Locked down in Wuhan: Exploring the evolution of public emotions during the COVID-19 pandemic

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Submitted to: Journal of Medical Internet Research
on: December 05, 2020

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Abstract

Background: In late December 2019, Wuhan Municipal Health Commission reported the first cases of SARS-CoV-2, the underlying virus that caused the devastating outbreak of the coronavirus (COVID-19). On 23 January 2020, the government of Wuhan announced a city-wide lockdown with the aim of controlling the spread of the virus. With outbreaks of COVID-19 around the world, lockdown restrictions are routinely imposed to limit the spread of the virus and reduce the strain on healthcare services. During periods of lockdown, social media has become the main channel for citizens to exchange information and communicate with friends and family. Public emotions and opinions are being generated and shared rapidly online with citizens using internet platforms to reduce anxiety and stress, and stay connected while isolated.

Objective: This study aims to explore the regularity of emotional evolution by examining public emotions expressed in online discussions during the lockdown of Wuhan in January 2020. We divide the lockdown into different phases and analyze the distribution of emotions against different dimensions. Further, the temporal evolution of emotion and the topic-based emotional distribution during each phase of the Wuhan lockdown is determined.

Methods: Data related to the Wuhan lockdown was collected from Sina Weibo, the most active microblogging site in China, 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 found in each phase, while topic emotional evolution was visualized.

Results: Based on the OCC model, seven types of emotions were categorized to describe emotional distribution during the Wuhan lockdown: admiration, hope, joy, neutral, fear, reproach, and distress. Among these, admiration and reproach held the largest proportions of emotional expression. Further, expressions of emotion were significantly related to users' gender, location, and whether or not their account was verified. The lockdown was divided into five phases, incubation phase, explosive phase, declining phase, stable phase, and unblocked phase, which showed citizens emotions transition from reproach and fear, through reproach and admiration, hope and admiration, to reproach and admiration, then to joy and admiration. Admiration and joy increased while fear declined. There were statistically significant correlations between different emotions within the subtle emotional categories. The topics showed that public attitudes towards the lockdown gradually improved. In addition, emotional evolution was influenced by topics, but not limited to them.

Conclusions: This study revealed insights into public emotions expressed on Sina Weibo during the lockdown of Wuhan in January 2020. Seven emotion categories were determined, providing governments with greater appreciation of citizen emotions to support them and develop appropriate policies to minimize stress and anxiety. The responses of the government of Wuhan were found to comfort citizens during lockdown which can be used as best practice or a case for other countries and regions

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(JMIR Preprints 05/12/2020:26269)
DOI: https://doi.org/10.2196/preprints.26269

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KEYWORDS: emotion analysis; OCC model; COVID-19; public opinion; emotional evolution; Wuhan lockdown; machine learning.

1 Introduction

1.1 Background

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]. By September 2020, more than 26 million confirmed cases and 870,000 deaths had been reported worldwide, covering more than 200 countries and regions. The World Health Organization (WHO) declared COVID-19 a pandemic on the 11 March 2020 [2]. On the 27 December, 2019, the WHO China Country Office were informed that a novel pneumonia had been found in Wuhan, Mainland China, with unknown causes. 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]. After 76 days of restrictions, 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 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 spreads worldwide, regional and national governments have imposed restrictions based on physical social distancing, and implemented tiered measures to limit or halt human contact [9].

During the lockdown of Wuhan, citizens required isolation which led to an increase of online communications [10]. 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 [11]. Accordingly, we can start to understand the timely changes in citizens’ emotions and opinions on social media, during the city-wide lockdown, and determine best practices for risk response and public opinion guidance.

1.2 Related Works

1.2.1 Online Public Opinion during Emergencies

Public emergencies refer to natural disasters, accidents, incidents, and social security concerns that occur suddenly. Based on their severity, they may cause serious social harm and require emergency response measures [12]. The lockdown of Wuhan was a public emergency derived from a public health emergency. During public emergencies, citizens become netizens and exchange information on social media [13]. Discussions about the Wuhan lockdown were mainly shared on social media, which became an important channel for promoting risk communication [14]. 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 [15]. There are two main aspects of research that can be explored using social media data.

First, from an emergency management perspective, obtaining event information from related posts can provide valuable supplementary insights for victims, emergency personnel, and emergency services. Kryvasheyeu et al. [16] found the correlation between the heat of discussions about Hurricane Sandy on social networks and local losses, which can quickly assess the losses caused by large-scale disasters. Wang [17] studied space and content of Twitter posts related to wildfires and described the spatial and temporal distribution, and features of forest fires, establishing that social media can be used as an information-gathering tool to help emergency responders improve public situation awareness. Ye et al. [18] used the spatial and temporal information of tweets about dengue fever to simulate how confirmed cases arise and spread. Gruebner [19] pointed out that timely alleviation of negative emotions is of great importance to rescue activities and emergency management post-disaster.

Second, 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. By collecting data on Sina Weibo during the early outbreak of COVID-19 in China, researchers have analyzed the spatial distribution of public emotions and topics in the early stages of the crisis, which can help government agencies and emergency responders better understand citizen demands, support responses [20]. Tang et al. [21] investigated how measles was discussed on social media during the outbreak in the United States at the beginning of 2015 by constructing a semantic network method of the concept of urticaria. Li et al. [22] took the Susceptible Infected Recovered (SIR) model to simulate and analyze 101 emergencies. Their study found that timely and reasonable controls and guidance by governments can not only improve the management of online public emotions, but equally promote government credibility, support, and emergency management services. Mamidi et al. [23] analyzed the public negative sentiment about Zika through Twitter posts and found that most topics in the negative emotion category were related to symptoms. They suggested that government officials must focus greater attention on disseminating information about prevention and treatment research. In addition, other studies have used machine learning algorithms to monitor public opinions that may be generated through social media in real-time, which could find possible events that may be difficult to control [24].

1.2.2 Lockdowns caused by Epidemics

Extant studies on lockdowns have mainly focused on four key aspects. First, the effectiveness of lockdown policies have been discussed widely in controlling the spread epidemics [8,25]. It is agreed that imposing strict lockdown policies leads to poor responses from citizens, even disgust or resistance, which can greatly reduce the effectiveness of the lockdown [26]. Second, some studies have focused on the improvement effect of lockdowns on the natural environment [27,28]. Though reducing human activity, Wang [29] found that emissions reduced for those that could not avoid air pollution. Third, the impact of lockdowns on the social economy, education, and health care, have been widely studied [30, 31]. For example, Webster [32] concluded that forms of medicine and the provision of healthcare will change, with increasing virtual services being offered to citizens. Finally, studies have examined the impact of lockdowns on individuals, such as changes in habits and lifestyle [33], health problems of non-infected patients [6,34], and psychological distress caused by quarantined persons [35]. Emily [36] explored the outbreak of disasters, according to the Behavioral Immune System (BIS) theory, identifying that they can cause increased anxiety and depression symptoms and post-traumatic stress disorder [37]. A survey of the UK population found mental health had deteriorated during the COVID-19 [38].

1.2.3 Emotional Model and Emotion Detection

Sentiment analysis has been employed to determine the basic classes that underly opinion, such as positive or negative feelings [39]. However, the majority of classifications agree that text includes a set of moods, such as joy, sadness, and anger, which makes emotion analysis a difficult task [40, 41]. The emotional model forms the basis of emotion analysis, which defines the categories of emotions and how emotions are represented [42]. There is no unified model for analyzing emotions, with common emotion models for emotion classification typically being followed. Ekman [43] presented 6 basic categories, including happiness, sadness, anger, fear, disgust, and surprise. 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) [44]. 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. In addition, the Fox model [45] decomposed 6-dimensional sentiment features into 3 levels, a total of 18 subdivisions. Albert [46] introduced the Pleasure-Arousability-Dominance (PAD) Temperament Model which measures and represents specific emotions using a vector. In the evolution of different emotional models, the expression of emotions has gradually evolved from a simple binary classification (positive and negative) to complex and fine-grained emotional representations with higher-dimensional features.

When analyzing emotions, two main methods are typically employed, i.e., dictionary-based methods, and machine learning-based methods [47]. The dictionary-based method uses a dictionary with semantic orientation (polarity and intensity) annotations. The method judges the emotional categories of the text by the number of emotional words in the sentence [48]. Zhang et al. [49] extended the affective dictionary by extracting and constructing related dictionaries such as degree adverb dictionary, network word dictionary, negative word dictionary, etc., and obtained the emotional value of Sina Weibo text through weight calculation. The sentiment dictionary, part of the dictionary-based method, has shortcomings such as poor portability. In response to this problem, scholars have used Word2Vec, cosine word vector similarity calculation, and the Pointwise Mutual Information (PMI) algorithm to construct a sentiment dictionary for public emergencies through existing public sentiment dictionaries [50].

Compared to dictionary-based methods, machine learning can achieve higher accuracy in identification. Zhang et al. [51] combined sentence-level fine-grained embedding and semantics in feature selection and extraction and used the Support Vector Machine (SVM) classification model to conduct comparative experiments. They found that the feature selection method could improve the performance of sentiment analysis. With the application of artificial neural networks, deep learning has achieved enhanced performance in various fields of natural language processing. In the field of emotion recognition, neural networks are generally better than traditional machine learning algorithms [52,53].

1.3 Objectives

Lockdown restrictions are a strict measure for reducing public contact and socializing, and the spread of COVID-19. Therefore, there will undoubtedly be opposition during the implementation process. Previous studies have focused on the impact of lockdowns on environment, the epidemic situation, and individuals, yet few have analyzed online public opinions during lockdown. Therefore, this study aims to analyze the posts shared by citizens on Sina Weibo related to the Wuhan lockdown, to gain understanding on public emotional needs and changes. Further, most studies have analyzed emotions based on the three categories of positive, neutral, and negative. However, those categories lack subtle changes in emotion. For example, negative emotions include many sub-types, such as sadness and anger, which cannot be generalized. We, therefore, require a more detailed emotional analysis model to identify the real emotional demands of citizens. Specifically, there are four research questions we aim to answer in this paper:

RQ1. What are the different phases of public opinion evolution during the Wuhan lockdown?

RQ2. What is the distribution of emotion during the lockdown of Wuhan?

RQ3. What are the emotional changes on a time scale?

RQ4. How is the evolution of emotion on the topics?

2 Methods

2.1 Data Collection and Pre-Processing

Sina Weibo is one of the most popular social media sites in China. The leading microblogging platform has over 516 million monthly active users, as of Q4 2019, with about 200 million people using Sina Weibo every day [54]. We developed a web crawler using the Python language to obtain microblogging data from Sina Weibo using the keyword “Wuhan lockdown”. A total of 444,487 posts and 323,184 active users were downloaded in our study, from 21 January to 10 April, 2020, i.e., two days before the lockdown to two days after lockdown restrictions were removed. The dataset contains microblog data and user information, as shown in **Textbox 1**. We deleted non-textual data from the raw data, such as the Uniform Resource Locator of pictures and videos, the hash-tag represented by "#", and a series of emoji data like “😂”.

Textbox 1. Data fields extracted from Weibo.

