable people would still voice for help on social media during the whole recovery process. One society with high resilience should be able to learn from the past to prepare for the future and carry out institutions designed for individual welfare and sustainable societal robustness (Keck & Sakdapolrak, 2013). With the knowledge of help-seeking on social media from the early stage of COVID-19, people should be able to generate thoughtful response plans for future crises and facilitate global recovery.

## 2. Literature review

### 2.1. Help-seeking on social media and its relationship with the development of pandemic

Social media serve as an important platform where people generate, consume and disseminate informational and emotional content in daily life (Qu et al., 2009), thus becoming a potential attention space for help-seekers to voice for help during public crises (Alshaabi et al., 2021; Andersson & Sundin, 2021; Luo et al., 2020). Evidence from disaster studies has shown that people voice for help during disasters (Chu et al., 2021; Dahal et al., 2021). Several kinds of entities including communities, governments, individuals, organizations, and media outlets are active in the communication on social media during disasters (Houston et al., 2015). As a bottom-up information convergence platform empowering the exchanges of informational, emotional, and instrumental support among normal people, social media could help governments and volunteers coordinate and manage (Ding & Zhang, 2010) to monitor the real-time dynamics of hazards, capture the needs, locate victims (Sharp & Carter, 2020), and ease the problem of information asymmetry (Li et al., 2020a). In this way, the communication influences empowered by social media could eventually bring about actual help at last including aid and donations (Gurman & Ellenberger, 2015).

We are interested in how people used Weibo as a help-seeking platform during the early stage of COVID-19. Especially, we first examine the basic temporal, spatial, and theme distribution characteristics of help-seeking posts. During COVID-19, more attention has been paid to the hospitalization of infected patients. While other various voices asking for help beyond hospitalization during the pandemic shouldn't be ignored. So we will investigate the content typology of posts and look deeper into the proportions and fluctuation patterns of each category during different phases of the epidemic (Spence et al., 2015).

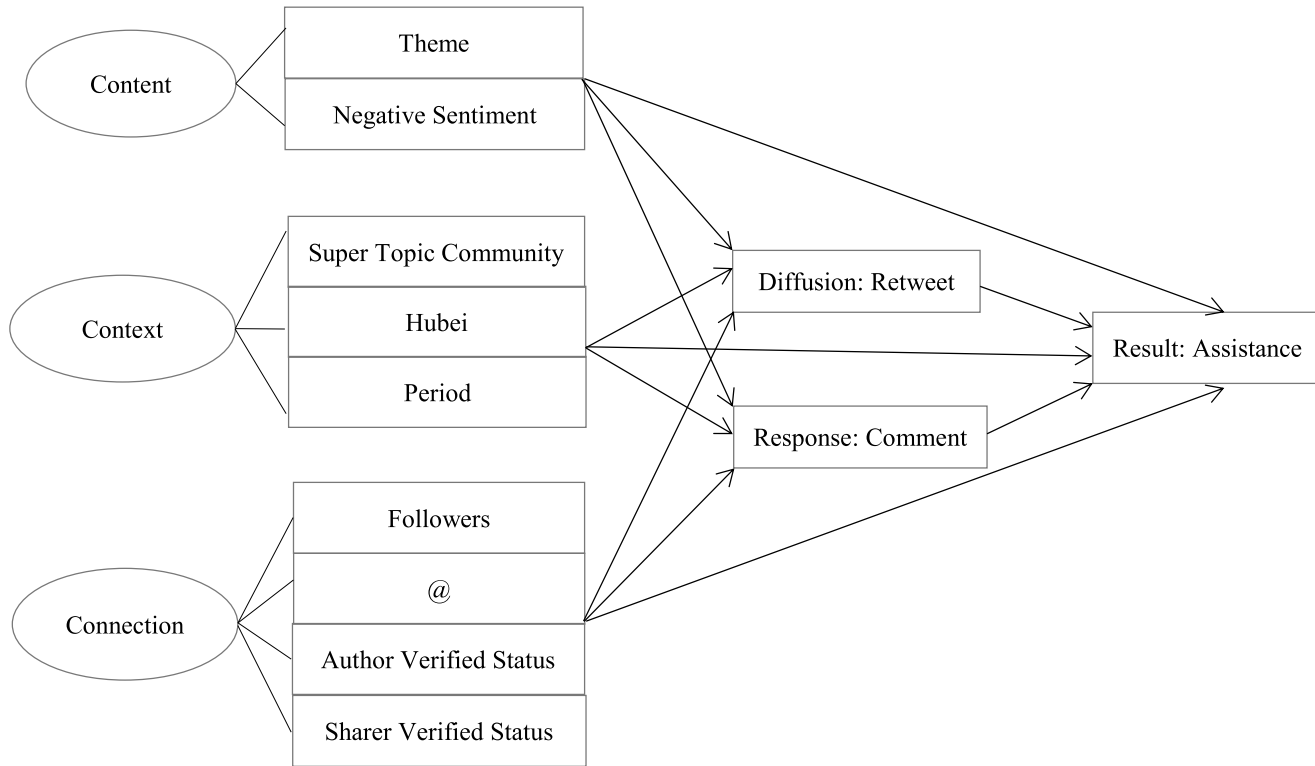
Based on these discussions, we propose the first research question:

**RQ1:** What are the temporal (RQ1a) and spatial (RQ1b) distribution, and main content types (RQ1c) of help-seeking posts on Weibo during the outbreak of COVID-19?

There is possible mutual predictability between epidemic development and help-seeking behavior at the aggregate level. On one hand, the more people infected, the more people would ask for help. The infection could have been the original trigger of help-seeking behavior online. On the other hand, the number of help-seeking posts on social media can be treated as an early warning of the COVID-19 development. There is always a time lag between infected signs and confirmed diagnoses, which could be even longer in the early stage of COVID-19 given the limited medical and social resources. In this way, the help-seeking posts could have released potential signs of a trend underlying the virus spreading process. Researchers have investigated the possibility of predicting the outbreak of pandemics based on social media data (Samaras et al., 2020; Shen et al., 2020). However, there is no empirical study to examine whether help-seeking posts could play as an indicator to predict the number of infected. Should the predictability be confirmed, we might be able to have help-seeking messages as supplement information for epidemic monitoring and offer a guide on the allocation of social resources when facing public health crises.

Granger (1969) raised a definition of "causality" in 1969, explaining  $Y_t$  causes  $X_t$  if including the past value of the time series  $Y_t$  can improve the prediction of future  $X_t$ . It is a statistically predictable relationship rather than real causality based on the logic of counterfactuals (Shojaie & Fox, 2022). Therefore, scholars call this relationship as "Granger causality" to distinguish it from other notions of causality. In later research, the Granger causality test has been widely used to determine whether a variable could serve as an indicator of another (Bastos et al., 2015; Freelon et al., 2018; Russell Neuman et al., 2014). So we propose the second question to test the possible bidirectional predictability between help-seeking on Weibo and the development of the epidemic for the first time:

**RQ2:** Is there a Granger causality relationship between help-seeking on Weibo and the development of the epidemic (measured by the number of new diagnoses)?



**Fig. 1.** A conceptual framework of 3C (content-context-connection) to explain the diffusion and effect of help-seeking information on social media.

