Depicting the Emotion Flow: Super-Spreaders of Emotional Messages on Weibo During the COVID-19 Pandemic

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Abstract

This study collected 2 million posts and reposts regarding the early stage of COVID-19 in China on Weibo from 26 December 2019 to 29 February 2020. Emotion analysis and social network analysis were used to examine the flow of emotional messages (emotion flow) by comparing them with the flow of general messages (information flow). Results indicated that both emotional messages and general messages present a multilayer diffusion pattern and follow network step flow models. In our dataset, emotion network has a higher transmission efficiency than information network; officially verified accounts were more likely to become super-spreaders of emotional messages; good emotions were predominant but isolated from other six emotions (joy, sadness, fear, disgust, surprise, anger) in online discussions; finally, government played a vital role in spreading good emotions.

Keywords

social media, network step flow models, emotion analysis, social network analysis, COVID-19
emotional messages, that is, the emotion flow on social media. Moreover, we take general posts on social media as a comparative reference to find out how emotional messages differ from other messages in the diffusion process. Specifically, we investigate the opinion leaders of the emotion flow on social media, that is, those who play the core roles in spreading online emotional messages. In addition, we divide emotional messages into discrete categories (e.g., joy, anger, fear) based on the dimensional model of emotion (Lang et al., 1995). This study also aims to find out what kinds of emotional messages are more commonly diffused during the pandemic. We use emotion analysis and social network analysis to understand the flow of emotional messages and identify opinion leaders by analyzing post-repost relationships related to COVID-19 on Weibo.

Context: Diffusion of Emotional Messages on Weibo During COVID-19

With its open-discussion environment, like Twitter, Weibo is one of the most important platforms for Chinese users to follow the latest news, share emotions, and discuss politics (Chan et al., 2012). As China had a relatively earlier outbreak of COVID-19 than other countries, we collected data from 26 December 2019 to 29 February 2020 on Weibo to examine the diffusion of emotional messages in the early stage of the COVID-19 outbreak. At that time, human society was not prepared for what was about to happen; thus, the emotional messages posted on Weibo reflected the real-time response to a sudden pandemic outbreak. In other words, Weibo is an appropriate setting to observe the emotional changes brought by the pandemic. However, due to the Great Firewall that inhibits normal Chinese citizens from accessing foreign social media platforms, many studies related to COVID-19, which employed data from Twitter, Reddit, or Facebook, could not include the discussion from China (e.g., Basile et al., 2021; Nemes & Kiss, 2021). In that case, we fill this research gap and contribute to the understanding of online information’s dissemination during the COVID-19 worldwide.

It is worth noting that not only common users but also the government, media outlets, and corporations use Weibo as a channel to gain more attention from the audience. Scholars have noted that government actions are significant external factors influencing online discussions toward COVID-19 (Basile et al., 2021). Compared with Twitter or Reddit, Weibo is a more authority-led discourse space. In the context of China, the government plays an important role in strategically responding to the pandemic and influencing emotional discussions on social media (Tong, 2015). Thus, this study also considers how government-led institutional accounts function in the diffusion of emotional messages. To distinguish the government-led accounts, Weibo has implemented an identity authentication strategy to verify users’ identities by showing a Blue V or Orange V badge. A Blue V (verified institutions) signifies an official account, mainly government, institutions, enterprises, schools, media agencies, and nongovernmental organizations (NGOs). An Orange V (verified individuals) refers to individuals who have more than 10,000 pageviews, including many celebrities. Unverified users are ordinary users whose identity have not been verified by Weibo. Although there are subcategories of Blue V like NGOs, schools, and news agencies, what they can or cannot post on social media platforms is still regulated by Chinese government surveillance (Zhou & Pan, 2017). Under the censorship mechanism for certain collective expressions (King et al., 2017), Weibo provides a different context from Twitter, which helps us to explore how emotional messages are produced and diffused in social media under an authoritarian system.

Emotional Messages in Step Flow Models

Scholars in the fields of psychology and communication have strived to understand the mechanism of emotion and its relationships with cognitive processes and collective behaviors. Many scholars have inherited Darwin’s idea which suggests emotions are “inside-out,” meaning that emotions are prepackaged in different biological types and derived from the functional needs of evolution (Ekman, 1993; Tomkins, 1992). By contrast, scholars who support the “outside-in” model postulate that emotions are constructed by historical, cultural, and contextual background (Ahmed, 2014; Averill, 1980). Regardless of the debate about the formation of emotions, researchers have found that emotions can also spread interpersonally through “expressions, vocalizations, postures, and movements,” which is the emotional contagion phenomenon (Hatfield et al., 1993, p. 5). Along with the emerging computer-mediated communication, evidence shows that emotional contagion also occurs in text-based emotional expression even without the nonverbal cues (Coviello et al., 2014; Derks et al., 2008; Hancock et al., 2008). Furthermore, studies about emotion-spreading on social media platforms like Facebook, YouTube, and Flickr (Kramer et al., 2014; Kwon & Gruzd, 2017; Yang et al., 2016) have significantly advanced the emotional contagion theory by indicating that emotional contagion is further amplified or mediated by the digital communication environment (Goldenberg & Gross, 2019). Emotional messages, defined as messages including emotional expressions, can be a potential agent to impact people’s emotional states and lead to emotional contagion.

