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Research on the Characteristics of Internet Public Opinion and Public Sentiment after the Sichuan Earthquake Based on the Perspective of Weibo

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Abstract: In this paper, based on Sina Weibo data, a natural language processing (NLP) analysis method was used to analyze the temporal and spatial sequence characteristics of people's attention and the characteristics of text content with the help of microblogs posted by people within 6 days after the 2022 Lushan M6.1, Maerkang M5.8 and Luding M6.8 earthquakes. Moreover, the same analysis method was used on the content of comments on microblogs posted by official media outlets within 6 days after the earthquakes to analyze the changes in people's sentiments and the differences in the sentiments in various regions, and the influencing factors were also analyzed. The results of this research show the following: In terms of the spatial and temporal distributions, people's attention was affected by the earthquakes themselves and their social impacts, and the first 2 h was often a period of an outbreak of attention, with the publishing areas mainly concentrated in Sichuan and Guangdong. In terms of people's sentiments, the overall microblogging sentiment of the three earthquakes was positive, and the sentiment value of the people in Sichuan was generally low compared with that of the people in the other regions. Not only was the fluctuation in sentiment affected by the influence of the region, but it was also positively related to the sentiment of official microblogs. The results of this research provide reference for guiding people's sentiments after earthquakes in the new media era.

Keywords: microblog data; Sichuan earthquake; public sentiment; natural language processing

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1. Introduction

China is one of the most seriously affected countries in the world in terms of natural disasters; natural disasters have had a great impact on China's property, society and economy. According to the national natural disaster data released by the Ministry of Emergency Management in the first half of 2022, a total of 39,143 million people were affected by various natural disasters in China in the first half of 2022, with direct economic losses of up to CNY 88.81 billion. While natural disasters have caused casualties and brought economic losses to the Chinese people, they have also sparked public concern and discussions about disaster events on social networking platforms. With the rapid development of Internet technology, information on post content, travel trajectories, retweets, likes and comments on social platforms, such as microblogs, has become one of the most effective means currently used to observe the activity patterns of human communities [1]. After a disaster occurs, all information related to it becomes the focus of public opinion debates on online platforms, including the intensity of the damage, the casualties, and the sentimental feelings [2]. Disaster events that attract great attention are very likely to form online public opinion, and if the relevant departments do not guide public sentiment in a timely manner, the public opinion is very likely to cause public panic and have a social impact, even endangering national security [3]. The "14th Five-Year" National Emergency Response System Plan released by the State Council clearly emphasizes the need to do a good job of producing public information propaganda, guiding public opinion in emergency situations, and actively responding to social concerns. In order to effectively guide public opinion after a disaster, it is especially important to clarify the change in people's concerns about the disaster and to identify the factors that influence sentiment. This paper takes an earthquake disaster as an entry point to quickly understand the concerns of social subjects in different time periods and regions and to study the factors that influence the changes in people's sentiments from the perspective of their concerns and changes in sentiments.

2. Literature Review

To date, many scholars at home and abroad have conducted research on the mining of public opinion information under natural disaster conditions, and the research focuses mainly on the characteristics of internet public opinion, the factors that influence public opinion and the research methods of public opinion. Since the main research in this paper includes the characteristics of public opinion and public sentiment, We divided the literature review into two parts: (1) the characteristics of public opinion and public sentiment and (2) the research on the factors that influence public sentiment.

2.1. Public Opinion and Public Sentiment Characteristics

Currently, microblogs, Twitter and other new media platforms have become the main tools used to study changes in public opinion and public sentiment after disasters. Single-region post-disaster research has previously been conducted. Qu et al. used a variety of methods, including content and trend analyses, with the help of microblogging data to study the sentiment changes of residents after the 2010 Yushu earthquake [4]. Liu Yaohui et al. studied the spatial and temporal characteristics of public opinion and people's sentiments in response to the 2021 Yangbi M6.4 earthquake in Yunnan, combining the changing trends of Weibo hot search terms [5]. Li Yafang et al. visualized the sentiments of Microbloggers based on their blog posts and comments posted on Sina Weibo 48 h after the M6.4 earthquake in Jiashi, Xinjiang [6]. However, research on multi-regional disaster events started late. Su Xiaohui et al. proposed an improved TF-PDF algorithm to compare residents' emotions with microblog messages published after the 2013 Sichuan Lushan M7.0 earthquake and the 2012 Yunnan Yiliang M5.7 earthquake [7]. Cao Yanbo analyzed the time series of people's sentiments and the spatial distribution characteristics of their responses in earthquake-stricken areas by comparing microblogging data published 24 h after the earthquake, taking the 2013 Sichuan Lushan M7.0 and the 2017 Jiuzhaigou M7.0 earthquakes as examples [8].