## 2.2. The diffusion and effect of help-seeking online: 3C (content-context-connection) framework

Besides the aggregate-level analysis of the basic distribution of help-seeking on Weibo and its relationship with the pandemic development, which could benefit the public governance, this study also examines the diffusion and effects of online help-seeking at the individual level, which might help individuals voice for help more efficiently during public crises. That is, we care about whether and under which conditions people's crying could be heard, responded to, and helped finally. The research regarding the online responses of help-seeking could be understood as macro-level information diffusion, which has been studied with various dimensions such as the diffusion size (Cheng et al., 2014), depth and breadth (Vosoughi et al., 2018), speed (Jiang & Scott, 2010), and structural features (Goel et al., 2015), among which diffusion size served as a basic dimension for most studies (Chen et al., 2022; Luo et al., 2020). So this study will examine the diffusion size measured by retweet and comment number of help-seeking behaviors. Different from previous studies, we not only examine the responses from the communication and information diffusion perspective but also examine the actual results that the help-seekers receive at last. It is still unclear which influence factors facilitate the helping result, and whether the collective participation in retweeting and commenting online could be translated into actual help. Thus, a new and comprehensive theoretical model is needed in this domain of research. Based on the synthesis of the literature, we propose a theoretical framework featured by 3C with mediation to explain the diffusion and effect of help-seeking on Weibo, which emphasizes two mechanisms: (1) 3C (Content, Context, and Connection) serve as three key factors to explain whether and to what extent that help-seeking posts get noticed by other netizens and their problems get resolved at last; (2) the diffusion of help-seeking information serves as a facilitating mediator between 3C and assistance (Fig. 1).

First coined by Gibson (1977) in ecological psychology field, and then adapted by Norman (1999) and other scholars, the concept of "affordance" is widely used to understand what artifacts such as media technologies allow people to do (Bucher & Helmond, 2017). In communication studies, the term "communicative affordances" proposed by Hutchby (2001) focuses specifically on the enabling and constraining potentials of technology for communication (Schrock, 2015). Following this conceptualization, scholars have analyzed the affordances of social media which structure the engagement of users such as visibility, editability, persistence and association (Troom & Leonardi, 2013) as well as lower-level affordances connected with specific features of particular platforms (Postigo, 2016). Various social media affordances are also highlighted to show beneficial for health-related help-seeking practice, such as the affordances of community co-creation and social relationships (Lin & Kishore, 2021) and the affordance of large-scale visibility (Chen et al., 2022; Stephens et al., 2020). For example, super topic community on Weibo can be taken as an example for community co-creation affordance, and retweeting and mentioning others with "@" could be perceived as representation of social relationship affordance, and both of them facilitate visibility affordance. These affordances thus encourage people to voice for help on Weibo.

Although social media affordances facilitate help-seeking, the highly-competitive information environment brings an obstacle for these help-seeking voices to be heard. Public attention is limited in load (Hilgartner & Bosk, 1988) and follows the zero-sum proposition (Zhu, 1992). To be heard, one help-seeking post should be equipped with abilities that enable itself to compete in the highly competitive attention space on social media and trigger certain reactions from the audience. Suggested by HSM model (Heuristic-Systematic Model), heuristic processing and systematic processing could happen at the same time to determine the attention and attitude towards messages (Chen & Chaiken, 1999; Zhang et al., 2014). The heuristic processing is based on simple informational cues (e.g. source credibility) while systematic processing relies on more comprehensive analysis of content, such as topic recognition (Chaiken, 1987). The competing abilities of help-seeking messages thus reside in their performance to arouse the dual-processing. Correspondingly, the abilities needed could be understood from three dimensions: the content's ability to arouse attention, to compete with other contextual factors, and to reach out to people by connection potentials. While the content dimension mainly works on the systematic processing, the context and connection dimensions mainly interact with heuristic processing.

### 2.2.1. Content: ability to arouse attention

First of all, content contains two sub-dimensions: theme and emotion. The attention patterns vary between discussions of different topics (Gruhl et al., 2004; Luo et al., 2020). It is reasonable to infer that different help-seeking themes could imply a different level of emergency. During the outbreak of COVID-19, the number of infected patients climbed up sharply, while the medical resources were limited especially in Wuhan city, and thus few proportions of the people were able to be tested for the virus and got admitted to hospitals. It was the most urgent need of the citizens since people were losing their lives if there was no adequate treatment. At that time, the available medical resources and patients do not have sufficient information about each other. Weibo thus became the most time-saving and labor-saving way for the government to know the detailed state of these patients. Under such a circumstance, the sharing behavior could help the patients to receive more attention from medical organizations and public health departments. Therefore, H1.1 is proposed to test the influence of theme on the diffusion and effect of help-seeking posts and especially focuses on the influence of asking for hospitalization.

**H1.1:** The theme of help-seeking posts could influence the retweets, comments, and assistance they receive, especially the theme of asking for hospitalization receives more retweets (H1.1a), comments (H1.1b), and have a higher chance to get assistance (H1.1c).

The degree of emotional expression in messages has been also found to influence the popularity of information diffusion on social media. According to previous studies (e.g., Schweiger & Quiring, 2005; Zhang et al., 2014), messages written in a more sentimental manner will create feelings of intimacy and magnify the effort of user input. Emotional words would arouse a higher level of brain responses and cause the attention of readers (Goldenberg & Gross, 2020). Research on Facebook and other social media have verified that the sentiment of messages could trigger more cognitive involvement (Mauri et al., 2011), which was in turn correlated with information

sharing behavior (Luminet et al., 2000; Peters et al., 2009; Stieglitz & Dang-Xuan, 2012), retweeting (Goldenberg & Gross, 2020), and feedback (Kramer et al., 2014). Compared with unemotional content, retweeting (Firdaus et al., 2018; Naveed et al., 2011) and commenting (Burke & Develin, 2016) generally occur more commonly with exposure to negative emotion. The negative sentiment was also proven to be associated with higher perceived risks (Lwin et al., 2022), thus significantly influencing the acceptance of policy (Rodriguez-Sanchez et al., 2018) and driving the timely help from the government to ensure social stability (Li et al., 2019).

**H1.2:** The help-seeking posts containing negative sentiment receive more retweets (H1.2a), comments (H1.2b), and have a higher chance to get assistance (H1.2c).

### 2.2.2. Context: ability to compete with other messages

We examine both spatial and temporal contextual factors. By spatial, we imply both cyberspace and geographic space.

In cyberspace, there is a specific “Super Topic” community for posting COVID-19-related help-seeking messages on Weibo, which increased their possibility of being diffused and assisted. First, the super topic community provided a supplementary channel of visibility. People who clicked into the super topic community could receive messages from help-seekers without bothering to search or follow particular help-seekers. People could even subscribe to this community to follow help-seeking messages continuously, which facilitates both information diffusion and matching between help-providers and help-seekers. Second, the super topic community was also featured by credibility. Evidence showed that posts in the COVID-19 super topic community followed a standard format with clear and detailed information (Li et al., 2020b), which helped increase credibility (Chen et al., 2021) and thus could facilitate diffusion and assistance.

**H2.1:** The help-seeking posts sent from the “Super Topic community” receive more retweets (H2.1a), comments (H2.1b), and have a higher chance to get assistance (H2.1c).