In this study, emotional messages on Weibo are specifically defined as posts containing emotional terms in a well-structured Chinese emotion lexicon (Xu et al., 2008). Although previous studies suggest that emotional messages in the form of text or visuals help to spread emotions in digital channels (Riordan & Kreuz, 2010), their diffusion patterns in large interpersonal social networks are unexplored. The emotional messages circulated in the digital space are computer-mediated communication of emotions, which are
certainly a type of information. Different from factual information, emotional messages are affective information that are directly related to feelings and emotions (Harris & Paradice, 2007). When diffused in the social networks, we argue that emotional messages as a type of affective information will follow the information diffusion structure proposed in the step flow models. Specifically, online emotional messages would diffuse following the step flow models through posting and reposting, which constitutes the emotion flow on social media. At the same time, there may be some differences between the information flow including all kinds of messages and emotional messages because of the unique affective features of the later ones. For example, emotional messages are reposted more often than other messages (Stieglitz & Dang-Xuan, 2013).

The step flow models are developed from the two-step flow theory, which aims to study the diffusion of information from opinion leaders among social groups (Lazarsfeld et al., 1968). Evidence from panel survey studies and big data analysis supports that the two-step flow of communication exists in online media platforms (Choi, 2015; Hilbert et al., 2017). Apart from that, there has been a revival of the concept of one-step flow, which is that individuals can directly get messages from media outlets and institutions in the digital age (Bennett & Manheim, 2006). On the other side, some scholars endorse complicated information diffusion mechanisms, such as the multistep flow model (Hilbert et al., 2017; Smith et al., 2013). However, most of the cited studies have adopted step flow models to investigate the overall information diffusion pattern and do not differentiate between emotional and general messages. To better understand the features of emotion flow, specifically the diffusion pattern of emotional messages, we compare it with the overall information flow. Thus, we posit the first research question:

*RQ1.* What are the similarities and differences in the structure and mechanism of information flow and emotion flow on Weibo during the COVID-19?

**Opinion Leaders in the Information Flow**

In mass communication, opinion leaders work as the bridge between media and audience to transfer information by means of interpersonal influence. They can also become superspreaders who diffuse text-based emotional messages on the Internet. In fact, emotions have already been studied in the contexts of opinions and political judgments (Brader et al., 2011; Marcus et al., 2000), and researchers have concluded that emotions can directly or indirectly influence opinion formation (Brader et al., 2011). The current sentiment analysis based on emotional content is also closely associated with online opinion mining (Liu, 2012). In addition, the interpersonal influence of opinion leaders can be understood as the persuasion process (Katz, 1957). Emotional messages play a role in the persuasion process (Nabi, 2007; Rosselli et al., 1995). Consistently, previous studies show that people’s emotional states are closer to those of opinion leaders than other people in the digital space (Nip & Fu, 2016; Yang et al., 2016).

Nevertheless, detecting opinion leaders is challenging because they are dispersed throughout every social group and stratum (Katz, 1957). The scales to measure opinion leaders have developed over time (Flynn et al., 1996), and recent studies have started to employ them (Yu et al., 2010). Led by certain opinion leaders, various topics (e.g., health, politics, social issues) are hotly discussed concerning COVID-19, many of which are posted with strong emotions. It is not clear, however, who the opinion leaders are in the current health emergency to lead the flow of emotional messages. Thus, the second research question is posited to guide this study’s attempt to identify opinion leaders through social network analysis by using the criteria of degree centrality and betweenness centrality:

*RQ2.* Who are the opinion leaders in sharing emotional messages and information on Weibo during the COVID-19?

Previous studies have investigated how opinion leaders’ demographic features, knowledge level, sentiments, and interest fields may influence the information flow in social networking sites (SNSs; Cho et al., 2012; Winter & Neubaum, 2016; Xu et al., 2014). The studies about these latent attributes of opinion leaders could create a better depiction of what and who drives the two-step flow of the information or emotion diffusion process in specific online discussions. However, extant studies of the attributes of opinion leaders have largely focused on individual and demographic traits and neglected the fact that the “give and take” (Katz, 1957, p. 33) of online social interactions and relationships occur not only for individuals but also for institutions and governments, who also play essential roles in affecting the directions of information and emotion flow. Opinion leadership should be a socially constructed power rather than a type of person (Choi, 2015). As such, including and investigating the account types of opinion leaders when studying the two-step flow is particularly important. In this study, “account type” refers to Blue V (institutional accounts), Orange V (personal accounts), and unverified users (personal accounts) on Weibo. During the COVID-19 pandemic, institutional and personal accounts could function differently in the information diffusion process. In the context of China, some official institutional accounts function like administration tools with the responsibility to update the latest information and rectify misinformation during crises (Zeng et al., 2017; Zhang & Negro, 2013), while some individual users may become central users who either challenge or support the official voice which is disseminated by news media or official accounts (Nip & Fu, 2016). In the scope of the current study, investigating the different account types of opinion leaders can
assist the understanding of their various influences in the contagion processes of different emotional messages:

**RQ3.** How do account types (Blue V, Orange V, and unverified users) relate to opinion leadership in emotional messages and engagement (i.e., repost, comment, and like) on Weibo during the COVID-19?

Numerous studies have investigated opinion leadership on social media platforms and support that opinion leaders’ influence might vary depending on topic types (Katz & Lazarsfeld, 2006). The results of some studies have also attested to the role of emotions in affecting popularity, user engagement, and opinion leadership of posts (Berger & Milkman, 2012; Chang, 2019), indicating that different emotions may also have various impacts on building up opinion leadership. There are two mainly used typologies of emotions in the related literature. First, scholars use the dimensional model of emotions to characterize emotions into two broad affective dimensions, which are arousal (high/low activation) and valence (pleasure/displeasure), to examine which types of emotions lead to stronger contagion (Guillory et al., 2011). However, there are inconsistent results about whether positive or negative emotions are more contagious (Coviello et al., 2014; Ferrara & Yang, 2015; Kramer et al., 2014). Another strand of research uses the discrete model to categorize emotions to evaluate the spread and influence of a particular emotion (e.g., anger, aggression, happiness) on social media platforms (Bliss et al., 2012; Kwon & Gruzd, 2017). The discrete model is more suitable and valuable when studying the communication phenomenon since it allows for more precise depictions of actions (Nabi, 2010).

