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Analysis of social media data for public emotion on the Wuhan lockdown event during the COVID-19 pandemic

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ABSTRACT

Background: With outbreaks of COVID-19 around the world, lockdown restrictions are routinely imposed to limit the spread of the virus. During periods of lockdown, social media has become the main channel for citizens to exchange information with others. Public emotions are being generated and shared rapidly online with citizens using internet platforms to reduce anxiety and stress, and stay connected while isolated.
Objectives: This study aims to explore the regularity of emotional evolution by examining public emotions expressed in online discussions about the Wuhan lockdown event in January 2020.
Methods: Data related to the Wuhan lockdown was collected from Sina Weibo by web crawler. In this study, the Ortony, Clore, and Collins (OCC) model, Word2Vec, and Bi-directional Long Short-Term Memory model were employed to determine emotional types, train vectorization of words, and identify each text emotion for the training set. Latent Dirichlet Allocation models were also employed to mine the various topic categories, while topic emotional evolution was visualized.
Results: Seven types of emotions and four phases were categorized to describe emotional evolution on the Wuhan lockdown event. The study found that negative emotions such as blame and fear dominated in the early days, and public attitudes towards the lockdown gradually alleviated and reached a balance as the situation improved. Emotional expression about Wuhan lockdown event were significantly related to users' gender, location, and whether or not their account was verified. There were statistically significant correlations between different emotions within the subtle emotional categories. In addition, the evolution of emotions presented a different path due to different topics.
Conclusions: Multiple emotional categories were determined in our study, providing a detailed and explainable emotion analysis to explored emotional appeal of citizen. The public emotions were gradually easing related to the Wuhan lockdown event, there yet exists regional discrimination and post-traumatic stress disorder in this process, which would lead us to pay continuous attention to citizens lives and psychological status post-pandemic. In addition, this study provided an appropriate method and reference case for the government's public opinion control and emotional appeasement.

1. Introduction

COVID-19, caused by SARS-CoV-2, is a novel infectious disease that was declared a public health emergency of International concern on the 30 January 2020 [1]. The World Health Organization (WHO) declared COVID-19 a pandemic on the 11 March 2020 [2]. In late December, 2019, the Wuhan Municipal Health Commission reported that an unknown pneumonia case had been found in Wuhan city, Mainland China. In the proceeding weeks, the number of confirmed cases in Wuhan city increased rapidly and began to spread to other provinces in Mainland China. To control the epidemic, the government of Wuhan announced a city-wide lockdown on 23 January 2020 [3]. The sudden and strict policy affected nearly 10 million people across the city which caused heated discussion on social media at the time. After 76 days of restrictions,

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the lockdown of Wuhan was lifted after the city declared that the virus was fully controlled [4].

The term 'Lockdown' refers to large-scale isolation and social distancing restrictions of citizens in response to public health emergencies in a specific area. Citizens are asked to self-isolate or home-quarantine and minimize contact with other households [5]. It is a derivative event of public health emergencies [6]. The 76-day lockdown of Wuhan was effective in controlling the spread of COVID-19 [7–8]. Throughout 2020, as COVID-19 spread worldwide, regional, and national governments have imposed restrictions based on physical social distancing and implemented tiered measures to limit or halt human contact [9]. Extant studies into lockdowns have mainly focused on four key aspects. First, the effectiveness of lockdown policies has been studied widely to control the spread of epidemics [7,10]. The imposing strict lockdown policies leads to poor responses from citizens, even disgust or resistance, which can greatly reduce the effectiveness of a lockdown [11]. Second, some studies have focused on the improvement effect of lockdowns on the natural environment [12,13]. Third, the impact of lockdowns on the social economy, education, and health care, have been widely studied [14,15]. For example, Webster [16] concluded that forms of medicine and the provision of healthcare will change, with increasing virtual services being offered to patients. Finally, other studies have examined the impact of lockdowns on individuals, such as changes in habits and lifestyle [17], health problems of non-infected patients [6,18], and psychological distress caused by quarantined persons [19]. The outbreak of disasters can cause increased anxiety and depression symptoms and post-traumatic stress disorder [20].

During the lockdown of Wuhan, citizens required isolation which led to an increase of online communications [21]. Social media platforms became the main channel for information exchange, allowing citizens to view facts and share opinions. Residents shared their daily experiences, epidemic-related news, and views about isolation, which became an important channel for risk communication [22]. During public emergencies, citizens become netizens and exchange information on social media [23]. Discussions about the Wuhan lockdown were mainly shared on social media which became an important channel for promoting risk communication [24]. Public opinion is a double-edged sword. Moderate responses can improve awareness of disease prevention and control the virus spreading between individuals, but overreaction can have a negative impact on the crowd [25]. From an emergency management perspective, obtaining event information from related posts can provide valuable insights for victims, emergency personnel, and emergency services [26–29]. From the perspective of public opinion, analyzing the opinions and psychological changes of citizens, in the face of emergencies, can provide relevant reference information for governments in their fight to prevent public outcry, anxiety and stress [30–33].

In review of public opinion studies, most have focused on public opinions towards COVID-19, while few studies have explored the public opinion on the Wuhan lockdown event. Further, most studies have analyzed emotions based on three categories: positive, neutral, and negative. However, these categories lack subtle changes in emotion. In some emotion analysis studies, the categories of emotion were not based on psychology, which the sensitivity and robustness of emotion categories need to be considered. This study, therefore, requires a more detailed emotional analysis model to gain an understanding on public emotional demands and changes. Accordingly, we can start to understand the timely changes in citizens' emotions and opinions for confinement measures on social media, during the city-wide lockdown, and determine best practices for risk response and public opinion guidance.

