Original Research

DIGITAL HEALTH

Digital Health
Volume 8: 1–15

DOI: 10.1177/20552076221085061
journals.sagepub.com/home/dhj
SAGE

What makes an online help-seeking message go far during the COVID-19 crisis in mainland China? A multilevel regression analysis

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Abstract

Various studies have explored the underlying mechanisms that enhance the overall reach of a support-seeking message on social media networks. However, little attention has been paid to an under-examined structural feature of help-seeking message diffusion, information diffusion depth, and how support-seeking messages can traverse vertically into social media networks to reach other users who are not directly connected to the help-seeker. Using the multilevel regression to analyze 705 help-seeking posts regarding COVID-19 on Sina Weibo, we examined sender, content, and environmental factors to investigate what makes help-seeking messages traverse deeply into social media networks. Results suggested that bandwagon cues, anger, instrumental appeal, and intermediate self-disclosure facilitate the diffusion depth of help-seeking messages. However, the effects of these factors were moderated by the epidemic severity. Implications of the findings on support-seeking behavior and narrative strategies on social media were also discussed.

Keywords

COVID-19, help-seeking, information diffusion, depth, heuristic-systematic model

Submission date: 16 August 2021; Acceptance date: 16 February 2022

Introduction

The COVID-19 pandemic has resulted in approximately four hundred million confirmed cases and five million deaths as of 27 January 2022.[1] During the initial outbreak in Wuhan, the local public health system was almost paralyzed by the massive caseload, as evident from a Wuhan Children's Hospital post, "there's a shortage of medical supplies, help!!!" on Chinese microblog service, Sina Weibo[2] (hereafter as Weibo). Medical care and attention could not meet demand. Many suspected COVID-19 patients could not get medical attention from the public health system, and many of them turned to social media for help.[3] They sought to gain admission to a hospital, obtain testing kits, or ask for emotional support, which is an unusual phenomenon in a society where public institutions are expected to hold a dominant role in mainland China's healthcare system. Using multilevel regression analysis, we found that a large number of followers, anger, instrumental need, intermediate self-disclosure, and situation severity facilitated the diffusion depth of the help-seeking message. Moreover, the severity of the situation can moderate the effects of the individual post and poster factors on the diffusion depth. The study contributed to the understanding of help-seeking information diffusion in two important ways: (1) analyzing one of the under-examined structural features of help-seeking information

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diffusion, information diffusion depth; and (2) differentiating the functions of the individual post and the poster in different situations.

The previous research[3–6] on online social support has largely focused on the impact of descriptions of user characteristics and motivations, or the typology and features of help-seeking messages. Nevertheless, the effectiveness of seeking help online is normally associated with the absolute number of end-users that a help-seeking message can reach, without considering the structural characteristics of information diffusion. Taking popularity data (e.g. the number of retweets) as a measurement of the outcome variable neglects that such end-user behaviors may mostly come from existing followers with a stronger relationship than non-followers.[3,7] Since the majority of help seekers aim to maximize the collection of wide-ranging resources when using internet technologies,[8–10] how a help-seeking post can spread among distant but significant others with available resources should also be investigated.

Additionally, existing information diffusion models consider sender or content-related predictors in isolation from the situation and context in which a help-seeking message is sent. Zhang and her colleagues' study[11] found that high-quality posts in an online discussion forum receive fewer replies in high-quality information environments relative to lower-quality ones because of the increased cognitive burden caused by processing high-quality information. Thus, factors that prompt the diffusion virality of a help-seeking post may not always produce a similar effect in other information environments. The inclusion of prior contextual factors into information diffusion models can deepen the understanding of the nuances in the diffusion of help-seeking messages on social media. To understand the dynamics of the diffusion of online help-seeking messages regarding COVID-19 in mainland China, our study examined the sender, content, and contextual factors that affect the diffusion depth of the help-seeking messages. In the following sections, we first introduce the theoretical framework of the study and then present our empirical data.

Literature review

Strong and weak ties when seeking help online

For many people, the Internet has become one of their main avenues of seeking information and social support. Previous studies have found that in many circumstances, close ties (e.g. relatives, family members, and friends) help people cope with daily stressful or aversive situations (e.g. conflicts with relational partners) or individual distress (e.g. life-threatening illnesses).[12,13] They can provide selfless, competent, and valuable support, regardless of whether it is troublesome or costly to offer a hand.[12,14]

However, seeking support from close ties has its inherent drawbacks. Suggestions from close others are normally homogeneous and similar to one's own thoughts. Support-seekers have difficulty obtaining diverse and alternative perspectives on overcoming problems.[12] Moreover, the intimate relations between help-seekers and support-givers may make the latter less sensitive to maintaining an appropriate boundary with the former. Some advice from support-givers provided out of concern may be too emotional and compulsive, which is not helpful for support-seekers to exercise their agency and obtain a dispassionate analysis of their predicaments.[15–17] How to respond to these emotional but less effective suggestions and reciprocate close others for what help-seekers have been offered could be another challenge.[15,16] Under these circumstances, compared with weak ties, seeking social support from strong ties may not be a preferential option.

More importantly, strong ties may be inadequate under unusual circumstances such as nationwide public health crises.[3,16] Firstly, such crises increase the threshold of accessing related knowledge and resources**.** As a rare infectious disease crisis, there were very few professionals who have relevant information and know the transmission mechanisms, treatment plans, and preventative measures of COVID-19 at the initial phase. And the possibility that these professionals happen to be acquaintances of help-seekers during this initial phase is even lower. Secondly, in a large-scale health crisis, anyone could be a potential victim. Individuals with close ties to and live near those seeking help may face the difficulties themselves, such as limited access to medical resources and failing to be admitted by a hospital. As a result, individuals with close ties to those seeking help are also likely to be concerned about their own health, which makes it difficult for them to spare energy and effort to support others. Thus, close ties may not be effective in seeking help to tide over difficulties.

Conversely, weak ties are relatively demographically dispersed and have a wide range of unique individuals with diverse resources.[12] Social tie theory also argues that weak ties link individuals with wide and heterogeneous communities. On social media platforms, reduced social tie strength can increase opportunities to access information and resources that might otherwise be inaccessible through linkage to homogeneous networks.[18] Hence, reaching weak-tie nodes when seeking help online seems to have numerous advantages in requesting social support under the circumstance of a nationwide public crisis.

Diffusion of online help-seeking messages on social media

Diffusion is a communication process in which information is spread through channels over time. For social networks, information is diffused among their users.[19,20] Previous studies[7] have examined the topological properties or the effectiveness of information diffusion in terms of diffusion size, diffusion speed, diffusion breadth, and structural characteristics of diffusion networks. Diffusion size indicates the aggregated number of involved entities during the spread of information,[21–23] which can be quantified by the number of reposts a message receives. Diffusion size is often a proxy for popularity or breadth.[7] Diffusion speed refers to the time interval of the message's first diffusion when users repost or share the message.[19,23–25] Diffusion breadth indicates the number of first-degree entities in the diffusion path.[19,26] An important dimension of structural characteristics of diffusion networks is diffusion depth or the number of intermediaries or the number of steps in the diffusion chain, which can be measured by the longest geodesic distance between the original tweet and retweets.[7,26,27]

Previous research on the diffusion of online help-seeking information has mainly focused on a narrow subset of the topological properties of information spread, such as the diffusion size and breadth, based on the number of retweets, comments, and likes that support-seekers have received.[3,28] Little attention has been paid to examining the structural characteristics of the evolution of support-seeking networks (i.e. diffusion depth). A previous study[29] found that the tie strength between the information sender and receiver will decrease when the information diffusion depth increases. However, similar associations between tie strength and diffusion breadth/size may not hold true. On social media platforms, information typically traverses from original post to immediate followers, then to these followers' followers, and so on. Thus, the first-step sharing by those who directly disseminate the information from the source (i.e. breadth) are normally the followers who have more interactions and closer ties with the source than non-followers.[30] Moreover, the large number of retweets does not necessarily lead to close contact with weak ties. Luo et al.'s study[3] on help-seeking on social media found that the majority of those who share social media posts have followed the help-seekers' accounts before spreading their support-seeking messages. Therefore, diffusion depth is more appropriate to represent the extent of heterogeneity in the community that a help-seeking post has reached. Social media platforms' affordance on connecting weak-tie nodes makes them attractive for posting help-seeking messages. However, the factors that affect the diffusion depth of help-seeking messages are under-explored, especially on Chinese social media.