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

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

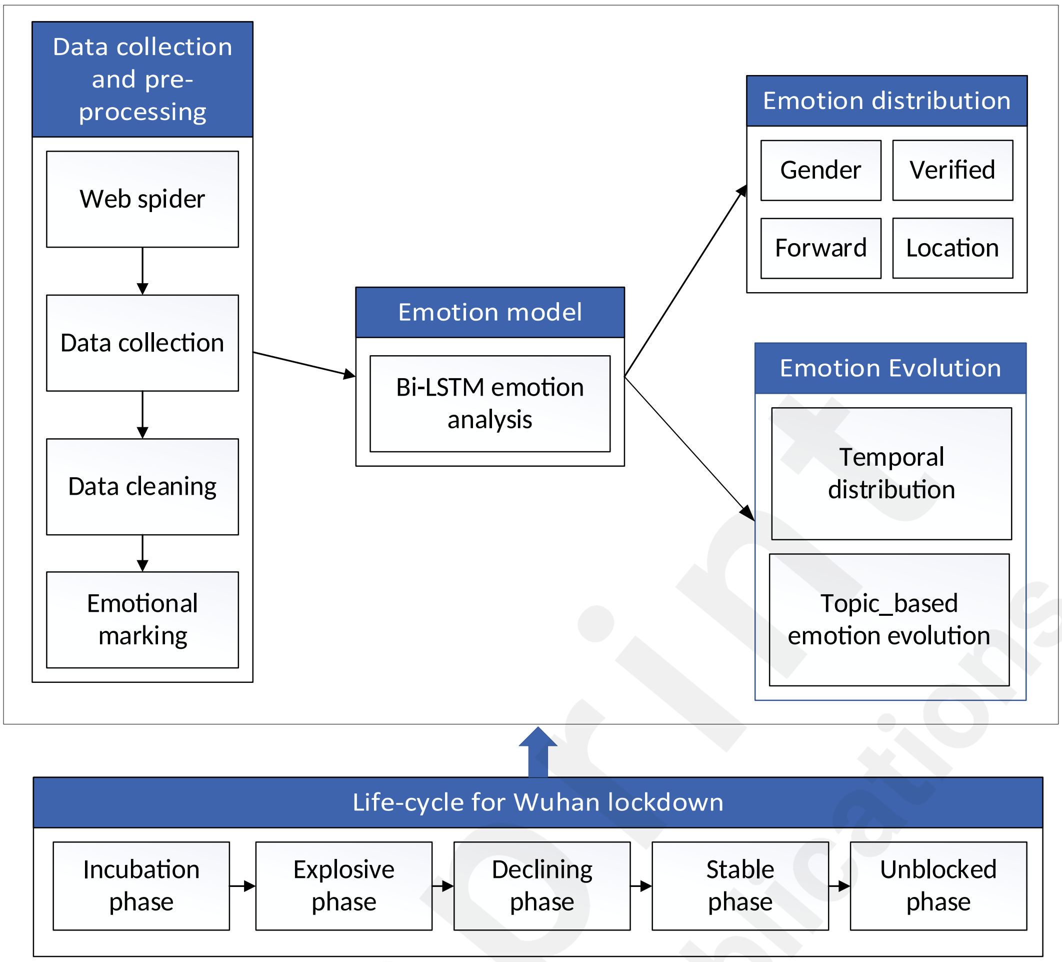

Figure 1. Flowchart of emotion analysis during the Wuhan lockdown event.

2.2 Life Cycle of Online Public Opinions

Life Cycle is a concept commonly used in the biological field, 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, economy, environment, technology, society, and many other fields [55]. Online public opinions refer to a collection of information about a certain event which also arises and dies with the progress of the event [56]. 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 [57]. On the basis of Fink's model, scholars have further divided the life cycle of online public opinions during emergencies into four stages [58,59]. According to the number of posts and changes imposed by the government of Wuhan, we divided the lockdown event into five phases over time.

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. As a classic evaluation theory in cognitive psychology, the OCC model has been widely used in various fields of artificial intelligence, in recent years, due to its ability to clearly explain and distinguish different emotion categories [60].

During the pre-analysis of posts, we found that posts did not involve the dimension of aspects of objects. They only concern perspectives of consequences of events and actions of agents (desirability, praise/blameworthiness). Also, this study included a secondary dimension, 'likelihood', as the supernumerary emotional dimension variable in the model. Finally, six emotion categories (admiration, reproach, hope, fear, joy, and distress) and a neutral emotion were taken to classify the emotion of microblog text, as shown in Table 1. In Figure 2, a tree structure was used to determine the emotional classifications for a specific post, according to the emotion division rules proposed in the OCC model.

Table 1. Basic emotion categories in Internet public opinions.

Emotional classification	Description
Admiration	Endorse or approve the actions of certain characters during the event
Reproach	Condemn or disapprove the actions of certain characters during the event
Hope	Individual feeling of optimism and hope for the prospected outcomes that may arise from the event
Neutral	Does not show obvious emotional tendency or does not belong to the above emotional expression category
Fear	Individual feeling of upset and fear for the undesirable outcomes that may arise from the event
Joy	Individual feeling of satisfaction or happiness towards the desirable outcomes of the event
Distress	Individual feeling of sadness or upset for the undesirable outcomes of the event.

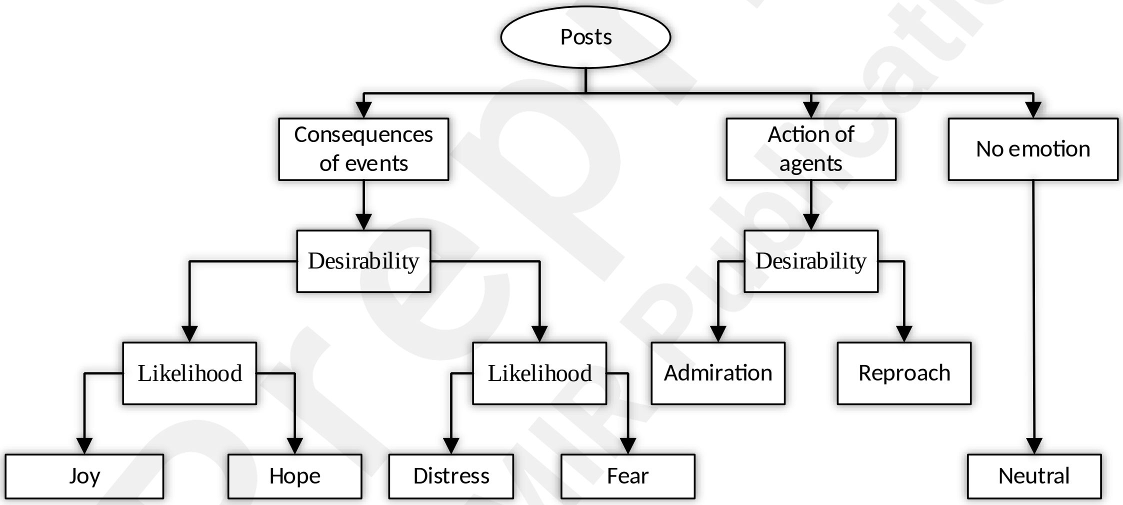

Figure 2. Emotional classification rules based on the OCC emotion model.

In order 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 more detailed labeling rules. 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. Long Short-Term Memory (LSTM) is a variant of the Recurrent Neural Network (RNN) which has three 'gate' structures for forgetting and remembering. Compared with traditional RNNs, LSTM can solve problems of gradient disappearance and explosion which are suitable for modeling sequence data [61]. Bi-LSTM is a combination of two unidirectional LSTMs in different directions. When processing information at each time point, contextual information can be considered at the same time.

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 [62]. In the beginning, Word2Vec was employed to train the word vector based on segmented words. Then, 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 and test set (8:2) with 5600 cases in the training set and 1400 cases in the test set. The 'genism' was used to train the Word2Vec word vectors while TensorFlow was employed to build a deep learning model. 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 2.**

Table 2. 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.

After determining the trained emotional classifier, we used it to predict the emotion category of each post. Hence, we conducted statistical analysis of emotional distribution by gender, authentication, forwarding, and region to explore which factors may influence emotional expression. In addition, we analyzed the dynamic changes in the distribution of emotions over time.

2.3.3 Topic Mining and its Emotional Distribution

In 2003, Blei et al. [63] proposed the Latent Dirichlet allocation method. LDA is a Bayesian probability model that includes a three-layer structure: document-topic-vocabulary. In the model, documents are represented as a random mixture of latent topics. Each topic is characterized by word distribution which is then used to identify semantic topic information in large-scale document sets or corpus. The approach has been widely used in topic mining by researchers on account of its extension ability. This study used the LDA method to extract the topics of posts in each life cycle.

First, jieba 0.42 [64], 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. Finally, 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.

There was a long-term span of Wuhan lockdown, with the derivative events of lockdown occurring most frequently. Therefore, independent LDA topic modeling was carried out for each phase so that more detailed topics could be obtained and compared with the modeling of the entire corpus. Due to the number of posts shared at each phase not being balanced, such as only 8000 pieces of post in the first phase, we randomly chose 8000 pieces of posts from each phase for the LDA topic analysis. Besides, the perplexity for measuring the merits of a language model was concerned to determine the number of topics [65]. Since the results of the LDA model for each phase contained multiple topics, two RAs were hired to annotate each LDA category with 4-7 tags. Then, we merged the categories with similar annotations manually, under the supervision of two RAs, and calculated the categories of topics for each training post. Hence, the topic categories and emotional classification for each post were identified. Finally, we calculated the emotional distribution and evolution for each topic produced in each phase.

3 Results

3.1 The Wuhan Lockdown Life Cycle

Discussions on the city-wide lockdown of Wuhan began on 10 January, 2020, when the topic of ‘Whether Wuhan needed to be locked down’ gradually gained momentum on Sina Weibo. At 02:00 on 23 January, 2020, the government of Wuhan issued official ‘Announcement No. 1’ that required all traffic in the city to be suspended and the exit routes to be temporarily closed. Citizens were not allowed to leave the city of Wuhan from 10:00 on 23 January, 2020. On the 25 March, 2020, the Hubei Province began to lift control measures in an orderly manner. Subsequently, Wuhan fully lifted the lockdown with the transport routes from Wuhan to other provinces re-opening [J3]. According to the number of posts, we divided the event into five phases in time: Incubation Phase (Phase I), Explosive Phase (Phase Ⅱ), Declining Phase (Phase Ⅲ), Stable Phase (Phase Ⅳ), and Unblocked Phase (Phase V), as shown in **Figure 3**.

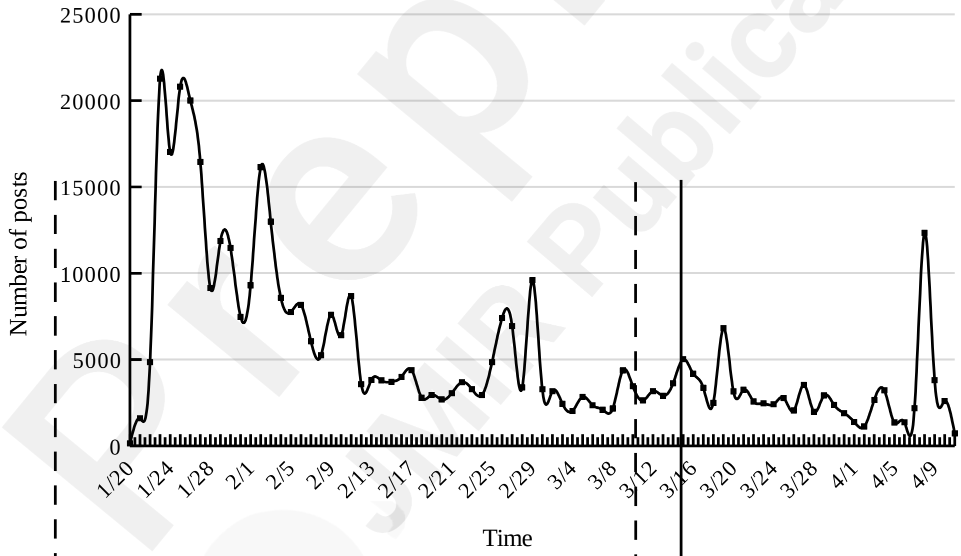

Figure 3. A timing chart of the number of posts related to the Wuhan lockdown.

The incubation phase occurred from 20 to 23 January 2020. The event of ‘Wuhan lockdown’ started on the Sina Weibo platform from 20 January, 2020, because Nanshan Zhong, China’s Academician, made it clear when he was interviewed that COVID-19 was transmitted from person to person [66]. 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 explosive 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. There were two peaks during this phase. The first was during the announcement of the Wuhan lockdown. The second was following the Vlog titled ‘Wuhan – 24 Hours after the Lockdown’ by the personal media star Mr. Lin Chen, which allowed citizens to more intuitively understand the status quo of Wuhan after the unexpected lockdown. The third phase was the declining 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 fourth phase was the stable 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. The final phase was the unblocked phase which took place from 8 to 11 April, 2020. 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. Nonetheless, discussions on the topic of the Wuhan lockdown did not cease which ushered in a small peak for unlocking which then stabilized at a low-level.

3.2 Emotional Distribution

3.2.1 Gender Differences in Emotional Expression

As shown in Figure 4, gender can create an effect on emotional expression. Males accounted for 36.88% (119,201/323,184) of total users included in our sample. 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. In general, men and women did not demonstrate a significant difference in the degree of attention. 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'.