2. Material and method

2.1. Data collection and pre-processing

Sina Weibo, the leading microblogging platform in China and one of the most popular social media sites, has over 516 million monthly active users, as of Q4 2019, with about 200 million users per day [34]. A web crawler was developed using Python to obtain data from the platform using the keyword "Wuhan lockdown". A total of 444,487 posts and 323,184 active users were downloaded from 21 January to 10 April, 2020, i.e., two days before the lockdown was enforced to two days after restrictions were removed. The dataset contained microblog data and user information, as shown in Textbox 1. To improve the data quality and follow-up specific task requirements, several data pre-processing activities were completed. First, non-text data was removed, including URL, HTML, and a series of emoji data like "***". Second, hashtags from posts, such as #Wuhan #Lockdown, were omitted which may affect subsequent topic analysis. Third, considering the differences in social media between Chinese mainland and Hong Kong, Macao and Taiwan, the posts and users related to Hong Kong, Macao and Taiwan were deleted. Fourth, special characters, punctuation and stop words were deleted to meet the requirements of specific tasks. Finally, a total of 443,082 posts and 322,040 active users were identified for subsequent analysis.

Textbox 1. Data fields extracted from Weibo.

Sina Weibo data
Id
User_id
Post-time
Text
Likes_count
Reposts_count
Comments_count
Is_reposted
Reposted_id
User info
User_id
Name
Gender
Verified
Followers_count
Follow_count
Posts_count
Location

A flowchart of emotion analysis during the Wuhan lockdown is shown in Fig. 1. Firstly, the data collected were denoised during pre-processing. On this basis, an appropriate amount of text was randomly selected to label emotional categories. Secondly, the lockdown event was divided into different phases according to changes in the volume of microblogging activity. Thirdly, to obtain the emotion category for each post, the emotion recognition model, based on the deep learning model, was built. Finally, the distribution of emotions in different dimensions and the evolution of emotions over time and topics were analyzed.

2.2. Life cycle of online public opinions

Life Cycle is a concept commonly used in the field of biology which describes the whole process of organic life from birth to death. During the energy crisis in the 1960s, the term 'life cycle' was widely used in various fields, especially in politics, economics,

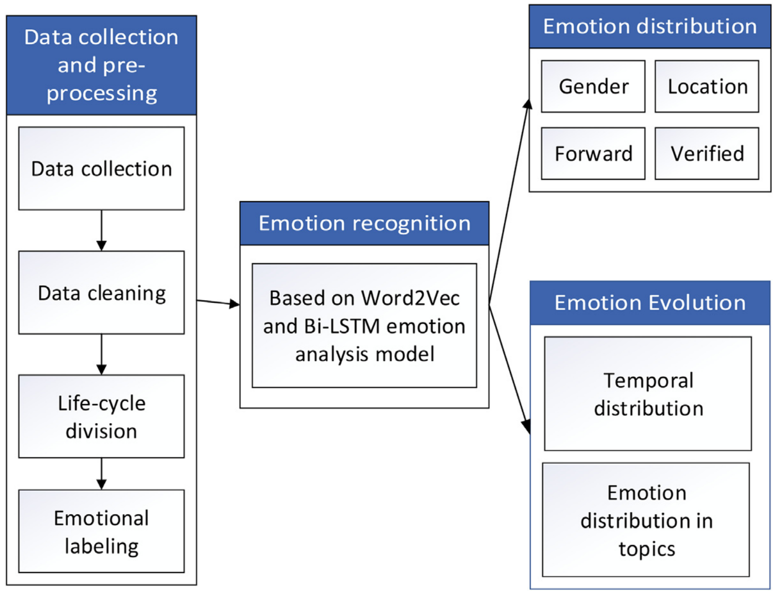

Fig. 1. Flowchart of emotion analysis during the Wuhan lockdown event.

environment, technology, society, and many other fields [35]. Online public opinions refer to a collection of information about a certain event which also arises and dies with the progress of the event [36]. One of the most influential division methods of crisis management is the Four-Stage Model of a Crisis Lifecycle: the prodromal stage, the acute stage, the chronic stage, and the resolution stage [37]. On the basis of Fink's model, scholars have further divided the life cycle of online public opinions during emergencies into four stages [38]. According to the number of posts and changes imposed by the government of Wuhan, online public opinions related to the lockdown event were divided into several phases over time, according to Fink's model.

2.3. Emotion analysis and topic mining

2.3.1. Emotion marking based on the Ortony, Clore, and Collins model

In emotion multi-classification tasks, the labeling of the training set is usually manually marked. Therefore, we require a unified sentiment labeling rule. The Ortony, Clore, and Collins model suggests that emotions are generated during the process of cognitive evaluation, which is determined by the consequences of events (desirability), aspects of objects (attractiveness), and actions of agents (praise/blameworthiness) [39]. The system corresponds to emotions through inducing factors, conditions, and their intensity. In the original model, the OCC model classified emotions into 22 emotion types. As a classic evaluation theory in cognitive psychology, the OCC model has been widely used in various fields, including artificial intelligence, in recent years, due to its ability to clearly explain and distinguish different emotion categories [40]. The emotional classifications of OCC model are very detailed based on psychology, which is robust and universal.

During the pre-analysis of posts, we found that posts did not involve the dimension of aspects of objects; in fact, they only concerned perspectives of consequences of events and actions of agents (desirability, praise). Meanwhile, we also referred to Ekman's 6 basic emotions [41], which was widely used in the study of emotion analysis. Finally, six emotion categories (admiration, reproach, hope, fear, joy, and distress) from the OCC model and a neutral emotion were taken to classify the emotions of microblog text. In Fig. 2, a tree structure was used to determine the emotional classifications for a specific post, based on elicitation conditions of the OCC model.