We also emphasize the geographic location from where the post was generated. Only a few studies examine this macro-level factor when analyzing the information diffusion on social media. During the disaster and crisis, the posts from where the disaster and crisis happened attracted more attention (An & Mendiola-Smith, 2020). Earthquake-related studies also found that the physical proximity between the user and the center of the disaster was an influencing factor in posts’ virality (Li et al., 2021). During the outbreak of COVID-19, the attention of the whole country was attracted to Hubei province, while its medical resources were most limited. So H2.2 is proposed to test the differential influence of Hubei for diffusion and assistance.

**H2.2:** The help-seeking posts sent from Hubei receive more retweets (H2.2a), comments (H2.2b), but have a lower chance to get assistance (H2.2c).

We consider the influence of temporal context on diffusion and effect in two ways: the medical resources available in different periods for explaining assistance, and netizens’ attention and exposure intention changes for explaining diffusion. The whole period is divided with the time spots of the 4th, 8th, and 13th of February. 4th February is selected because the *Leishenshan* hospital started to provide treatment for infected people on that day. On 8th February, another hospital called *Huoshenshan* and a field hospital were also put in use. Ten other field hospitals opened for treatment of patients with mild symptoms on 13th February. The assistance should be much more accessible with more medical resources available. On the other hand, research on commenting behavior revealed an avoidance of exposure to help-seeking messages due to powerlessness and frustration in the long term (Chen et al., 2021). People are faced with the risk of a low perceived sense of well-being or even depression and trauma if they keep exposed to bad information on social media (Khodabakhsh & Ahmadi, 2020; Zhong et al., 2021). Social media avoidance as a way of self-protection, together with the decline of attention, could result in fewer retweeting and commenting behaviors. Thus H2.3 is proposed:

**H2.3:** The help-seeking posts sent within periods with more medical resources (later time) receive fewer retweets (H2.3a) and comments (H2.3b) but have a higher chance to get assistance (H2.3c).

### 2.2.3. Connection: ability to reach out to people

This dimension denotes the ability of a post to connect to the potential audience in the diffusion network on social media, which includes at least four important factors: the number of author’s followers, whether the author is a verified user, whether the post mentions others by using @, and whether involving verified users in its retweet chain.

Previous studies have confirmed the importance of the number of the authors’ followers in the information diffusion process (Cheng et al., 2014; Firdaus et al., 2018). The number of followers on Twitter is associated with perceived source credibility (Westerman et al., 2012), leading to higher content acceptance (Rui et al., 2013). Moreover, people with a larger number of followers are more likely to become influencers in the network (Bakshy et al., 2011; Cha et al., 2010) with a higher ratio of being diffused (Petrovic et al., 2011). Besides, accounts with large follower numbers have a significant impact on the perceived seriousness of the health crisis of their followers (Bi et al., 2018), which could give it a priority in help-providing decisions conducted by the authorities.

**H3.1:** The help-seeking posts sent from authors with more followers receive more retweets (H3.1a), comments (H3.1b), and have a higher chance to get assistance (H3.1c).

Besides the original audience generated from the follower list, the mentioning function using “@” on Weibo allows users to draw

attention from certain users. It thus becomes an important strategy for connecting with other users on social media, reminding the people who are mentioned to respond to the original post by retweeting or commenting (Chen et al., 2021). Researchers have taken the "@" as a predictor of cascade size (Jiang & Scott, 2010) and the possibility of being retweeted (Naveed et al., 2011; Petrovic et al., 2011). Also, mentioning behavior created a directed and a repeated path between help-seekers and the mentioned people, which increased the possibility of bridging help-providers with help-seekers, thus promoting the chance to be helped.

**H3.2:** The help-seeking posts containing mentioning others with "@" receive more retweets (H3.2a), comments (H3.2b), and have a higher chance to get assistance (H3.2c).

According to Sundar (2008), authors' authoritativeness as a feature of connective affordance could assign credibility to a given message. Posts posted by authoritative authors would be more likely to be acted upon (Chaiken, 1987). The verified status of users is one of the most visible attributes of authors' authoritativeness. The verified users on Weibo have a special symbol "V" at the right bottom of their profile photo, meaning that the identities of these users were confirmed by Weibo. Evidence from Twitter indicated no significant effect of verified status on content credibility (Edgerly & Vraga, 2019; Vaidya et al., 2019). However, in the context of help-seeking, when people competed for limited attention in such a moment of severe resources shortage, the verified status becomes an important clue for higher self-disclosure and enhances the help-seeking trustworthiness. A study from China showed that the verified status was significantly negatively associated with the diffusion size of help-seeking posts about COVID-19 (Li et al., 2020b). However, the authors only considered two types of help-seeking including emotional support and supplies support from medical institutions and individuals, which were only a fraction of the whole help-seeking picture. Besides, participators involved not only individuals but also verified organizations or groups that could offer actual assistance. So the verified status of the author and sharers can be treated as an important sub-dimension of the connection ability. The verification status on Weibo is generally divided into two main types: verified individuals and verified organizations (blue V). We will distinguish these two types of verified users from common users in the following analysis.

**H3.3:** The help-seeking posts sent from authors with the verified status receive more retweets (H3.3a), comments (H3.3b), and have a higher chance to get assistance (H3.3c).

**H3.4:** The help-seeking posts with the verified status of the sharers receive more retweets (H3.4a), comments (H3.4b), and have a higher chance to get assistance (H3.4c).

#### 2.2.4. Diffusion as mediators

We argue that the diffusion of help-seeking information could serve as a mediator between 3C factors and assistance. The logic behind is twofold: diffusion is conceptually different from effect as either retweeting or commenting is relatively easily taken while assistance depends on additional social and medical resources; diffusion could facilitate the problem-resolving by amplifying people's voices and attracting help-providers' attention, which could then translate into the priority of assistance. One of the biggest obstacles in the rescue is that help-seekers and help-providers are not always well-connected. For example, a case study on the Nepal earthquake found that helpers turned to the official page of the police while victims didn't (Subba & Bui, 2017). In the case of Weibo, users can connect these two groups of people by both retweeting and commenting on help-seeking messages (Sharp & Carter, 2020). Besides, people who are exposed to a higher proportion of help-seeking messages in their information feed tend to provide physical help (DiCarlo & Berglund, 2020), suggesting the importance of continuous and repeated diffusion of help-seeking messages. The more times one message is shared, the higher chance it might have to reach help-providers. Also, the priority of assistance remained another problem in help-providing. Evidence from earthquake showed that collective participation in information sharing could also generate an impact on the response priority of help-providers (Subba & Bui, 2017). Thus, H4 and H5 are proposed:

**H4:** Retweet (H4a) and comment (H4b) are correlated with assistance.

**H5:** Retweet (H5a) and comment (H5b) mediate the relationship between 3C factors and assistance.

### 3. Method

#### 3.1. Data collection and processing

We collected all original posts that contained four expressions of "help" in Chinese ("求助", "求救", "求帮助", "求解决") and all posts from "pneumonia patients help-seeking Super Topic" community from Weibo between 1st December 2019 and 15th March 2020. The data was collected from a highest-level API which was directly authorized by the Weibo company, which allowed us to collect a complete dataset on this topic (the initial  $N = 29,453,546$ , among which 1,228,462 are original posts).