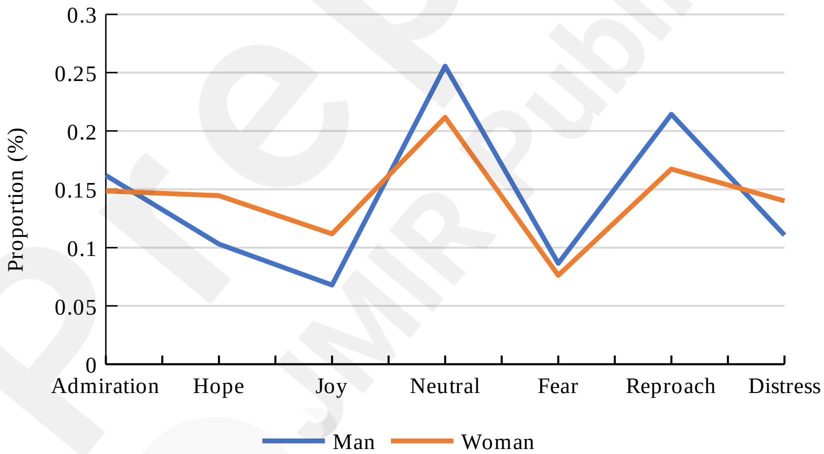

Figure 4. The emotional distribution of posts based on gender.

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

There are three user types officially certified by Sina Weibo: individuals, celebrities, and organizations. The total verified users accounted for 8.01% (25,908/323,184) of the sample. The proportion of positive emotions of certified users accounted for 41.84% (26,394/57,133), which was higher than that of non-certified users (145,893/387,354, 37.66%). Among them, the two emotions of admiration and reproach showed the most obvious difference, as shown in Figure 5.

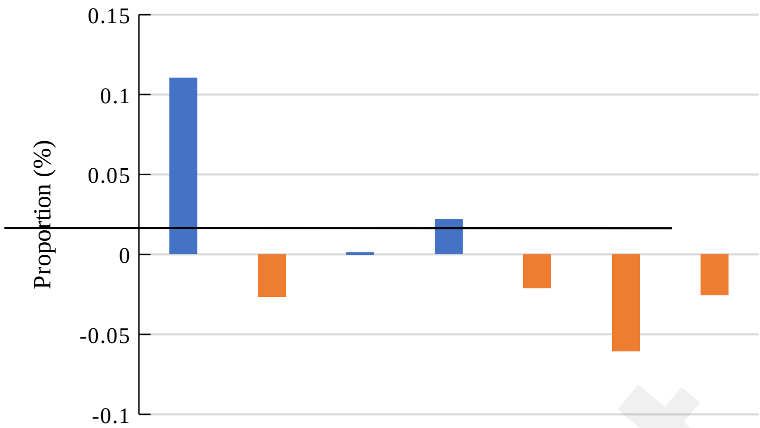

Figure 5. The discrepancy of emotional distribution based on whether an account is verified or not.

3.2.3 Differences Between Forwarded and Original Posts in Emotional Expression

Figure 6 shows that most posts related to the Wuhan lockdown were forwarded. Reposts (or the sharing of posts) held the highest proportion of posts (243,889/444,478, 54.87%). In terms of the emotional distribution of forwarded 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 accounted for a balanced proportion of all emotions. 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 (χ_1^2 = 1130, P<0.001).

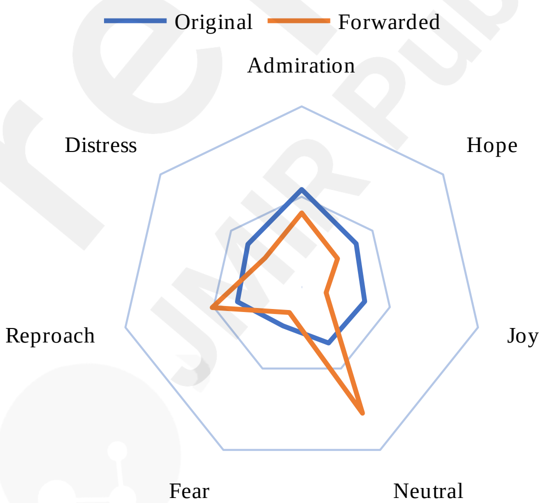

Figure 6. Distribution of emotions based on forwarded versus original posts.

Further, we compared the emotional changes of the post before and after being forwarded, as shown in Figure 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 31.8% (16,455/51,741) before being forwarded, but the proportion of reposts was 36.1% (14,275/ 39,498), with the difference showing statistically significant (χ_1^2 = 814.9, P<0.001).

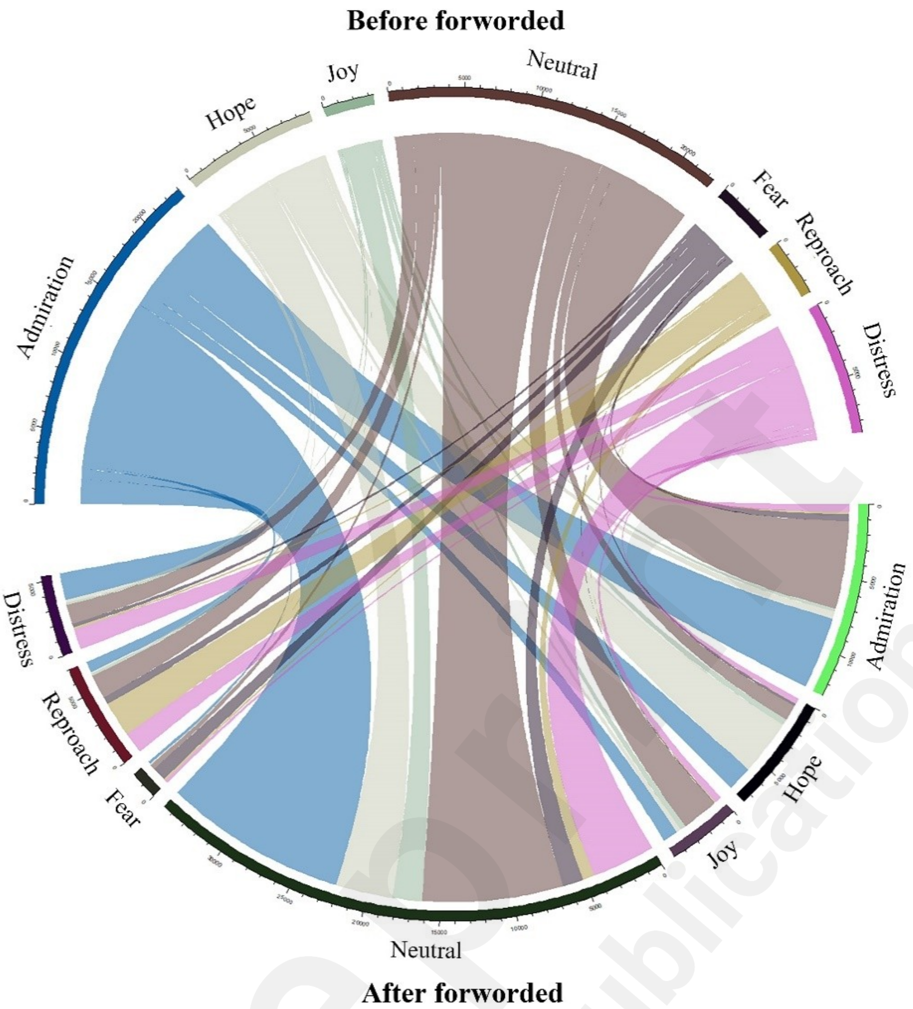

Figure 7. Chord chart showing emotional changes in forwarding.

3.2.4 Spatial Difference in Emotional Expression

The spatial distribution of posts during the Wuhan lockdownFigure 8. Spatial distribution of posts during the Wuhan lockdown is illustrated in Figure 8. From a geographical perspective, users 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 ($r=0.79$, $P<.001$).

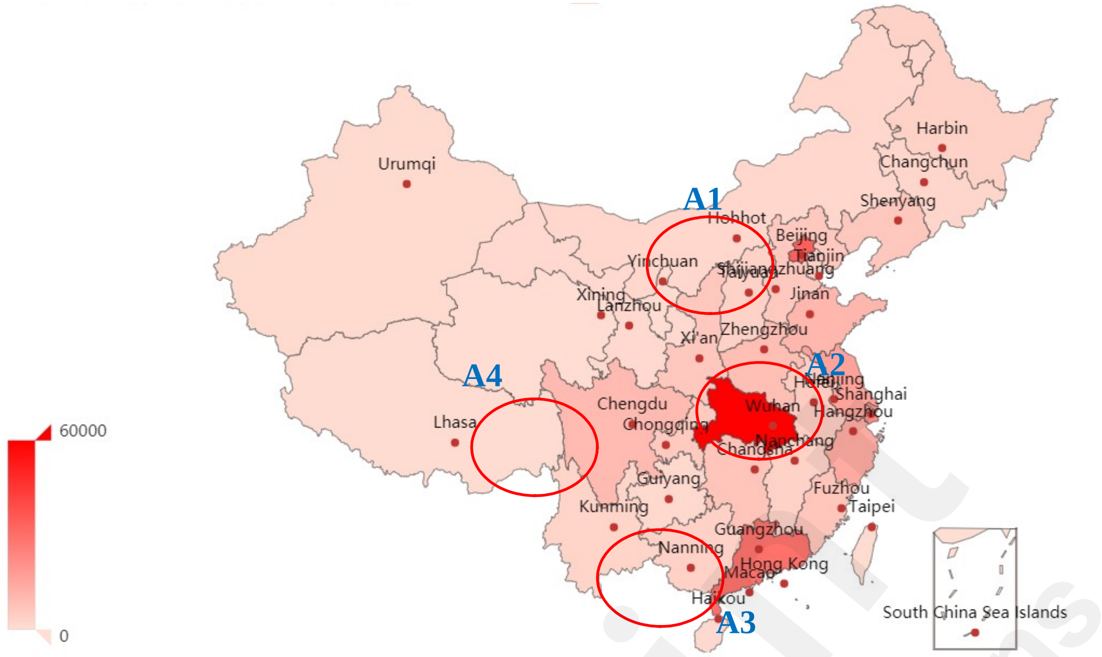

Figure 8. Spatial distribution of posts during the Wuhan lockdown.

From a geographical analysis of the emotions shared, as shown in Figure 9, the distribution of netizens in the Hubei Province and other provinces showed large differences, but the distribution of emotions among provinces, except Hubei, was relatively similar. 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, and Tianjin. In other regions, neutral emotions were almost the largest proportion of demonstrated emotions.

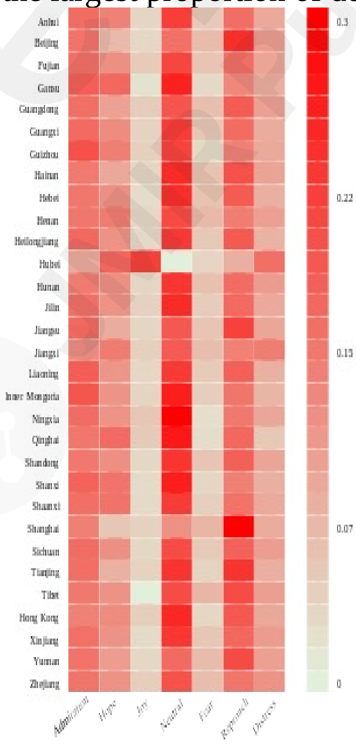

Figure 9. Heatmap of emotion proportions in different regions.

The correlation between the number of posts, number of confirmed cases, and the proportion of each sentiment for all regions, except the Hubei province, is shown in Table 3. The number of posts and confirmed cases had a negative correlation with neutrality and fear. In addition, the number of posts and reproach represented a significant positive correlation.

Table 3. Correlation coefficient between the number of posts and confirmed cases with proportion of emotion, except for the Hubei Province.

	Admiration	Hope	Joy	Neutral	Fear	Reproach	Distress
Num_posts	-0.029	-0.479**	0.013	-0.655**	0.425*	0.595**	0.162
Num_confirmeds	-0.228	-0.099	0.005	-0.420*	0.521**	0.113	0.336

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

We found that the epicenter of the COVID-19 outbreak, Hubei Province, showed discrepancies in emotional expression from others provinces. The distinction between the Hubei Province and other regions, from a time perspective, is shown in Figure 10, where the red box indicates that the proportion in the Hubei Province exceeded the average value found in other regions. The distribution of sentiment in the Hubei Province, before the explosive phase, was not significantly different from that of other regions, while when the government of Wuhan announced the city-wide lockdown, the sentiment of the Hubei Province in the dimension of 'desirability', such as joy and distress, increased to a higher level. To sum up, Sina Weibo users in non-Hubei regions demonstrated higher 'praise/blameworthiness' dimensions, such as admiration and reproach, than that of users in Hubei.