To achieve consistency in labeling, three Research Assistants (RAs) were hired to pre-label using the OCC rules. Then, the authors and RAs discussed the controversial content to determine a specification versus guidelines. Due to space confinement, please refer to the supplementary file for the specification versus guidelines. 10,000 posts were randomly selected from the preprocessed data to ensure 1,000 pieces at each phase. Then, after removing duplicates, they were manually labeled using the OCC-based emotion classification rules to obtain 1000 labeled posts for each emotion category, using a program written in Python, an annotation tool.

2.3.2. Emotional classifier using deep learning

Deep learning algorithms have generally achieved good performance, especially for multi-class emotion recognition as the neural network has a strong nonlinear fitting ability which can automatically extract complex features. Bi-directional Long Short-Term Memory (Bi-LSTM) is a variant of the Recurrent Neural Network (RNN) which has three 'gate' structures for forgetting and remembering. Compared with traditional RNNs, it can solve problems of gradient disappearance and explosion which are suitable for modeling sequence data [42].

This study used Word2Vec and Bi-LSTM to build an emotional classification model. Word2Vec is a deep learning model that generates word vectors that can effectively reflect the relationship between different words [43]. In the beginning, Word2Vec was employed to train the word vector for segmented words, performed using genism package in Python. Then, the word vector matrix converting by Word2Vec was entered into the Bi-LSTM model and connected the model to the Softmax layer to calculate the probability of the predicted target. The labeled samples were divided into a training set, validation set, and test set (8:1:1). After constantly adjusting the parameters, the final model on the test set represented a precision rate of 0.714, recall rate of 0.704, and F1 score of 0.706. Compared with the selection of four classic machine learning and deep learning algorithms, the LSTM classifier performed best on the same corpus, as shown in Table 1**.** Among others, the SVM model was performed using sklearn package; the deep learning algorithm was performed based on tensorflow platform and the keras package.

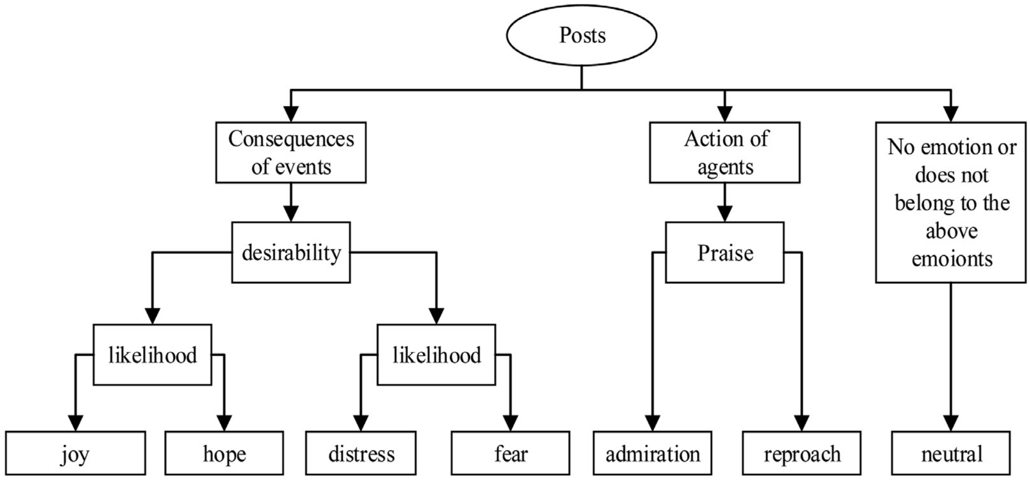

Fig. 2. Emotional classification rules based on the elicitation conditions of the OCC emotion model.

Table 1
Performance of the models for Emotion classification.

Type	Precision	Recall	F1-score
SVM[a]	0.854	0.258	0.223
RNN[c]	0.492	0.484	0.479
CNN[d]	0.614	0.597	0.603
Single-LSTM[b]	0.650	0.649	0.641
Bi-LSTM[e]	0.714	0.704	0.706

SVM[a]: Support Vector Machine.
Single-LSTM[b]: Long Short-Term Memory.
RNN[c]: Recurrent Neural Network.
CNN[d]: Convolutional Neural Network.
Bi-LSTM[e]: Bi-directional Long Short-Term.

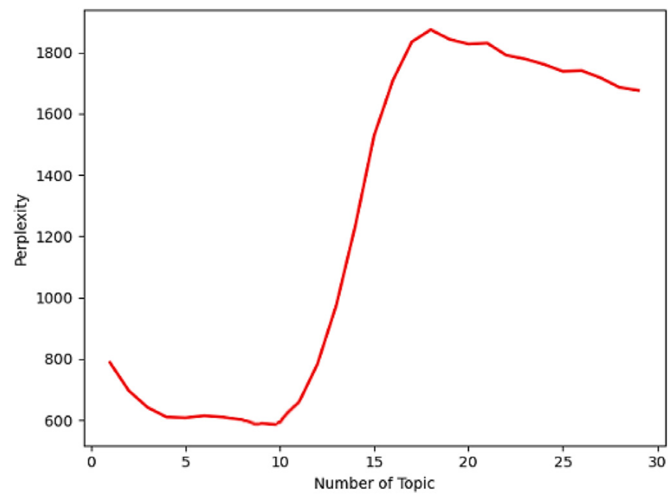

Fig. 3. The perplexity for the number of topics.