2.2. Research on Factors That Influence People's Sentiments

The study of the factors that influence people's sentiments mainly includes natural attributes and social attributes. The natural attributes are related to the spatial location of the people and the degree of their connection with the disaster. Neppalli et al. used Twitter data posted during Hurricane Sandy to visualize and analyze user sentiment, and they concluded that user sentiment was highly correlated with user location [9]. Chen et al. analyzed Hurricane Harvey microblogs in a spatio-temporal manner and found that people's sentiments were affected by different phases of the disaster, showing more negativity during the hurricane than before and after the hurricane [10]. Li et al. drew on Twitter data to reveal that people's emotional reactions are closely related to the events themselves, using the 2011 earthquake in Japan, the 2010 earthquake in Haiti, and influenza A (H1N1) as examples [11]. The social attributes mainly involve changes in disaster relief policies and the basic characteristics of individuals. Taking the 2013 Ya'an earthquake as an example, Liu Wen et al. analyzed the effect of the content of blog posts on residents' positive and negative sentiments, and they concluded that the factors that affect the fluctuations in residents' sentiments include relevant news media reports and the strength of government credibility [12]. Wen Hong analyzed the relationship between people's sentiments and cognitive differences in disaster scenarios by constructing an analytical framework of the disaster attribution theory [13].

To sum up, the information posted by the public on microblogs and other new media platforms after a disaster reflect, to a certain extent, the degree of public concern and the changes in public sentiment regarding the disaster itself. The current research on changes in public opinion and sentiment mostly focuses on a single disaster or two similar disasters, and relatively little research is conducted on three or more disasters at the same time. Furthermore, the research on the influencing factors of the concerns and sentiments regarding earthquake disasters is still dominated by feature analyses, and it is still lacking in terms of specific influences. Therefore, based on Sina Weibo data, this paper takes the Sichuan Lushan M6.1 earthquake, the Maerkang M5.8 earthquake and the Luding M6.8 earthquake that occurred in 2022 as the research objects; mines the Weibo contents related to the three earthquakes; analyzes the spatial and temporal evolution characteristics of the number of relevant Weibo posts; presents the results in a visualized manner; and studies the influencing factors of people's attention. By using natural language processing to identify people's sentiments and to explore whether people's sentiments are influenced by the sentiments regarding disaster areas and official microblogs, this paper provides a reference for relevant government departments to monitor public opinion and guide people's sentiments after a disaster.

3. Summary of the Basic Situation of the Sichuan Earthquake

On 1 June 2022, at 17:00 in Lushan County, Ya'an City, Sichuan Province, a M6.1 earthquake occurred with a source depth of 17 km, followed 3 min later by a M4.5 earthquake in Baoxing County with a source depth of 18 km, ultimately causing four deaths and many injuries. At 0:03 on the 10th day of the same month, a M5.8 earthquake occurred in Maerkang, Aba Prefecture, Sichuan Province, with a depth of 10 km, followed by several aftershocks. According to the China Earthquake Network, as of 07:00, there were 10 earthquakes of M3.0 or higher, resulting in four deaths and more than 20,000 people injured. At 12:52 on 5 September, a M6.8 earthquake occurred in Luding County, Ganzi Prefecture, Sichuan Province, with a depth of 16 km, resulting in the deaths of 93 people and 25 people reported missing. Combined with the data released by the China Earthquake Network, this paper compiled statistics about the mainshocks and aftershocks of these three earthquakes, as shown in Table 1.

Table 1. Earthquake Occurrence Statistics.