Factors driving the diffusion depth of help-seeking information online

Considerable research has found that people often rely on heuristics and mental shortcuts to process health information on social media.[6,31] However, the heuristic-systematic model (HSM) posits two ways of information processing: heuristic processing that depends on simple cues such as message source, and systematic processing involving more deliberative pondering on elements of message content and narrative style.[32] Message content and source characteristics are vital factors driving individual-level processing of information.[32,33] Information diffusion is a complex socio-cognitive process in which decisions to share and disseminate information is made after assessing the information. Hence, it is essential to examine the implicit cues embedded in help-seeking messages generated by the support seekers, including the features of support seekers[3,13,34] and the typology and features of support-seeking messages.[3,6,35] Moreover, given that a post may traverse through different information environments since inception, it is also necessary to explore how such external environment factors affect the diffusion of help-seeking messages.

Heuristic factors: sender factors

In computer-mediated communication (CMC) environments, position and status cues are often concealed. Cues filtered-out theory suggests that communication media that are incapable of transmitting sufficient non-verbal or non-textual cues (i.e. "low bandwidth") can inhibit the formation of online social relationships.[36,37] The lack of visible and verified cues in CMC forces people to process information and make judgments based on accessible contextual clues, such as the traits of information senders.[38] Social presence theory posits that the larger the number of personal and social context cues, the greater the perceived salience of online communicators.[9,39] People's perceptions of source cues allow them to extend the senders' appraisals to the content they have produced. Source cues such as the bandwagon and credibility cues have been found to significantly affect the diffusion size or breadth of a message in CMC.[40]

Bandwagon cues suggest that people's appraisal of an information source can be influenced by the opinions of other peers.[38] Sources with larger peer followings and higher ratings possess greater bandwagon heuristics than those with fewer followers or lower ratings. Endorsement from the majority represents a good reputation and recognition of the source's past utterances and behaviors.[40] Lee and Sundar's study[41] found that bandwagon heuristics induce a larger number of retweets and trustworthiness when a Twitter post regarding health information comes from a source with a larger number of followers. In the field of social networks, the "rich get richer" principle indicates that a node gains new connections in proportion to the number of nodes it already owns.[42] A help-seeking post posted by a source with more followers may thus enjoy a head-start and attract a wider range of audiences. A large number of first-step retweets may increase the chances of the message traversing deeply into the weak-tie networks on social media.

Credibility cues refer to the characteristics that can enhance one's perceived trustworthiness and reliability of a source.[34] On social media platforms, a key credibility cue is the verification of one's real-world identity by platforms such as a Weibo account with a yellow/blue "V" icon.[7] Credibility cues affirm the correctness of a source's opinions and lead the receiver to favor their validity.[43,44] When the source is identifiable, the reduced sense of doubt and increased certainty can elicit positive impressions and more extensive interactions. Starbird and Palen[45] have found that users are more likely to retweet health content posted by credible sources like the mass media and the Red Cross in emergent and highly uncertain situations. Since audiences select information more cautiously and carefully during such situations, credible sources are more likely to stand out, and their help-seeking messages will experience greater vertical traversal. We thus propose:

H1a. The help-seeking messages of users with more followers are more likely to diffuse in-depth than users with fewer followers (bandwagon cue effect).
H1b. Verified users' help-seeking messages are more likely to diffuse in-depth than those of regular users (credibility cue effect).

Systematic cues: content factors

Apart from the identity cues disclosed by the platform, one's real-world identity can also be revealed by self-disclosure. Self-disclosure refers to the disclosure of personally identifiable information.[46] As social penetration theory argues, self-disclosure can enrich the relationship between two or more individuals. The difference in types and attributes of self-disclosed information can represent the closeness between individuals.[47] There are two main layers within the dimension of self-disclosure, namely, peripheral and intermediate layers.[47] Peripheral self-disclosure refers to personal biographical data such as one's name, address, and telephone number, which reduces recipients' perceived anonymity of a message source. Intermediate self-disclosure includes one's feelings, attitudes, and opinions about the situation the message source is experiencing. Help-seeking posts with intermediate self-disclosures trigger greater interaction involvement (e.g. lengthier replies or using more emotional words) than those containing peripheral self-disclosure.[31] A higher level of trust and intimacy is positively related to greater intermediate self-disclosure, strengthening the emotional bonds between senders and recipients.[48,49]

However, although intermediate self-disclosure is more private, it cannot serve as an accurate indicator of the source's identity and thus can hardly reduce the recipients' perceived uncertainty as compared to the peripheral self-disclosure.[50] Pan et al.[51] found that recipients tend to view the source with peripheral cues as more familiar and trustworthy than those with intermediate cues or without personal disclosures. Moreover, Luo and colleagues[3] found that the greater the detail in shared biographical information (i.e. peripheral self-disclosure), the higher the possibility the posts would gain large numbers of reposts. The reduced uncertainty can generate positive impressions and facilitate more engaging interactions. Because biographical information is more tangible, it inhibits doubts about the authenticity of the information compared to subjective experience, thus generating positive impressions and facilitating more extensive interactions.[51,52] We thus propose,

H2: As compared to the intermediate self-disclosure, (a) help-seeking messages with peripheral self-disclosure is associated with higher diffusion depth, but (b) help-seeking messages without self-disclosure is associated with lower diffusion depth.

In addition to source identity cues, content-specific factors such as emotion and types of requested support may also affect the transmission of help-seeking messages. For emotions, both positive and negative emotions have been found to be influential in affecting the contagion of health information on social media.[3,53,54] For instance, posts with negative emotions are more likely to be retweeted. Negativity implies problems, and the problematic situation will not be reversed without immediate action.[53] Moreover, different types of negative emotions can trigger various depths of information processing. Anger, for instance, is characterized by antagonism and heightened arousal.[55] Exposure to anger gives individuals a way to vent negative feelings and motivates them to change the current situation. Conversely, exposure to fear or sadness can give rise to escapist and defensive behaviors.[56,57] Individuals may similarly learn to fear or feel sad about the circumstances in which they have been exposed to stress and pain, and subsequently undergo shallow information processing to avoid the discomfort caused by absorbing the upsetting information.[58] In the context of a health crisis, previous studies[55,59–61] found that anger-related posts are more influential and contagious and can trigger a larger number of reposts than those with sadness and positive emotions (e.g. gratitude). Drawing from these studies, we posit:

H3: Help-seeking messages containing anger is associated with greater diffusion depth relative to messages containing (a) fear, (b) sadness, and (c) positive emotions.

Previous studies on social support have identified five key types of support: informational support (e.g. advice), tangible support (e.g. money), self-esteem support (e.g. validate one's experience), emotional support (e.g. demonstrate concern), and network support (e.g. increase one's size of support network).[6,62,63] Rains et al.'s[13] meta-analysis on 41 studies on online support messages found that informational and emotional support were most commonly requested by help-seekers, while the network and self-esteem support were seldom requested. Broadly, social support can be classified into two main types: emotional and instrumental support, which the former consists of feelings of love, trust, and encouragement, while the latter encompasses the provision of money, materials, information, or suggestions.[3]

Coulson and colleagues' study[62] found that support-givers are reluctant to spread information regarding requests for emotional support because support-givers often feel they are betraying the help-seekers' trust if they speak openly about the latter's pains and experiences.[62,64] In the Chinese context, Luo et al.'s study[3] found that help-seeking messages with instrumental needs are more likely to be reposted than those with emotional needs. In a society that attaches great importance to pride or face (*mianzi*) and leaving positive impressions in others' minds,[65,66] the Chinese are likely to publicly display weakness and helplessness as a last resort. Thus, help-seeking messages in the Chinese context are likely to be instrumental in nature. We thus propose,

H4: Help-seeking messages with instrumental needs is associated with greater diffusion depth relative to messages with (a) emotional needs and (b) no specific needs.