2.3.3. Topic mining and its emotional distribution

In 2003, Blei et al. [44] proposed the Latent Dirichlet allocation method. Latent Dirichlet allocation (LDA) is a Bayesian probability model that includes a three-layer structure: document-topic-vocabulary. The approach has been widely used in topic mining by researchers on account of its extension ability. First, jieba 0.42, the Chinese word segmentation tool, was employed for word segmentation. In using the stop-word list, we were able to delete words without practical meaning to obtain neat and structured data. Second, the Term Frequency-Inverse Document Frequency (TF-IDF) was used to extract document information and encode into Chinese digitally. Third, the TF-IDF matrix was input into the LDA topic model for training in the environment of genism, an open-source toolkit based on Python language. Finally, the perplexity of each topic was calculated to determine the optimal number of topics [45], as shown in Fig. 3. After removing the stop words and the low frequency words (118,599 null posts that can't work on topic analysis were deleted), the remaining 325,888 non-null posts were put into the LDA model. We calculated the topic distance, and formed a visual chart of the distance between topics with 8 topics as the best was identified. Two RAs were hired to annotate each LDA category with an appropriate name. Then, the categories of topics for each training post were calculated, so the topic categories and emotional classification for each post could be identified. Finally, we calculated the public attention, emotional distribution, and evolution for each topic over time.

3. Results

3.1. The Wuhan lockdown life cycle

To comprehensively understand the more detailed emotional changes during the entire event, the event was divided into four periods from 7 April to 11 April, 2020 refer to the Fink model: Prodromal Phase (Phase I), Acute Phase (Phase II), Chronic Phase (Phase III), and Resolution Phase (Phase IV), as shown in Fig. 4.

The incubation phase occurred from 20 to 23 January 2020. The 'Wuhan lockdown' event started on the Sina Weibo platform on the 20 January, 2020, because Nanshan Zhong, a Chinese Academician, made it clear, when he was interviewed, that COVID-19 was transmitted from person to person [46]. After one day, the government of Wuhan began to implement restrictions on people entering and leaving the city. At the same time, cases of infection had been reported in some cities or provinces across Mainland China, including Chongqing, Shanghai, and Sichuan. The acute phase was recorded from 23 to 27 January 2020. At 02:00 on 23 January 2020, the government of Wuhan issued the city-wide lockdown notification. Discussions about the Wuhan lockdown on Sina Weibo surged abruptly and reached a climax at 07:00 on the 23 January 2020. The third phase was the chronic phase which took place from 28 January to 12 February, 2020. Five days after the announcement of the city-wide lockdown, discussions on Sina Weibo began to decline, while the number of confirmed cases rapidly decreased. The final phase was the resolution phase, observed from 13 February to 7 April, 2020. Twenty days after the lockdown, the number of newly confirmed cases decreased significantly. In the following two months, the epidemic in Wuhan was gradually improving and the popularity of the topic remained stable at a low-level. In addition,

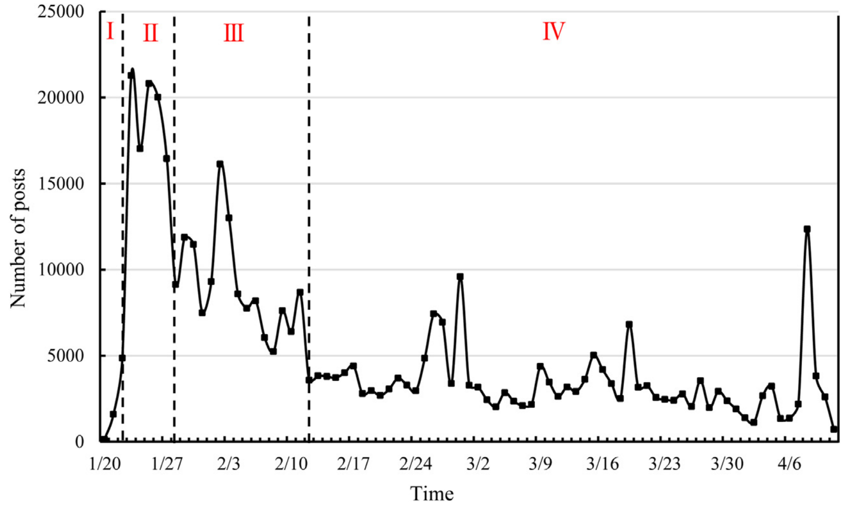

Fig. 4. A timing chart of the number of posts related to the Wuhan lockdown.

Table 2
The emotional distribution of posts based on gender. The column "z" was hypothesis test on the difference of the emotional proportion of male and female.

Emotional categories	Male (N=169,901), n (%)	Female (N=273,181), n (%)	z	p-value
Admiration	27,533(16.21)	40,591(14.86)	12.08	<.001
Hope	17,498(10.30)	39,504(14.46)	40.22	<.001
Joy	11,538(6.79)	30,541(11.18)	48.44	<.001
Neutral	43,433(25.56)	57,757(21.14)	34.08	<.001
Fear	14,682(8.64)	20,782(7.61)	12.32	<.001
Reproach	36,420(21.44)	45,737(16.74)	39.09	<.001
Distress	18,797(11.06)	38,269(14.01)	28.45	<.001

in the early morning of 8 April 2020, the government of Wuhan announced a complete lifting of traffic restrictions and the city-wide lockdown, which declared the end of the Wuhan lockdown.

3.2. Emotional distribution

3.2.1. Gender differences in emotional expression

As shown in Table 2, gender can create an effect on emotional expression. Males accounted for 36.88% (118,779/322,040) of total users included in our sample, which contributed 38.35% (169,901/443,082) of all posts. In general, male and female did not demonstrate a significant difference in the degree of attention. In terms of emotional expression, men demonstrated greater admiration, reproach and neutral, than hope, joy, and distress, when compared with women, but both genders expressed the same emotion of fear. However, in terms of emotional distribution, men held a higher proportion in the emotional dimension of 'object behavior', while females paid greater attention to the 'outcome of events'.