Nonetheless, only a few studies have done a comprehensive analysis to investigate which kind of emotion is more contagious in the digital environment. Fan et al. (2016) recently acknowledged this limitation and used four emotional categories (i.e., anger, disgust, joy, and sadness) to analyze Weibo posts; they concluded that anger was the most-spread emotion, especially in weak ties. To partly replicate but further advance their study, we adopt a Chinese-context emotion categorization which contains seven categories: good, joy, anger, sadness, fear, surprise, and disgust (Xu et al., 2008). The following research question guides this aspect of the study:

**RQ4.** Which kinds of emotional messages (joy, good, anger, sadness, fear, surprise, disgust) are more likely to be diffused through opinion leaders on Weibo during the COVID-19?

**Method**

To depict and compare the diffusion patterns of emotional messages and all messages regarding COVID-19 on Weibo, a combination of emotion analysis and social network analysis was conducted in this study.

**Population and Sample**

The population of this study is all the discussion regarding COVID-19 on Weibo during the early period of the disease outbreak in China. Due to technical limitations of Weibo for data mining, we applied a keyword-based sampling method by extracting six high-frequency COVID-19-related keywords from the Weibo Hot Searches website (https://s.weibo.com/top/summary?cate=realtimehot) over the period 26 December 2019 to 2 February 2020. The keywords we used to select posts are “epidemic” (疫情), “virus” (病毒), “new coronavirus” (新冠肺炎), “pneumonia” (肺炎), “anti-epidemic” (防疫), and “mask” (口罩). Thus, our sample is all the posts containing these keywords published on Weibo.

**Data Collection**

We employed Python programming language to design a web scraping program that used the above-mentioned keywords listed to automatically obtain data from Weibo. All the data were returned by Weibo’s official search function, whose URL was https://s.weibo.com/. Notably, Weibo does have a limitation about data collection: every search returns only 50 pages of posts (20 posts per page). For example, if we search “virus” (病毒) on 2 February 2020, the website will return 50 pages of posts containing the keyword “virus,” but the actual number of posts that day may be bigger. To ensure that the data cover the discussion of COVID-19 as fully as possible, we improved the search logic of our scraping program. We used “hour” rather than “day” as the search unit to trace all the visible Weibo texts. In this way, we could get 1,200 pages (24 hr × 50 pages) for each keyword each day. Data collection started on 2 February 2020. The data went back to 26 December 2019, because coronavirus was first detected in samples by researchers in China on that day, which caused a large-scale discussion on Weibo. Then, we collected real-time data every day until 29 February 2020. Some Weibo posts may simultaneously contain multiple keywords, so there were duplicate posts based on our searching rules. We conducted a de-duplication processing of these duplicate posts. Less-shared posts (fewer than 10 reposts) had too few data points and were also filtered out. After de-duplication of the raw data, 535,826 original Weibo posts were finally caught, corresponding to 2,140,352 Weibo reposts, which were stored as the original dataset in chronological order. These posts and reposts were further labeled with three account types: Blue V, Orange V, and unverified users.

**Emotion Analysis Based on Improved Emotion Lexicon**

Emotion analysis and sentiment analysis aim to detect and analyze people’s sentiments or emotions toward entities such as products, organizations, individuals, events, or topics (Liu, 2012). Unlike sentiment analysis, which only distinguishes terms by their sentiment polarities (e.g., positive,
neutral, and negative), emotion analysis attempts to identify more discrete emotional categories like anger, fear, and joy (Sailunaz & Alhajj, 2019). This study applied the lexicon method to track the emotions contained in the Weibo texts. The emotion of each post was coded by the most frequent emotion category in it. Posts without emotional terms were coded as “none” emotion.

The lexicon we utilized is Affective Lexicon Ontology, one of the most mature Chinese emotion lexicons, which was created by the Dalian University of Technology (Xu et al., 2008). To improve the lexicon to fit the discussions on Weibo, we added some emotional terms related to COVID-19 context, like “共克时艰,” which means “overcome difficulties together,” as a “good” term for this unique period. Eventually, we got 27,736 Chinese terms in our lexicon (see the appendix).

In addition, the current dictionary-based method only considers the number of emotional terms, which may underestimate the influence of negation (e.g., “not”). For instance, “not happy” would be detected as “joy” if we ignore “not.” Thus, we conducted validation work to estimate our method. First, we counted how many times the emotional terms in our lexicon were used by Weibo users, denoted by N. Second, we constructed a list of Chinese version negation cues2. Then, we counted how many times the emotional terms were directly preceded by a negation cue, denoted by n. At last, we computed the percentage of negation usage by \( n/N \), which showed that only 2.0% detected emotional terms had the negation issue. Therefore, we could state that the impact of the negotiations was limited in our dataset, and the overall analysis of the current results was credible.