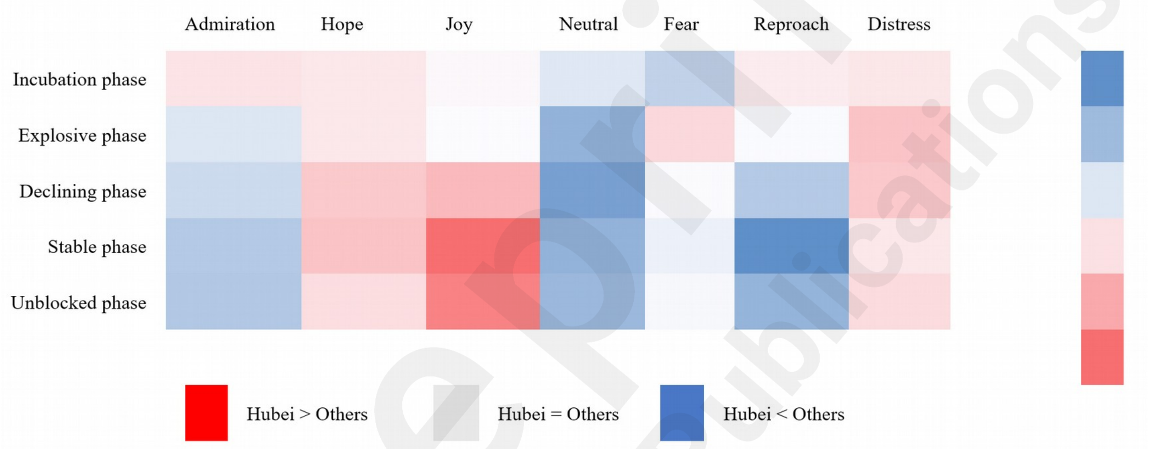

Figure 10. Proportions of emotions between Hubei and other provinces.

3.3 Emotional Evolution

3.3.1 Temporal Distribution of Emotions

Figure 11 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 and reproach. Overall, the proportion of emotions showed a tendency towards convergence in time. 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.

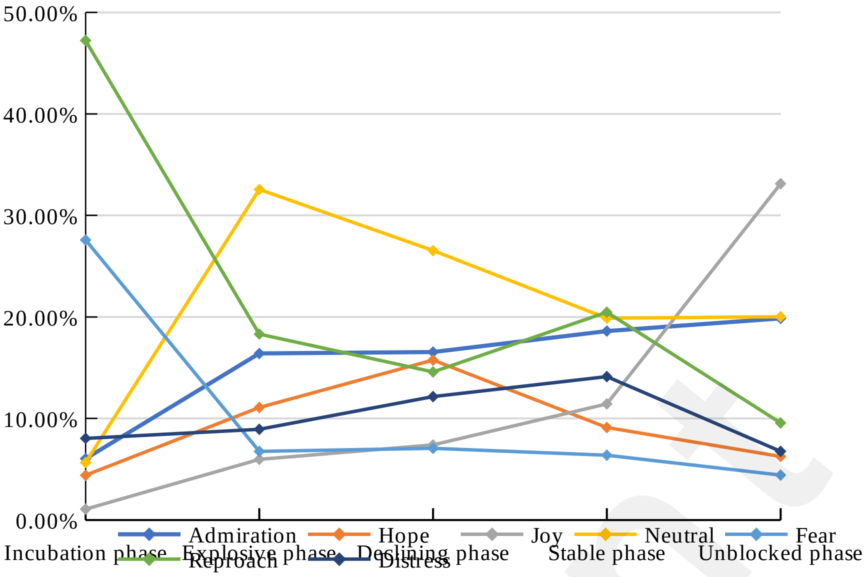

Figure 6. Emotional evolution during each phase of the Wuhan lockdown.

In order to explore the quantitative relationship between changes in the various emotions, the correlation analysis of the proportion of various emotions in time was completed, as shown in Table 5. 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 = -0.306, P = .005). In addition, we found a strong positive correlation between fear and reproach.

Table 4. The correlation coefficient matrix among emotions

	Admiration	Hope	Joy	Neutral	Fear	Reproach	Distress
Admiration	1.000						
Hope	-0.306**	1.000					
Joy	0.300**	-0.205	1.000				
Neutral	0.104	-0.100	-0.081	1.000			
Fear	-0.397**	-0.024	-0.427**	-0.399**	1.000		
Reproach	-0.379**	-0.368**	-0.345**	-0.459**	0.474**	1.000	
Distress	-0.235*	0.279*	-0.048	-0.262*	-0.179	-0.283**	1.000

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

3.3.2 Integrated Analysis of Topics and Emotions

The distribution of each topic, observed by topic mining and emotional analysis, is shown in Figure 12. Due to space confinement, please refer to Multimedia Appendix 1 for the results of each phase of the LDA, topic category names and their explanations, examples and induction process. During the incubation phase, three categories from 12 topics were generated by the LDA model: COVID-19 outbreak in Wuhan, virus spread from Wuhan, request for lockdown. The main concerns of this phase related to the spread of the virus and whether municipal governments should impose lockdown restrictions. The distribution of emotions was extremely uneven, with fear and reproach being dominant emotions. During the second phase, four categories were identified from 30 topics of the LDA. These included: fight the epidemic, discussion of the Wuhan lockdown, share lives, and epidemic spread. Compared to the previous phase, fear and reproach declined, while admiration towards the Wuhan lockdown, and the hope of Wuhan's recovery, emerged. Moreover, public attitudes towards the Wuhan lockdown showed a bimodal distribution of admiration and reproach; life under the Wuhan lockdown represented emotional stability. In this phase, discussions focused on whether correct policies were being implemented and the situation post-lockdown.

We obtained five categories from 14 topics of the LDA in the declining phase. During this phase, the focus of discussions shifted to the issue of fighting the virus. Besides, the remaining topics about community life, material supplies, epidemic situation, and expectations for Wuhan were relatively flat in emotional expression. In the fourth phase, seven categories were refined from 19 topics of the LDA, with fault details of the lockdown, epidemic situation, evaluation of lockdown, life under lockdown, foreign epidemic situation, and praise for medical teams. After the phase victory, people began to reflect on policies imposed during the Wuhan lockdown, with discussions being more positive than negative. Moreover, appreciation towards medical workers and the work of the government of Wuhan to fight the epidemic rose. In addition, the epidemic gradually spread around the world, so the first priority was to fight against the epidemic for people in all parts of the world. In this phase, focus shifted to the assessment of domestic and international responses towards the epidemic. During the last phase, four categories were refined from 10 topics of the LDA, including the unblock of Wuhan, retrospect of the epidemic, development of foreign epidemics, and rumors of the lockdown. The epidemic situation in Wuhan was ultimately brought under control and a temporary victory was achieved. The joy emotion of lifting the lockdown in Wuhan increased rapidly and all emotions remained stable. In this phase, citizens focused on evaluating the actions of the government of Wuhan and the fight against the epidemic.

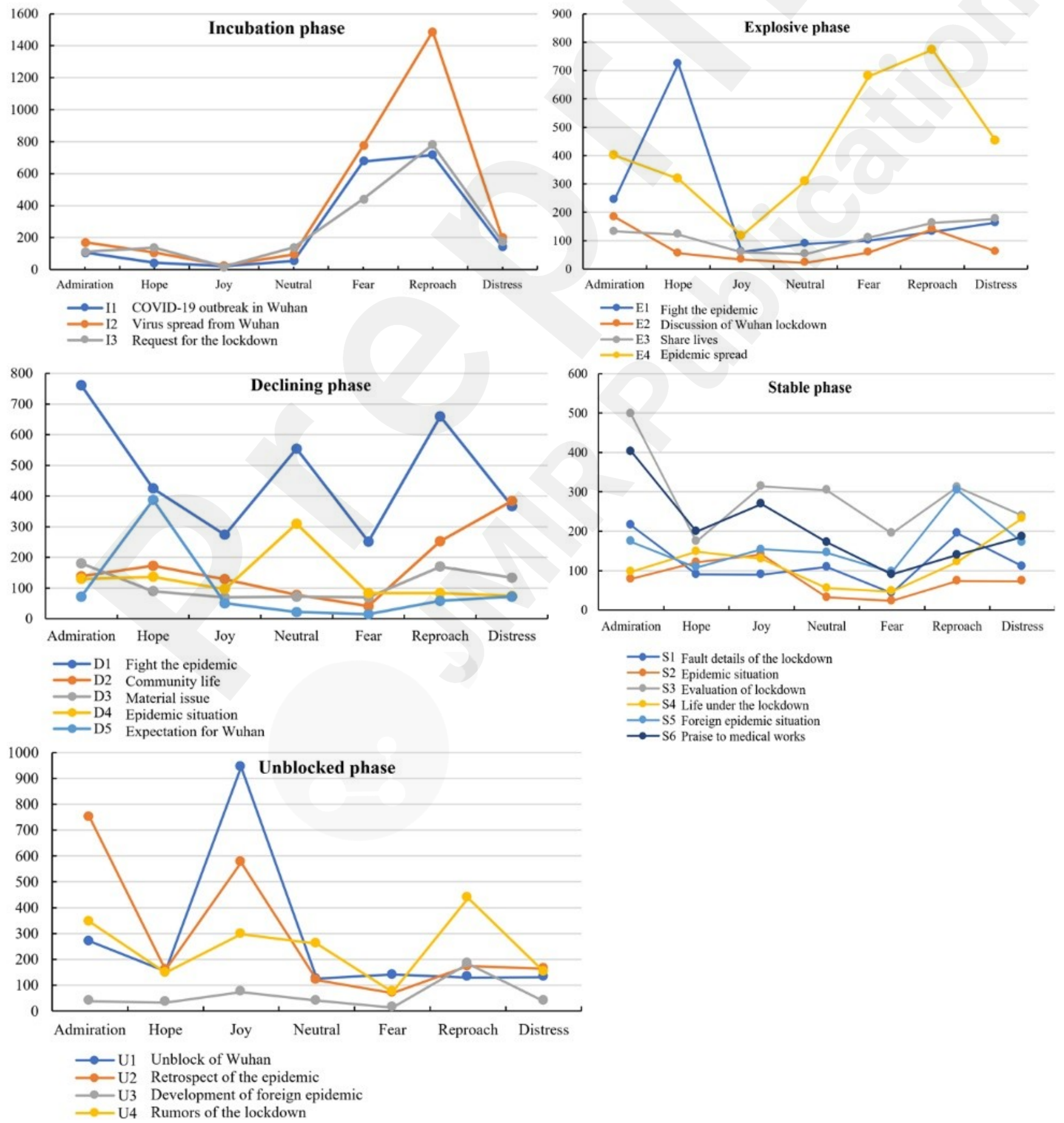

Figure 7. Emotional distribution of topics during each phase of the Wuhan lockdown.

4 Discussion

4.1 Principal Findings

This study combined lifecycle theory to explore the emotional distribution and topic-based evolution of users of Sina Weibo during the Wuhan lockdown, using deep learning and LDA thematic analysis. We identified 7 classifications of emotions with differences existing in the expression of emotions between gender, account verification, region, and whether or not the post was forwarded or original. In the lifecycle for online public opinion, there was an evolution tendency for emotions, i.e., from reproach and fear, through reproach and admiration, hope and admiration, to reproach and admiration, then to joy and admiration.

4.2 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 their own emotions, while males were apt at expressing their views. 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 [67]. Moreover, netizens, who are certified by Sina-Weibo with higher information integrity and influence, tended to present positive and correct information [68]. 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 [69]. 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.

4.3 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 [20,70,71]. 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 incubation and explosive phase, the stigmatization surrounding Wuhan, the information leakage of Wuhan citizens, and even regional discrimination [72], put further blame and pressure on the public. 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 is more optimistic and positive than in accident disasters [73]. 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.

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 [50]. In addition, nationwide activities were launched to divert people's attention from COVID-19. Studies [35] indicate that reducing the frequency of attention to news about the epidemic can reduce anxiety. The intake of delicious food can also effectively alleviate the accumulation of negative emotions [74]; for example, the nationwide writing activity of 'Lockdown Diary' and the food wave of 'Home Food' called on residents to create delicious food. This was the main contribution for the emotion of joy during the Wuhan lockdown.