3.2.2. Emotional Distribution based on Whether or Not an Account is Verified

There are three user types officially verified by Sina Weibo: individuals, celebrities, and organizations. The total percentage of verified users accounted for 8.04% (25,901/322,040) of the sample, which contributed 12.89% (57,119/443,082) of all posts. The proportion of positive emotions (Admiration, Hope and Joy) of verified users accounted for 46.20% (26,388/57,119), which was higher than that of non-verified users 37.68% (145,416/385,963). Among them, differences in emotional distribution between verified and non-verified users was statistically significant except for joy, as shown in Fig. 5.

3.2.3. Differences between forwarded and original posts in emotional expression

Fig. 6 shows that most posts related to the Wuhan lockdown were forwarded. Reposts (or the sharing of posts) held the highest proportion of posts (243,038/443,082, 54.85%). In terms of the emotional distribution of forwarded posts which were comments on original posts, those forwarded accounted for more neutral and reproach than the original Sina Weibo post. Forwarded posts that demonstrated hope, joy, fear, and distress were lower than that expressed in original posts. Original posts, which were new pages created by users to express their views, accounted for a balanced proportion of all emotions. The differences of emotional distribution between original and forwarded posts was statistically significant. This emotional distribution of forwarded posts was similar to the distribution between genders. In addition, there exists a higher forwarding rate for males than females ($\chi_1^2 = 1130$, $P<0.001$).

The emotional changes of the post before and after being forwarded were also compared, as shown in Fig. 7. Among the forwarded posts, those showing admiration and neutral emotions were the two most sentiments. After forwarding, many users simply reposted without commenting, so neutral was the most sentiment emotion. The proportion of positive emotions always outweighed negative emotions before and after forwarding. In ignoring the interference of neutral emotions, negative emotions (fear, reproach, and distress) accounted for 31.7% (16,355/51,621) before being forwarded, but the proportion of reposts was 36.1% (14,225/39,368), with the difference being statistically significant ($\chi_1^2 = 198.3$, $P<0.001$).

3.2.4. Spatial Difference in Emotional Expression

The spatial distribution of posts during the Wuhan lockdown is illustrated in Fig. 8. From a geographical perspective, users

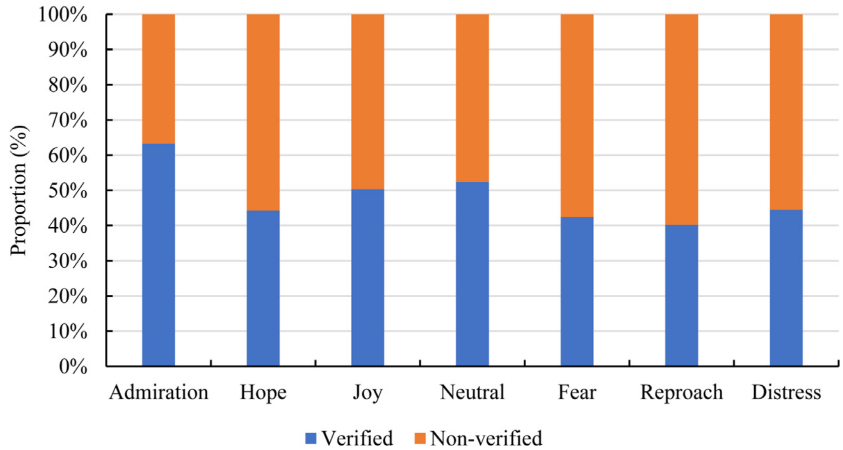

Fig. 5. The discrepancy of emotional distribution based on whether an account is verified or not. The y-axis represents the proportion of each emotion in the posts sent by verified users and non-verified users.

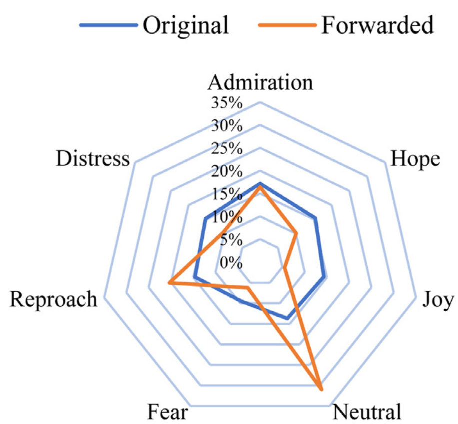

Fig. 6. Distribution of emotions based on forwarded versus original posts. The scale represents the proportion of a certain emotional posts.

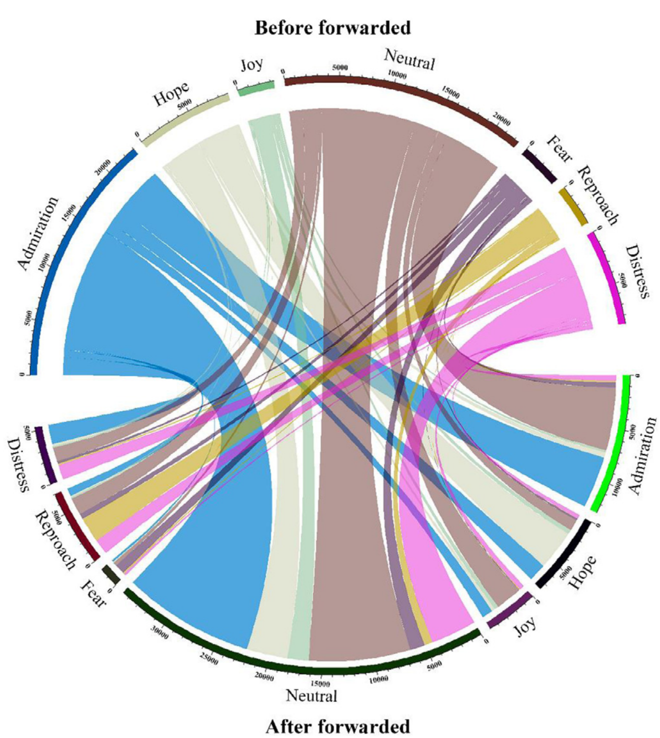

Fig. 7. Chord chart showing emotional changes in forwarding.