**Social Network Analysis and Three Kinds of Relationships**

Social network analysis is a broad strategy for investigating social structures (Otte & Rousseau, 2002). Briefly, a social network “consists of a finite set or sets of actors and the relation or relations defined on them” (Wasserman & Faust, 1994, p. 20). The actors in the social network could be people, institutions, topics, or other abstract concepts. There are two types of networks. A 1-mode network refers to data recording links between the same entities, like the relationship between people (e.g., friendship and marital relationship), while a 2-mode network reflects the relationship between two sets of entities (Borgatti, 2009), such as the relationship between scholars and their affiliations, news, and its topics, or posts and their contained emotion. In the interest of comparing the different patterns between the diffusion of information and emotion, we constructed three networks: “information network” (1-mode), “emotion network” (1-mode), and “user-emotion network” (2-mode).

The “information network” reflects the “post-repost” relationship (like the tweet–retweet relationship on Twitter) between Weibo users. The formation of this network is based on the official repost function provided by Weibo. When a user’s post is reposted by another user, despite whether the user adds a comment or not, a link would be established between the poster and the reposter. It means that the information has been disseminated from the poster to the reposter successfully.

The “emotion network” reflects the “post-repost” relationship regarding emotional messages between Weibo users. The formation of this network in this study is based on the successful spread of emotional messages between users. When a user reposts an original post with comments using similar emotional terms or expressing the same emotion as the poster, it is considered that the emotional message has been successfully spread from the poster to the reposter. Accordingly, a link would be established between the poster and the reposter in the network. However, if a reposter expresses different emotions in the added comments or reposts without comment, there would be no link of emotional message diffusion established between the poster and the reposter.

The “user-emotion network” reflects the relationship between the user and the emotion contained in their posts/reposts. This network is identified as a 2-mode network because it includes links between two kinds of entities: people (users) and abstract concepts (emotional messages). Different from the information network and emotion network which are built on users’ digital behavior on social media (post-repost), the links in a user-emotion network are constructed by artificial rules. First, all posts would be recognized through emotion analysis as a certain type of emotional message (e.g., fear, anger, sadness) according to the most frequent emotion terms in the posts. Second, if a user posted or reposted a kind of emotional message, we would record it as a link between the user and this kind of emotional message. For example, if one user named X posted an “anger” post, then there would be an “X-anger” link. Some users may post many kinds of emotional messages in a certain period, and these users could link with multiple emotions at the same time. Although the user-emotion network is a human-made network based on our rules, it helps interpret the relationship between users and their preferable emotional messages and provides us an in-depth dimension to analyze the relationship between the seven emotional messages.

Finally, we use Gephi software to visualize the networks. Because the full parts of “information network” and “emotion network” are too large, for clearer visualization, we only presented the core parts of the two, which were composed of the dyads that have more than 10 weighted edges (see Figures 1 and 2). Notably, we conducted the “10 weighted edges filter” standard only for drawing Figures 1 and 2, which retained the patterns like their full networks and were more readable for comparison. However, for the data analysis, we did not filter the network by this standard. All the social network analyses and their results were based on the whole dataset.
Results

Information Versus Emotion: Similarities and Differences

 Millions of people participated in the discussion of COVID-19 on Weibo from 26 December 2019 to 29 February 2020. Our dataset is the discussion that contains the six most relevant COVID-19 keywords, which should be regarded as a case of the whole discussion. In online discussions, information and emotion are spread interpersonally, and two kinds of networks are ultimately formed. Similar to information flow, emotion flow also depends on the repost function of Weibo. Among all the posts containing emotional terms, 62.7% successfully spread emotional messages, which means that more than half of people in the emotion network would repost with comments to express the same emotions during that period. These successfully delivered emotions connected posters and reposters and constructed a network of emotions. Essentially, the emotion network is part of the overall information network that successfully spreads emotional messages. Thus, the emotion network in our sample is slightly smaller than the overall information network (see Table 1). The main parts of these two networks are shown in Figures 1 and 2.

Overall, based on the current data, although the emotion network has its unique features, the structures of these two networks are similar. First, the information network and emotion network are both sparse networks. Density and component are two indicators that describe the connectedness and cohesion of a network separately (Otte & Rousseau, 2002). Density is counted as “the number of links divided by the number of vertices in a complete graph with the same number of nodes” (Otte & Rousseau, 2002, p. 442). If every vertex is directly connected to the others in a network, it is a complete network. A component of a network refers to “a subset with the characteristic that there is a path between any node and any other one of this subset” (Otte & Rousseau, 2002, p. 442). If a network only forms one component, it is totally connected. The density of these two networks is both low (see Table 1). The information network is composed of 13,654 components isolated from each other, whereas the emotion network is 11,752 components (see Table 1). The diasporic structure suggests that both information flow and emotion flow in our study follow a less decentralized, multi-level communication pattern rather than a closely linked network structure.

Second, according to our data, the diffusion patterns of all messages and emotional messages are analogous. As presented in Figures 1 and 2, the vertices refer to the users who participated in the production or diffusion. The lines linking

Table 1. Comparison Between Information Network and Emotion Network.

| Metric                  | Information network | Emotion network |
|-------------------------|---------------------|-----------------|
| Vertex                  | 1,209,393           | 771,347         |
| Edge                    | 1,591,998           | 956,025         |
| Average degree          | 2.63                | 2.48            |
| Average shortest path length | 8.13                | 4.91            |
| Density                 | 1.09E–06            | 1.61E–06        |
| Number of components    | 13,654              | 11,752          |
| Normalized degree centralization | 0.061               | 0.074           |
| Reciprocity             | 2.49E–04            | 2.83E–04        |
the vertices represent the flow path of information and emotions. Obviously, the information and emotional messages are not directly delivered to most users. Instead, they are related to certain users first and then flow to the vast majority, forming a radial network based on some cores.

