Learning public engagement and government responsiveness in the communications about COVID-19 during the early epidemic stage in China: an analysis of social media data

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Abstract

Background: Effective risk communication about the outbreak of a newly emerging infectious disease in the early outbreak stage is challenging but critical for managing public anxiety and particularly promoting behavioural compliance. China has experienced the unprecedented epidemic due to the outbreak of the coronavirus infection 2019 (COVID-19) in an era when social media has fundamentally transformed information production and consumption patterns.

Objective: This study retrieved data from a major social media platform in China, Sina Weibo, to examine public responses to and government's engagement in communications about COVID-19 during the early epidemic stage.

Methods: We retrieved and screened Weibo data relevant to COVID-19, from December 1, 2019 to January 31, 2020. Government engagement in communications about COVID-19 on social media was evaluated using an engagement index calculated by aggregating main engagement metrics: Likes, Comments, Shares and Followers; to posts delivered by government accounts. Content analyses were conducted for a random subset of 644 posts from personal accounts, and 274 posts from 10 relatively more active official accounts of government agencies and the National Health Commission of China, to identify major thematic categories in online discussions. Chi-square for trend examined how proportions of thematic categories changed by time within the study timeframe.

Results: Temporal change of daily numbers of Weibo posts was aligned with daily numbers of newly confirmed cases of COVID-19 and government announcements of situation update and control actions. The accounts of government agencies generally had low engagement with online users in the communication about COVID-19. Some municipal health commissions from health sector and public safety organizations (e.g., police and fire service departments) from non-health sector were found to be relatively more active in risk communication. The content analysis showed that government agencies mainly used social media to inform public about the epidemic situation, general knowledge of the new disease, policies, guidelines and government actions, and advise on preventive measures, despite a slight increase in post proportion of showing empathy to affected people and appreciation to health care workers as the epidemic evolved. Posts created by personal accounts more likely showed empathy to affected people and blame others who put individuals at risk and government failure with an increasing trend as the epidemic evolved.

Conclusion: Social media data can be used as a sentinel to understand public responses to policy changes and risk perceptions during the early epidemic stage. The Chinese government mainly used social media to provide knowledge and information to the general public. As the epidemic evolved, the government may adopt a more empathic style in risk communication to improve audience's interactivity with the messages and improve public trust and credibility.

Conclusions: Social media data can be used as a sentinel to understand public responses to policy changes and risk perceptions during the early stage of COVID-19 epidemic. The Chinese government agencies mainly used social media for one-way communication to provide knowledge and information to the general public while general individuals were more likely to share emotions including showing empathy to affected people and blaming others or the government. The tendency of increasingly attributing blame to other individuals or the government may push the Chinese government to seek accountability and refine the compensation system for affected people. As the epidemic evolves, the government may adopt a more empathic style in risk communication to improve audience's interactivity with the messages and improve public trust and credibility.

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Learning public engagement and government responsiveness in the communications about COVID-19 during the early epidemic stage in China: an analysis of social media data

Abstract

Background: Effective risk communication about the outbreak of a newly emerging infectious disease in the early stage is critical for managing public anxiety and promoting behavioural compliance. China has experienced the unprecedented epidemic of coronavirus disease 2019 (COVID-19) in an era when social media has fundamentally transformed information production and consumption patterns.

Objectives: This study examined public engagement and government responsiveness in the communications about COVID-19 during the early epidemic stage based on analysis of data from Sina Weibo, a major social media platform in China.

Methods: Weibo data relevant to COVID-19 from December 1, 2019 to January 31, 2020 were retrieved. Engagement data (Likes, Comments, Shares and Followers) of posts from government agency accounts were extracted to evaluate public engagement with government posts online. Content analyses were conducted for a random subset of 644 posts from personal accounts of individuals, and 273 posts from 10 relatively more active government agency accounts and the National Health Commission of China to identify major thematic contents in online discussions. Latent class analysis (LCA) was employed to further explore main content patterns while Chi-square for trend examined how proportions of main content patterns changed by time within the study timeframe.

Results: Public response to COVID-19 seemed to follow the spread of the disease and government actions but was earlier on Weibo than the government. Online users generally had low engagement with posts relevant COVID-19 from government agency accounts. The common content patterns identified in personal and government posts included sharing epidemic situation, general knowledge of the new disease, and policies, guidelines and official actions. However, personal posts more likely showed empathy to affected people (χ^2_1=13.3, P<.001), attributed blame to other individuals or government (χ^2_1=28.9, P<.001), and expressed worry about the epidemic (χ^2_1=32.1, P<.001) while government posts more likely shared instrumental support (χ^2_1=32.5, P<.001) and praised people or organizations (χ^2_1=8.7, P=.003). As the epidemic evolved, sharing situation update (χ^2_1 for trend=19.7, P<.001), and policies, guidelines and official actions (χ^2_1 for trend=15.3, P<.001) became less frequent in personal posts but remained stable or increased significantly in government posts. Moreover, as the epidemic evolved, showing empathy and attributing blame (χ^2_1 for trend=25.3, P<.001) became more frequent in personal posts, corresponding to a slight increase in sharing instrumental support, praising and empathy in government posts (χ^2_1 for trend=9.0, P=.003).