Prior contextual factors

In addition to source and content-related factors, contextual factors also influence how help-seeking messages traverse on social media. Online interactions are dynamic and can change over time. Li and Feng[67] studied the contextual factor of information environment affects responses to a help-seeking message. They found that when existing comments are lengthy, emotional, and well-considered, similar high-quality responses are triggered. Moreover, such contextual information can confer help-seeking messages with legitimacy. When existing comments are generally supportive of what help seekers said they have suffered, it will reinforce other people's belief that the seeker is worthy of assistance. Conversely, when the authenticity of a help-seeking message is doubted in the responses of others, recipients would perceive seekers' requests as illegitimate and leave unconstructive messages.[68]

In alignment with Li and Feng's[67] insights, another prior contextual factor, situational severity, can also play a similar role conferring legitimacy during a health crisis. Several studies[69,70] on newsframes of SARS in China found that increased epidemic severity increases news coverage of symptoms, protective measures, and medical resources. Wright and colleagues[6] call such information in serious situations "evidence-based information," which can be cross-validated with the descriptions of help-seekers' and helps reduce the perceived uncertainty about the authenticity of help-seeking messages. Thus, recipients could be more likely to share the original post with more and more evidence of the situation greatly reducing their doubts. Additionally, many agenda-setting studies[71] have elucidated the importance of "triggering events" or "contingent factors" on influencing the relative salience of various issues and agendas. For instance, the conduct of parliamentary elections in Singapore during the COVID-19 pandemic resulted in crisis management becoming an important voting consideration, which was quite rare in past elections.[72] Thus, the salience of health-related help-seeking messages posted during the COVID-19 pandemic would be much higher than a non-epidemic or minor outbreak context, which has implications on the diffusion depth of such help-seeking messages. Hence, we propose:

H5: Help-seeking messages posted during a more serious public health situation is associated with greater diffusion depth than those posted in a less serious situation.

The seriousness of the situation may also moderate the effect of help-seeking post factors or characteristics on diffusion depth. Several studies on online discussions have shown that a change in the opinion climate on a discussion forum can affect discussion activity.[11,73] Specifically, a disagreeing view is more likely to stand out and gain a reply in a more heterogeneous opinion environment. However, few studies have explored the moderating effect of information climate external to social media, such as the severity of a public health crisis, on the relationship between individual post factors (e.g. bandwagon cues, credibility cues, emotion expression, self-disclosure, and type of social support) diffusion depths in the context of online help-seeking. We thus ask:

RQ1: How does the external information climate moderate the relationship between individual post factors and the diffusion depth of a help-seeking message?

Research method

Data collection

To investigate the diffusion depth of help-seeking information on social media, content analysis was conducted with multilevel regression analysis to address our research hypotheses and question proposed above. We retrieved help-seeking posts regarding COVID-19 from Weibo, one of the most popular microblogging platforms in China with 560 million monthly active users at the end of 2019. Following best practices of content analysis,[74–77] we used keywords (i.e. "pneumonia/COVID [肺炎/新冠] + ask for help [呼救]," "pneumonia/COVID [肺炎/新冠] + seek help [求救]," and "pneumonia/COVID [肺炎/新冠] + help me [救我]") to retrieve related posts during the period from 20 January 2020 to 1 March 2020. The time-frame was set to this period because the starting point was the time when Dr Nanshang Zhong confirmed the transmissibility of COVID-19 on China Central Television (CCTV). Also, the first Fang Cang makeshift hospital in Wuhan closed at the ending point, indicating that the epidemic was under control in mainland China. After removing duplicate and irrelevant posts (e.g. other types of pneumonia) via manual screening, our keyword search finally yielded 705 original Weibo posts that were reposted.

Measurements of information diffusion and driving factors

Dependent Variable (DV)

In this study, our DV was the diffusion depth. It indicates the largest number of steps that a node in a network needs to take to connect with the information source through re-posting of the source's post.[7] A higher diffusion depth means that the help-seeking information is more likely to be spread among more heterogeneous communities and thus may acquire alternative types of support that homogeneous communities may not offer. We measured DV through WeiboEvents (http://vis.pku.edu.cn/weibova/weiboevents/), an open-access Weibo analytic system that retrospectively tracks and collects each post's retweeting information based on the uniform resource locator (URL) of the original post, which was conducted from 1 August 2020 to 11 August 2020. Overall, the diffusion depths of the 705 original posts varied from 0 to 6, with an average number of 1.15.

We developed a comprehensive coding scheme to manually code each post based on three categories of factors: sender (i.e. bandwagon/credibility cue), content (i.e. emotion, type of requested support, type of self-disclosure). We also regarded the width of a repost (i.e. the number of reposts at each level of reach) as a control variable when constructing the model. The coding scheme was iteratively pilot-tested with 114 randomly sampled Weibo posts from the dataset. Six Chinese native speakers were trained and coded IVs independently. Intercoder-reliability was satisfactory, with average Krippendorff's alpha of emotion types, type of requested support, type of self-disclosure being 0.837, 0.905, and 0.891, respectively. Details of measurements of each variable are listed as follows:

Bandwagon cue. We measured this variable by counting the number of followers of the help-seekers' Weibo accounts. On average, a user has 9386.22 followers.

Credibility cue. We measured this variable by identifying whether a user's account is verified or not. In total, there were 144 verified (=1, 20.43%) and 561 unverified users (=0, 79.57%) in our sample.

Emotion types in the post content. The emotion expressed in a post was ascribed to any one of the four categories, including 1 = anger (10.1%), 2 = fear (43.1%), 3 = sadness (36.5%), and 4 = positive emotion (e.g. hope, gratitude) (10.4%). Anger referred to a kind of sentiment evoked by health systems and governments for their incapability of providing necessary protection, and by particular individuals for transmitting the disease.[78] Fear was conceptualized as an emotion experienced in anticipation of some specific pain or danger synonym. Fear was conceptualized as a belief that of impending danger over which he or she may have little or no control.[79] Sorrow and sadness were conceptualized as loss and irrevocable failure to meet goal.[79] Positive emotions were conceptualized as the feelings of trust and the eagerness to return kindness.[78] In this study, anger was treated as a reference group to contrast the effects of other groups on diffusion depth.

Type of requested social support. We categorized the requested support from help seekers into four groups: 1 = no specific request (35.6%), 2 = emotional request (13.3%), 3 = both emotional and instrumental request (14.3%), and 4 = instrumental request (36.7%). Posts with emotional requests relate to the desire for love, care, and encouragement, while those with instrumental requests relate to the need for material or informational resources.[3,6,63] Help-seeking posts without specific requests often convey signals of being in trouble without clarifying what kinds of assistance are needed (e.g. "Please help us!! [救救我们吧!!]"). We took group one (no specific request) as the reference to compare the effects of three other groups on the outcome.

Type of self-disclosure. We divided this variable into four groups: 1 = intermediate self-disclosure (20.0%), 2 = peripheral self-disclosure (9.8%), 3 = both of intermediate and peripheral self-disclosures (25.4%), and 4 = no self-disclosure (44.8%). In our study, a post with the disclosure of any personal biographical data (e.g. name, age, phone number, diagnostic report) were classified as peripheral self-disclosure.[31,49,51] Posts about one's subjective experiences, perceptions, and attitudes toward help-seekers' difficulties were classified as intermediate self-disclosure.[31,49,51] Posts that only convey a signal of being in trouble, but do not disclose any identifiable information about one's identity or subjective perceptions of experiencing hardships would be coded as non-self-disclosure (e.g. "Help these suffering people! # The updated confirmed cases of new pneumonia across the nation # [帮帮这些受难的普通人吧！#全国确诊新型肺炎病例#!!]"). We took group one (intermediate self-disclosure) as the reference and the three others as comparison groups.

The severity of the situation (SOS). This variable was measured by the number of hospitalized cases across the country on the day of posting help-seeking messages. We obtained the data from the National Health Commission of the People's Republic of China (http://www.nhc.gov.cn/). Since 20 January 2020, it has updated these numbers across the country on a daily basis. The larger the number of hospitalized cases, the more serious the epidemic situation. On average, the daily number of hospitalized cases during our search timeframe was 45482.30.

Width as the control variable. The width of repost can be defined as the diversity and openness of interactions at different levels of depth.[80] Wider and more diverse interactions at a certain level may bring higher exposure to the post, thus promoting its vertical traversal.[81] In order to reduce the impact of the differences of widths between posts at different levels, we regard it as the control factor. We measured this variable by calculating the average number of retweets at different layers of depth. For instance, if a post traverses vertically to a depth of two levels, then its width should be the average number of reposts at levels 1 and 2. On average, each level of depth results in 133.08 reposts.