mainly presented two geographical distribution features. One was converged in Wuhan city and its surrounding provinces, while the other was concentrated in Beijing-Tianjin-Hebei (Northern China, A1), the Yangtze River Delta (Eastern China, A2), the Pearl River Delta (Southern China, A3), and the Chengdu-Chongqing metropolitan area (Western China, A4). Further, the statistical test results show a statistically significant correlation between the number of posts issued by each province and the cumulative number of confirmed cases officially reported from 20 January to 8 April 2020 ($r = 0.79$, $P < .001$).

The number of posts and confirmed cases had a negative correlation with the proportion of neutrality and fear, which was performed with two independent sample rate tests using IBM SPSS 19.0, as shown in Table 3. In addition, the number of posts and reproach represented a significant positive correlation. In the Hubei Province, the epicenter of the COVID-19 lockdown, neutral and reproach emotions were less, while joy and hope accounted for a larger proportion of posts; distress was more. It should be noted that reproach was relatively large in densely populated areas, such as Shanghai, Beijing, Guangdong Province, and Tianjin in China.

3.3. Emotional Evolution

3.3.1. Temporal Distribution of Emotions

Fig. 9 presents the emotional distribution in each phase. We found that in the first phase, the emotional distribution presented was extreme, with negative emotions focused on fear (28%, 1,818/6,593) and reproach (47.23%, 3,114/6,593). The proportion of joy and admiration rose in every phase, while fear was the opposite. Further, the emotion of distress increased before the unblocked phase. Temporal changes presented relevance between different emotions. For example, the proportion of posts related to joy and admiration, with fear, seemed to show a correlation. On the whole, the proportion of emotions showed a gradual convergence over time.

The correlation analysis of the proportion of various emotions in time was completed, performed using two independent sample rate tests, as shown in Table 4. Many emotions showed significant correlations with each other over time. Positive emotions were found to be negatively correlated with negative emotions, while neutral emotions and the other six emotions were negatively correlated, in general. It is worth noting that there was a negative correlation between admiration and hope, with the coefficient of association ($r = -0.303$, $P = .005$).

Table 3
Pearson Correlation coefficient between the number of posts and confirmed cases with proportion of emotion, except for the Hubei Province. Please refer to the supplementary file for the original data.

	Admiration	Hope	Joy	Neutral	Fear	Reproach	Distress
Num_posts	-0.095	-0.588**	0.146	-0.716**	0.540**	0.603**	0.236
Num_confirmeds	-0.244	-0.148	0.138	-0.531**	0.581**	0.119	0.433*

*P < .05, **P < .01.

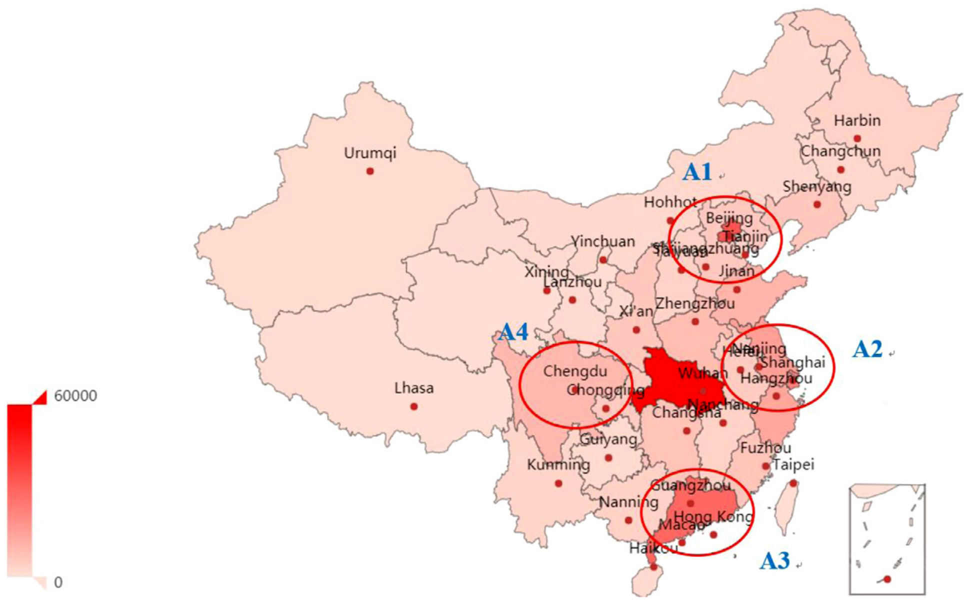

Fig. 8. Spatial distribution of users posted in the Wuhan Lockdown event.