Conclusion: The government should closely monitor social media data to improve the timing of communications about an epidemic. As the epidemic evolves, merely sharing situation update and policies may be insufficient to capture public interest in the messages. The government may adopt a more empathic communication style as more people are affected by the disease to address public concerns.

Introduction

On December 31, 2019, a cluster of pneumonia cases of unknown aetiology were first reported in Wuhan, the capital city of Hubei province, China [1]. The causative pathogen was soon identified as a novel coronavirus, severe acute respiratory syndrome coronavirus 2 (SARS-coV-2) [2] and the disease caused by SARS-coV-2 was termed coronavirus disease 2019 (COVID-19) [3]. Epidemiological investigation of the first 41 laboratory-confirmed human cases revealed that most had a history of exposure to a seafood wholesale market (Huanan Market) in Wuhan where live wild animals were also sold for human consumption [4], but later human-to-human transmission was confirmed as cases without a history of visiting the market increased dramatically [5-7]. The outbreak of COVID-19 in Wuhan rapidly evolved into a severe pneumonia epidemic nationally and later globally. As of May 13, 2020, a total of 84,458 confirmed human cases of COVID-19 including 4,644 deaths in China were reported to the World Health Organization (WHO) [8]. Globally, the COVID-19 has been a pandemic affecting more than 200 countries or territories with a total of 4,170,424 human cases of COVID-19 including 287,399 deaths as of May 13, 2020.

Communication about outbreaks

The outbreak of a newly emerging respiratory infectious disease usually put individuals at a high risk of infection and constitutes a highly uncertain situation that changes rapidly, threatening serious potential loss, prompting considerable psychological distress [9, 10]. Feelings of uncertainty provoke great public anxiety, which if not properly addressed can develop into public panic and herd behaviours that may harm social order and population health [11, 12]. Effective outbreak communication, particularly at the early stage, become critically important for dealing with excessive public fear, promoting risk awareness, empowering the public in taking protective actions, and gaining public confidence and trust [11, 13, 14]. Conceptual models for guiding outbreak communications have been developed since the 2003 outbreak of severe acute respiratory syndrome (SARS) [14-17] and used in empirical research for examining communication practices during the

2009 influenza A/H1N1 pandemic [14], the 2013-2016 Ebola outbreak in West Africa [18] and most recently the outbreak of COVID-19 [19]. These communication models and empirical research indicate that effective outbreak communication should be prompt and transparent, dynamic as the situation evolves to meet changes in public needs, relevant and able to engage the community, and show empathic and care to address public emotional distress [14-19].

Social media as a platform for outbreak communication

The high penetration of internet usage and rapid development of information and communication technologies have made the internet an increasingly important health information source worldwide [20-23]. Reading, commenting, sharing and seeking health information from social media particularly through a mobile device has become an increasingly important pattern of health information consumption in China [20, 24, 25]. During an epidemic, social medial can facilitate the spread of epidemic awareness, attitudes towards control and preventive measures, emotional responses and behaviours as well as misinformation and rumours in the public through online interactivity [26-30]. As the epidemic evolves, this may facilitate homogeneous mental representations of the epidemic, leading to collective behavioural responses [31]. In China, Sina Weibo (Chinese version of Twitter) is one of the most popular platforms that attracted 486 million active monthly users in 2019 [32] most of whom accessed their user accounts through a mobile device [24]. Its microblogging function allows users to create and share short messages in multimedia format while other users can “share”, “like”, “comment” and “follow” the initial posts. Numerous government agencies in China also make use of Weibo to communicate with the public. As of June 2019, there were a total of 139,270 verified government microblogs in Weibo [24].

With the proliferation of internet and social media used as health information sources, infodemiology (or inforveilance), the study (or surveillance) of "distribution and determinants of information", in the internet or a population, for the aim of guiding policy making and public health interventions [33] has been commonly used in the case of infectious disease outbreaks. Among various applications of infodemiology or inforveillance methods for social media data about infectious disease outbreaks, tracking information (concept) prevalence data [27, 34-38] and qualitatively analysing and categorizing contents of the social media data [19, 27, 36-41] are believed to be able to provide important insights into outbreak communications. However, existing studies mainly focused on tracking specific concepts or information such as blame [27], misinformation [34], stigma [30], specific keywords and sentiment [35], organization trust and managing uncertainty [39] possibly due to specific research interests or using machine-aided analysis which does not allow flexible content analysis [42]. Moreover, existing studies mainly focused on one side of the outbreak communication either the public response or response of health authorities [19, 27, 34-41]. This only provides partial understanding about the interactivity between the general public and health authorities whereas two-way communication is believed to be crucial for effective outbreak communication [40]. While a recent infoveillance study on Weibo data about COVID-19 provided some qualitative descriptions about the potential interactions between the public and government online about COVID-19 by time, the study did not quantify public engagement and government responsiveness regarding COVID-19 and how these changed by time as the pandemic unfolded [38]. In addition, this study's qualitative results seem lack of a clear structure for understanding public perceptions and emotions [38]. The study conducted by Chew

and Eysenbach provides more comprehensive methods for guiding coding of social media data related to discussion topics, emotions and online behaviours as well as quantifying and tracking the changes of these contents as the epidemic unfolded [37].