Data analysis

Given that our data were collected at two different levels (i.e. individual post/poster vs. epidemic situation), we adopted a multilevel analysis to assess the nested and hierarchical data. In addition, the dependent variable, information diffusion depth, is a count variable, reflecting the number of occurrences of behavior in a period of time. The count dependent variables can violate the assumptions of linear regression because they often display heteroscedasticity and non-normal conditional distributions of errors. Then, we conducted an overdispersion test by dividing the residual deviance by the degree of freedom. Overdispersion indicates that the variance of the count is greater than the mean of the count if the error term was really Poisson or binomial. If the quotient is greater than one, the model would violate the assumptions of the Poisson distribution.[82,83] Given our quotient is 1.45, it indicates that the residual deviance is greater by 45% and there exists an overdispersion problem. Hence, multilevel regression models with negative binomial distributions were adopted for data analysis in this study. We employed a robust maximum likelihood estimator for the overdispersion parameter when running the negative binomial analysis. The multilevel regression equations were listed in the following:

$E(\text{Level}|\text{NB}) = \lambda$
$\text{Log}[\lambda] = \eta$
Level-1 Model
$\eta = B0 + B1^*(\text{CREDIBILITY}) + B2^*(\text{BANDWAGEN}) + B3^*(\text{DISCLOSURE}) + B4^*(\text{EMOTION}) + B5^*(\text{SUPPORT}) + B6^*(\text{WIDTH})$
Level-2 Model
$B0 = G00 + G01^*(\text{SOS}) + U0$
$B1 = G10 + G11^*(\text{SOS}) + U1$
$B2 = G20 + G21^*(\text{SOS}) + U2$
$B3 = G30 + G31^*(\text{SOS}) + U3$
$B4 = G40 + G41^*(\text{SOS}) + U4$
$B5 = G50 + G51^*(\text{SOS}) + U5$

The level-1 model indicates the main effects of the original post and poster factors at the individual level. Then, we added the environmental factor and random effects (U0–U5) to the level-2 model. Although equation B0 is to test the effects of SOS on the intercept of the level-1 model, B1 to B5 equations are to test the cross-level interactions between the individual- and environment-level variables. To satisfy the assumption of no multicollinearity, we took equation B0 out of the interaction model 3 in Table 1.

How the level-1 variables are centered can affect the meaning of the outcome variable, although there are no statistically correct options.[84] We decided to regard the level-1 predictors as the raw values because almost all individual-level variables in our model (except for bandwagon cues) are categorical variables, so they have no meaningful means. In terms of the environment variable, we used grand mean centering to reduce the impact of multicollinearity. In Table 1, all final models do not suggest multicollinearity issues (variance inflation factor (VIF)<5). To test the predictions, multilevel regression analysis with negative binomial distribution was conducted by R, using sender-, content-, and environment-specific variables as IVs, whereas the diffusion depth as the DV.

Results

Table 1 revealed how the source-, content-, and context-specific variables were incorporated into the multilevel regression model with the negative binomial distribution. Our negative binomial model generated a standard set of coefficients and an exponentiated set of coefficients that reflect incidence rate ratios (IRR). Negative binomial regression coefficient can be interpreted as follows: given all other independent variables are held constant, one unit change of an independent variable can lead to the change in the logs of expected counts of the dependent variable by the repressive regression coefficient. IRR indicates that the estimated rate ratio for a one-unit increase in the occurrence of an independent variable on the premise that other variables are held constant in the model.

Model 1 showed that the bandwagon cues did significantly help ($B = 0.14$, $IRR = 1.15$, $SE = 0.07$, $p < 0.05$) enhance the depth of the transmission of support-seeking posts. IRR shows that a one-unit increase in the occurrence of the bandwagon cue would result in a 15% increase in the depth of repost. H1a was supported. Conversely, in comparison with the help-seeking messages posted by an ordinary user, the possibility of transmitting the information to a deeper level for a post posted by a verified user did not

Table 1. Estimated effects of individual and contextual variables on diffusion depth.

	Model 1			Model 2			Model 3		
Dependent variable	B	IRR	SE	B	IRR	SE	B	IRR	SE
Level-1 post and poster factors									
Credibility cue (reference: non-verified user)									
Verified user	0.13	1.16	0.13	0.12	1.13	0.13	0.20	1.23	0.13
Bandwagon cue	0.14*	1.15	0.07	0.14*	1.16	0.07	0.15*	1.18	0.07
Self-disclosure (reference: intermediate disclosure)									
Peripheral disclosure	−0.49**	0.46	0.23	−0.47*	0.65	0.23	−0.55*	0.60	0.24
Intermediate and peripheral disclosure	−0.01	0.96	0.13	−0.03	0.94	0.13	−0.06	0.93	0.13
No disclosure	−2.21***	0.12	0.20	−2.15***	0.10	0.19	−2.16***	0.10	0.22
Emotion (reference: anger)									
Fear	−0.67**	0.56	0.21	−0.62**	0.56	0.21	−0.58**	0.59	−0.22
Sadness	−0.65**	0.54	0.21	−0.64**	0.54	0.26	−0.72***	0.50	0.21
Positive emotions	−0.41	0.64	0.26	−0.41	0.63	0.26	−0.40#	0.61	0.24
Requested support (reference: no request)									
Emotional request	0.45#	1.47	0.24	0.44#	1.37	0.23	0.38#	1.31	0.23
Instrumental request	0.68**	1.91	0.23	0.63**	1.52	0.21	0.56*	1.45	0.22
Emotional and instrumental request	0.58*	1.73	0.23	0.54*	1.43	0.22	0.52*	1.43	0.22
Width	−0.04	0.96	0.03	−0.03	0.97	0.04	−0.02	0.97	0.04
Level-2 contextual factors									
The severity of the situation (SOS)				0.09*	1.07	0.05			
Cross-level interactions									
SOS* Credibility cue (reference: verified user)									
Ordinary user							0.37*	1.37	0.18
SOS* Bandwagon cue							−0.03	0.98	0.08
SOS*Self-disclosure (reference: intermediate disclosure)									
Peripheral disclosure							0.13	1.18	0.20
Intermediate and peripheral disclosure							0.05	1.04	0.10
No disclosure							−0.29*	0.80	0.12

(continued)

Table 1. Continued.

Dependent variable	Model 1 B	Model 1 IRR	Model 1 SE	Model 2 B	Model 2 IRR	Model 2 SE	Model 3 B	Model 3 IRR	Model 3 SE
SOS*Emotion (reference: anger)									
Fear							−0.32*	0.75	0.14
Sadness							−0.02	0.98	0.15
Positive emotions							−0.08	0.86	0.18
SOS*Requested support (reference: no request)									
Emotional request							−0.16	0.85	0.12
Emotional and instrumental request							−0.08	0.89	0.14
Instrumental request							0.12	1.08	0.15
N			705			705			705
df			704			704			704
Pseudo R^2			0.23			0.63			0.68
Log-likelihood			−852.78			−850.00			−829.80

SE: standard error; B: unstandardized coefficient; IRR: Incidence Rate Ratios.
$^{\#}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

reveal a significant difference (B = 0.13, IRR = 1.16, SE = 0.13, $p > 0.05$). Thus, H1b was rejected.

The self-disclosure variable, which was categorized as peripheral, intermediate, and no self-disclosure, revealed that intermediate disclosure was essential to increase the depth of transmission. Taking the intermediate self-disclosure as the reference, posts with peripheral self-disclosure (B = −0.49, IRR = 0.46, SE = 0.23, $p < 0.05$) and no disclosure (B = −2.21, IRR = 0.12, SE = 0.20, $p < 0.001$) both illustrated significantly lower-level transmission. IRRs show that a one-unit increase of the presence of peripheral self-disclosure would result in a 54% decrease in the depth of repost. A one-unit increase in the presence of no self-disclosure would result in an 88% decrease in the depth of transmission. Hence, H2b was rejected, but H2a was supported.

In terms of emotional factors, as compared to anger-related posts, fear- (B = −0.67, IRR = 0.56, SE = 0.21, $p < 0.01$) and sadness-related (B = −0.65, IRR = 0.54, SE = 0.21, $p < 0.01$) posts were less likely to diffuse in-depth. As shown in two IRRs, a one-unit increase in the presence of fear and sadness would result in a 44% and 46% decrease in the depth of repost, respectively, supporting H3a and H3b. In contrast, posts with positive emotions (B = −0.41, IRR = 0.64, SE = 0.26, $p > 0.05$) were not significantly less disadvantageous than angry posts in gaining more diffusion depth. We thus rejected H3c.