We then used the following cleaning method on original posts first and then collected all the forwarded posts based on the original ones. The classification task for data cleaning aimed to extract COVID-19-related help-seeking posts. We designed different cleaning strategies for posts before and after 21st January 2020.<sup>1</sup> For posts before that time ( $n = 452,035$ ), we firstly used the matching rule

<sup>1</sup> On 20<sup>th</sup> January 2020, President Xi Jinping gave instructions on the pandemic prevention and control for the first time. On the same day, a senior medical scientist Zhong Nanshan first announced the virus was contagious among people.

based on the TF-IDF results of posts ( $n = 28,107$ ) that contained “coronavirus”, “pneumonia” or “COVID-19” to get 3246 COVID-related messages; we then manually checked all these posts and found only 119 COVID-19 help-seeking posts posted by individuals or organizations, which excluded the noises such as news reporting on help-seeking as our research purpose was to examine whether the voices of people crying for help could be heard rather than analyzing news reporting about help-seeking. To ensure this strategy worked, we again manually checked a random sample ( $n = 2672$ ) from the 448,789 posts left and found none of them were related to COVID-19 help-seeking. For posts after 21st January 2020 ( $n = 776,427$ ), we conducted a supervised pretrained Bert model with a manually-coded sample of 5000 with a sound performance (precision=0.94, recall=0.92, F1=0.93) and recognized 64,127 help-seeking posts. We further manually checked a random sample ( $n = 5000$ ) and found a precision of 0.95. Thus, we got a clean dataset of original help-seeking posts on Weibo during the COVID-19 outbreak in China ( $N = 64,246$ ).

After identifying related original posts, we collected all their retweets and got 3640,942 retweets, which form the final corpus for analysis ( $N = 3705,188$ ), together with the original posts.

### 3.2. Measurements and data analysis

The measurements of key variables are shown in Table 1. To determine the categories of help-seeking posts, we manually labeled the help-seeking categories of 5000 posts sampled from 64,246 original posts and identified nine themes. Then we applied the Bert model using annotated posts as a training set with a sound performance (precision=0.77~0.94, recall=0.81~0.96, F1=0.80~0.95, please refer to Table 2 for details) to determine the categories of all other help-seeking posts.

To answer the second research question referring to the relationship between the number of help-seeking posts and the diagnoses numbers national wide and in Hubei, we conducted a Granger causality test between these two variables. It helps us to determine if the past value of the independent variable has the predictive function for the current value of the dependent variable.

We then run a logistic regression model with mediation to test research hypotheses, using the “BruceR” package in R (with 5000 Bootstrap samples). As shown in Table 1, the responses received by help-seeking posts were measured by retweet number and comment number. To find out the posts that received assistance eventually, we extracted retweets with the keywords method first (a combination of “already” and “thank you”) and then checked the results ( $n = 3979$ ) manually to get the final results ( $n = 988$ ).

## 4. Results

### 4.1. Basic description and granger analysis (RQ1 & 2)

#### 4.1.1. Temporal distribution

For RQ1a, we found 64,246 original posts seeking help in the dataset, and 15,017 of them were posted in the Super Topic community. The number of help-seeking posts reached its peak on 5th February 2020. The Super Topic community witnessed the biggest volume on 8th February 2020 and posts from other channels peaked on 25th January 2020 (Fig. 2).

#### 4.1.2. Spatial distribution

Until 15th March, Hubei ( $N = 21,860$ ) ranked first among all provinces in terms of the number of help-seeking posts, corresponding to its worst status of the epidemic during the outbreak of COVID-19. It is worth mentioning that the second place was occupied by Beijing ( $N = 5042$ ) whose number of confirmed cases ranked only 13th. While Hunan, whose diagnoses ranked 5th place only sent 1745 posts to seek help (ranked 10th place, see Table 3).

#### 4.1.3. Content distribution

We calculated the proportions of each help-seeking type (RQ1c). As we argued, not all help-seeking posts on social media ask for hospitalization. The request for hospitalization accounts for 38.2% of all help-seeking posts, followed by prevention supplies requests from organizations (19.9%) and daily life assistance (14.3%). The various help-seeking voices deserve to be heard (Fig. 3).

People started to ask for help with daily life after Wuhan announced to lockdown on 23rd January, same was the help-seeking of “prevention method and symptom counselling”. After two days, the need for prevention supplies from both individuals and organizations reached its peaks. The “donation’s transportation” and “prevention supplies request from organizations” were two major help-seeking types during the early stage of the COVID-19 outbreak before February. The second main peak of “prevention supplies request from organizations” occurs with a sharp increase of “being hospitalized”. The request of “being hospitalized” reached two highest volumes on 5th and 8th February respectively, around the days *Huoshenshan* (4th February) and *Leishenshan* (8th February) hospitals were put in use. It could be inferred that to some extent, the establishment of these two hospitals released the shortage of hospitalization resources needed by people. There was a roughly steady upward trend of “other diseases” help-seeking posts all over the time until “being hospitalized” fell back on 18th February. The limited medical resources started to incline to other diseases when the tremendous tension brought by the COVID-19 outbreak was slightly alleviated. As one of the key ingredients in the treatment of COVID-19, the call for plasma started to climb up after 11th February, when more patients were admitted to hospitals (Figs. 4 and 5).

#### 4.1.4. Relationship between the number of confirmed cases and help-seeking posts (RQ2)

Before we run the Granger causality test, a Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992) was conducted to assess the stability of the time series. The result of KPSS ensured that after first-order difference processing, the number of posts across areas and topics, as well as the number of diagnoses didn’t have a unit root on the 1% level, and thus we had stable time

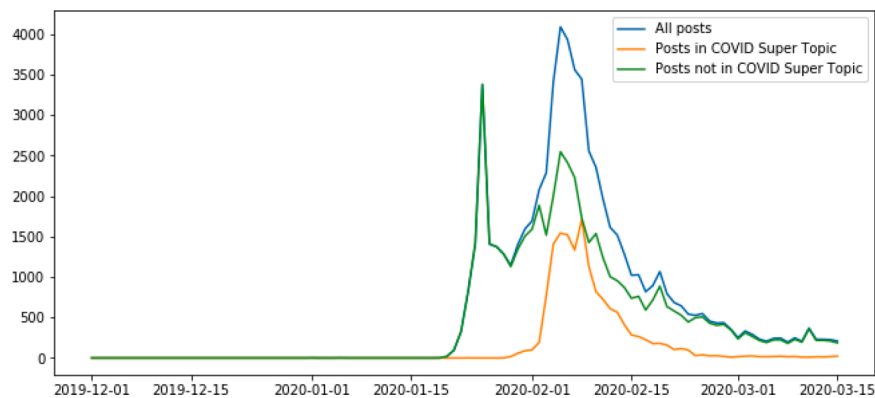


**Table 1**  
Measures of key variables.

	Dimension	Variable	Calculation
Mediators	Response	<i>Retweet</i>	The number of retweets
		<i>Comment</i>	The number of comments
Dependent variable	Assistance	<i>Assisted</i>	Is there any progress of assistance measured by later expressions on problem-resolving or appreciations (e.g., <i>Thanks, Thanks for helping, Thanks a lot, My problem has been resolved</i> , among others)
Independent variables	Content	<i>Theme</i>	Nine types of help-seeking content detected using Bert algorithm (see Table 2)
		<i>NegSen</i>	The ratio of negative sentiment words calculated with LIWC (Simplified Chinese version)
	Context	<i>SuperTopic</i>	Whether these posts were sent in super topic community
		<i>Hubei</i>	Whether these posts were sent from Hubei province
	Connection	<i>Period</i>	Divided by 4th Feb., 8th Feb., and 13th Feb.
		<i>Followers</i>	Number of the author's followers
<i>@</i>		Whether the author mentioned other users using "@"	
	<i>V_type</i>	Whether the author's verification status was blue V, verified individual, or not verified user	
	<i>V_in_chain</i>	Number of verified users in retweet chain	