Study objectives

The outbreak of COVID-19 was an unprecedented epidemic that China experienced for the first time in this digital era. Based on the above literature review on important principles of effective outbreak communication and the knowledge gaps of current infodemiology or infoveillance studies examining outbreak communication using social media data, this study was aimed to make use of the Weibo data about COVID-19 from December 2019 to January 2020 in China to answer the following research questions:

1. How did the public respond to the outbreak of COVID-19 as cases of COVID increased and increasingly stringent containment measures were implemented and how quickly could the government respond to public discussions about COVID-19?

2. To what extent could government messages about COVID-19 engage the general online users?

3. What contents did the public discussed online and how did these contents change as the epidemic evolved? To what extent could government respond to the temporal change of public discussion online?

Methods

Data extraction

Four keywords in Chinese characters were used to capture data relevant to COVID-19 from Weibo: “Wuhan pneumonia”, “novel coronavirus”, “novel coronavirus pneumonia” and “novel pneumonia” December 1, 2019 to January 31, 2020. Data were retrieved using the built-in Weibo searching function and were subsequently screened by the Python Web Crawler (PWC), a tool having been demonstrated to be efficient to identify the most relevant posts that contain the set keywords [43]. A total of 1,028,204 relevant posts were initially retrieved. We also tried the key words of "unknown pneumonia" and "SARS" in Chinese characters to capture Weibo data from December 1, 2019 to January 9, 2020 when the aetiology of COVID-19 was not yet confirmed [2]. Since "Wuhan pneumonia" is a less specific term for COVID-19 before official announcement of unknown pneumonia in Wuhan on January 9, 2020, we manually checked the relevant posts by January 9, 2020 in the database. This excluded 466 from 469 posts on December 30, 2019 but this term successfully detected over 99% of the posts relevant to COVID-19 in the subsequent days. The final database included a total of 1,027,738 posts comprising 914,247 (89.0%) posts from personal accounts of the general public, 45,398 (4.4%) posts from accounts of government agencies and 67,746 (6.6%) posts from accounts of media and commercial agencies. Accounts of government, media and commercial agencies were verified by Weibo to be "official" at registration by submitting relevant documents of their organizations for verification. Each post record comprises account name, contents, post time, engagement data of each post including numbers of Likes (i.e., showing confirmation or agreement with the post contents), Comments, Shares and Followers.

Engagement analysis

This study evaluated how much government posts can engage online users in the communications about COVID-19 by calculating the engagement index of the posts delivered by government agency accounts [44, 45]. The engagement data comprising Likes, Shares, and Comments on the posts from each government account and the number of Followers of these accounts were first extracted. These engagement data were then used to calculate the three metrics of social media engagement: popularity (Likes per post and per 1000 followers), commitment (Comments per post and per 1000 followers) and virality (Shares per post and per 1000 followers), all three metrics subsequently being aggregated to generate the overall engagement index. Based on the engagement index, we identified the top 5 most active government agencies in the health and non-health sectors, respectively. When ranking engagement, we specifically excluded any government account that delivered fewer than the average number of posts generated by all government accounts combined during the study period because these government account could rank high based on engagement index but were considered inactive in interacting with online audience. We used mean but not median number of posts as the cut-off because over 50% of government agencies only had one post during the study period. In addition, since the National Health Commission (NHC) of China is regarded as the lead agency in coordinating the national effort to combat the COVID-19 outbreak in China, its engagement data were included in comparison with other government agencies despite that its engagement index was not ranked in the Top 5.

Content analysis

There is currently no consensus about how to best sample social media data for content analysis [42] but random sampling has been commonly used and seems to be suitable for social media data [46]. However, for random sampling, sample sizes differ a lot across studies due to different study purposes, duration of study period, resources and whether data were coded automatically or manually [42]. Manual coding can generate richer information by accommodating new codes emerging during data analysis but the sample size must be kept at a manageable level to avoid fatigue and improve accuracy in coding. Since we were interested in temporal changes in the discussion contents about COVID-19 general online users, we focused on the personal account posts for content analysis. We first excluded personal account posts that lacked all engagement (zero Likes, Comments and Shares) because these posts may have captured little attention and interest of other online users. Thereafter, 20 posts per calendar day between December 31, 2019 and January 31, 2020 were randomly selected for content analysis. Four posts delivered by personal accounts (one on December 29, 2019 and three on December 30, 2019) before the first official announcement of the unknown pneumonia cases in Wuhan on December 31, 2019 were also included for content analysis. Therefore, a total of 644 personal account posts were finally included for content analysis.

As a comparison with personal account posts and supplement for understanding government responsiveness in the communications about COVID-19, we also analysed the contents of all posts from the first five government accounts of the health and non-health sectors, respectively, based on the rank of engagement index, and posts from the NHC in the same period. The first government post relevant to COVID-19 was posted on December 31, 2019. A total of 273 government posts were included in content analysis.