Third, the reciprocities of these two networks are close. Reciprocity refers to the tendency of vertex pairs to form mutual connections between each other, which is also related to the communication efficiency of the network (Garlaschelli & Loffredo, 2004). As shown in Table 1, the reciprocities of both networks are small, indicating that the flows of information and emotion in our sample are one-way in most cases.

As for differences, the emotion network shows a more centralized structure than the information network according to the degree centralization (see Table 1), which reflects the overall centripetal trend of the network based on degree (Freeman, 1978). Degree centralization is a normalization measurement based on the normalized variance in vertex centrality of any chosen centrality measure, which aims to allow a comparison of distinct networks (Krnc & Škrekovski, 2020). A larger degree centralization means that the points on the network are more likely to gather around a core. Put differently, in our dataset, the flow of emotion is more likely to be controlled by core roles in the network.

The average shortest path length (ASPL) refers to “the average number of steps along the shortest paths for all possible pairs of network nodes” (Mao & Zhang, 2013, p. 1), that is, the mean of the least number of people or steps to deliver the information from the original posts to the target users. This value is a way to conduct quantitative analysis of networks’ information flow efficiency (Ye et al., 2010) in that a network with low ASPL provides efficient data transmission (Shimizu & Mori, 2016). Table 2 shows that the average shortest path of the information network is almost twice the length of the ones in the emotion network. Shorter paths indicate that the diffusion of emotion in our emotion network is faster and more efficient compared with its reference (i.e., overall information in our information network).

### Diverse Leaderships of Blue V, Orange V, and Unverified Users in Two Networks

To answer RQ2 that who are the opinion leaders in sharing emotional messages and information on Weibo during COVID-19, we draw on some indicators from social network analysis, such as degree (indegree/outdegree) and betweenness to show the centrality of a vertex in the networks (Scott, 1991).

Degree refers to “the number of other points to which a point is adjacent” (Scott, 1991, p. 23) and can be used to reflect the importance of a point in the network. In a directed network, there are two kinds of degrees based on direction: indegree and outdegree. “The indegree of a point is the total number of other points which have lines directed towards it; and its outdegree is the total number of other points to which it directs lines” (Scott, 1991, p. 18). Generally, the higher the indegree of a user, the more that user accepts information or emotion from others. By contrast, the higher the outdegree of a user, the more times that user successfully disseminated information or affective information.

The betweenness of a vertex in the social network measures “the extent to which an agent can play the role of a ‘broker’ or ‘gatekeeper’ with a potential for control over others” (Scott, 1991, p. 24). Vertices that have higher betweenness tend to be in the middle of other vertices, which could be seen as the “intermediary” and “bridge” of the information and emotion flows. In a word, users in the two networks who have high outdegree tend to disseminate more information and emotion. In addition, users with higher betweenness tend to be “brokers” between other users, meaning that they have more potential to impact the flow of information and emotions between others. Therefore, the high-outdegree and high-betweenness users in this study are more likely to be opinion leaders.

RQ3 focuses on the relationship between account types (Blue V, Orange V, and unverified users) and opinion leadership in emotional messages and engagement (repost, comment, like) on Weibo. In the information network (see Figure 1) and emotion network (see Figure 2), the size of a vertex is proportional

### Table 2. Cross Table of Account Types and Emotional Messages.

| Account type       | Good, N (%) | Fear, N (%) | Disgust, N (%) | Joy, N (%) | Sadness, N (%) | Anger, N (%) | Surprise, N (%) | None, N (%) |
|--------------------|-------------|-------------|----------------|------------|----------------|--------------|----------------|-------------|
| Blue V             | 192,709 (36)| 33,868 (6.3)| 20,663 (3.9)   | 15,231 (2.8)| 6,160 (1.1)    | 756 (1)      | 447 (1)        | 11,017 (2.1) |
| N=280,851 (52.4)   |             |             |                |            |                |              |                |             |
| Expected N         | 166,159.3   | 33,613.9    | 26,110.6       | 17,247.2   | 8,363.9        | 1,305.1      | 752.2          | 27,298.9    |
| Orange V           | 102,016 (19)| 21,289 (4.0)| 21,275 (4.0)   | 13,393 (2.5)| 6,441 (1.2)    | 1,258 (2)    | 833 (2)        | 30,612 (5.7) |
| N=197,117 (36.8)   |             |             |                |            |                |              |                |             |
| Expected N         | 116,619.9   | 23,592.1    | 18,325.9       | 12,105.1   | 5,870.2        | 916          | 527.9          | 19,159.9    |
| Unverified Users   | 22,281 (4.2)| 8,973 (1.7) | 7,877 (1.5)    | 4,281 (0.8)| 3,356 (0.6)    | 476 (1)      | 155 (0)        | 10,453 (2.0) |
| N=57,852 (10.8)    |             |             |                |            |                |              |                |             |
| Expected N         | 34,226.9    | 6,924.1     | 5,378.5        | 3,552.7    | 1,722.9        | 268.8        | 154.9          | 5,623.2     |
| Total              | 317,006 (59.2)| 64,130 (12)| 49,815 (9.3)  | 32,905 (6.1)| 15,957 (3.0)  | 2,490 (0.5) | 1,435 (0.3)    | 52,082 (9.7) |
to the outdegree. The color of the vertices represents different account types: Blue V (blue), Orange V (orange), and unverified user (gray). The lines show the path of emotion diffusion, and the color of these lines corresponds to the color of the original posters, which helps us to identify the account types of the sources of information and emotion. We adopted the Yi Fan Hu algorithm to lay out the network (Hu, 2005). This algorithm combines the advantages of force-directed algorithms and a multilevel algorithm to reduce complexity, which is efficient to depict high-quality large networks. In general, there are many cores in the different subgroups, which means no one can influence all people in both information and emotion networks. Conversely, different subgroups have their own opinion leaders. Considering the diffusion paths of emotion, most lines are blue and orange, indicating that Blue V and Orange V are major generators and senders of emotional messages (i.e., opinion leaders), while most unverified users are receivers. Moreover, Orange V is often between Blue V and unverified users, acting as a bridge by reposting Blue V’s information and emotions to more unverified users.