For the type of requested support, which was categorized as emotional, instrumental, or no specific request, results revealed that posts without specific requests had a smaller depth than those with instrumental (B = 0.68, IRR = 1.91, SE = 0.23, $p < 0.01$) and a mixture of instrumental and emotional needs (B = 0.58, IRR = 1.73, SE = 0.23, $p < 0.05$). A one-unit increase in the occurrences of instrumental request and the mixture of instrumental and emotional requests would result in a 91% and 73% increase in the depth of repost. Therefore, H4b was supported. To compare the effect between instrumental and emotional requests, we changed the reference group into instrumental needs. The result illustrated that posts with emotional requests did not reveal a significant weakness (B = −0.23, IRR = 0.73, SE = 0.21, $p > 0.05$) in the vertical traversal. We thus rejected H4a.

The external information climate variable of the severity of the situation (SOS) was then added into Model 2. We found that the more serious the situation was when posting the support-seeking message (B = 0.09, IRR = 1.07, SE = 0.04, $p < 0.05$), the greater the depth of transmission. IRR indicates that a one-unit increase in the presence

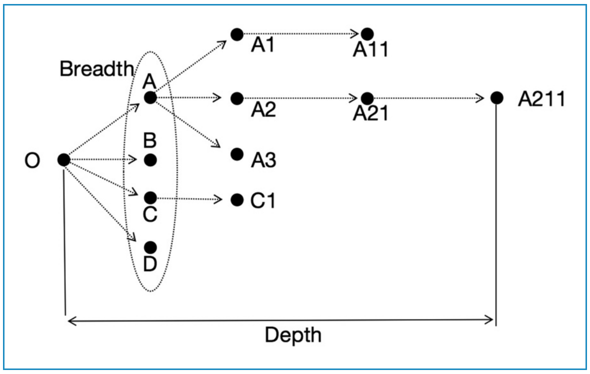

Figure 1. An example of information diffusion and key measures. In this example, the diffusion size is 11, diffusion breadth is 4, and depth is 4.

of a severe situation would result in a 7% increase in the depth of transmission supporting H5.

To answer RQ1, Model 3 illustrated the result of cross-level interactions. The moderation effects of SOS on the individual poster and post variables were found to influence the slopes (B1, B3, B4) in the level-1 equation. Specifically, as compared to the help-seeking posts with bandwagon cues, a serious situation was more conducive to strengthening the vertical traversal of posts posted by ordinary users ($B = 0.37$, $IRR = 1.37$, $SE = 0.18$, $p < 0.05$) (see Figure 2). The second pair of significant moderation effects manifested in the types of emotions. An unfavorable external information climate intensified the advantages of angry messages over fearful ones ($B = -0.32$, $IRR = 0.80$, $SE = 0.14$, $p < 0.05$), making the latter become the least contagious emotional type when the epidemic severity exceeded the average level (see Figure 3). Lastly, in comparison with the intermediate disclosure, a post without self-disclosure ($B = -0.29$, $IRR = 0.75$, $SE = 0.12$, $p < 0.05$) was much harder to traverse vertically as the situation worsened. The deteriorating situation strengthened the advantages of posts with any types of self-disclosures over those without disclosing identifiable information in terms of diffusion depth (see Figure 4).

Discussion

This study contributed to understanding the effectiveness of help-seeking messages circulating on Chinese social media by considering another dimension of information spread: diffusion depth. We also disclosed the means and mechanisms underlying the increased depth of transmission of help-seeking messages. Specifically, the number of followers had a significantly positive association with the diffusion depth of retweets. As for the type of requested support, posts with instrumental requests can induce a higher-level diffusion depth than the emotional and those without specific requests. Additionally, our results also revealed that help-seeking posts containing the subjective experiences about COVID-19 exhibited greater diffusion depth of reposts than those with mere biographical cues or without self-disclosure. The emotional factor also affected the vertical traversal of online help-seeking information. Among emotion types, posts with anger exhibit greater vertical traversal than posts with fear and sadness.

In the context of COVID-19 in China, we found that bandwagon cues, instrumental request, and anger, which can contribute to the spread of help-seeking messages within levels,[3,34,62,64] are also effective in facilitating information diffusion across levels. A help-seeking post with high-arousal emotion and high-threshold request posted by a poster with many followers (i.e. "head-start" advantage[42]) is conducive to reaching both homogeneous and heterogeneous communities. Conversely, credibility cues, and peripheral self-disclosure, which normally facilitate diffusion breadth or size, did not facilitate the diffusion depth. One possible explanation could be social compensation. Earlier experimental studies[67,68] have found that even if the profile of a support seeker does not have clear, credible, and identifiable cues, support givers tend to perceive the support seeker to be more trustworthy if there exist credible supporters and positive supporter comments. Social media can offer account information about users who reposted support seeking messages earlier (e.g. the status of verification, number of followers, comments on support seekers, etc.) to other users, which can serve as a credibility proxy to make up for the insufficient provision of personal information in the original post, thus facilitating diffusion depth. In contrast, intermediate self-disclosure, such as personal symptoms, painful experiences, and the current mental status of victims, cannot be proxied. Only those who have experienced a disease personally can have a deeper comprehension of the disruption of COVID-19. Thus, contrary to previous studies on diffusion breadth and size,[3,9,51] intermediate self-disclosure is more effective than peripheral self-disclosure in increasing diffusion depth because the authenticity conferred by personal experience is unique and cannot be substituted by others.

In addition to testing the predictions in the first-level equation, the environment factor was found to have moderation effects on the level-1 predictors. We further illustrated that credibility cues are not so conducive to the diffusion depth of help-seeking messages when adding the environment factor to the model. As shown in Figure 1, the contrasting pattern revealed that posters without verification tags are more likely to achieve vertical traversal than verified sources under serious situations. Wright and colleagues[6] argued that the ever-increasing information and knowledge regarding the epidemic prevention and disease diagnosis released by mass media and governments during serious conditions could be used to validate the authenticity of the descriptions of support seekers. In this sense, when the user's descriptions are consistent with widely circulated health knowledge, the latter can become compensation

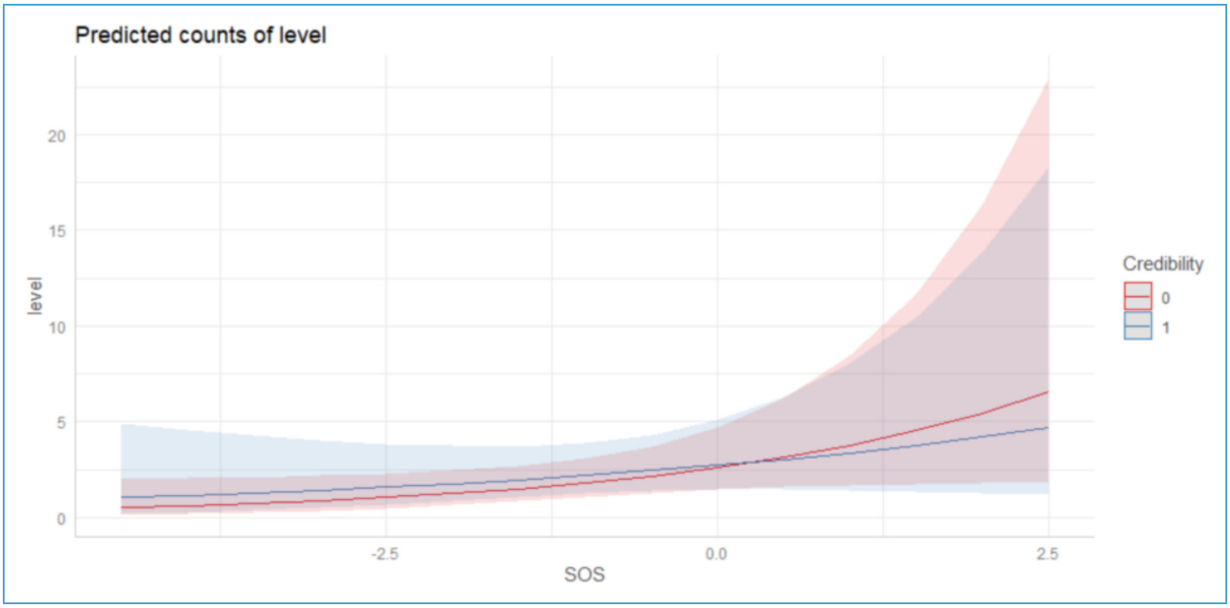

Figure 2. The interaction effect between the credibility cue and the severity of the situation (SOS).