A tentative coding scheme was first developed based on preliminary analysis of a random training subset of 100 posts using open coding by on author (QL) and iteratively refined by through independent analysis of another 100 training posts the first three authors and the discussion of the team. Then, the coding scheme was used by two authors (JY and DM) to analyse the 274 selected government posts and 644 selected individual posts for final content analysis, each analysing one half of these posts. Although the coding scheme was used, the coders were advised to be open to new codes during the analysis. After both coders finished their part, they mutually checked 10% of the posts from each other’s subset to ensure consistency in coding. Finally, one author (QL) double checked a random subset of 10% of all posts for content analysis to ensure the accuracy and reliability of the coding. Any inconsistencies were solved by going back to relevant data and the joint discussions among the first three authors to reach an agreement. Inter-rater reliability was assessed by calculating Cohen’s Kappa of which a value of 0.6 or above indicates adequate reliability. The set of codes finally generated were then constant compared to develop thematic categories.

Statistical analysis

Pearson chi-square test was used to compare the overall percentages of each thematic category between personal account posts and government agency posts. Latent class analysis (LCA) was used to explore main patterns of post contents by type of account. To conduct the LCA, we first generated binary-coded variable (1=the specific thematic category is present and 0=the specific thematic category is absent) for each thematic category coded for each post. Then these variables were entered into Mplus 7.3 for LCA. Major fit indices provided by Mplus including Akaike information criterion (AIC), Bayesian information criterion (BIC), sample size adjusted BIC (aBIC), and entropy value were used to determine the optimal number of class for the post contents of personal accounts and government agency accounts, respectively. A model with smaller values of AIC, BIC and aBIC but higher entropy value is preferred but we also consider the interpretability of the model and model parsimony [47]. The LCA would finally determine the content pattern (i.e., latent class) of each post. Then, Chi-square for trend was used to examine the temporal change of the proportion of each content pattern by week by type of account after checking the linearity of the distribution of proportion of each content pattern by week. The temporal trend analysis excluding the four personal posts delivered before December 31, 2019. The LCA was conducted using Mplus 7.3 (Muthen & Muthen, 2012-2014) while other statistical analyses were conducted using STATA 15.1 for Windows (StataCorp LLC, 1985-2017).

Results

Weibo activity

We detected information prevalence in relation to the outbreak by plotted daily numbers of Weibo posts by type of accounts with daily numbers of newly confirmed cases of COVID-19 in Figure 1. The Weibo "top search enquires" automatically identified by the built-in function of Weibo based on the number of relevant posts on that day were also marked on observable peak days of Weibo activity (Figure 1). There was a peak on December 31, 2019 when a cluster of unknown pneumonia cases in Wuhan were officially announced for the first time. Another small peak was detected on January 9, 2020 when there was a hot discussion about naming the etiology of unknown pneumonia in Wuhan as 2019-nCoV. Weibo activity increased dramatically starting from January 18, 2020 when daily newly confirmed cases of COVID-19 substantially increased. For personal account posts, a third peak was found on January 22, 2020 when the Wuhan government announced a policy of mandatory wearing of face masks in public places and human-to-human transmission of COVID-19 was announced by an expert who had just visited Wuhan for investigations, and the last peak within our study timeframe was detected on January 24, 2020, within 24 hours after Wuhan city was locked down. For posts from government agencies, and media and commercial agencies, the third peak was not observed and the last peak within the study timeframe occurred two days later. Overall, it appeared that public online reactions followed the spread of the disease and government actions and responded earlier than the government.

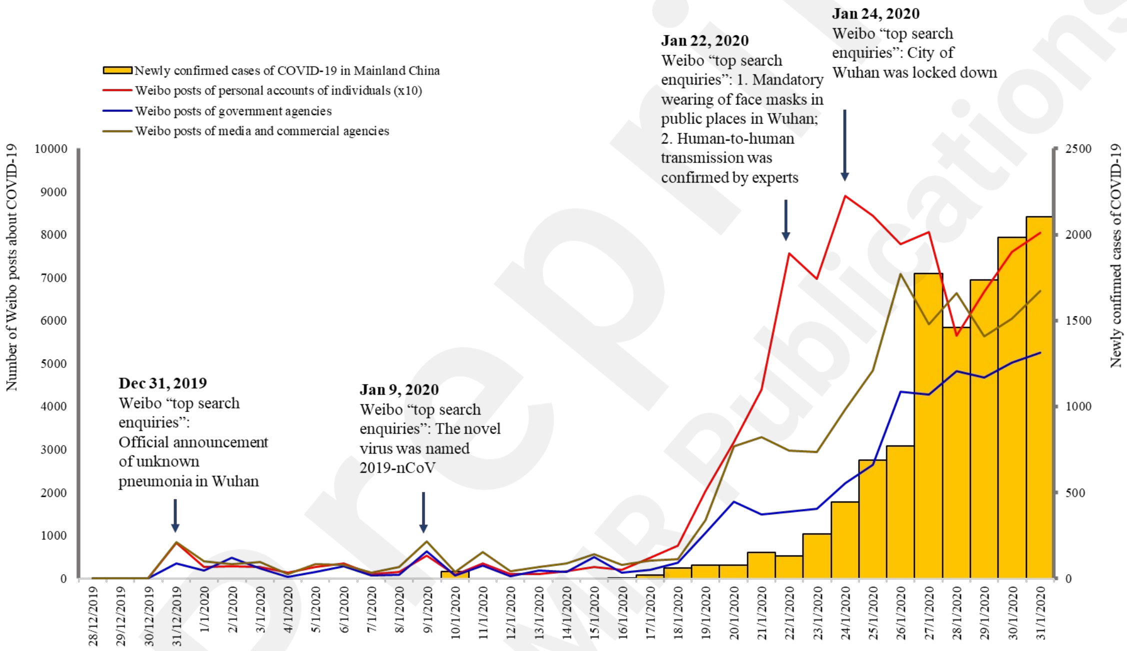


Figure 1 Daily numbers of newly confirmed cases of COVID-19 in Mainland China, daily numbers of Sina Weibo posts relevant toCOVID-19 by account and Weibo "top search enquiries" on peak days, December 2019-January 2020