4.4 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 [75]. For example, economic difficulties and hypochondriasis, induced by epidemic news, can impact on the physiological and psychological behaviors of the uninfected [76, 77].

This study found that there was a significant correlation between some emotions. When trying to explain this complex correlation, we found that this is not a special phenomenon. The correlation between emotions reflected the emotion of continuity [78], i.e., there is correlation between different emotions and continuous variation. Scholars have put forth the continuous emotion model [79, 80], which defines emotion as a continuous vector in the emotion space. The direction Angle of the vector reflects different emotions and further defines emotion as the emotion of the existence of a continuous in space vector, the direction of the vector Angle reflects the different emotions, while vector model reflects the emotional polarity size. On this basis, considering the influence and effect of factors such as emotional intensity, and different user groups and time, emotions can often be represented by spatial models with different dimensions. This shows that emotions are not independent of each other and we can propose a multi-dimensional emotion analysis model to measure textual emotions. 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.

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

Topics related to the Wuhan lockdown varied department on lifecycle phase. At the beginning, the outbreak and transmission of COVID-19 during the incubation and explosive phase caused emotions to be dominated by fear for virus and reproach to government agencies. Then, people gradually accepted the lockdown, which represented the beginning of emotional diversification. In the mid-term, coinciding with the peak of new confirmed cases in Wuhan, citizens concentrated on the development trend of the epidemic, the situation of city-wide lockdown, and the distribution of materials, with a balanced emotional distribution. As the epidemic improved in Wuhan, attention turned to the epidemic situation in other countries and the preparation for lifting restrictions of the lockdown, with positive emotions towards the Wuhan lockdown increasing. In the end, citizens mainly focused on the retrospect, praising the lifting of the lockdown.

During the lockdown of Wuhan, information flows presented a closed loop between fact, social media, and individuals [11]. Social media became the main channel for individuals to obtain information. 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. However, emotions are a special state produced by people's cognition for the outside world [81]. Their changes are subjective, i.e., emotions do not just arise from the topic. The part reason why the mood of citizens in the lockdown shifted from reproach to admiration was the result of comparison: the 'Lockdown of Wuhan' and other countries' strategies of fighting against the epidemic, which potentially changed previous public opinions to praise the actions of the government of Wuhan. By consciously setting comparison objects, citizens can direct their emotions in a specific direction. On social media, pent-up emotions require an outlet. A reasonable comparison object can guide emotional catharsis.

5 Limitations and Implications

5.1 Limitations

Several limitations exist in our study. First, data was only obtained from Sina-Weibo. Due to the privacy of some instant messaging software, such as QQ and WeChat, we did not collect data from these platforms. Therefore, it does not include all conversations on social media during the Wuhan lockdown. Second, we can only obtain up to 1,000 pieces of posts within one hour, yet the number of posts at most times exceeded this ceiling. Finally, we manually merged and generalized after obtaining the results from the LDA model which may bring bias towards the results and discussions presented in our study.

5.2 Implications

COVID-19 has affected almost all countries and regions worldwide, with the number of confirmed cases increasing rapidly up until now. The lockdown of cities, once criticized as an authoritarian invention from China, has become a universal response to contain the epidemic and minimize the spread of the virus. It was not an easy decision to seal off a modern city with 11 million inhabitants. Against different cultural backgrounds, public attitudes towards the lockdown of the city are also different [82]. Due to the support or opposition of the public, effective lockdown policies are not common [26]. Therefore, we must understand the attitudes and requirements of citizens during lockdowns. Regional governments should create countermeasures to ensure the success of lockdowns.

This study, based on the OCC model, divided emotions into seven categories and used the deep learning algorithm to realize the emotion analysis model. It provided a multi-category emotion recognition method for social media which can analyze the public emotional demands in a more detailed way. The city-wide lockdown of Wuhan is one of the successful cases in the international fight against COVID-19. Through analysis of emotion and the topics discussed during the Wuhan lockdown, we identified problems that arose and the corresponding countermeasures proposed by the government agency. This provides certain experiences and methods for other countries to reduce public negative emotions and appease public psychology.

6 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. 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.

Acknowledgments

This study was supported by the Fundamental Research Funds for the Central Universities, HUST (No. 2019WKYXZX011). The authors would like to thank all anonymous reviewers for their valuable comments and input to this research.

Authors' Contributions

GC, the co-first author, designed the study and contributed to the collection of data and writing of the manuscript. LS, the co-first author and corresponding author, designed and conducted the study, and finalized the draft manuscript. RE, the third author, contributed to the writing of the manuscript and final proofreading. QB, the fourth author, contributed to the discussion and writing of the draft manuscript. All other authors contributed to the preparation and approval of the final accepted version.

Conflicts of Interest

None declared.

Multimedia Appendix 1

The topics at different phase total 5 results obtained from LDA model, as well as their merging process.

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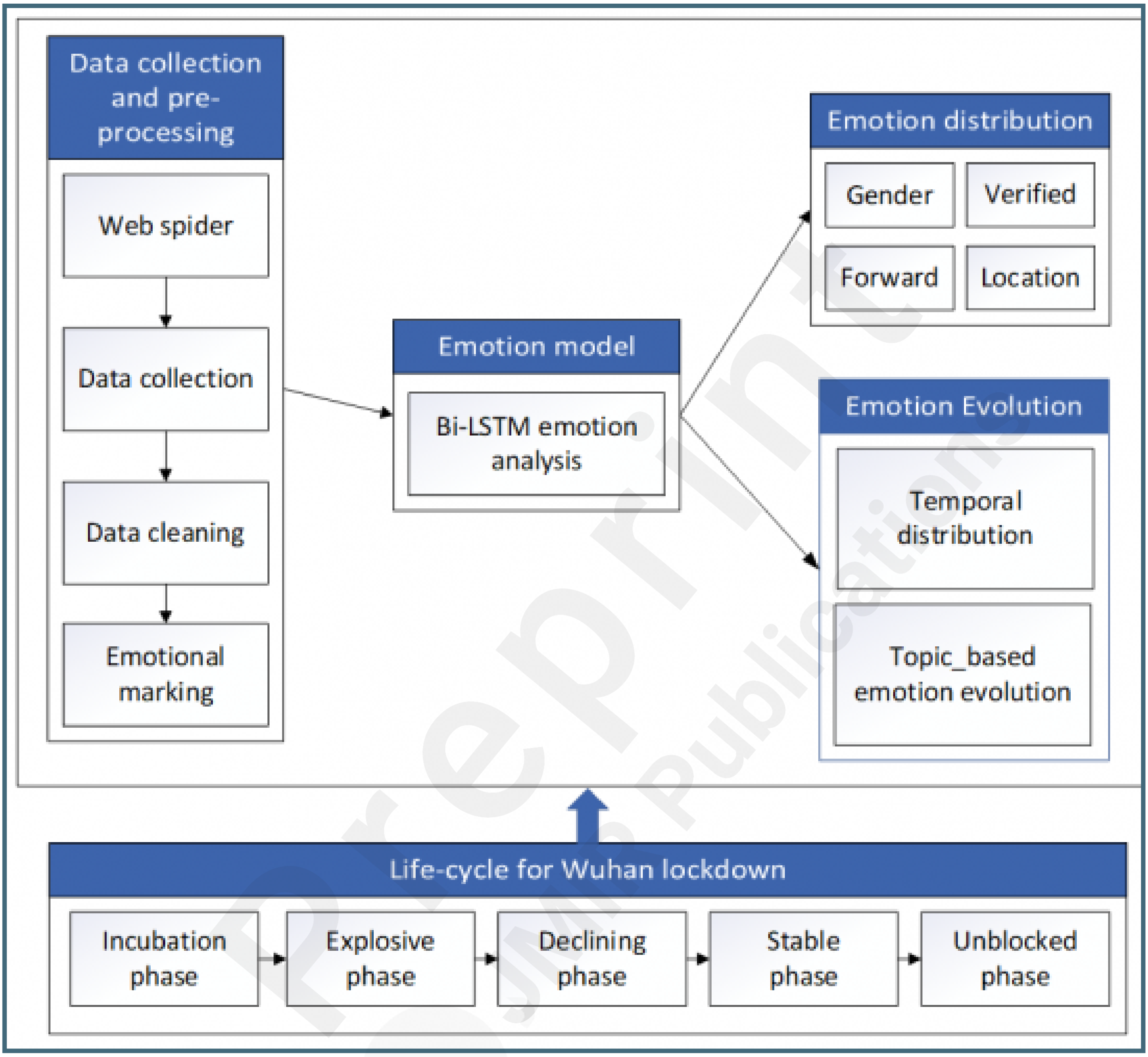
Abbreviations

Bi-LSTM: Bi-directional Long Short-Term.
CNN: Convolutional neural network.
COVID-19: Corona Virus Disease 2019.
LDA: Latent Dirichlet allocation.
LSTM: Long Short-Term Memory.
OCC: Ortony-Clore-Collins model
RAs: Research Assistants.
RNN: Recurrent Neural Network.
SARS-CoV-2: Severe Acute Respiratory Syndrome Coronavirus 2.
Single-LSTM: long short-term memory.
SVM: Support vector machine.
TF-IDF: term frequency-inverse document frequency.