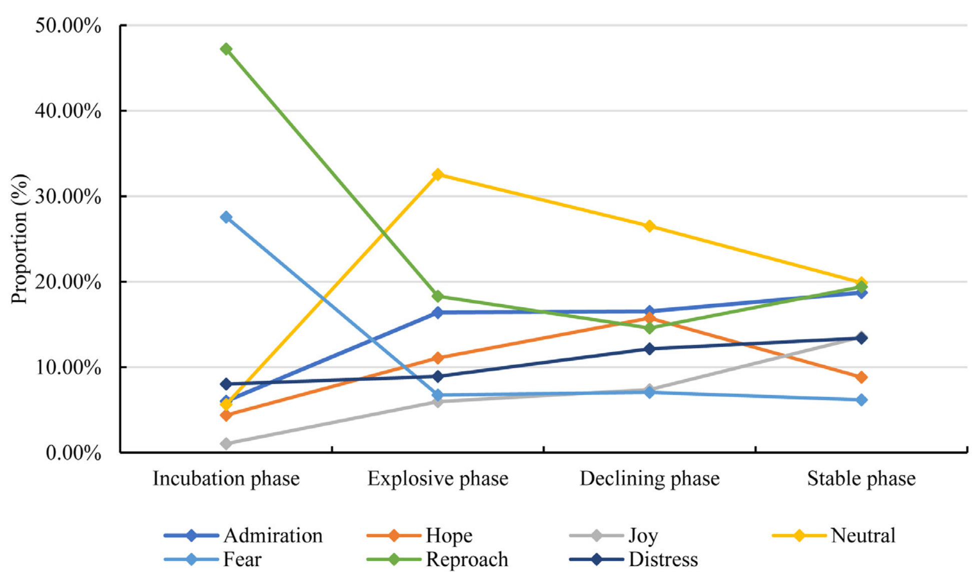

Fig. 9. Emotional evolution during each phase of the Wuhan lockdown.

3.3.2. Integrated Analysis of Topics and Emotions

There is no overlap among the 8 topics, as shown in Fig. 10, which indicates the independence between them: daily life under lockdown, traffic and travel restrictions, epidemic prevention, materials supply security, medical assistance, unblock of Wuhan, quarantine and treatment, and pray for safety. Due to confinement of space, please refer to the supplementary file for the results of each phase of the LDA.

Fig. 11 demonstrated the change of Emotional distribution for each topic on five phases. In the topic of daily life under lockdown, distress (22.32%) and joy (20.65%) accounted for more. As time goes on, the reproach and fear decreased, and the joy increased. In the topic of traffic and travel restrictions, and epidemic prevention, reproach and fear accounted for the majority of posts, which show public concern and dissatisfaction with the restrictions. In the topic of quarantine and treatment, reproach (30.80%), admiration (18.13%), and distress (15.78%) constituted the main emotion of posts. In the topic of materials supplies, reproach (22.95%) and admiration (29.22%) constituted the main emotion of posts, with admiration began to surpass reproach in the third phase.

Fig. 10. Intertopic distance map. PC: principal component.

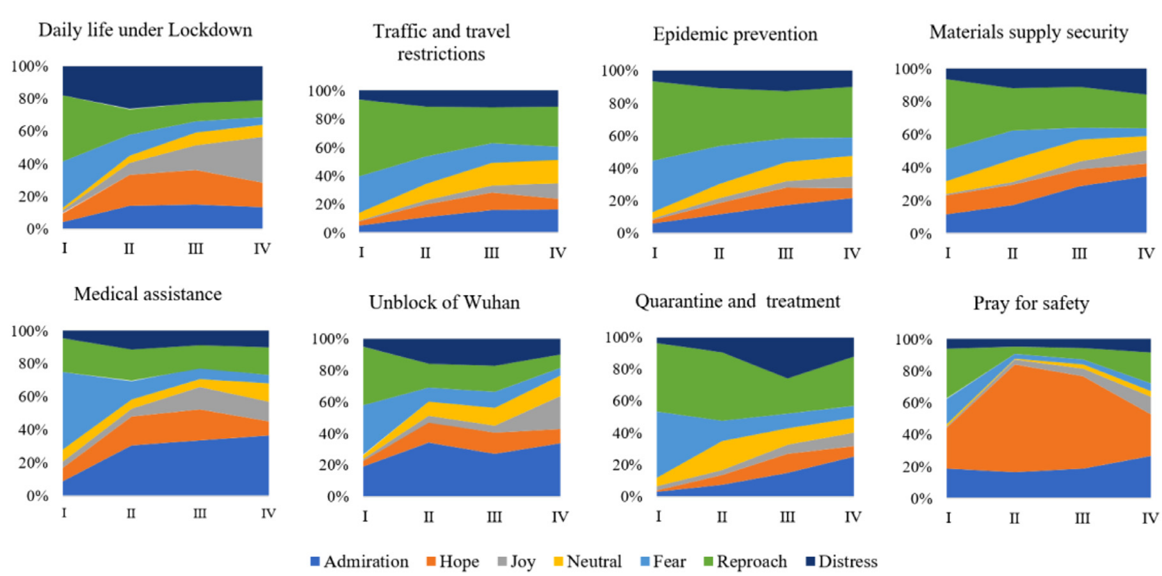

Fig. 11. Emotional distribution of topics during each phase of the Wuhan lockdown event. Vertical axes show the proportion of per emotion; horizontal axes depict the change of time in five phases. The area of each color represents proportion of per emotion in a topic.

Table 4
The Pearson correlation coefficient matrix among the proportion of emotions. Please refer to the supplementary file for the original data.

	Admiration	Hope	Joy	Neutral	Fear	Reproach	Distress
Admiration	1.000						
Hope	-0.303**	1.000					
Joy	0.300**	-0.202	1.000				
Neutral	0.103	-0.098	-0.082	1.000			
Fear	-0.379**	-0.370**	-0.345**	-0.458**	1.000		
Reproach	-0.397**	-0.031	-0.428**	-0.398**	0.476**	1.000	
Distress	-0.235*	0.280*	-0.048	-0.262*	-0.282**	-0.179	1.000

*$P < .05$, **$P < .01$.

In the topic of medical assistance, reproach (16.29%) and admiration (34.31%) constituted the main emotion of posts, yet reproach quickly dwindled that indicate the prompt of medical help from other areas. In contrast to the topic of traffic and travel restrictions, the topic of unblock of Wuhan showed more positive with the admiration accounted for 31.89% total. In the final topic of pray for safety, the emotion of hope accounted for 52.43% total and reached the maximum in the second and third phase.