**Table 2**  
The Bert model performance on content classification (N = 5000).

Categories	Precision	Recall	F1
ask for being hospitalized	94.74%	96.49%	95.60%
epidemic prevention supplies (organization)	93.71%	92.41%	93.06%
epidemic prevention supplies (individual)	88.06%	95.16%	91.47%
daily life assistance	78.79%	81.89%	80.31%
other diseases	81.25%	89.66%	85.25%
prevention method and symptom counseling	94.57%	85.31%	89.71%
transportation of donations	80.00%	84.21%	82.05%
plasma	77.78%	93.33%	84.85%
Pets	85.71%	100.00%	92.31%



**Fig. 2.** Number of help-seeking posts over time.

**Table 3**  
The top 5 provinces that sent the most help-seeking posts.

Rank	Province	Number of posts	Rank of confirmed cases
1	Hubei	21,860	1
2	Beijing	5042	13
3	Guangdong	4176	2
4	Zhejiang	2998	4
5	Henan	2971	3
...	...	...	...
10	Hunan	1745	5

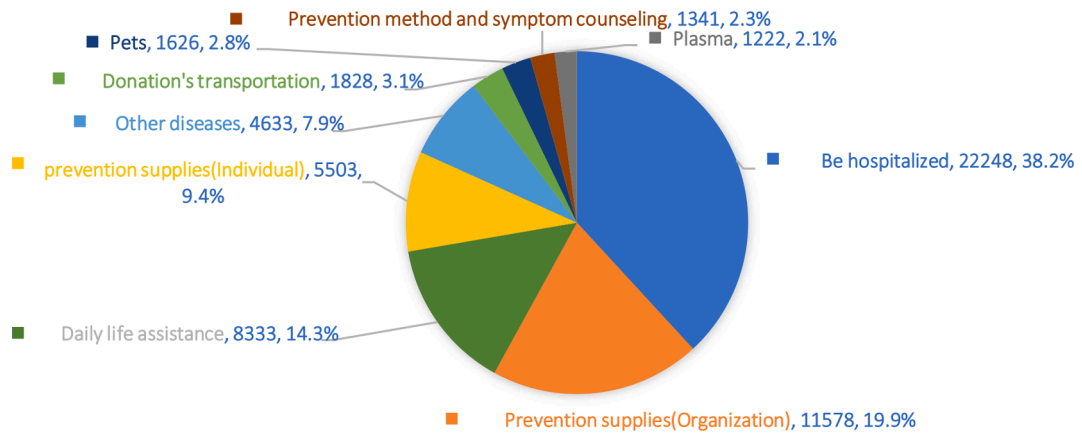


Fig. 3. The proportions of each help-seeking category overall.

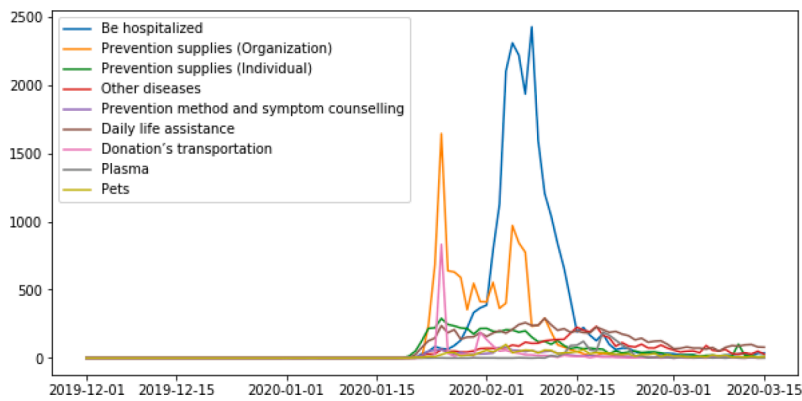


Fig. 4. The trend of number of posts in each help-seeking category over time.

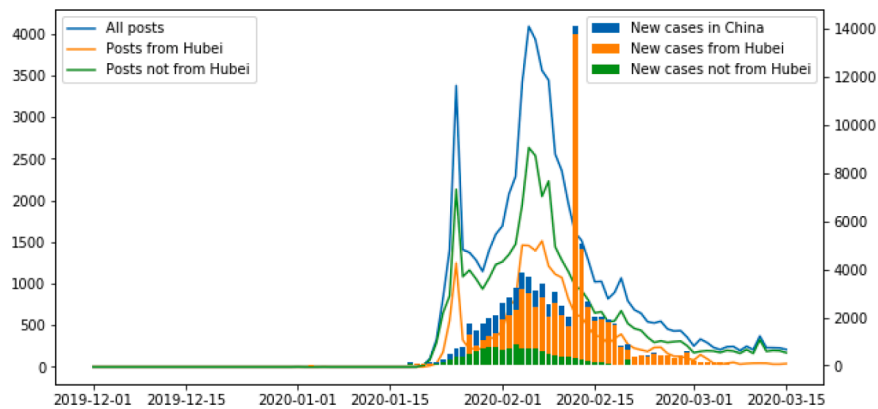


Fig. 5. The trend of number of confirmed cases and help-seeking posts.

series. The Granger test result shows that the number of help-seeking posts helped in the prediction of the confirmed cases with a time lag of 8 days for both nationwide and Hubei province. Nationally the prevention method and symptom counselling, daily life assistance and to be hospitalized can also predict confirmed cases with a time lag of 1, 2, and 3 days respectively. In Hubei, calls for prevention supplies from organizations and to be hospitalized can provide information about diagnoses numbers 4 days ahead [Table 4](#).

In the reverse direction, no Granger causality relationship was found from diagnoses numbers to help-seeking posts. The diagnoses numbers helped in the prediction of several help-seeking themes such as other diseases (3 days lag nationally and in Hubei) and plasma (4 days nationally and 1 day in Hubei) [Table 4](#).

4.2. Predicting response and assistance (Hypotheses testing)

The average number of retweets of all help-seeking posts was 58.27, and 22.86 for comments. In total 988 (1.69%) help-seeking posts received help at last Table 5.

4.2.1. Direct influence of content

For the content dimension, after controlling for all other variables, compared with daily life assistance, the theme "be hospitalized" has a significant positive correlation with the retweet ( $B = 51.360, p = 0.000$ ) (H1.1a) and comment ( $B = 10.730, p = 0.004$ ) (H1.1b), as well as assistance ( $B = 1.772, p = 0.000$ ) (H1.1c). Another theme associated with medical treatment, "other diseases" receives more retweets ( $B = 34.94, p = 0.029$ ) and are likely to get assistance ( $B = 1.233, p = 0.000$ ). The theme of "plasma" and "Donation's transportation", however, turned out to be significantly negatively related to the comments received, but have higher odds to receive help at last. "Prevention supplies (Organization)" received fewer comments.