We generated the top 1,000 users of the information network and the emotion network based on the size of outdegree, indegree, and betweenness. Figures 3 and 4 show the proportions of the three account types in the list of the top 1,000 in the two networks, respectively. In the information network, Orange V is the largest group in the top 1,000 of outdegree scores, reaching 47%, while 79% of the highest indegree scores are unverified users. In terms of betweenness, 58% of the users are Orange V. Analogously, in the emotion network, Blue V is the most prominent type in terms of outdegree, accounting for 46%. Unverified users (76%) and Orange V (54%) are still the most dominant types in the list of indegree and betweenness. The result implies that both types of verified accounts (Blue V and Orange V) function to produce information and emotional messages. Furthermore, Blue V tends to spread emotional messages, Orange V tends to spread information, and unverified users tend to receive both information and emotional messages.

Table 2 shows that Weibo posts related to COVID-19 from 26 December 2019, to 29 February 2020, were dominated by Blue V and good emotions. Meanwhile, unverified users shared the least voice in the posts in our dataset. Good was the most common emotion, followed by fear and disgust, while anger and surprise were only a minority. The results from a cross table further illustrated the relationship between account types and emotions (see Table 2). Blue V accounts controlled by official institutions or companies tended to post more good emotions and less negative emotions than expected. The results for Orange V were opposite to Blue V in that they expressed less good and fear but more...
disgust, sadness, anger, surprise, and joy. Unverified users also had more negative posts with fear, disgust, sadness, and anger. In addition, Blue V and unverified users tended to use emotional terms in their posts and posted fewer no-emotion posts than expected.

The Weibo engagements, including repost, comment, and like, were summarized for the three account types and seven emotional messages. Unverified users received fewer reposts, comments, and likes than verified users. Although Blue V received more reposts, they had fewer comments than Orange V (see Table 3). Positive emotions like good and joy had higher engagements than negative emotions of fear, sadness, and anger (see Table 3). Notably, all 45,397 posts which received more than 10 million reposts were posted by Blue V users and expressed “good” messages.

“Good” Emotional Messages: Mainstream but Isolated

To answer RQ4, which aims to explore the emotional messages most likely to be distributed on Weibo, the percentage of links with the same emotion between posts and reposts among different account types and emotional messages was generated (see Figure 5). “Good” messages were

| Account type  | Repost | Comment | Like |
|--------------|--------|---------|------|
|              | M      | SD      | M    | SD    | M    | SD    |
| Blue V       | 2,377.52 | 4,548.39 | 21.78 | 49.61 | 209.65 | 363.04 |
| Orange V     | 156.54  | 323.89  | 50.85 | 140.78 | 203.55 | 463.85 |
| Unverified user | 20.79  | 72.01   | 3.80  | 13.69  | 54.32  | 180.13 |

Table 3. Engagements (Repost, Comment, Like) of Different Account Types and Emotional Messages.

Note. The numbers are divided by 1,000.

Figure 5. The percentage of successful emotion links between posts and reposts among different emotions and account types.
most likely to be diffused, with 75.45% of reposts expressing the same emotion; the other emotional messages were diffused in less than 50% of reposts. Furthermore, Blue V’s posts were more likely to be reposted with the same emotion than posts from Orange V and unverified users. Moreover, account types interacted with different emotional messages to determine whether the emotion link would be successfully built. The diffusion rate of “good” messages between posts and reposts was relatively even across different types of accounts, but Blue V had a much higher success rate to disseminate emotional messages containing surprise, anger, fear, and no emotion.

Figure 6 shows the “user-emotion network,” which is a 2-mode network composed of emotional messages and users. The eight bigger vertices represent the seven emotions and no emotion: the size of the point is directly proportional to the number of Weibo posts containing certain emotions. Around them are users who express such emotions in Weibo posts and reposts. To spatialize a network, we employed the ForceAtlas2 algorithm to rearrange the “user-emotion network” to convert it to a force-directed layout which simulates a physical system. The advantage of this technique is that it turns structural proximities into visual proximities (Jacomy et al., 2014). Concisely, the distance on the graph can reflect the real distance in the network structure.

Meanwhile, we used the “modularity” function in Gephi to make vertices in different subgroups appear in different colors, which helps us to detect the communities, groups, or modules in a network (Newman, 2006). Among all the emotions expressed by Weibo users, “good” (degree: 1,285) was the most dominant emotion in the user-emotion network. It can be said that the “good” message was the mainstream of epidemic discussion. However, “good” messages were far away from other emotional messages in the network, meaning that “good” emotions often exist in isolation, and people who expressed good emotion often only expressed this kind of emotion. Several other emotional messages were intertwined to form another close group compared to “good” messages. Among them, sadness (degree: 84), anger (degree: 10), and surprise (degree: 10) are all red, which means that these three emotions often appeared together because many users were expressing these three emotions at the same time.