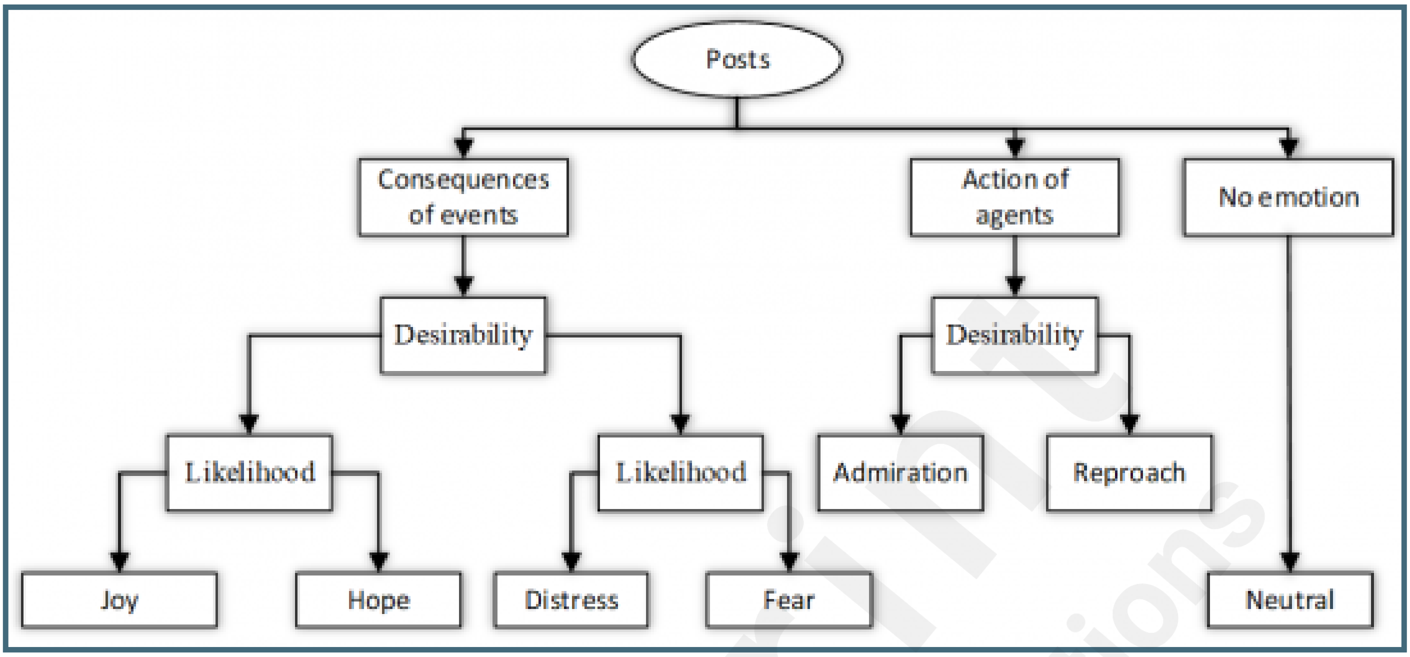
Supplementary Files

Figures

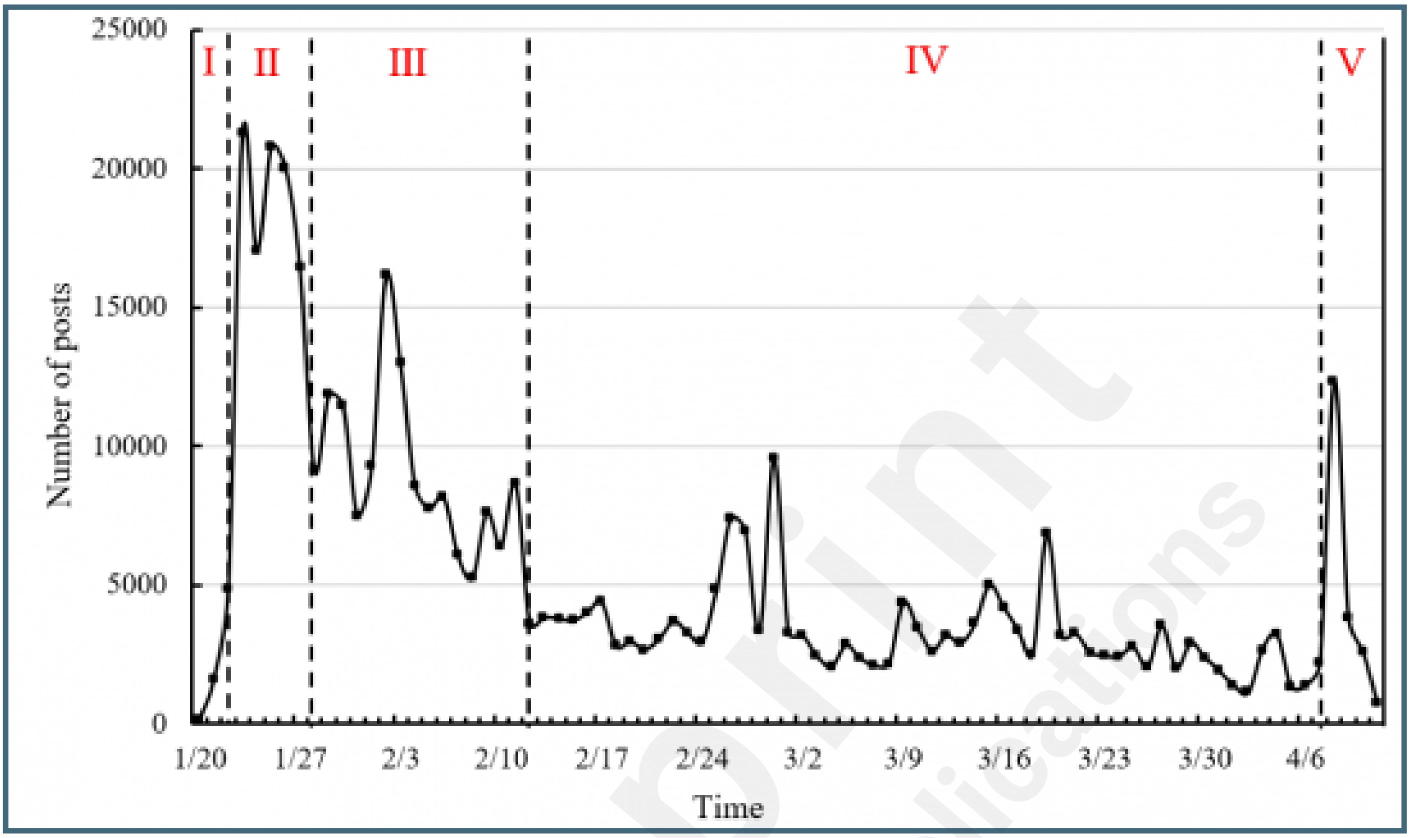
Flowchart of emotion analysis during the Wuhan lockdown event.



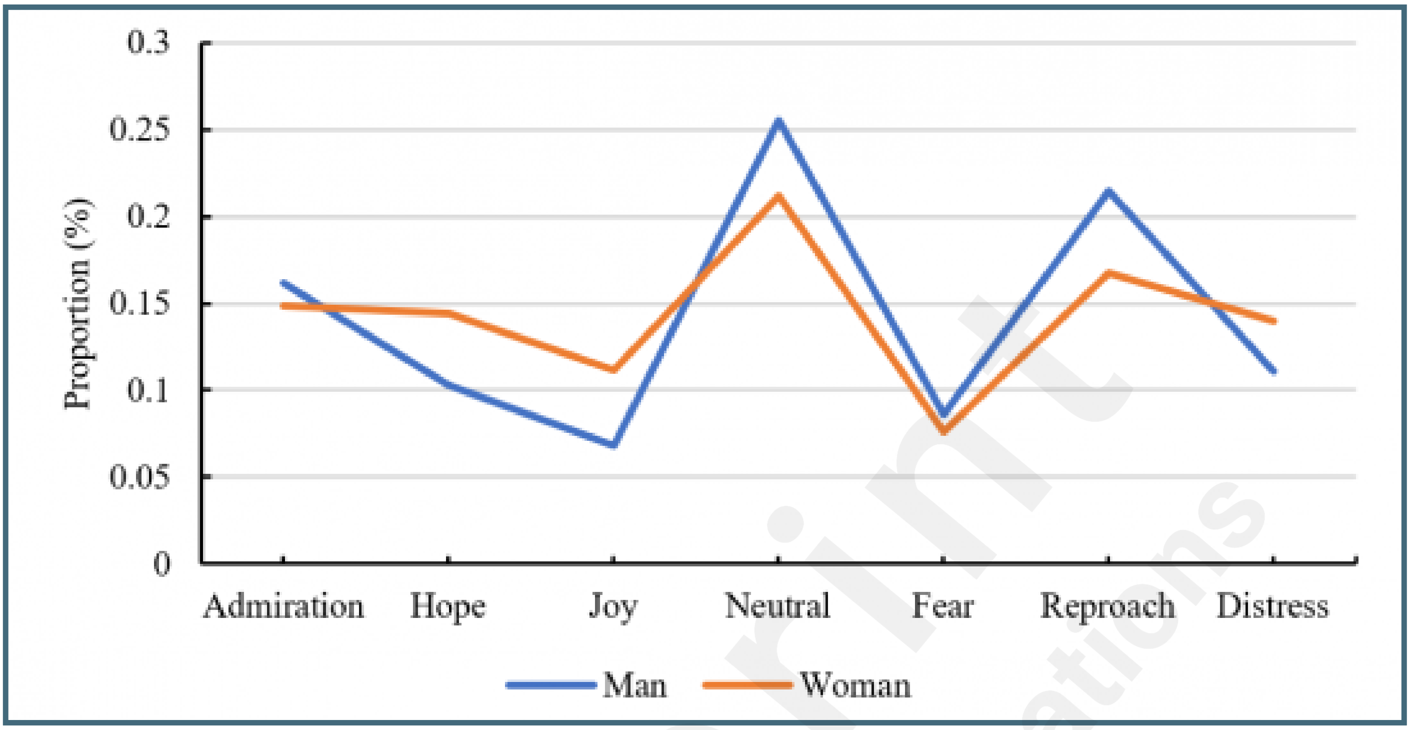
Emotional classification rules based on the OCC emotion model.



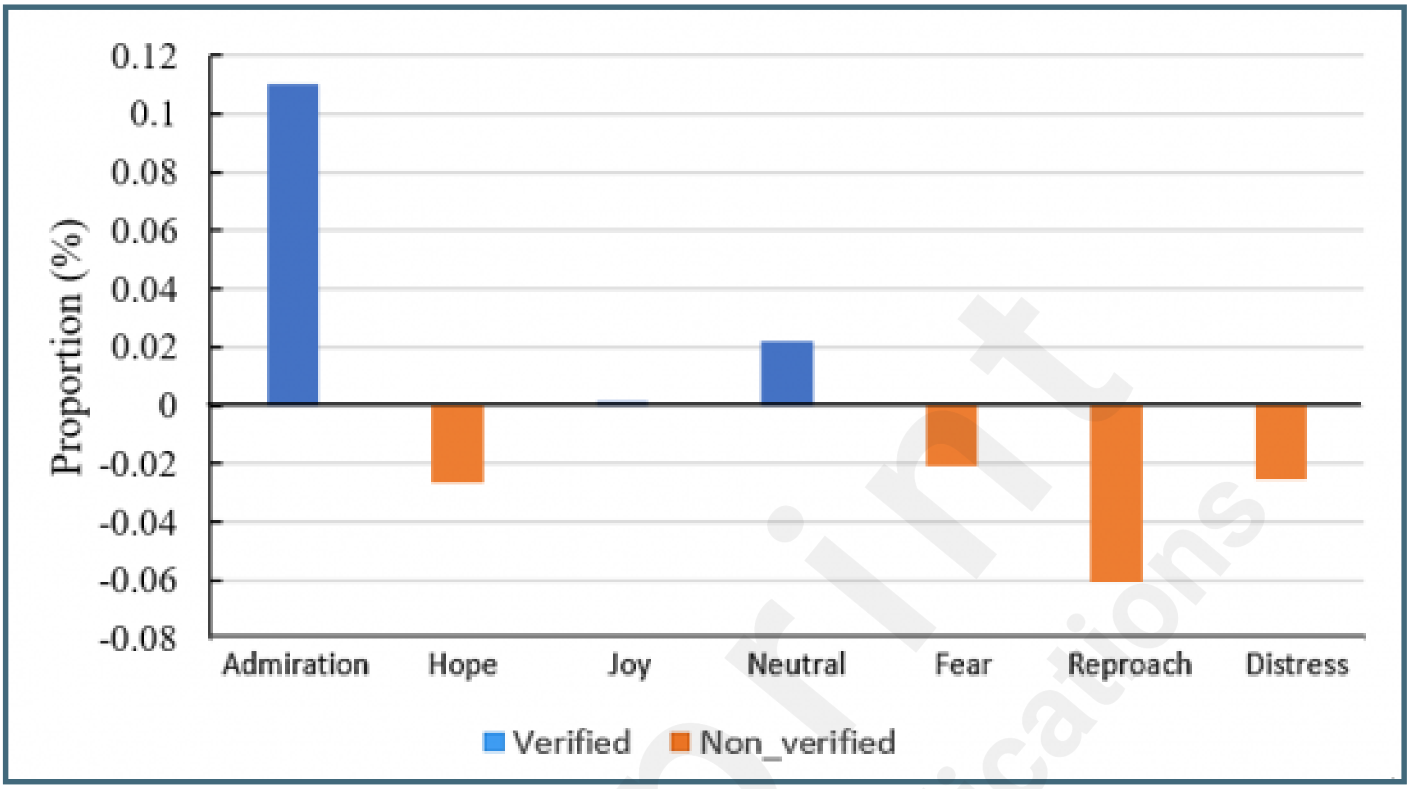
A timing chart of the number of posts related to the Wuhan lockdown.