Earthquake Name	Time	Magnitude of Earthquake	Depth of Earthquake
Lushan Earthquake	1 June, 17:00 p.m.	M6.1	17 km
	1 June, 17:03 p.m.	M4.5	18 km
	2 June, 7:48 p.m.	M3.2	18 km
Maerkang Earthquake	10 June, 0:03 a.m.	M5.8	10 km
	10 June, 0:06 a.m.	M4.1	10 km
	10 June, 0:19 a.m.	M3.4	15 km
	10 June, 0:21 a.m.	M4.4	10 km
	10 June, 1:28 a.m.	M6.0	13 km
	10 June, 3:27 a.m.	M5.2	15 km
	10 June, 4:35 a.m.	M3.0	19 km
	10 June, 4:37 a.m.	M4.4	12 km
	10 June, 4:54 a.m.	M3.9	17 km
	10 June, 7:49 a.m.	M3.0	12 km
Luding Earthquake	5 September, 12:52 p.m.	M6.8	16 km
	5 September, 12:56 p.m.	M4.2	15 km
	5 September, 13:03 p.m.	M3.1	9 km
	5 September, 13:28 p.m.	M3.2	12 km
	5 September, 17:39 p.m.	M3.6	17 km
	5 September, 18:31 p.m.	M3.0	11 km
	5 September, 19:26 p.m.	M3.6	15 km
	5 September, 21:00 p.m.	M3.0	15 km
	6 September, 01:24 a.m.	M3.1	16 km
	6 September, 05:15 a.m.	M3.0	9 km
	6 September, 05:28 a.m.	M3.1	11 km
	6 September, 17:54 p.m.	M3.2	8 km
	7 September, 02:42 a.m.	M4.5	11 km
	7 September, 05:39 a.m.	M3.3	8 km
	7 September, 08:34 a.m.	M3.0	12 km
	7 September, 09:46 a.m.	M3.1	9 km
	8 September, 15:12 p.m.	M3.3	10 km

4. Data Source

The data source of this paper is the Sina Weibo client. The keywords "Lushan earthquake", "Maerkang earthquake" and "Luding earthquake" were used to retrieve information on the microblogging platform, including text, images, videos, and links. The search time was set from 24 h (1 day) before the earthquake to 144 h (6 days) after the earthquake. The python technique was used to crawl 10,546 pieces of data related to the Lushan earthquake, 7871 pieces of data related to the Maerkang earthquake and 143,623 pieces of data related to the Luding earthquake; after data processing, such as filtering, de-duplication and denoising, 8845, 6499 and 117,014 pieces of data were obtained for the experiments, respectively.

5. Research Methods

5.1. Sentiment Analysis Method

A text sentiment analysis, also known as opinion mining, propensity analysis, etc., is a modality represented by textual information, and its relevant sentiment information is extracted via computer technology [14]. At present, the research on text sentiment analysis methods is mainly based on two components: text sentiment analyses based on sentiment dictionaries and machine learning algorithms [15]. A sentiment analysis of text based on sentiment dictionaries is generally carried out by querying the sentiment values of sentiment words in sentiment dictionaries to obtain the sentimental tendency expressed by the text. In sentiment analyses, sentiment dictionaries take into account not only the text content but also the emoticons and the text expressions [16]. Machine-learning-based sentiment analysis methods first use manual methods to screen features from a large corpus, then represent the whole text with the selected features and, finally, use machine learning algorithms to classify the text, while deep learning, as a special kind of machine learning, does not require manual feature extraction, and it can automatically extract features, combine them and perform automatic sentiment classification [17].

Since the vocabulary of microblog text is time-sensitive and the update speed of the sentiment dictionary cannot meet the current needs of online terms, this paper uses a machine learning algorithm to analyze the expressions of people's sentiments. The Tencent Cloud natural language processing (NLP), based on massive data and deep learning algorithms, can more accurately describe people's sentiments in different scenarios, meeting the research needs of this paper. Therefore, this paper uses the Tencent Cloud natural language processing platform with API sentiment analysis tools, based on a large-scale Internet corpus and deep neural network models, such as LSTM and BERT, for training, to identify and analyze people's post-disaster sentiments.