Discussion

Employing social network analysis and emotion analysis, we used the six most relevant keywords to investigate the diffusion pattern of emotional messages about COVID-19 and compared it with the diffusion pattern of all posts on Weibo. Like the dissemination of information, our results show that emotion flow and information flow roughly follow the two-step flow model with more complicated and diverse patterns in the social media context. This finding echoes the claim that different models such as one-step, two-step, multistep, and network-step can coexist in the same network (Hilbert et al., 2017), while the two-step flow model still plays a dominant role within subgroups.

According to the findings, emotion flow has some unique features. The higher centripetal trend implies that the discussions in the emotion network are more likely to be impacted by the core roles, that is, opinion leaders. These leaders may be responsible for the dominance of “good” messages and interfere with netizens’ own ability to interpret pandemic events with multiple emotions. For example, some Blue V accounts may turn the angry reaction toward the death of medical workers during COVID-19 into singing the praises of heroes and martyrs. Such emotional strategies can be generalized to other public events in China and are consistent with previous findings that traditional Chinese media outlets are unlikely to report or help the public to release negative emotions (Tong, 2015). The results suggest that emerging digital media technologies did not help to change this situation as expected. The diffusion of emotional messages is also faster and more efficient compared with the diffusion of all messages in our two networks. The effectiveness of emotional message diffusion may be related to the higher reciprocity in the “emotion network,” which indicates that there are frequently bidirectional transmissions between users in the groups. Another reason for this faster diffusion of emotional messages could be the ability of emotional content in increasing people’s attention and keeping them engaged, which subsequently influences their online interactive behaviors (Goldenberg & Gross, 2019; Stieglitz & Dang-Xuan, 2013).

By explicitly visualizing cores in both emotion and overall information diffusion patterns during COVID-19, our main findings show that both verified Blue V (institutional) and Orange V (personal) accounts function as main spreaders, whereas unverified accounts mainly receive messages
from them. Moreover, official institutions’ accounts (Blue V) are the predominant sources of transmitted emotional messages that receive the most reposts and likes compared to the other two types of users. The top ten Blue V accounts that transmitted the most emotional messages to others are state-owned media agencies except “Pear Video” (a privately owned short video website). The predominant proportion corresponds to the features of the Chinese media system, in which the government-led media has more power and influence even in social media platforms like Weibo. This observation indicates that normal unverified Weibo users’ information sources may be limited and reminds us to reconsider the information diversity on social media platforms.

Verified individual accounts (Orange V), who have the highest betweenness scores, are more like intermediaries to bridge different groups and transmit emotional messages to those unverified individual accounts who do not follow the Blue V accounts. The broker role of Orange V accounts also indicates that they are likely to communicate better with the public. Thus, although Blue V accounts have the power to produce and lead mainstream emotional messages, they need to collaborate with Orange V accounts to reach more subgroups. For example, many accounts of young celebrities become transfer stations for official accounts like Chinese Communist Youth League (共青团中央). This observation further supports our claim that emotional messages have similar diffusion patterns to those proposed by the two-step flow theory in terms of information diffusion. Moreover, Blue V accounts play an influencing role in promoting “good” messages to become the dominant emotional messages in our dataset. In contrast to the “negativity bias” that negative emotional messages are more likely to be transmitted than other messages (Vaish et al., 2008), our dataset shows that positive “good” is the most transmitted emotion in Weibo during the COVID-19 pandemic.

The leading role of Blue V accounts in discussions related to COVID-19 may shed light on this distinct phenomenon. First, because of the state-owned character of most mainstream media in China, the government-led political system has a relatively strong control of media outlets and treats them as an apparatus to promote the national image as well as manage public discussions (Zhao, 2011). In the context of the pandemic, those official media accounts can follow the government’s lead and take a more strategic perspective to control the spread of negative emotional expressions, especially during the early, uncertain period of the COVID-19 outbreak. Thus, Blue V accounts post more “good” posts while avoiding negative emotional messages like disgust and anger to encourage people to stay positive. This intentional intervention of Blue V seems to be supported by the additional analysis of the timeline. For instance, the Blue V accounts made more posts containing good emotion during mid-January and early February, when people had more negative attitudes because of the government’s dereliction of duty in the early stages of the outbreak and the death of Dr. Li Wenliang.

Although the “good” messages took an identifiably larger part than other emotional messages, this dissemination effect might not be as functional as expected. According to the 2-mode user-emotion network, “good” messages were isolated from the other emotional messages, which means that only one group of accounts consistently advocated positive attitudes while keeping silent about negative ones. On the contrary, people who raised angry voices also expressed sadness and surprise, which made them more like regular people with complicated emotions in such a miserable disaster. This also corresponds to the result that both verified and unverified individual accounts posted more negative posts containing disgust, anger, and sadness than expected.

Unlike the Blue V accounts, which intended to foster “good” emotion through “good” messages, Orange V accounts posted more diverse emotions and reflected the voice of the public better. Although “good” emotion still dominated the Orange V posts, there were a remarkable number of posts containing negative emotions like disgust, sadness, anger, and surprise. The larger amounts of negative emotions may attribute to the relatively more flexible stance of Orange V compared to Blue V accounts. Notably, Orange V accounts had more effective comments than Blue V accounts. These findings may indicate that Orange V posters focused more on covering individual lives during the COVID-19 pandemic, thus becoming a venue for people to share their suffering and critical opinions toward government reactions.

Many negative-emotion Orange V posts with fear, anger, disgust, sadness, and surprise failed to transfer widely by means of reposting similar emotions. Unlike the “good” messages, which were transmitted quite evenly through all three account types, negative emotional messages were more likely to be transmitted only by Blue V posters, who posted far fewer negative posts than expected. This hints that there might be an invisible hand not only promoting good emotions through Blue V accounts but also restraining the diffusion of individuals’ negative messages among the public. This invisible hand may also violate the data we got and mask a more vivid emotional media environment online. It is worth noting that despite the pervasive illusion of harmony on Weibo, there may be a more complicated and diversified emotion flow for us to explore.