The degree of negative sentiment is positively related with both comments ( $B = 163.200, p = 0.036$ ) (H1.2b) and assistance ( $B = 11.260, p = 0.000$ ) (H1.2c), but not retweets (H1.2a).

4.2.2. Direct influence of context

Contextually, help-seeking posts from the super topic community received more comments ( $B = 17.670, p = 0.000$ ) (H2.1b) and higher odds of being helped ( $B = 0.208, p = 0.011$ ) (H2.1c) as expected, but not more retweets (H2.1a).

Help-seeking posts from Hubei get more retweets ( $B = 33.510, p = 0.000$ ) (H2.2a) and comments ( $B = 17.880, p = 0.000$ ) (H2.2b) but lower odds to receive actual help ( $B = -0.408, p = 0.000$ ) (H2.2c) as expected.

Compared with posts sent before 3rd February, help-seeking posts from 4th to 7th February received fewer retweets ( $B = -49.620, p = 0.000$ ) and posts from 8th to 12th received higher odds of being assisted ( $B = 0.600, p = 0.000$ ), which partly supported H2.3a and H2.3c. All three later periods received fewer comments as expected by H2.3b.

4.2.3. Direct influence of connection

Follower numbers showed a positive relationship with retweet ( $B = 4.71E-05, p = 0.000$ ) and comment ( $B = 2.79E-05, p = 0.000$ ) as expected (H3.1a and H3.1b), but couldn't directly influence the odds of being helped (H3.1c).

Mentioning others in the posts results in more retweet ( $B = 19.410, p = 0.000$ ) (H3.2a), but no significant improvement in comment (H3.2b) or assistance (H3.2c).

The results for H3.3 were interesting: posts sent by verified individuals received more retweets and comments but no significant increase in the odds of being helped; posts sent by verified organizations received fewer retweets and comments but a significant increase in the odds of being helped.

The verified status of sharers has a significant positive correlation with retweet ( $B = 251.300, p = 0.000$ ), comment ( $B = 72.140, p = 0.000$ ), and assistance ( $B = 2.521, p = 0.000$ ) as expected.

**Table 4**  
Granger causality analysis of diagnose number and help-seeking posts.

Independent variable	China			Hubei		
	Min lag	F	p	Min lag	F	p
All posts	8	3.71	0.001	8	3.76	0.001
Daily life assistance	2	7.641	0.001	13	2.132	0.023
Pet	6	2.629	0.022	10	2.719	0.007
Prevention supplies (Individual)	12	3.47	0.001	5	2.95	0.016
Prevention supplies (Organization)	7	3.52	0.002	4	4.26	0.003
Donation's transportation	/	/	/	/	/	/
Be hospitalized	3	5.31	0.002	4	4.11	0.004
Plasma	11	2.08	0.030	14	2.19	0.018
Prevention method and symptom counselling	1	4.27	0.041	9	8.94	0.000
Other diseases	/	/	/	12	2.4	0.014
Dependent variable	China	F	p	Hubei	F	p
	Min lag			Min lag		
All posts		/			/	
Daily life assistance		/		6	2.228	0.048
Pet	4	2.767	0.032	3	3.475	0.019
Prevention supplies (Individual)		/			/	
Prevention supplies (Organization)		/			/	
Donation's transportation		/			/	
Be hospitalized	5	5.855	0.000	12	2.139	0.025
Plasma	4	7.626	0.000	1	4.052	0.047
Prevention method and symptom counselling		/		12	2.159	0.024
Other diseases	3	6.612	0.000	3	18.021	0.000

**Table 5**  
The retweet, comment and assistance help-seeking posts received.

	Number	Retweet		Comment		Assistance	
		Max	Average	Max	Average	Being helped	Ratios of being helped
Total	58,312	70,663	58.27	27,107	22.86	988	1.69%
Daily life assistance	8333	11,423	9.15	11,117	10.84	24	0.29%
Pet	1626	45,867	72.53	3603	11.60	15	0.92%
Prevention supplies (Individual)	5503	2084	4.27	1708	8.43	12	0.22%
Prevention supplies (Organization)	11,578	70,663	51.15	18,156	12.19	30	0.26%
Donation's transportation	1828	7919	24.38	414	4.23	22	1.20%
Be hospitalized	22,248	69,960	104.03	27,107	43.51	791	3.56%
Plasma	1222	12,355	59.82	1044	7.91	27	2.21%
Prevention method and symptom counselling	1341	2640	5.63	1241	14.70	3	0.22%
Other diseases	4633	12,421	67.46	2913	15.36	64	1.38%

Note. We excluded 5934 help-seeking posts (9.2%) fell out of the main categories in this table.

#### 4.2.4. Diffusion as mediators

We found that retweet number was positively related to actual help received (H4a), while comment number showed no significant relationship with the odds of being assisted, rejecting H4b.

On the content dimension, hospitalization ( $B = 1.17E-04$ ,  $p = 0.012$ ) and other diseases ( $B = 1.24E-04$ ,  $p = 0.024$ ) showed positive indirect effects on assistance mediated by retweet. Contextually, the positive indirect effect from Hubei ( $B = 7.21E-05$ ,  $p = 0.010$ ) and negative indirect effect during the period of 4th to 7th February ( $B = -1.11E-04$ ,  $p = 0.002$ ) to assistance were mediated by retweet. In terms of connection, there were significant positive indirect effects from the verified status of authors ( $B = 9.50E-05$ ,  $p = 0.018$ ) and sharers ( $B = 1.19E-03$ ,  $p = 0.004$ ) to the odds of getting assistance mediated by retweet. So H5a predicting the mediation role of retweet was partly supported, while H5b predicting the mediation role of comment was not supported.

#### Table 6

## 5. Discussion and conclusion

### 5.1. Summary

#### 5.1.1. On aggregate-level analysis results

Based on a systematic computational analysis of Weibo posts, we answered the first research question regarding the basic statistics of help-seeking posts. The data showed that people sent most help-seeking posts on 5th February 2020, and the rank of help-seeking post numbers across areas didn't necessarily align with the number of confirmed cases. After the launch of the COVID-19 Super Topic community, it became an important help-seeking space for users on Weibo and the number of posts there had a sharp increase, showing the value of building a focused special section for people to post help-seeking requests during large-scale social crises like COVID-19 pandemic.

Our study went beyond the myth that hospitalization occupied help-seeking content during the outbreak of COVID-19 by examining the various types of help-seeking posts. It found that the content of help-seeking posts could be grouping into nine main categories. Their differential influences on diffusion and assistance in the later analysis also proved the value of examining various types of help-seeking.

For research question 2, a Granger causality relationship from the number of help-seeking posts to the number of diagnoses was found with a time lag of 8 days both nationally and in Hubei province. Different types of help-seeking also showed various predictability for epidemic development. Especially, the request for hospitalization could improve the prediction of diagnoses with a time lag of 3 days nationally and 4 days in Hubei. Prevention method and symptom counselling could predict diagnoses with a time lag of 1 day nationally and 9 days in Hubei. The longer time lag in Hubei possibly reflects the difficulty in being diagnosed at the early stage. Comparatively speaking, the power of predictability from epidemic development to help-seeking is weaker. These results suggest that the online data of help-seeking posts could be used to forecast the number of diagnoses of COVID-19 and be used as an important indicator to monitor other pandemics in the future.