5.2. Behavioral Influence Model

The Theory of Planned Behavior (TPB), proposed by Ajzen I [18], states that individuals' behavioral intentions can be influenced by a combination of behavioral attitudes, subjective norms and perceived behavioral control. Behavioral attitudes comprise psychological dispositions and sentiments about the target behavior, which can be positive or negative [19], and it is expressed in microblogs as an instinctive expression of sentiments in the aftermath of the earthquake. Subjective norms comprise spontaneous changes in one's behavior as a result of some societal influence [20]. Based on the above theories, we propose a model of influencing factors that affect people's behavior in microblogs, where information released by the government and other media affects people's microblog posts. Perceived behavioral control is the degree to which individuals have mastery over factors that facilitate or hinder their behavioral performance [21], and it is expressed in microblogging as whether people feel the earthquake and whether the information posted by official media outlets that they view also changes their behavior with regard to posting microblogs. Therefore, in addition to the people's own perceptions of earthquake risk in the process of posting microblogs, information from government media and other media and whether they browse such information in time also have some influence on people's behavioral sentiments. The model of the factors that influencing people's behavior is shown in Figure 1.

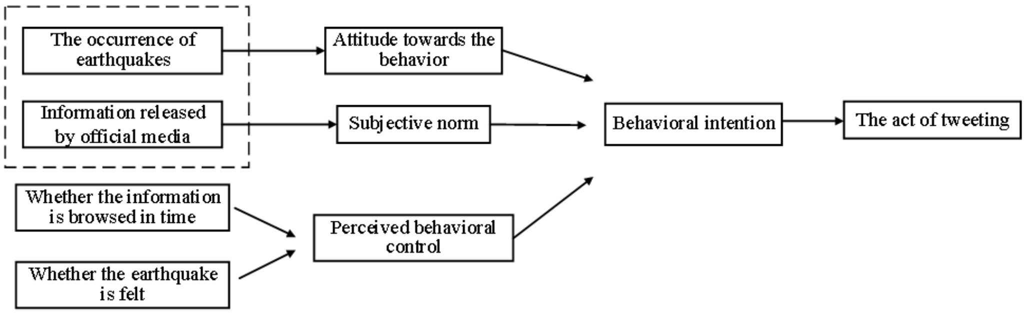
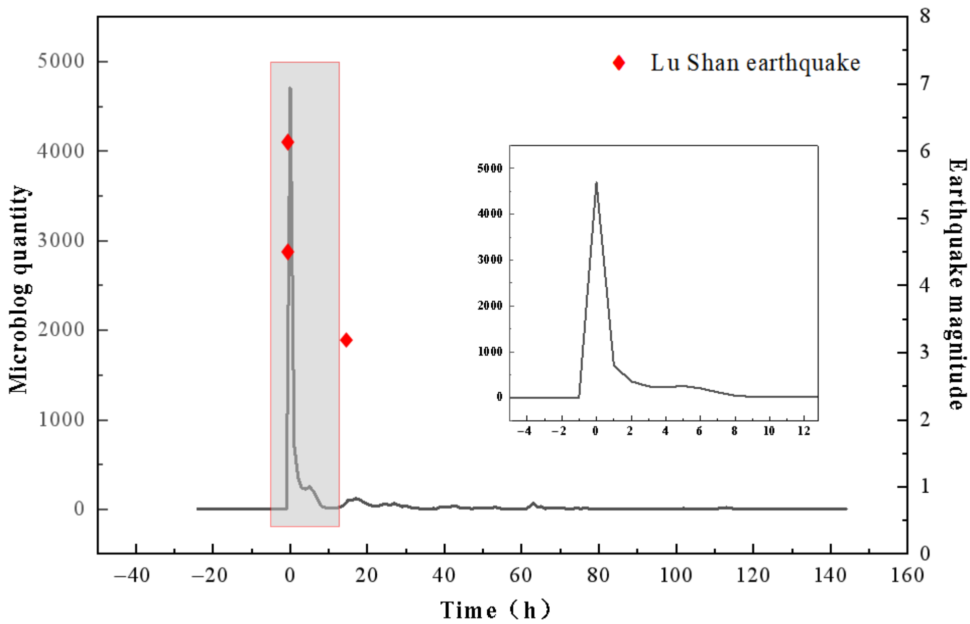


Figure 1. Model of factors that influence people's behavior.