Conclusion

The current study employed social network analysis and emotion analysis to analyze the emotional messages on Weibo in China during the early period of COVID-19. We presented how emotional messages are diffused compared with the general information flow during the COVID-19, in which the diffusion pattern can be generalized on other platforms and for other contexts. In addition, we used computational approaches to identify the potential opinion leaders and the emotion they spread. Specifically, the results illustrate the government’s
role in emotional intervention on social media in public health emergencies.

In summary, we have three main findings: First, emotional messages follow the two-step model and are diffused faster compared with the overall information. Second, verified accounts play the opinion leader role on Weibo, in which verified Blue V (institutional) and Orange V (personal) accounts are collaborating in disseminating messages on Weibo. Third, Blue V posts express good emotion, while Orange V and unverified accounts delivered diverse emotions on social media during the COVID-19.

**Practical Implications**

The findings of this study bring some practical implications. The majority of Weibo users are unverified users, while the information diffused on Weibo is controlled by a small group of Blue V and Orange V accounts. We recommend Weibo users follow different types of accounts rather than simply endorsing Blue V. As for the government, emotional messages are important in detecting and managing public opinions. According to our findings, official accounts are actively engaging in emotional discussions on Weibo by posting positive messages and restricting negative messages. However, the effectiveness of such emotional strategies is unclear considering the complexity of the public’s emotions. On the one hand, inspiring good emotions might be helpful to normalize and calm down the public. On the other hand, the restriction and censorship of negative expressions may not achieve harmony as expected. The public needs digital channels to release negative emotions, especially during a public health emergency. The data also support this argument as individual accounts post more diversified emotional messages including negative emotions. In that case, blocking Weibo’s function of expressing opinions, whether positive or negative, may cause more problems. For instance, Dr. Li Wenliang’s Weibo comments were intentionally deleted, which aroused public discontent. Now, the Dr. Li Wenliang’s Weibo post is compared with the Wailing Wall in Jerusalem, which records people’s feelings and memories during the COVID-19 pandemic. Weibo as a powerful platform needs to keep these special memories as well as to protect users’ rights.

**Limitations and Future Studies**

There are some limitations of this study. First, it was hard to get the full sample of Weibo posts about COVID-19 even though we monitored and crawled data every day. According to the Internet policy in China, some negative posts will be deleted automatically. This is another possible reason for the dominance of “good” messages and Blue V posts in the current data. Second, we directly borrowed a Chinese emotion dictionary (Xu et al., 2008) to code emotional messages. Although we have added some words related to COVID-19, there is a chance that we missed several trendy Internet slang terms. In that case, we recommend that future researchers use in-depth digital ethnography to study emotional expressions on social media. Furthermore, we noticed a massive collective expression of similar emotional terms during the pandemic. Future studies can examine how this kind of digital collective emotional expression influences people’s emotional states. Third, posts and reposts were coded arbitrarily by the emotion which took the largest portion. However, many texts contained expressions of various emotions and few negations were lost during the coding process. Future researchers may include manual coding or deep learning based on pre-trained language models (e.g., BERT) to supplement these limitations. Fourth, part of the current findings is limited to the Chinese context. For example, the dominance of “good” messages on Weibo could be attributed to the government’s censorship and endorsement of collectivism in Chinese society. Thus, we call for scholars to analyze emotional messages and government interventions on social media in other countries. Finally, this study did not include emojis and emoticons because our data did not include visuals. It will improve the current findings to add emojis and emoticons as important components of emotional messages in the future.

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**Notes**

1. As a whistleblower in the early outbreak of COVID-19, Dr. Li shared the inner diagnosed reports about COVID-19 to some people and reminded them to be cautious about the new
disease. He was once arrested for transmitting “false comments” and finally died because of COVID-19. This event caused large-scale public discussions and self-organized digital memorial activities on Weibo.

2. List of Chinese version negation cues: 不,不是,没,无,非,莫,毋,勿,未,否,别,休,不被,未必,没有,不要,并非,绝无,不可.

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Appendix. Improved Emotion Lexicon.

| Emotion | Number of terms | Sample terms |
|---------|-----------------|--------------|
| Joy (乐) | 1,949 | Happy (喜悦), smile (笑眯眯), relief (宽心), certainty (踏实), laugh (哈哈哈), honeymoon (蜜月) |
| Good (好) | 11,134 | Respect (尊敬), praise (赞), belief (相信), love (喜爱), awesome (666), overcome difficulties together (共克时艰) |
| Anger (怒) | 432 | Angry (气愤), irritated (恼火), furious (大发雷霆), fuming (七窍生烟), despise (biss), brain-impaired (脑残) |
| Sadness (哀) | 2,416 | Sad (忧伤), desperate (绝望), guilt (内疚), miss (思念), farewell (永别), dust (尘埃) |
| Fear (惧) | 1,218 | Panic (慌张), fear (害怕), shy (害羞), timid (胆怯), trembling (颤栗), death (死神) |
| Disgust (恶) | 10,359 | Detest (脱衣), disgust (厌恶), jealous (眼红), suspicious (生疑), escape (逃离), take the blame for others (背锅) |
| Surprise (惊) | 228 | Strange (奇怪), miracle (奇迹), surprised (大吃一惊), dumbfounded (瞪目结舌), coincidentally (恰巧), circuit breaker (熔断) |