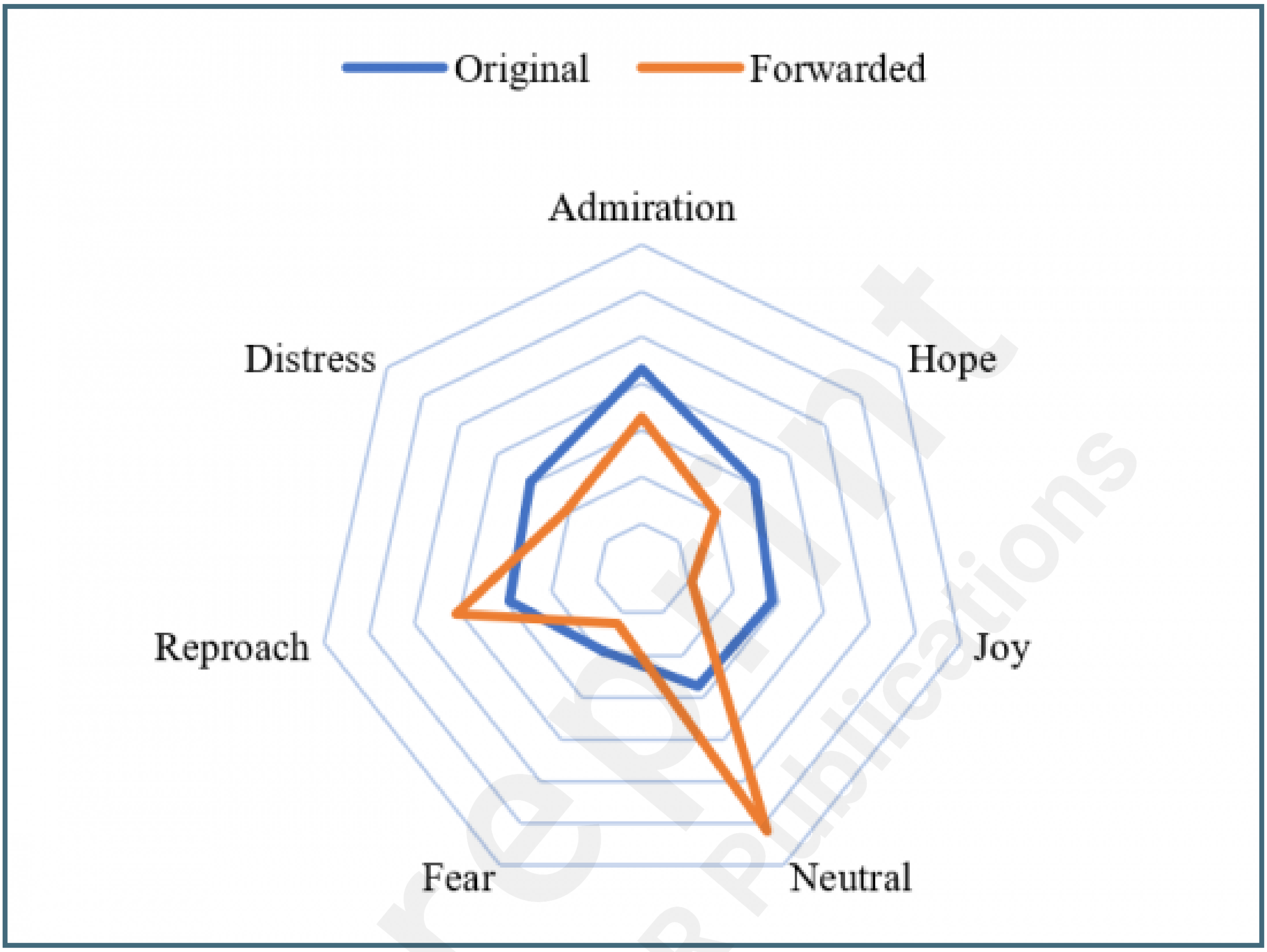
The emotional distribution of posts based on gender.



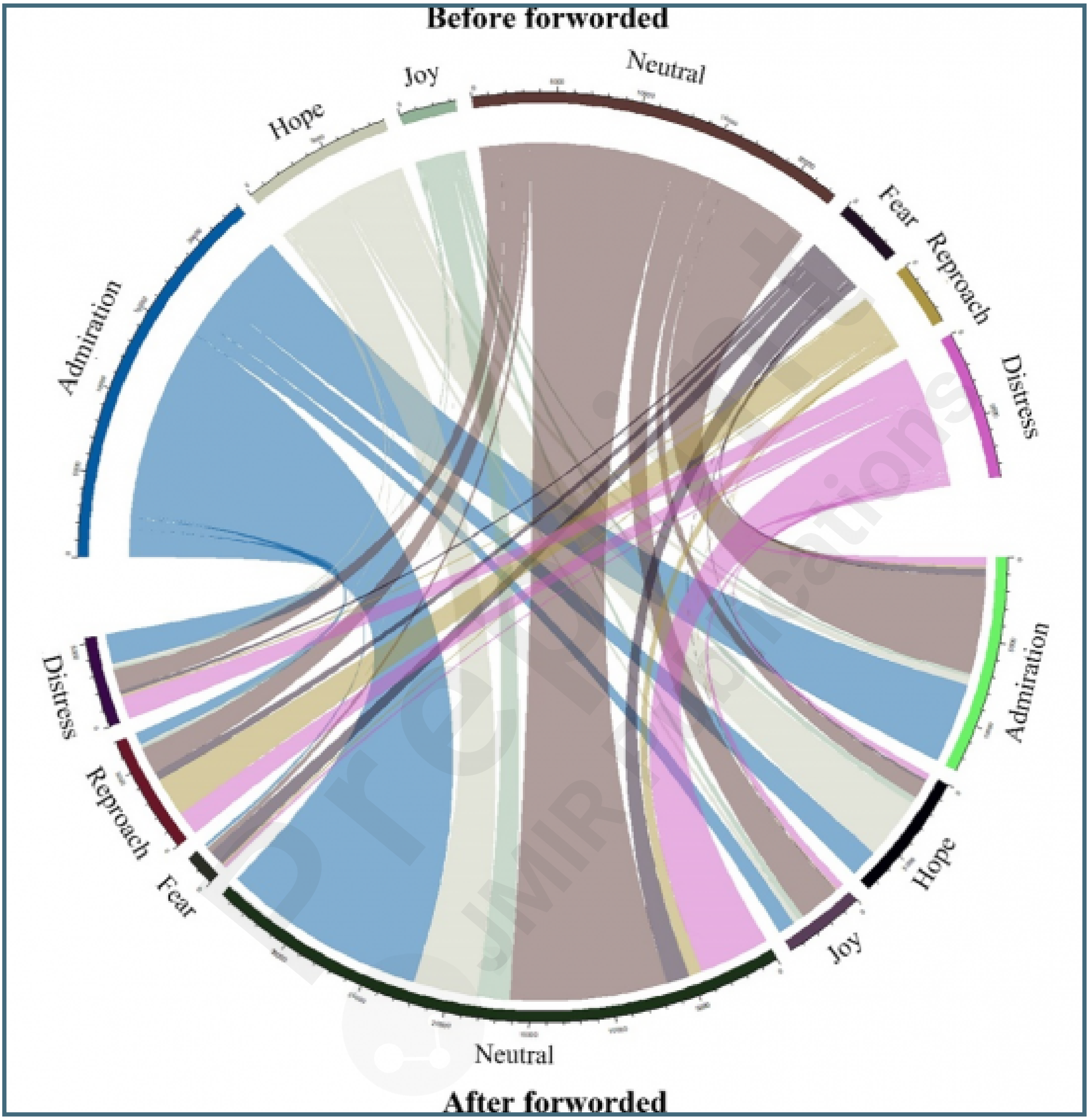
The discrepancy of emotional distribution based on whether an account is verified or not.



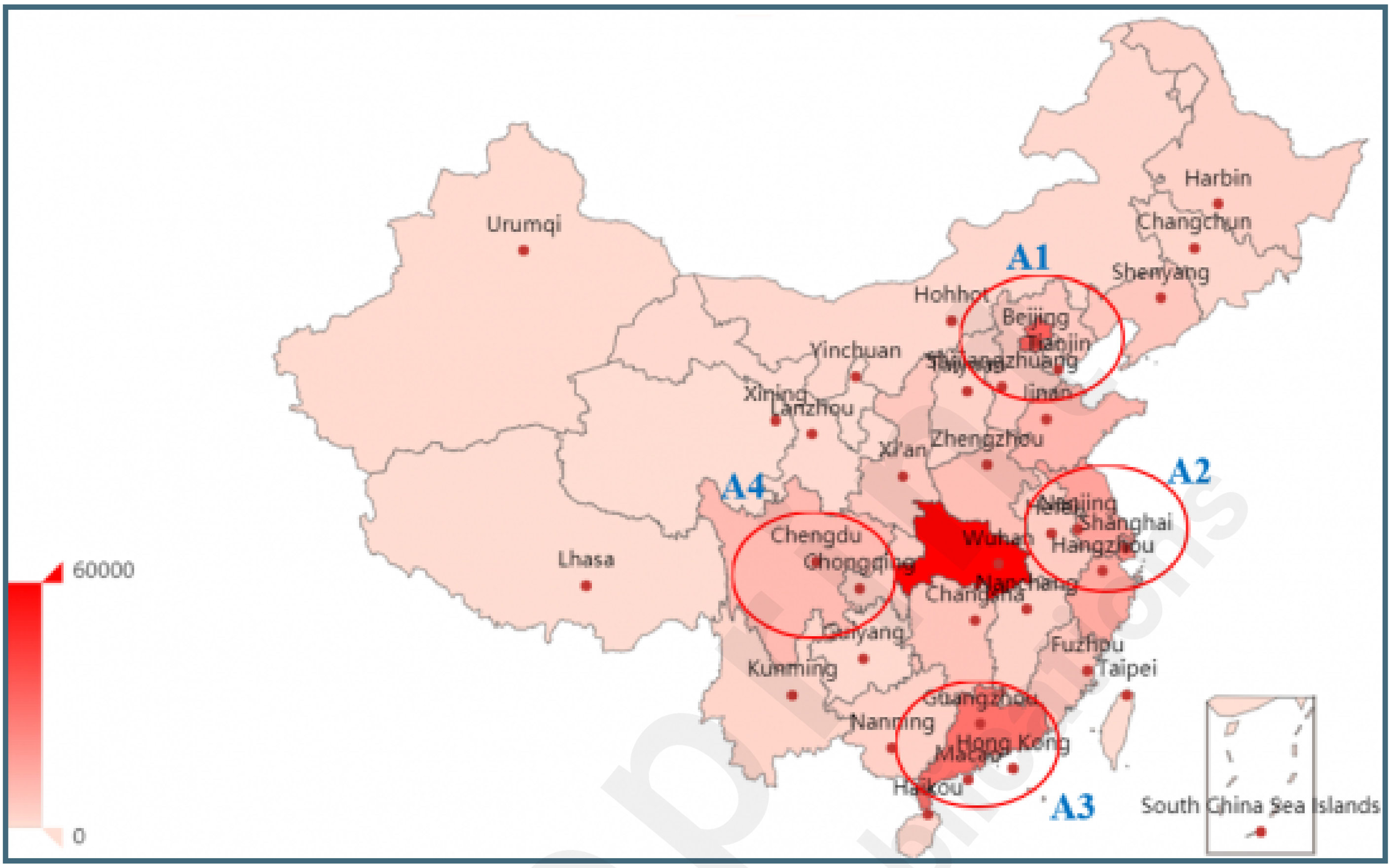
Distribution of emotions based on forwarded versus original posts.



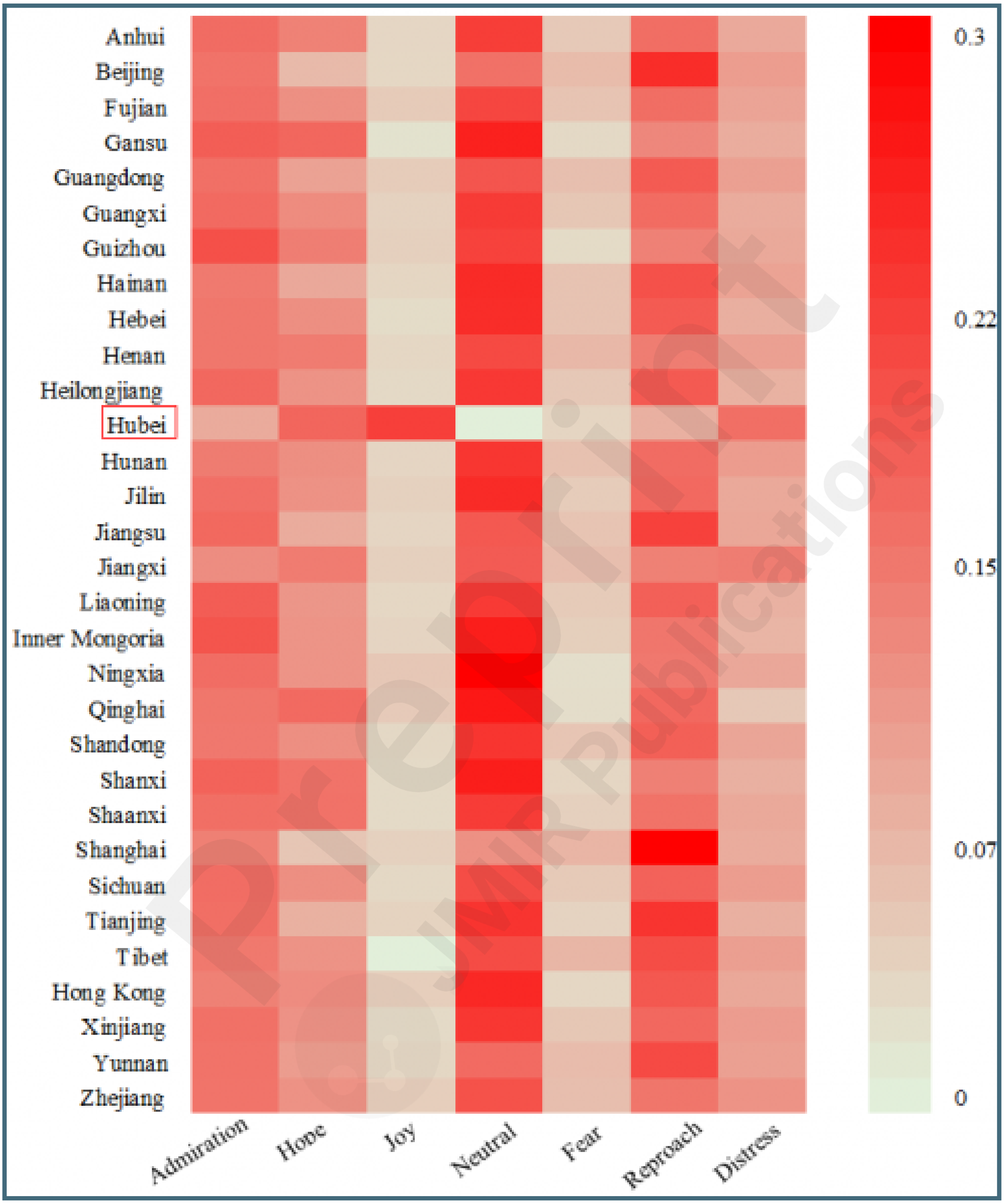
Chord chart showing emotional changes in forwarding.