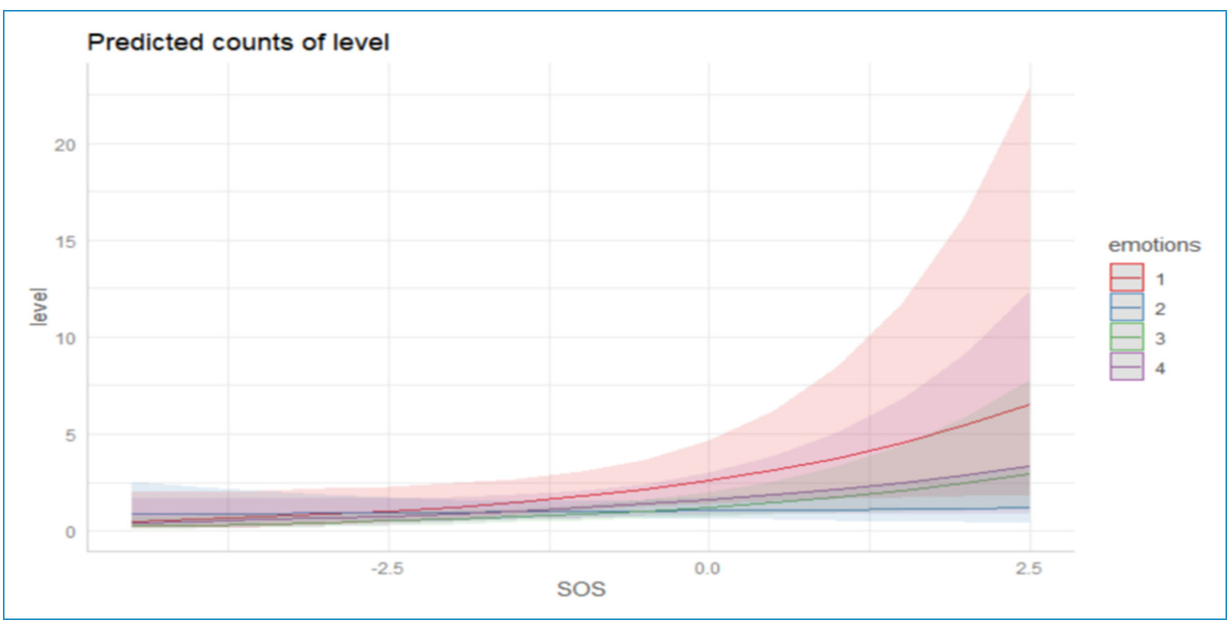

Figure 3. The interaction effect between post emotion and the severity of the situation (SOS).

information as well and help erase recipients' uncertainty due to the unverified and unknown status of the credibility of help-seekers. Thus, the original credibility cues become less important when circumstantial evidence has emerged.

Additionally, our results also echoed previous studies'[3,11] insights that the environment can signify urgency and the distributional priority of scarce resources. The radial patterns shown in Figures 2 and 3 suggested that a help-seeking post with intermediate self-disclosure and anger was more likely to be introduced to distant and significant supporters. In a critical situation, expressing painful experiences and constructive emotions is an effective way to show the severity and urgency of one's illness to the outside world, thus increasing the likelihood of preferential treatment. Conversely, a fearful post that aggravates a depressing situation and would be ignored at the first stage in emergent situations. As negativity avoidance theory[85,86] suggests, individuals are inclined to avoid an unpleasant situation, especially when the situation is judged as likely to occur. In this sense, a worsening external information climate can prime recipients to prevent them from

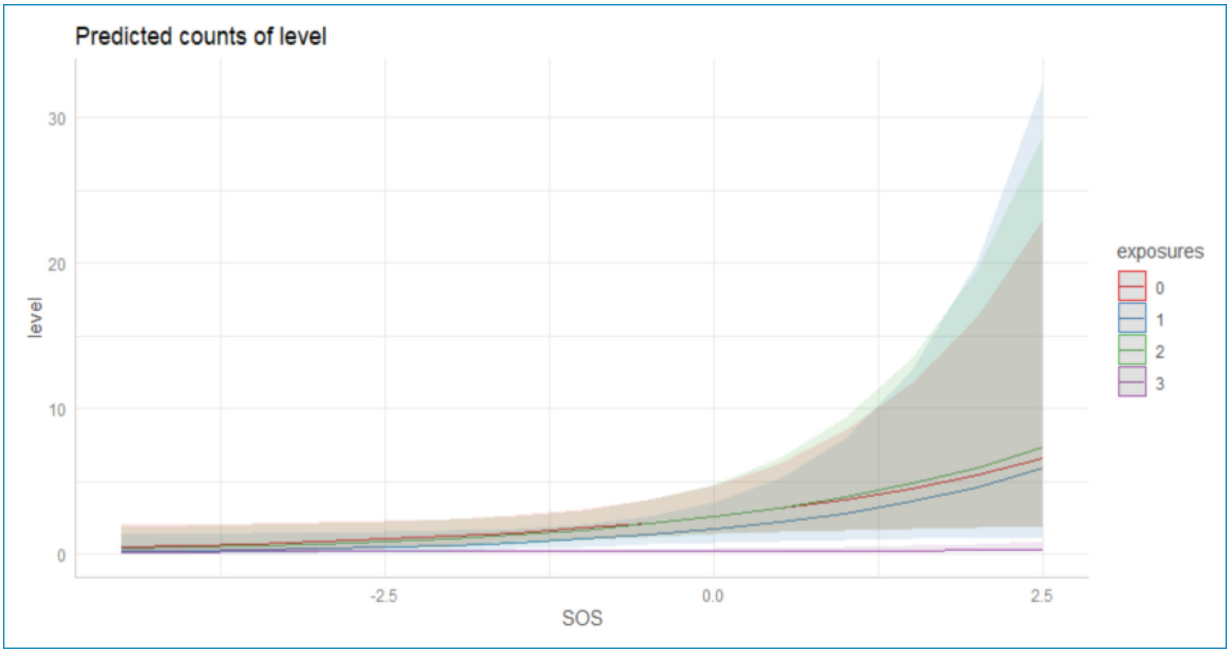

Figure 4. The interaction effect between the type of self-disclosure and the severity of the situation (SOS).

interacting with those messages that are depressive and escapist to prevent experiencing more unpleasant moods. However, negative avoidance theory may not hold true for the post with sadness. While sadness can trigger empathetic behaviors, extensive disclosure to fear elicits more self-concentrated examinations, and maladaptive behaviors,[55] thus avoiding interacting extensively with the victims. Taken together, help-seekers need to consider the external information environment when seeking help. A worsening situation would make it easier for ordinary help-seekers who show the severity of their personal suffering to reach distant others.

Limitations, implications, and conclusion

A few limitations of this study should be noted. Firstly, the sample posts that we retrieved were the sectional data rather than the real time, which may result in the loss of quite a number of posts deleted by help-seekers because they have received the assistance before our data collection. In addition, we only investigated the features of help-seekers and their posts that can elicit reposting behavior. However, whether help-seekers have gained satisfactory assistance still remains unknown. Future research could replicate the current study by going beyond the reposts to consider help-seekers' attitudes toward the support they have received. Thirdly, the social network environment and structure (e.g. modularity, density, and network diameter) may also influence the help-seeking information diffusion depth. We did not incorporate them into the current study, which should be accounted for in future studies.

Despite these limitations, our study did practically and theoretically contribute to understanding an alternative view on evaluating the effectiveness of help-seeking on social media. We used the heuristic-systematic model (HSM) as a framework to analyze the diffusion depth of help-seeking information in the context of the COVID-19 crisis in China. The findings indicate that sender, post content, and situational factors can impact the diffusion depth of information. In addition, the influence of these factors on information diffusion depth appears to vary with epidemic severity. Hence, in the context of health crisis, expressing suffering and their material demands with anger is an effective strategy for help-seeking posts to traverse more deeply into social media networks when the situation is relatively serious. Reaching close and weak ties is both important for widening the scope and enhancing the quality of resource collection. To obtain useful resources to the utmost extent in times of a nationwide health crisis, it is necessary for help-seekers to understand the driving factors of information diffusion size, breadth, and depth. Disassociating the depth of information diffusion from the strategies of seeking help on social media result in significant missed opportunities to reach a significant support giver.

Acknowledgments: The authors would like to thank Chen Luo for his assistance and guidance in this research.

Conflict of interest: The authors have no conflicts of interest to declare.