6. Weibo Data Results and Analysis

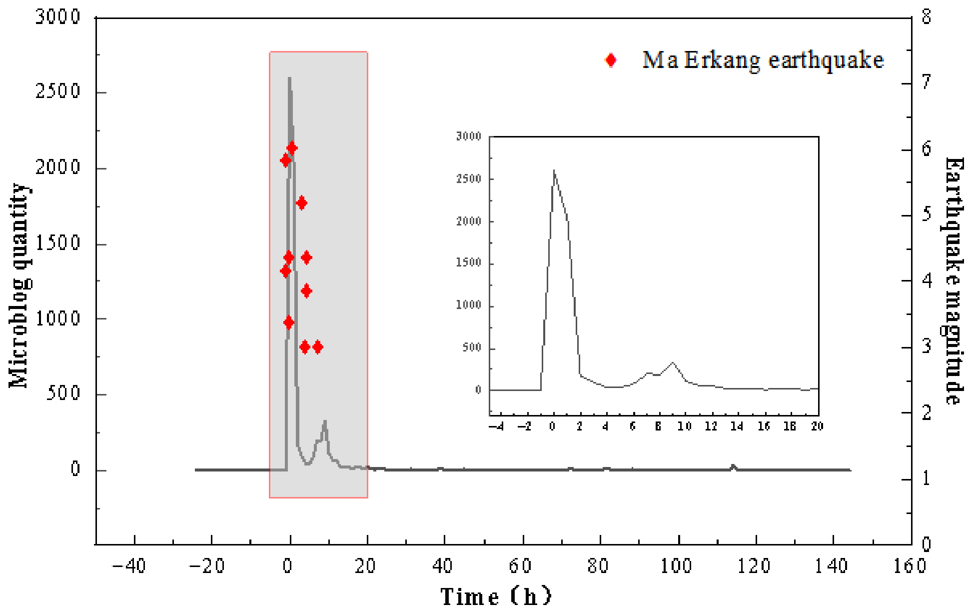
6.1. Microblogging Time-Series Distribution Chart

Figure 2a–c show the change in the number of people's microblog posts over time during and 144 h after the Lushan, Maerkang and Luding earthquakes, respectively. The data from the Lushan and Maerkang earthquakes show that the number of microblog posts reached a peak within an hour after the quake (4704 for the Lushan earthquake and 2602 for the Maerkang earthquake) and then showed a rapid downward trend thereafter. On the morning after the Malcolm earthquake, there was a small fluctuation in the number of microblogs, as people were concerned about the earthquake situation, and there was a small peak of 328 at 9 h (9:00) after the quake, followed by another decline. The first peak of 5177 microblogs was reached within two hours after the earthquake in Luding, and aftershocks occurred many times afterwards, with seven aftershocks of M3.0 and above up to 21:00 on 5 September. These frequent earthquakes triggered a second round of public opinion, and the number of microblogs reached a maximum of 7121 within 10 h after the earthquake (22:00–23:00 on 5 September) until 0:00 on 6 September. The number of microblog posts was mainly concentrated in the daytime, with fewer posts in the evening, while the number of microblog posts showed a trend of gradually decreasing.



(a)

Figure 2. *Cont.*



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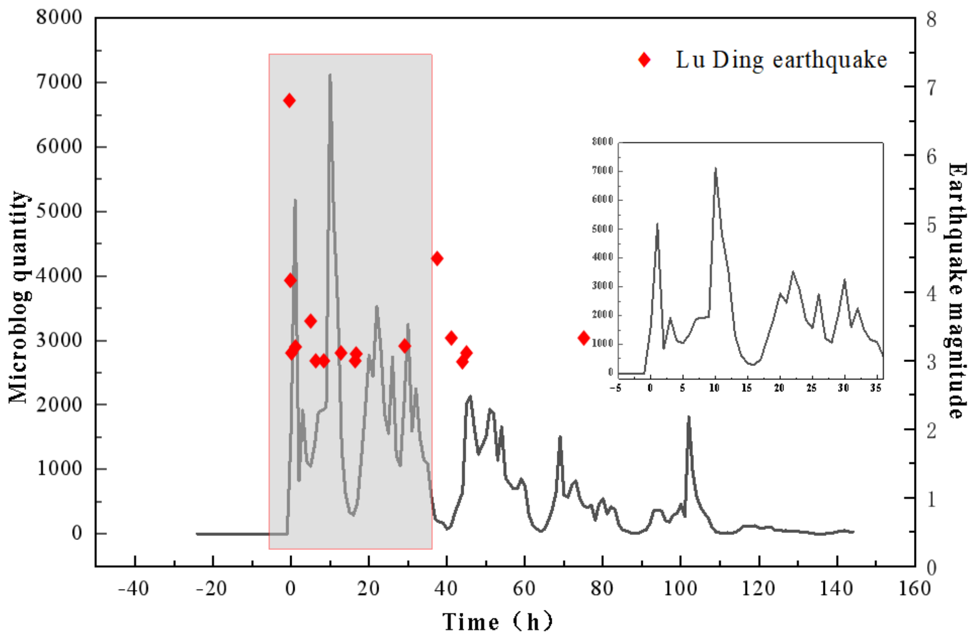