4. Discussion

4.1. Netizens are inclined to express Varying Emotions due to differences in Gender, Forwarding, and Account Verification

In this study, we found that a user's gender, whether or not the post was original or forwarded, and whether their account was verified, had different effects on emotional expression. Females were inclined to express the desirability of event, while males were apt at expressing the blameworthiness of event. This behavior reflected that the demands of men and women are discrepant in emergencies. That is, men seek an explanation about the cause of emergency while women expect a good outcome. Similarly, a month after the outbreak of COVID-19, a survey in China showed that women have a higher post-traumatic response [47]. Moreover, netizens, who are verified by Sina-Weibo with higher information integrity and influence, tended to present positive and correct information [48]. As forwarded posts aimed to express one's views, they had a strong sense of evaluation. This study found that the proportion of negative posts increased after forwarding, which may lead to 'group polarization' in emotional evolution [49]. Therefore, we must create targeted strategies that guide different populations in the management of online public opinions, in view of the differences in the needs of different genders. Moreover, increasing the proportion of verified users may reduce the dissemination of false and negative information.

4.2. Different Measures should be taken to Solve Netizens' Responses from Different Regions

From a geographical perspective, there was a positive correlation between netizens' attention and the scope of public health incidents, which is comparable to similar studies [30]. With confirmed cases rising in their own regions, citizens expressed their concerns which led to changes in perception, attitudes, and behavior towards the Wuhan lockdown. This may intensify the contradiction between the epicenter and surrounding areas. For example, during the prodromal and acute phase, the stigmatization surrounding Wuhan, the information leakage of Wuhan citizens, and even regional discrimination [50], put further blame and pressure on the public. The more negative emotions were expressed by residents in developed areas. The proportion of joy and distress emotions in the Hubei Province remained larger than those in other regions, which may not be what was expected. Studies have shown that public opinion about natural disasters are more optimistic and positive than in accident disasters [51]. Compared with residents of other provinces, people who reside in the epicenter of the epidemic are more concerned about their lives during the incident. With regards to residents in other provinces, the correctness, effectiveness, and immediacy of the lockdown were discussed. To sum up, citizens of the epicenter and surrounding regions represented completely diverse perspectives on public emergency, which derives from their different interests towards crises.

4.3. Continuing Concerns of Residents should be Necessary because Emotions are not Independent

Public attitudes towards the Wuhan lockdown gradually changed for the better during various phases as the epidemic situation improved. This shows that Wuhan's response to the city-wide lockdown was a successful case. However, it is undeniable that the online public opinion was out of control during the early days of the epidemic, with some of the negative emotions continuing now. We can clearly see that the emotion of sadness gradually rose, indicating citizens' psychological problems during the event. Studies have shown that one in three patients have suffered from post-traumatic stress disorder following lockdown due to COVID-19 [52]. For example, economic difficulties and hypochondriasis, induced by epidemic news, can impact on the physiological and psychological behaviors of the uninfected [53]. Although the lockdown ended with the outbreak, citizens' psychological trauma continues. Continuous attention to people's psychological and living conditions should be paid by emergency departments to reduce the occurrence of posttraumatic stress disorder.

4.4. Evolution of Emotions Presented a Different Path due to Different Topics

Emotions are generated in the process of cognitive evaluation using the OCC model. During the Wuhan lockdown, individuals and reality were closely linked via the Internet which indicates that individual emotions are their response to reality. The proportion of three positive emotions gradually rose, while the negative emotion decreased during the lockdown, which reflected an improving and calming down of the epidemic. For example, the emotions of admire and joy are the expression of desirable things with certainty, while the emotion of hope is generated from desirable things with uncertainty. With the epidemic improving, expectations turned to reality, which answers why hope declined, but admiration and joy increased. During the lockdown of Wuhan, information flows presented a closed loop between fact, social media, and individuals [22]. Social media became the main channel for individuals to obtain information. However, the phenomenon of 'group polarization' may be more obvious in the lockdown, due to the lack of accurate information feedback from offline channels. Drawing lessons from the early stage of the Wuhan lockdown, we should increase information disclosure to avoid panic among citizens in disaster-stricken regions. Timely information disclosure can effectively reduce the dissemination of false information among individuals, reducing the likelihood of negative emotions [54].

5. Conclusions

This study, through the OCC model and deep learning algorithm built 7 classified emotion models, successfully identifying public emotions on social media during the Wuhan lockdown. Further, we explored the topic features using lifecycle based LDA, which can help in the understanding of the real psychological status and emotional appeals under emergencies, and provide an experience for public opinion guidance under the blockades. There were several limitations existing in our study. First, we can only obtain up to 1,000 pieces of posts within one hour, yet the number of posts at most times didn't exceed this ceiling. Second, the information of users' locations and gender were from the registration of users instead of those of the actual post or comment, but this may be different from reality which may introduce bias towards the results and discussions. Finally, repeating posts exist between the original posts or between the forwarding posts, which also brought bias to the results and discussions to some extent. Further research is needed to find out the influencing factors of the spread of public emotions on social media. Researches should also consider the emotional diversity of text and adopt appropriate emotion recognition models to judge the multi-emotions expressed in social media texts.

Declaration of interests

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

CRediT authorship contribution statement

Guang Cao: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Lining Shen:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Funding acquisition. **Richard Evans:** Writing – original draft, Writing – review & editing. **Zhiguo Zhang:** Writing – review & editing. **Qiqing Bi:** Methodology, Validation. **Wenjing Huang:** Writing – original draft. **Rui Yao:** Methodology, Software. **Wenli Zhang:** Software, Visualization.

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