Contributorship: Anfan Chen, Yipeng Xi and Aaron Ng researched literature and conceived the study. Anfan Chen was involved in gaining ethical approval, data collection and data analysis. Anfan Chen, Yipeng Xi, Aaron Ng, and Yong Hu wrote the first draft of the manuscript. All authors reviewed and edited the manuscript and approved the final version of the manuscript.

Ethical approval: The ethics committee of University of Science and Technology of China approved this study (REC number: DA2110251001).

Funding: The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by the National Social Science Foundation of China (grant number 21CXW018).

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Note

1. We only provided Krippendorff's alpha for credibility cue, emotion types, and type of requested support. The other variables including the severity of the situation, diffusion depth, diffusion width, bandwagon cue, credibility cue were not manually coded. For bandwagon cue and credibility cue, we measured them according to the information by Weibo. Severity of the situation was operationalized as the number of hospitalized cases across the country on the day of posting help-seeking messages, according to the data provided by the National Health Commission of the People's Republic of China. For diffusion width and diffusion depth, they are provided by WeiboEvents.

References

1. World Health Organization (WHO). Coronavirus disease (COVID-19) pandemic. Available at: https://covid19.who.int/ (2022, assessed 27 January 2022).
2. Weibo. Weibo Pneumonia patients help-seeking forum. Retrieved from https://weibo.com/p/1008084882401a015244a2ab18ee43f7772d6f/super_index?current_page=3&since_id=4496652075516856&page=20#_rnd1601645412345 (2020, assessed 21 July 2020).
3. Luo C, Li Y, Chen A, et al. What triggers online help-seeking retransmission during the COVID-19 period? Empirical evidence from Chinese social media. *PLoS One* 2020; 15(11): e0241465. DOI: 10.1371/journal.pone.0241465.
4. Im E-O and Chee W. The use of internet cancer support groups by ethnic minorities. *J Transcult Nurs* 2008; 19: 74–82.
5. Shaw BR, Hawkins R, Arora N, et al. An exploratory study of predictors of participation in a computer support group for women with breast cancer. *Comput Inform Nursing* 2006; 24: 18–27.
6. Wright KB, Cai X, Fisher C, et al. A content analysis of social support messages about environmental breast cancer risk within blogs for mothers. *Health Commun* 2021; 36(13): 1796–1804.
7. Wang X, Chen L, Shi J, et al. What makes cancer information viral on social media? *Comput Hum Behav* 2019; 93: 149–156.
8. Blank TO, Schmidt SD, Vangsness SA, et al. Differences among breast and prostate cancer online support groups. *Comput Hum Behav* 2010; 26: 1400–1404.
9. Li S, Feng B, Li N, et al. How social context cues in online support-seeking influence self-disclosure in support provision. *Commun Q* 2015; 63: 586–602.
10. Xie B. Multimodal computer-mediated communication and social support among older Chinese internet users. *J Comput Mediat Commun* 2008; 13: 728–750.
11. Zhang W, Xi Y and Chen A. Why do replies appear? A multi-level event history analysis of online policy discussions. *New Media Soc* 2020; 22: 1484–1504.
12. Rains SA, Peterson E and Wright KB. Communicating social support in computer-mediated contexts among individuals coping with illness: a meta-analytic review of content analyses examining support messages shared online. *Commun Monogr* 2015; 82: 403–430.
13. Wright KB and Miller CH. A measure of weak-tie/strong-tie support network preference. *Commun Monogr* 2010; 77: 500–517.
14. Wellman B and Wortley S. Different strokes from different folks: community ties and social support. *Am J Sociol* 1990; 96: 558–588.
15. Wright KB, Rains S and Banas J. Weak-tie support network preference and perceived life stress among participants in health-related, computer-mediated support groups. *J Comput Mediat Commun* 2010; 15: 606–624.
16. Wright KB, Bell SB, Wright KB, et al. Health-related support groups on the internet: linking empirical findings to social support and computer-mediated communication theory. *J Health Psychol* 2003; 8: 39–54.
17. Tsai S, Crawford E and Strong J. Seeking virtual social support through blogging: a content analysis of published blog posts written by people with chronic pain. *Digit Health* 2018; 4: 2055207618772669.
18. Granovetter M. *Getting a job: a study of contacts and careers*. Chicago, IL: University of Chicago, 1991.
19. Zhang L and Peng TQ. Breadth, depth, and speed: diffusion of advertising messages on microblogging sites. *Internet Res* 2015; 25: 453–470.
20. Wang F, Wang H and Xu K. Diffusive logistic model towards predicting information diffusion in online social networks. In: *2012 32nd international conference on distributed computing systems workshops*. Macau: IEEE, 2012, pp.133–139.
21. Meng J, Peng W, Tan PN, et al. Diffusion size and structural virality: the effects of message and network features on spreading health information on twitter. *Comput Hum Behav* 2018; 89: 111–120.
22. Chen L, Wang X and Peng TQ. Nature and diffusion of gynecologic cancer related misinformation on social media: analysis of tweets. *J Med Internet Res* 2018; 20: e11515.
23. Goel S, Watts DJ and Goldstein DG. The structure of online diffusion networks. In: *Proceedings of the 13th ACM conference on electronic commerce*. Valencia: Association for Computing Machinery, 2012, pp.623–638.

24. Yang J and Counts S. Predicting the speed, scale, and range of information diffusion in twitter. *ICWSM* 2010; 10: 355–358.
25. Cha M, Mislove A and Gummadi KP. A measurement-driven analysis of information propagation in the Flickr social network. In: *Proceedings of the 18th international conference on the world wide web*. Madrid: Association for Computing Machinery, 2009, pp.721–730.
26. Liang H, Fung ICH, Tse ZTH, et al. How did ebola information spread on twitter: broadcasting or viral spreading? *BMC Public Health* 2019; 19: 438.
27. Liang H. Broadcast versus viral spreading: the structure of diffusion cascades and selective sharing on social media. *J Commun* 2018; 68: 525–546.
28. Yang Q, Tufts C, Ungar L, et al. To retweet or not to retweet: understanding what features of cardiovascular tweets influence their retransmission. *J Health Commun* 2018; 23: 1026–1035.
29. Cao Q, Shen H, Cen K, et al. DeepHawkes: bridging the gap between prediction and understanding of information cascades. In: *Proceedings of the 2017 ACM on conference on information and knowledge management*. Singapore: Association for Computing Machinery, 2017, pp.1149–1158.
30. Huszti éva DB and Vajda K. Strong tie, weak tie and in-betweens: a continuous measure of tie strength based on contact diary datasets. *Procedia – Soc Behav Sci* 2013; 79: 38–61.
31. Pan W, Feng B and Wingate VS. What you say is what you get: how self-disclosure in support seeking affects language use in support provision in online support forums. *J Lang Soc Psychol* 2018; 37: 3–27.
32. Chaiken S. Heuristic versus systematic information processing and the use of source versus message cues in persuasion. *J Pers Soc Psychol* 1980; 39: 752–766.
33. Cacioppo J and Petty RE. The elaboration likelihood model of persuasion. *Adv Consum Res* 1984; 19: 123–205.
34. Feng B, Li S and Li N. Is a profile worth a thousand words? How online support-seeker's profile features may influence the quality of received support messages. *Commun Res* 2016; 4: 253–276.
35. Barney LJ, Griffiths KM and Banfield MA. Explicit and implicit information needs of people with depression: a qualitative investigation of problems reported on an online depression support forum. *BMC Psychiatry*. 2011; 11(1).
36. Culnan MJ and Markus ML. Information technologies. In: Jablin FM, Putnam LL, Robert KH and Porter LW (eds) *Handbook of organizational communication: an interdisciplinary perspective*. Newbury Park, CA: Sage, 1987, pp.420–443.
37. Kiesler S, Siegel J and McGuire TW. Social psychological aspects of computer-mediated communication. *Am Psychol* 1984; 39: 1123–1134.
38. Sundar SS, Oeldorf-Hirsch A and Xu Q. The bandwagon effect of collaborative filtering technology. In: *Proceedings of CHI' extended abstracts on human factors in computing systems*. Florence: Association for Computing Machinery, 2008, pp.3453–3458.
39. Walther JB and Parks MR Cues filtered out, cues filtered in: computer-mediated communication and relationships. In: Knapp ML and Daly JA (eds) *Handbook of interpersonal communication*. Thousand Oaks, CA: Sage, 2002, pp.529–563.
40. Song Y and Wu Y. Tracking the viral spread of incivility on social networking sites: the case of cursing in online discussions of Hong Kong–Mainland China conflict. *Commun Public* 2018; 3: 46–61.
41. Lee JY and Sundar SS. To tweet or to retweet? That is the question for health professionals on twitter. *Health Commun* 2013; 28: 509–524.
42. Barabási AL and Albert R. Emergence of scaling in random networks. *Science* 1999; 286: 509–512.
43. Chaiken S, Liberman A and Eagly A. Heuristic and systematic processing within and beyond the persuasion context. In: Uleman JS and Bargh JA (eds) *Unintended thought*. New York, NY: Guilford, 1989, pp.122–252.
44. Liu Z, Liu L and Li H. Determinants of information retweeting in microblogging. *Internet Res* 2012; 22: 443–466.
45. Starbird K and Palen L. Pass it on? Retweeting in mass emergency. Paper presented at Proceedings of the 7th International ISCRAM Conference, Seattle, WA; 2010. Retrieved from https://doi.org/10.1111/j.1556- 4029.2009.01231.x.
46. Derlega VJ, Metts S, Petronio S, et al. *Self-disclosure*. Newbury Park, CA: Sage, 1993.
47. Altman I and Taylor DA. *Social penetration: the development of interpersonal relationships*. New York, NY: Holt, Rinehart & Winston, 1973.
48. Tidwell LC and Walther JB. Computer-mediated communication effects on disclosure, impressions, and interpersonal evaluations: getting to know one another a bit at a time. *Hum Commun Res* 2002; 28: 317–348.
49. Wingate VS, Feng B, Kim C, et al. The influence of self-disclosure in online support seeking on quality of received advice. *J Lang Soc Psychol* 2020; 39: 397–413.
50. Qian H and Scott CR. Anonymity and self-disclosure on weblogs. *J Comput Med Commun* 2007; 12: 1428–1451.
51. Pan W, Feng B, Wingate VS, et al. What to say when seeking support online: a comparison among different levels of self-disclosure. *Front Psychol* 2020; 11: 978.
52. Berger CR. Communicating under uncertainty. In: Roloff ME and Miller GR (eds) *Interpersonal processes: new directions in communication research*. Newbury Park, CA: Sage, 1987, pp.39–62.
53. Hornik J, Shaanan-Satchi R, Cesareo L, et al. Information dissemination via electronic word-of-mouth: good news travels fast, bad news travels faster!. *Comput Hum Behav* 2015; 45: 273–280.
54. Kim J and Song H. Celebrity's self-disclosure on twitter and parasocial relationships. *Comput Hum Behav* 2016; 62: 570–577.
55. Li L, Wang Z, Zhang Q, et al. Effect of anger, anxiety, and sadness on the propagation scale of social media posts after natural disasters. *Inf Process Manag* 2020; 57: 1–19.
56. Kanavos A, Perikos I, Hatzilygeroudis I, et al. Emotional community detection in social networks. *Comput Electr Eng* 2018; 65: 449–460.
57. Nabi RL. Exploring the framing effects of emotion: do discrete emotions differentially influence information accessibility, information seeking, and policy preference? *Commun Res* 2003; 30: 224–247.
58. Cameron GT and Kim HJ. Emotions matter in crisis: the role of anger and sadness in the publics' response to crisis news framing and corporate crisis response. *Commun Res* 2011; 38(6): 826–855.