#### 5.1.2. On 3C model analysis results

We tested the hypotheses about the influential factors of response and assistance posts received based on the 3C (content-context-connection) framework proposed in this study. The results revealed that all three dimensions did show influences on the information diffusion and actual assistance received, though their influential directions, paths, and effect sizes vary across different sub-dimensions. The differences might come from the different logics behind three dependent variables (retweet, comment, and result) as well as their interactions with 3C factors. For example, retweet and comment mainly require and compete for people's attention resources, while actual assistance requires additional medical and social resources. So, the types of resources of help-seeking content require, the supply and competition of resources in various contexts, as well as different abilities to connect with resources for connection factors, could help understand the various results in terms of 3C's influences on the retweet, comment, and assistance. Furthermore, retweet and comment are different from each other in terms of their visibility as well as the ability to connect help-

**Table 6**  
Predicting retweet, comment, and assistance on help-seeking posts.

		<i>retweet</i>		<i>comment</i>		<i>assistance</i>		<i>retweet as mediator</i>			<i>comment as mediator</i>				
		B		B		B		indirect effect	LLCI	ULCI	indirect effect	LLCI	ULCI		
<b>content</b>	constant	-17.720 (12.710)		9.225 (3.596)	*	-6.701 (0.234)	***								
	<i>Theme (Daily life assistance as baseline)</i>														
	<i>Pet</i>	16.230 (23.480)		-5.355 (6.644)		0.412 (0.345)		4.18E-05 (8.17E-05)	-5.03E-05	3.19E-04	-1.18E-05 (2.20E-05)	-7.69E-05	4.76E-06		
	<i>Prevention supplies (Individual)</i>	2.763 (15.430)		-2.922 (4.366)		-0.110 (0.358)		5.75E-06 (9.51E-06)	-9.81E-06	2.92E-05	-5.20E-06 (1.05E-05)	-3.73E-05	1.18E-06		
	<i>Prevention supplies (Organization)</i>	22.120 (13.530)		-11.850 (3.829)	**	-0.514 (0.296)		4.03E-05 (2.16E-05)	7.88E-06	9.53E-05	-1.85E-05 (2.67E-05)	-8.63E-05	7.16E-06		
	<i>Donation's transportation</i>	3.608 (23.080)		-14.650 (6.531)	*	1.423 (0.308)	***	1.44E-05 (3.45E-05)	-4.40E-05	1.00E-04	-5.00E-05 (7.02E-05)	-2.24E-04	2.00E-05		
	<i>Be hospitalized</i>	51.360 (13.270)	***	10.730 (3.755)	**	1.772 (0.220)	***	1.17E-04 (4.65E-05)	* 5.22E-05	2.40E-04	2.09E-05 (2.46E-05)	-8.18E-06	8.96E-05		
	<i>Plasma</i>	4.445 (27.220)		-16.550 (7.701)	*	1.672 (0.296)	***	1.97E-05 (7.43E-05)	-8.61E-05	2.19E-04	-6.28E-05 (8.67E-05)	-2.76E-04	2.54E-05		
	<i>Prevention method and symptom counselling</i>	6.769 (25.710)		2.746 (7.275)		-0.075 (0.616)		1.43E-05 (1.37E-05)	-2.79E-06	5.56E-05	4.95E-06 (9.49E-06)	-3.15E-06	4.49E-05		
	<i>Other diseases</i>	34.940 (16.030)	*	-2.857 (4.536)		1.233 (0.245)	***	1.24E-04 (5.50E-05)	* 5.20E-05	2.71E-04	-8.69E-06 (1.80E-05)	-6.60E-05	2.43E-06		
<b>context</b>	<i>Negative Sentiment</i>	318.000 (275.200)		163.200 (77.850)	*	11.260 (2.912)	***	4.46E-04 (1.64E-03)	-4.45E-04	5.58E-03	1.96E-04 (1.33E-03)	-2.43E-04	3.07E-03		
	<i>Super topic community</i>	16.300 (10.590)		17.670 (2.997)	***	0.208 (0.082)	*	3.54E-05 (2.68E-05)	-1.43E-05	9.18E-05	3.28E-05 (4.53E-05)	-1.18E-05	1.46E-04		
	<i>Hubei</i>	33.510 (10.590)	***	17.880 (2.997)	***	-0.408 (0.082)	***	7.21E-05 (2.68E-05)	* 2.93E-05	1.42E-04	3.29E-05 (4.53E-05)	-1.65E-05	1.22E-04		

(continued on next page)

Table 6 (continued)

		<i>retweet</i>		<i>comment</i>		<i>assistance</i>		<i>retweet as mediator</i>			<i>comment as mediator</i>			
		B		B		B		indirect effect	LLCI	ULCI	indirect effect	LLCI	ULCI	
		(7.968)		(2.254)		(0.072)		(2.80E-05)			(3.79E-05)			
<b>connection</b>	<i>Period (1st Jan. ~3rd Feb. as baseline)</i>													
	<i>4th ~ 7th Feb.</i>	-49.620	***	-21.420	***	0.197		-1.11E-04	**	-2.07E-04	-5.74E-05	-4.12E-05	-1.74E-04	1.66E-05
	<i>8th ~ 12th Feb.</i>	(10.340)		(2.926)		(0.113)		(3.64E-05)			(5.53E-05)			
		-20.840		-22.790	***	0.600	***	-5.15E-05		-1.56E-04	4.05E-06	-4.82E-05	-1.95E-04	2.27E-05
	<i>13th Feb. ~ 15th Mar.</i>	(11.290)		(3.193)		(0.112)		(3.99E-05)			(6.05E-05)			
		-11.170		-17.180	***	0.231		-2.58E-05		-8.58E-05	1.55E-05	-3.40E-05	-1.41E-04	1.47E-05
		(11.150)		(3.153)		(0.131)		(2.48E-05)				(4.39E-05)		
	<i>Follower</i>	4.71E-05	***	2.79E-05	***	-1.58E-08		1.02E-10		1.46E-11	2.94E-10	5.20E-11	-8.27E-12	2.81E-10
		(3.04E-06)		(8.61E-07)		(1.49E-08)		(6.68E-11)				(7.11E-11)		
	<i>@</i>	19.410	*	4.685		0.151		4.36E-05		5.74E-06	1.16E-04	8.99E-06	-4.00E-06	4.75E-05
	(8.586)		(2.429)		(0.078)		(2.75E-05)				(1.20E-05)			
<b>V_type</b>														
<i>Verified Individual</i>	44.470	***	13.210	***	-0.089		9.50E-05	*	3.63E-05	1.95E-04	2.41E-05	-1.01E-05	1.11E-04	
	(9.535)		(2.698)		(0.081)		(4.00E-05)				(3.39E-05)			
<i>Blue V</i>	-99.010	***	-60.790	***	1.081	***	-3.38E-04		-1.03E-03	-1.16E-05	-1.78E-04	-9.60E-04	2.87E-05	
	(28.670)		(8.110)		(0.219)		(2.40E-04)				(2.44E-04)			
<i>V_in_chain</i>	251.300	***	72.140	***	2.521	***	1.19E-03	**	5.95E-04	2.21E-03	2.92E-04	-1.29E-04	1.20E-03	
	(11.510)		(3.257)		(0.076)		(4.11E-04)				(3.77E-04)			
<b>mediator</b>	<i>retweet</i>				1.44E-04	***								
	<i>comment</i>				(2.34E-05)									
					1.24E-04									
					(7.94E-05)									

Note. \* $p < 0.05$ , \*\* $p < 0.01$ , \*\*\* $p < 0.001$ .

seekers with help-providers, which could lead to different abilities to facilitate actual assistance. We will discuss these logics in detail.