Public engagement with government messages

Table 1 presents the engagement metrics of the five most active Weibo accounts of government agencies from the health and non-health sectors, respectively, in the communications about COVID-19 on Weibo. In health sector, the most active government agencies are the Municipal Health Commission (MHC) in several cities of China, including Wuhan, Zhuhai, Shanghai and Beijing, and one city-level hospital in Sichuan province, China. In China, the MHC in different cities are required to report duties to the provincial and national health commissions. In non-health sector, the most active government agency was the Hubei Branch of the Red Cross Society of China, an organization supervised by Chinese government that is mainly responsible for encouraging donation to support affected people during the epidemic. The remainders are from the system of public security bureaus that are responsible for tracking close contacts of COVID-19 patients, and implementing local policies of traffic restrictions during the epidemic. The engagement analysis shows that, despite being relatively more active compared with other government agency accounts based on the rank of engagement index, other than Wuhan MHC, all government agencies had low popularity (Likes per post per 1,000 followers), commitment (Comments per post per 1,000 followers) and virality (Shares per post per 1,000 followers). The NHC though having attracted a large number of followers had extremely low popularity, commitment and virality.

Table 1 Government agencies with greatest engagement and associated engagement metrices for COVID-19 communications in December 2019-January 2020

Government agencies	Number of posts	Followers	Popularity	Commitment	Virality	Engagement index
Top 5 from health sector						
Wuhan MHC	40	58,144	242.73	9.72	2.62	255.07
Zigong No.4 People's Hospital	21	298	42.03	5.27	0.96	48.26
Zhuhai MPC	18	11,844	27.82	3.53	1.18	32.52
Shanghai MPC	11	403,603	25.35	1.84	1.14	28.34
Daxing (in Beijing) MPC	12	65,707	14.41	1.61	1.38	17.41
Top 5 from non-health sector						
Hubei Branch of the Red Cross Society of China	21	97,523	78.20	8.70	1.10	88.01

Gaolan People's Procuratorate (in Gansu province)	22	550	13.06	4.71	1.82	19.59
Suixian People's Procuratorate (in Hubei province)	59	435	6.97	4.71	2.42	14.10
Longchang Public Security Bureau (in Sichuan Province)	26	8,803	12.51	0.73	0.20	13.44
Datong Fire Services Department (in Shanxi province)	13	2,155	8.07	2.75	0.82	11.64
National Health Commission of China	30	5,371,595	7.51	0.33	0.22	8.04

Popularity: Likes per post and per 1000 followers

Commitment: Comments per post and per 1000 followers

Virality: Shares per post and per 1000 followers

Engagement index= Popularity + Commitment + Virality

MPC: Municipal Health Commission

Individual and government post contents

Frequencies and proportions of thematic categories of post contents of personal and government accounts are shown in Table 2 while detailed descriptions of the thematic categories identified in our study can be found in the Multimedia Appendix 1.

We noted three cyber-support behaviours from personal account posts: *sharing knowledge/information*, *emotional exchange* and *seeking information* of which only the first two were identified in government posts. As is shown in Table 2, for *sharing knowledge/information* in both groups, the most common thematic categories were situation updates of COVID-19 followed by general knowledge about coronavirus pneumonia and advice on preventive measures. Government agency posts were more likely to share information about policies, guidelines, and official actions (χ^2_1=14.5, *P*<.001), and instrumental support (χ^2_1=32.5, *P*<.001), while personal account posts were more likely to share information on public responses to the epidemic (χ^2_1=19.1, *P*<.001). Personal account posts were more likely to be classified as *emotional exchange* (χ^2_1=30.5, *P*<.001) including showing empathy to affected people (χ^2_1=13.3, *P*<.001), attributing blame to people or organization for malpractice during the epidemic (χ^2_1=28.9, *P*<.001), and expressing worry about the epidemic (χ^2_1=32.1, *P*<.001). The government posts more likely praised people or organization (χ^2_1=8.7, *P*=.003). The main groups of people praised by both groups were health care workers, while the main people/organizations being blamed in personal account posts included other individuals (e.g. individuals who consumed wild animals, breached the infection containment measures and committed medical violence) and the government (individual government officers or government in general). Regarding *seeking information*, the main information sought was about the update epidemic situation.

Compared with post contents of government agencies from health sector, we found that the four government agencies from system of public security bureaus were more likely to share information about situation update (χ^2_2=15.9, *P*<.001), while the Hubei Red Cross Society of China were more likely to post contents about instrumental support (e.g. donation of materials or money) (χ^2_2=25.3, *P*<.001) and showing empathy to affected people (χ^2_1=25.7, *P*<.001).