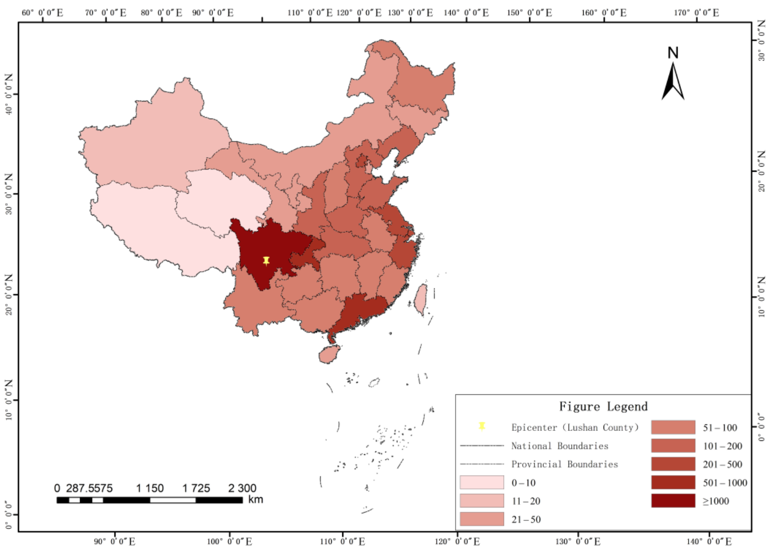
(**c**)

Figure 2. (**a**) Time series of Lushan earthquake. (**b**) Time series of Maerkang earthquake. (**c**) Time series of Luding earthquake.

A comparative analysis of the three earthquake events showed that people's attention was influenced by the time of the earthquake. As the number of people's microblog posts increased sharply 1~2 h after the earthquake, people's attention increased sharply, and they had a stronger desire to express themselves. Thereafter people's sentiments will be changed by the ongoing social impact of the earthquake. The larger the social influence range, the deeper the severity, and the more the number of microblog posts, the stronger the attention.

6.2. Spatial Sequence Distribution of Microblogs

The spatial sequence distributions of the microblog posts posted 144 h after the earthquakes in Lushan, Maerkang and Luding are shown in Figure 3a–c. In terms of spatial distribution, the three earthquakes received a high degree of attention from people in the southern region and relatively less attention from people in the northwestern region. The people in the main quake area posted the highest number of posts for all three earthquakes, and the people in Guangdong Province posted the second highest number (4422, 5195 and 15,261 microblogs were posted by people in Sichuan, and 753, 439 and 14,005 microblogs were posted by people in Guangdong), with the people in Sichuan, as the location of the source of these three earthquakes, posting the highest number of microblogs with the most attention. There are two main reasons for the high level of public concern in Guangdong: (1) Guangdong, as a major region for natural disasters, such as meteorology, is prone to "empathic" behavior and also has a high level of concern for earthquake events; (2) most of the laborers transferred from outside Sichuan Province are distributed in Guangdong (Chencheng 2014) [22], a developed region with service and manufacturing industries, and when the earthquake occurred in Sichuan, the phenomenon of "empathy" was generated out of concern for their hometowns and loved ones, so they focused on the Sichuan disaster. Other regions with high concern are mainly concentrated in Beijing, Jiangsu and Zhejiang.