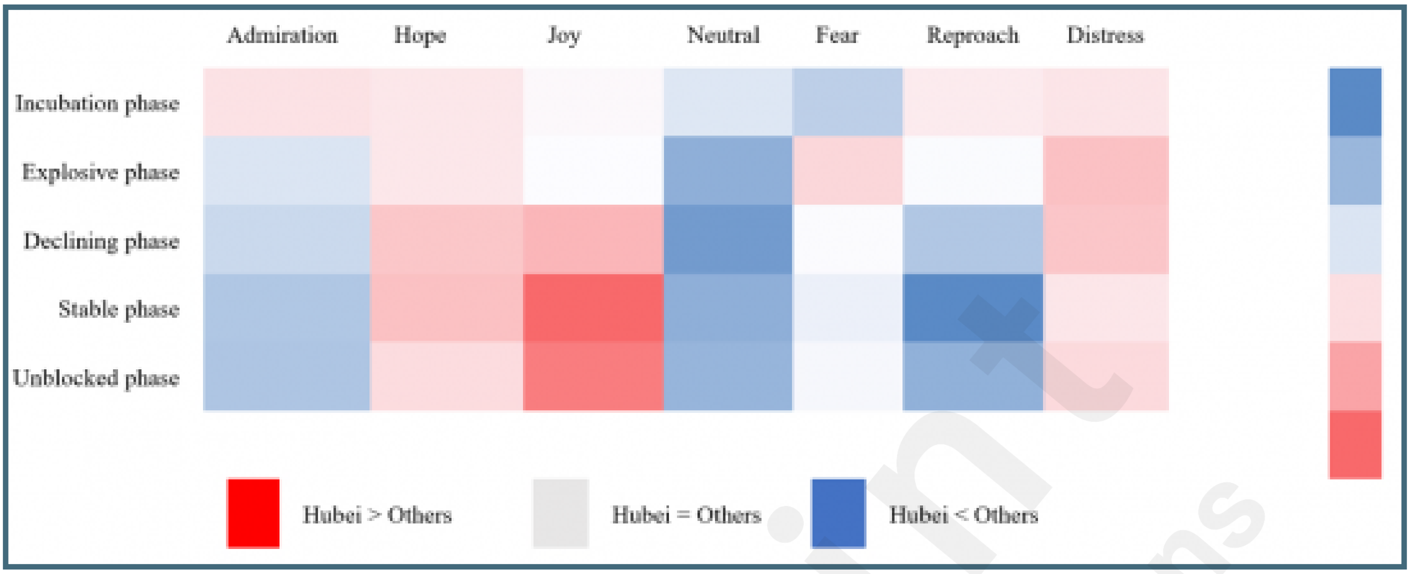
Spatial distribution of posts during the Wuhan lockdown.



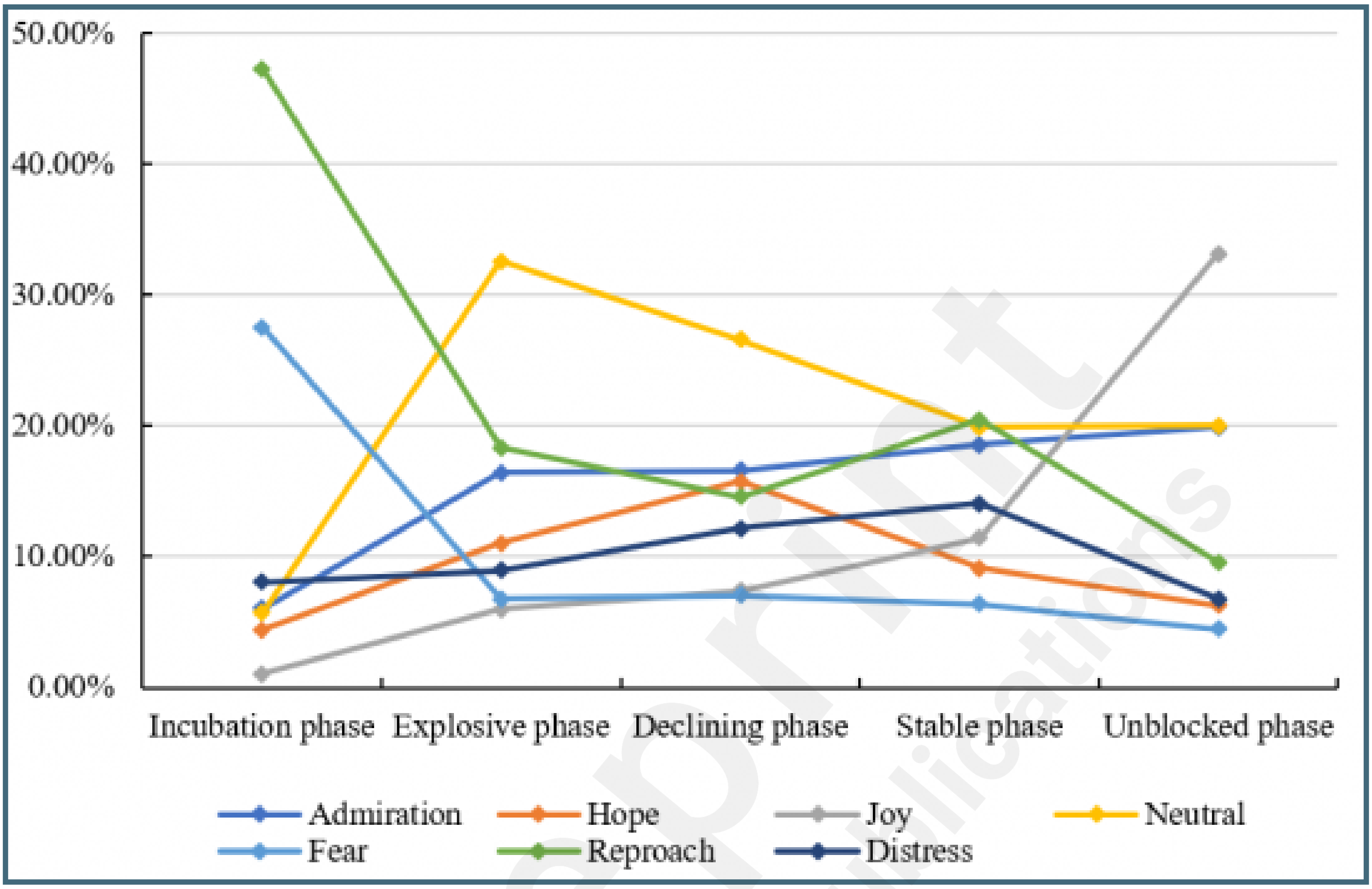
Heatmap of emotion proportions in different regions.



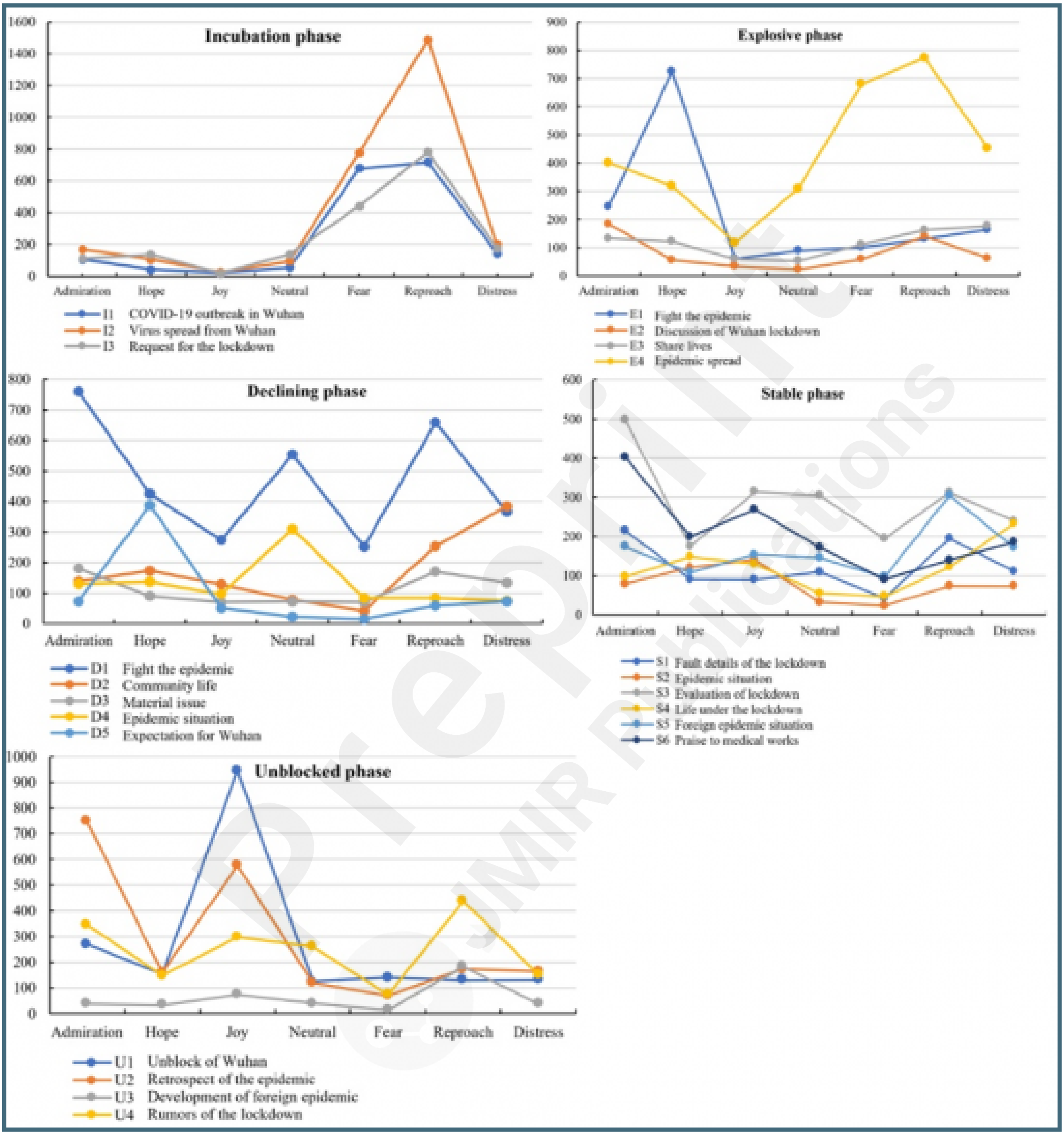
Proportions of emotions between Hubei and other provinces.



Emotional evolution during each phase of the Wuhan lockdown.



Emotional distribution of topics during each phase of the Wuhan lockdown.



Multimedia Appendixes

The topics at different phase total 5 results obtained from LDA model, as well as their merging process.
URL: https://asset.jmir.pub/assets/90fd072deb7cab402069e935c3f8d2ae.docx