Table 2 Frequency of thematic categories from posts delivered by individual and government accounts

Thematic categories	Individuals (N=644)[a] (N, %)	Government (N=273)[b] (N, %)	*P*-value [a]
Sharing knowledge/information	567 (88.0)	258 (94.5)	.003
Situation update of COVID-19	287 (44.6)	108 (39.6)	.16
General knowledge about coronavirus pneumonia	206 (32.0)	82 (30.0)	.39
Advice on preventive measures	114 (17.7)	56 (20.5)	.32
Policies, guidelines and official actions	95 (14.8)	69 (25.3)	<.001

Human-to-human transmission	79 (12.3)	27 (9.9)	.30
Fight against rumours	46 (7.1)	23 (8.4)	.50
Cause of viral emergence	44 (6.8)	14 (5.1)	.33
Public response during the epidemic	43 (6.7)	0	<.001
Instrumental support	13 (2.0)	29 (10.6)	<.001
Infection and illness experience	10 (1.6)	2 (0.7)	_[b]
Seeking social support	10 (1.6)	0	_[d]
Request for information transparency	8 (1.2)	0	_[d]
Reports of scientific research	3 (0.5)	0	_[d]
Seeking close contact	0	2 (0.7)	_[d]
Emotional exchange	321 (49.8)	82 (30.0)	<.001
Showing empathy to or blessing affected people	86 (13.4)	14 (5.1)	<.001
Blaming people or organizations	78 (12.1)	3 (1.1)	<.001
Providing reassurance about risk	73 (11.3)	30 (11.0)	.88
Expressing worry or fear about the risk	70 (10.9)	0	<.001
Praising people or organizations	53 (8.2)	40 (14.7)	.003
Warning about the epidemic	48 (7.5)	11 (4.0)	.05
Seeking information	36 (5.6)	0	<.001

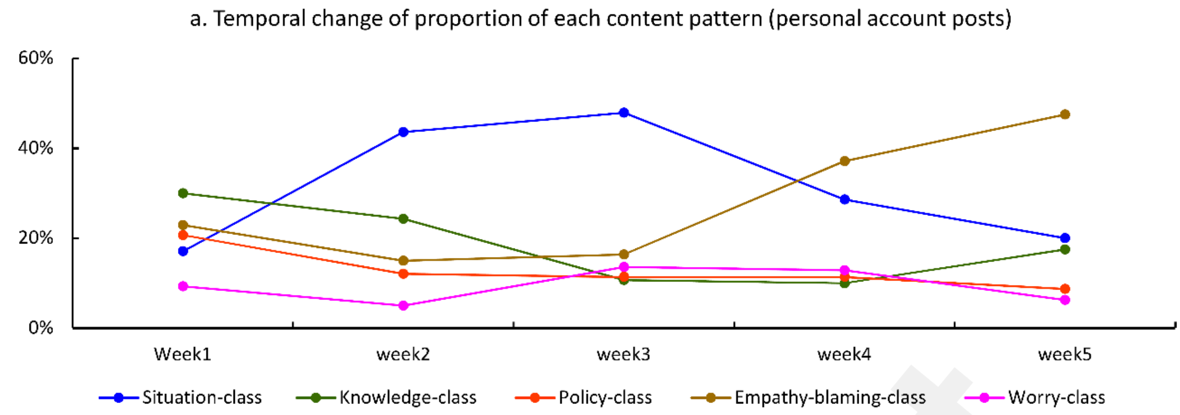
[a] *P*-values were calculated using Pearson chi-square test.

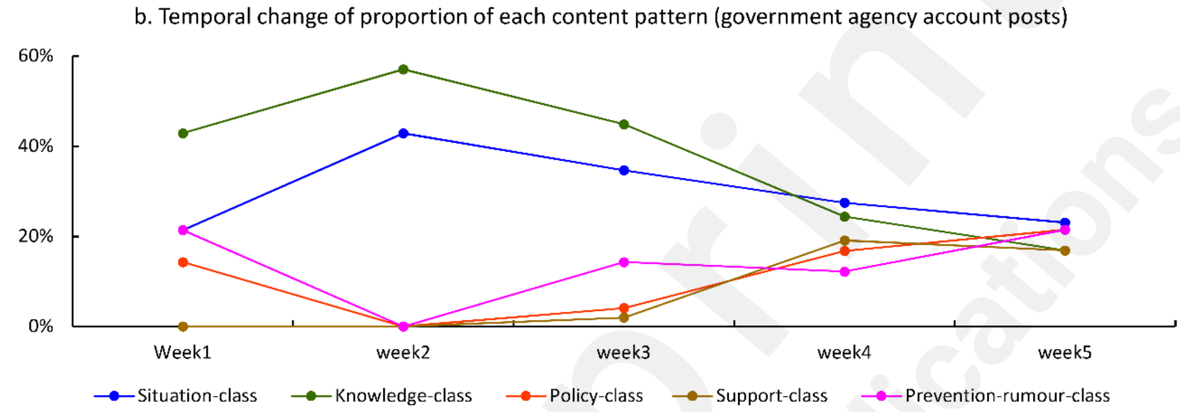
[b] Cell with expected frequency less than 5 and thereby *P*-values of chi-square test were not available.