59. Jin Y, Pang A and Cameron GT. Toward a publics-driven, emotion-based conceptualization in crisis communication: unearthing dominant emotions in multi-staged testing of the integrated crisis mapping (ICM) model. *J. Public Relat Res* 2012; 24: 266–298.
60. Fan R, Zhao J, Chen Y, et al. Anger is more influential than joy: sentiment correlation in weibo. *PLoS One* 2014; 9: e11018.
61. Fan R, Xu K and Zhao J. Easier contagion and weaker ties make anger spread faster than joy in social media. *arXiv preprint arXiv:1608.03656* 2016.
62. Coulson NS, Buchanan H and Aubeeluck A. Social support in cyberspace: a content analysis of communication within a Huntington's disease online support group. *Patient Educ Couns* 2007; 68: 173–178.
63. Rains SA. The implications of stigma and anonymity for self-disclosure in health blogs. *Health Commun* 2014; 29: 23–31.
64. Graneheim UH and Lundman B. Qualitative content analysis in nursing research: concepts, procedures and measures to achieve trustworthiness. *Nurse Educ Today* 2004; 24: 105–112.
65. Yang S and Stening BW. Cultural and ideological roots of materialism in China. *Soc Indic Res* 2012; 108: 441–452.
66. Gold MR, Stevenson D, Fryback DG, et al. Oh my: similarities and differences in summary measures of population health. *Annu Rev Public Health* 2002; 23: 115–134.
67. Li S and Feng B. What to say to an online support-seeker? The influence of others' responses and support-seekers' replies. *Hum Commun Res* 2015; 41: 303–326.
68. Rains SA, Tsetsi E, Akers C, et al. Factors influencing the quality of social support messages produced online: the role of responsibility for distress and others' support attempts. *Commun Res* 2019; 46: 866–886.
69. Hong T. Information control in time of crisis: the framing of SARS in China-based newspapers and internet sources. *Cyberpsychol Behav* 2007; 10: 696–699.
70. Luther CA and Zhou X. Within the boundaries of politics: news framing of Sars in China and the United States. *J Mass Commun Q*. 2005; 82: 857–872.
71. Althaus S and Tewksbury D. Agenda setting and the "new" news: patterns of issue importance among readers of the paper and online versions of The New York Times. *Commun Res* 2002; 29: 180–207.
72. Henson B. Comment: Singapore, we deserve an 'A'. Retrieved from https://sg.news.yahoo.com/comment-singapore-we-deserve-an-a-043947165.html?guccounter = 1 (2020, assessed on 11 July 2020).
73. Medaglia R and Yang Y. Online public deliberation in China: evolution of interaction patterns and network homophily in the Tianya discussion forum. *Inf Commun Soc* 2017; 20: 1–21.
74. Li P, Cho H, Qin Y, et al. #Metoo as a connective movement: examining the frames adopted in the anti-sexual harassment movement in China. *Soc Sci Comput Rev* 2021; 39(5): 1030–1049.
75. Zhang X, Nekmat E and Chen A. Crisis collective memory making on social media: a case study of three Chinese crises on weibo. *Public Relat Rev* 2020; 46: 101960.
76. Chen Z, Su CC and Chen A. Top-down or bottom-up? A network agenda-setting study of Chinese nationalism on social media. *J Broadcast Electron Media* 2019; 63: 512–533.
77. Li Y, Luo C and Chen A. The evolution of online discussions about GMOs in China over the past decade: changes, causes and characteristics. *Sci Cult* 2019; 2: 311–325.
78. Zhuang J, Peng T, Tang J, et al. Mixed and blended emotional reactions to 2014 Ebola outbreak. *J Glob Health* 2020; 10: 010304. pmid:32257132.
79. Dillard JP and Nabi RL. The persuasive influence of emotion in cancer prevention and detection messages. *J Commun* 2006; 56: S123–S139.
80. Balcells J and Padró-Solanet A. Crossing lines in the twitter debate on Catalonia's independence. *Int J Press-Polit* 2019; 25: 28–52.
81. Gómez V, Andreas K and Vicente L. Statistical analysis of the social network and discussion threads in slash. *In Proceedings of the 17th international conference on World Wide Web. Beijing*: Academy of Computing Machinery, 2008, pp.645–654.
82. Payne EH, Gebregziabher M, Hardin JW, et al. An empirical approach to determine a threshold for assessing overdispersion in Poisson and negative binomial models for count data. *Commun Stat Simul Comput* 2018; 47: 1722–1738.
83. Xi Y, Chen A and Ng A. Conditional transparency: differentiated news framings of COVID-19 severity in the pre-crisis stage in China. *PLoS One* 2021; 16: e0252062.
84. Enders CK and Tofighi D. Centering predictor variables in cross-sectional multilevel models: a new look at an old issue. *Psychol Methods* 2007; 12: 121–138.
85. Boelen PA, Bout JVD and Hout M. Negative cognitions and avoidance in emotional problems after bereavement: a prospective study. *Behav Res Ther* 2006; 44: 1657–1672.
86. Brown EC, Tas C, Kuzu D, et al. Social approach and avoidance behavior for negative emotions is modulated by endogenous oxytocin and paranoia in schizophrenia. *Psychiatry Res* 2014; 219: 436–442.