For the content dimension, the request for hospitalization received more retweets and comments, and showed a higher chance of being helped directly and indirectly (through the mediation of retweet). It is the only type that has all the above influential paths among all studied variables. This finding confirms that during the outbreak of COVID-19 hospitalization serves as the most emergent request for patients to cry on social media which attracts relatively larger audience attention and the public opinion (especially retweet) has been translated into actual assistance. At the same time, "other disease" also showed a positive relationship with retweet and assistance, suggesting the possibility that people tend to diffuse and help those crying for life-related problems. The medical treatment, which was in extreme shortage during the outbreak of the pandemic, required a priority arrangement, which could be influenced by public opinion. The life-related theme of "plasma" was also positively correlated with assistance while negatively correlated with comment. This pattern also applied to "donation's transportation". The possible explanation resides in that request for plasma occurred only at the later stage of the COVID-19 outbreak, when the medical recourses were released while attention resources declined. The help-seeking on donations transportation was mainly sent by organizations, which could result in fewer supports in the form of commenting but more actual help. During crises, on one hand, individuals could be perceived as much more vulnerable compared with organizations, and thus people would be more willing to spread the information when faced with help-seeking messages from individuals; on the other hand, help-seeking messages sent from organizations implied larger group-level demands, which could be awarded priority in help-providing.

As the other dimension of content, the negative sentiment contained in help-seeking posts brings more comments and assistance, but not retweets. The expression of negative emotion could imply a severer situation of help-seekers and arouse the perceived urgency of the audience, who then offer emotional support in the form of commenting, a more convenient and safer way to respond.

The super topic community as a cyberspace context brought more comments and a higher possibility of being assisted, which confirmed the value of setting a special section for people to cry for help during public crises like the pandemic by platforms, which could facilitate more efficient information exchange and bridging between help-providers and the help-seekers. The geographic dimension (from Hubei) is positively related to both retweet and comment but negatively correlated with assistance, which proved our hypothesis about two different resources required by diffusion and actual help. The results on the influence of temporal factor also showed the validity of the same logic: with the help of more medical as well as social resources, help-seeking during the later time was more likely to be solved though they received fewer retweets or comments as the attention resources turned out to be more competitive.

In terms of connection dimension, having verified sharers was the only factor showing significant positive direct influences on all three variables as well as indirect influence on assistance with the mediation of retweet. The relatively central position in the communication network and the higher credibility of verified sharers could help explain this finding. Having more followers brought more retweets and comments, which unfortunately couldn't be translated into the actual helping results. The follower number does not guarantee a shorter distance from the resources to the help-seekers. Mentioning others in posts did show a positive correlation with the number of retweets while didn't raise the number of comments or the chance of being helped. A study with interviews of help-providers has found that repeated and messy mentions could make the help-providing process less efficient (Chen et al., 2021). Interestingly, there is a roughly fair chance between verified individuals and organizations in terms of their influences on diffusion and assistance: verified individuals received more retweets and comments and then a higher chance of being helped with the mediation of retweet although the verified status couldn't influence assistance directly; verified organizations received fewer retweets and comments but showed higher chance of being helped. The possible reason explaining the difference between individual and organizational help-seeking has been discussed earlier in this section.

Retweet was positively related to assistance, while comments showed no such impact. The key to getting actual help is to get closer to certain resources. Retweet can better facilitate this goal by making the message more visible. Indirect effects through the mediation of retweet were found from two themes (hospitalization and other diseases), being sent from Hubei and during 4th and 7th February, as well as the verified status of authors and sharers on assistance. So retweet plays an essential role in connecting help-seekers with resources in the situation.

## 5.2. Importance and contributions

This study contributes to the existing literature by systematically examining help-seeking on Weibo during the outbreak of COVID-19 using computational methods with a large-scale dataset for the first time. It has significant theoretical as well as empirical meanings.

### 5.2.1 Theoretical contribution

The theoretical contribution is as following:

- This paper analyzes the relationship between help-seeking posts on social media and the epidemic development at the aggregate level and explaining the influential factors for diffusion and effect of help-seeking by proposing a 3C framework at the individual level, inspired by media affordance framework and HSM model. It has shown that the number of help-seeking posts could become an important predictor to forecast the development of the epidemic eight days earlier. It has also proved the effectiveness of 3C (content, context, and connection) in determining whether and to what extent the help-seeking crying could be heard.

- Furthermore, this study goes beyond the extant studies focusing only on diffusion and examines the relationship between 3C and effect (being helped) with diffusion factors (retweet) as mediator for the first time. This model could thus help better understand the diffusion and effectiveness of help-seeking messages on social media and could be further developed in later studies.

### 5.2.2. Empirical contribution

Empirically, we summarize the contribution as following:

- This study collected a rare complete dataset of help-seeking posts and re-posts with  $N = 3705,188$  across the whole period of the COVID-19 outbreak to make a clear mapping of help-seeking during the pandemic, which has never been done by any previous studies. The data also enabled us to generate robust results for the testing of the theoretical model.
- It also sheds light on the communicative dynamics of various types of help-seeking, including but not limited to the request for hospitalization. It could help the authorities to better understand the various help-seeking during the pandemic and work out possible solutions to meet these needs with careful balance.

### 5.3. Implications for global recovery

With the findings of this study, there are several implications for global recovery. First, the help-seeking crying is not limited to hospitalization, which reminds us that we should pay attention to other themes of help-seeking to avoid possible secondary crises. Second, the predictability between help-seeking messages and diagnoses numbers suggests a possible way to monitor another outbreak of pandemic as well as prepare resources ahead of the crisis. Third, results from the 3C framework confirmed the mediation role of retweeting in generating a higher chance of actual assistance, inspiring common people how to voice for help more efficiently in the pandemic. Last but not least, platform actions such as setting the super topic community were proven to be beneficial for receiving actual help, indicating the important role of digital platforms and their useful strategies could be further applied during global recovery.

### 5.4. Limitation and future studies

First, the measurement of assistance relied on the updated information provided by users. And thus, for those who didn't share the assistance received, the result could not be traced by the dataset we used. Second, we assumed the retweeting behavior conducted by human beings in this study, while in fact, there could be noises brought by automated algorithms on Weibo. Future studies could use other assistance data as a complement and examine the possible retweeting algorithms during the diffusion process.

### 5.5. Conclusion

By investigating the response and assistance received by help-seeking posts during the period of COVID-19, we showed a clear picture of the need of people during a public health crisis, which is of great reference value for the prevention of social crises brought by pandemics global wide. At the same time, we proposed a 3C framework regarding the influencing factors of response and assistance those help-seeking posts could receive, which also leads to a guide for the better management and social governance of help-providing.

### CRedit authorship contribution statement

**Baohua Zhou:** Funding acquisition, Resources, Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Rong Miao:** Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Danting Jiang:** Methodology, Data curation. **Lingyun Zhang:** Methodology, Data curation.

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