Content patterns and temporal changes

The LCA revealed five main content patterns within personal posts and government posts, respectively (Multimedia Appendix 2). For personal posts excluding the four posts before December 31, 2019, the most prevalent content pattern comprising posts that mainly sharing situation update (situation-class) (208/640, 32.5%), followed by those with greater probabilities of showing empathy and blaming (empathy-blaming-class) (166/640, 25.9%), those mainly sharing general knowledge (knowledge-class) (119/640, 18.6%), those mainly sharing policy, guidelines and official actions (policy-class) (85/640, 13.3%) and those mainly sharing worry about the epidemic (worry-class) (62/640, 9.7%). For the government posts, three similar classes as those in the personal posts were found, including the situation-class (77/273, 28.2%), knowledge-class (79/273, 28.9%) and policy-class (40/273, 14.7%) (Multimedia Appendix 3). Another two classes were different from those of the personal posts including posts that mainly sharing prevention tips and fighting against rumours (prevention-rumours-class) (40/273, 14.7%) and those mainly providing instrumental support, praising people and slightly higher probability of showing empathy (support-class) (37/273, 13.6%) (Multimedia Appendix 3).

The temporal change of each content pattern by type of account were shown in Figure 2. The Chi-square for rend analyses found that for personal posts, proportions of posts sharing situation update increased from Week 1 (Dec 31, 2019-Jan 6, 2020) to Week 3 (Jan 14-20, 2020) (χ^2_1 for trend=28.6, *P*<.001) but declined thereafter (χ^2_1 for trend=19.7, *P*<.001), sharing general knowledge (χ^2_1 for trend=15.3, *P*<.001) and policies, guidelines and official actions (χ^2_1 for trend=15.3, *P*<.001) declined by week, while showing empathy and blaming increased significantly in later weeks (χ^2_1 for trend=25.3, *P*<.001) and worry about the epidemic remained stable and low. For government agency account posts, sharing situation update, prevention tips and fighting against rumours remained stable, sharing general knowledge declined by week (χ^2_1 for trend=14.7, *P*<.001), while sharing policies, guideline and official actions (χ^2_1 for trend=8.9, *P*=.003), and providing instrumental and emotional (empathy and praising people) (χ^2_1 for trend=9.0, *P*=.003) increased significantly at the last two weeks within the study timeframe.





We also specifically how providing reassurance, a main emotional content in government posts, changed as the epidemic evolved. We found that providing reassurance in government posts was more frequent at the first three weeks but declined in the last two weeks within the study timeframe (χ^2_1 for trend=4.2, *P*=.04)

Discussion

Principal findings

The Weibo activity in the early stage of COVID-19 epidemic showed that public reactions seemed to follow the spread of the disease and government actions in China. This again evidences the value of infodemiology or infoveillance studies to understand public response to the disease and government actions during the early epidemic stage despite a concern over censorship of online information for propaganda purposes in China. One post blaming people who consumed wild animals for causing “Wuhan pneumonia” was captured on December 29, 2019. On December 30, 2019, three more posts were identified: two seeking confirmation about unknown pneumonia cases detected in Hunan Seafood Market in Wuhan and one sharing information about unknown pneumonia cases found in the market. All four posts were from accounts of individuals who lived in Wuhan. This indicates that before official announcement of the first cluster of unknown pneumonia in Wuhan on December 31, 2019 [1], relevant information had been spread in the public through interpersonal communication, social media or other channels. The first government post was delivered on December 31, 2019, two days after the first individual post, indicating that although the Chinese government's outbreak communication has been more timely and transparent compared with their response to the 2003 SARS outbreak [48], more efforts are required to improve early outbreak communication when uncertainty usually challenges communication. Early posts should be treated as alarms and responded timely rather than being silenced which could receive harsh criticism and worsen the epidemic control [49].

Our study evidences the use of social media among the Chinese government agencies in the communications about COVID-19 at the early epidemic stage but remained limited. The engagement analysis indicates that the general public generally had low engagement with government agency posts even those from the most active government agencies. In China, the NHC is expected to play a leading role in risk communication during an epidemic while provincial and municipal health commissions are expected to report duties and provide epidemic information of their own provinces and cities, respectively, to the NHC. However, although the NHC and provincial health commissions have attracted a large number of followers on social media during the epidemic, compared with municipal health commissions, messages of these high-level health authorities were more disengaged by the general public. The generally low values of engagement metrics, popularity (Likes per post per 1,000 followers), commitments (Comments per post per 1,000 followers) and virality (Shares per post per 1,000 followers), may indicate low level of interest, utilization, emotional arousal or even credibility of the government information among the online audience [50, 51].This may partly reflect a population inertia effect, where it takes a certain amount of time, or threat before there is a noticeable change in the bulk practices of a population. The duration of such a period of inertia would be valuable to know.

The content analysis suggests that the Chinese government agencies mainly used social media to “inform” public about the update of epidemic situation, knowledge of coronavirus pneumonia, policies, guidelines and government actions, and prevention tips, all being the key risk messages included in the official websites of health authorities for communicating about an epidemic [40]. This suggests that government agencies mainly adopt a top-down approach in risk communication and use the social media for one-way communication. The temporal changes of content patterns of personal posts indicate that the public have less interest in situation update, general knowledge, policies and guidelines as the epidemic evolves. However, the public may feel more empathic with the affected people and angry about other individuals or government who put people at risk as increasingly number of people are affected by the disease and the control measures. Government seemed to keep on frequently sharing situation update, policies, guidelines and official actions, and prevention tips despite a decline in public interest. However, we also observed a significant increase in frequency of instrumental and emotional support in government posts as the epidemic evolved. This provides in-depth understanding about why sentiment analysis indicates decline in negative sentiment but increase in positive sentiment as the epidemic unfold [35]. The inconsistent temporal changes in content patterns between personal and government posts and insufficient emotional support of government posts indicates overall inadequate government responsiveness to public concerns. Reassuring the public about the epidemic risk was one main emotional content identified from the government posts and was particularly apparent in the first two weeks even Weibo data indicates generally low risk awareness and concern among the general public. This is consistent with the public response to the 2009 influenza A/H1N1 pandemic shown by twitter data [37]. Our study indicates that this may be because the government over-reassured the public at the early epidemic stage, which is against Sandman's guidelines that risk communication should lean towards the alarming side particularly when the situation is uncertain [52]. However, reassurance should be provided as more people are infected to deal with excessive or prolonged fear. The increasing use of blame in personal posts as more people were infected coincides with Douglas' idea that contemporary risk is highly politicized [53]. As more people are affected, "whose fault?" become a primary question to seek the accountability of certain persons or organization and make sense of the epidemic [27]. Our study found that the public blamed not only individuals who put others at greater risk during the epidemic but also government, particularly local government figures for their perceived failures in risk communication and control measures. This also aligns with Beck's works on global risk society in which authorities are increasingly questioned and blamed for failing to protect individuals [54]. Current data reveal seldom use of conspiracy theories in the attribution of blame and blame as a way to spread rumours [55]. In contrast, the government agencies tend to praise people who had made contribution to the control of the epidemic. This is viewed as a blame avoidance strategy, called heroization [55], to direct public outrage to the appreciation of another group of people. Working with heroes in outbreak communication may be critical to improve communication effectiveness.

Limitation

First, individual posts were sampled by randomly choosing equal numbers of posts per calendar day for content analysis rather than using the common probability-based random sampling which would generate a large sample size due to vast amount of social media data. However, there is current no consensus about how to best sample social media data, and our sampling strategy was able to draw a random manageable sample using manual coding. Second, only posts of government agencies that were relatively more actively engaged with the general public in online communication about

COVID-19 were included for content analysis. This means that the sample of government posts for content analysis may not be representative of all government posts. However, this sample was considered to have greater impact on online audience's knowledge, perceptions, attitudes and behaviours due to greater audience's interest and attention to their messages. Third, our study did not evaluate the responses to and concerns over COVID-19 among non-netizens particularly those living in rural areas, and older people in China [24], and Chinese government's communications about COVID-19 through other channels. In addition, our data only covered the first five weeks after unknown pneumonia cases in Wuhan were first officially announced which is a relative short but critical period for outbreak communication. Furthermore, due to the problem of censorship on Weibo data in China, our data based on keywords extraction may lose a considerate part of Weibo data particularly those posted before the official announcement of the outbreak in Wuhan. This means that our data may not be able to accurately assess the delay of government responsiveness to the threat online.

Implications

The governments can closely monitor the social media discussions to identify public concerns to further improve government responsiveness in outbreak communication. To improve government responsiveness and public engagement, first, persons who have received training in risk communication can be designated for monitoring public concerns online, delivering timely messages, communicating about the uncertainty, and also making efforts to address public concerns online. Second, municipal health commission can communicate more locally relevant information to attract local followers' interest and motivate their information sharing. Third, the provincial and national health commissions can organize direct dialogues with online audience on social media (e.g. Weibo Chats) jointly with trustworthy health care workers to capture audience's attentions and interests, and facilitate the rapid spread of fact-related messages [39]. While the main role of NHC in risk communication may be to disseminate facts, increasing messages showing empathy and care to affected people as the epidemic evolves is believed to be essential for maintaining credibility and trust in the public during a crisis [14].

Conclusion

The public seemed to respond earlier to the outbreak of COVID-19 online than government agencies. The Chinese government agencies' use of social media for outbreak communications remained limited to provide knowledge and information to the general public. As the epidemic evolved, the public had declining interest in fact-related messages but became more empathic with the affected people and tend to attribute blame to other individuals or the government. The tendency of increasingly attributing blame to other individuals or the government may push the Chinese government to seek accountability and refine the compensation system for affected people. As more people are affected, the government may adopt a more empathic communication style to address public emotional response.

Multimedia Appendix 1: Descriptions of thematic categories of post contents

Multimedia Appendix 2: Comparing model fit indices of LCA Models with different number of latent class by personal accounts and government agency account

Multimedia Appendix 3: Item-response probabilities of each latent class of the five-class model by personal account and government agency account

Conflicts of Interest

None declared.

Abbreviations

COVID-19: the coronavirus disease 2019

LCA: Latent class analysis

MHC: Municipal Health Commission

NHC: National Health Commission of China

PWC: Python Web Crawler

SARS-coV-2: severe acute respiratory syndrome coronavirus 2

SARS: severe acute respiratory syndrome

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Supplementary Files

Multimedia Appendixes

Figures

Multimedia Appendixes

Other materials for editor/reviewers onlies