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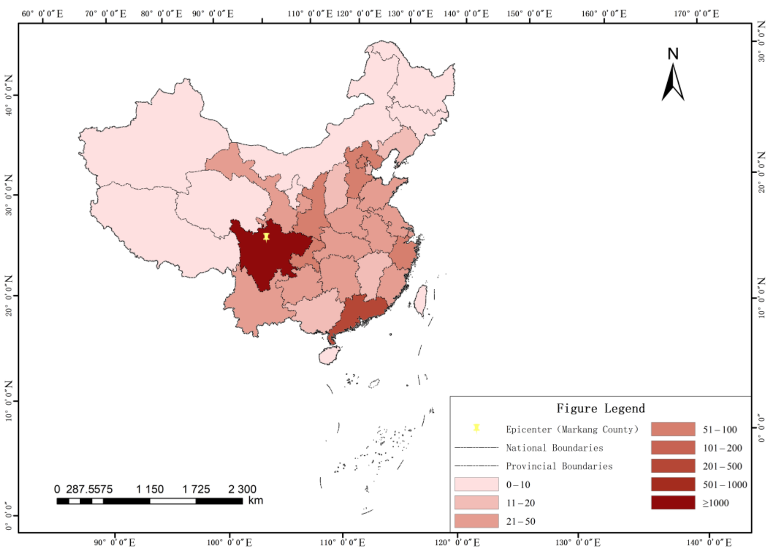

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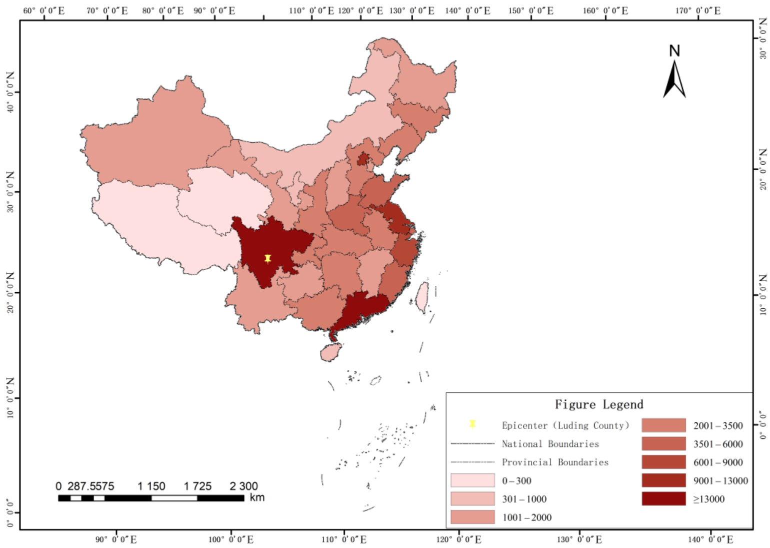
Figure 3. *Cont.*



(**c**)

Figure 3. (**a**) Spatial sequence of microblogs posted after the Lushan earthquake, (**b**) spatial sequence of microblogs posted after the Maerkang earthquake, (**c**) spatial sequence of microblogs posted after the Luding earthquake.

A comprehensive analysis of the results of the spatial distribution of people's concerns after the three earthquakes showed that there was a certain relationship between people's concern and their regions, with the people in the disaster area showing the highest concern; the people in coastal areas, such as Guangdong, Jiangsu and Zhejiang, also showing a high concern; and the people in the northwestern region showing the lowest concern.

6.3. Data Characterization

We used the "jieba" Chinese analysis library in python to separate words from the text of microblogs. In order to optimize the word separation effect, we added user-defined dictionaries with earthquake-related terminology and industry-related standards, imported them into the word separation system and combined them with manual judgment to extract the words published regarding the three earthquakes. For statistical convenience, the top 30 words with the highest word frequency were selected in this paper, and the statistical results are shown in Table 2. In general, the number of blog posts extracted regarding the Luding earthquake was significantly higher than that extracted regarding the Lushan earthquake and the Maerkang earthquake; the word "earthquake" ranked first among the three earthquakes, with 55,059, 15,934 and 571,660 mentions, respectively. Geographical location words, such as "Lushan", "Maerkang", "Sichuan" and "Luding", also ranked among the top words. Other high-frequency words, such as "casualties", "focal depth", "seismic network" and "aftershock", were closely related to the three seismic events.

Table 2. Frequency statistics of words in microblogs posted 24 h after the earthquake (top 30).

	Words	Word Frequencies	Words	Word Frequencies	Words	Word Frequencies
Lushan Earthquake	Earthquake	55,059	Lushan	15,735	Search & Rescue	2948
	Sichuan	29,647	Baoxing County	7015	Epicenter	2924
	Ya'an City	27,701	Ya'an	5777	First Time	2741
	Lushan County	25,887	Depth of Earthquake	4793	Earthquake Relief	2718
	Divided in	17,318	June 1	4398	Command	2682
	Information	16,867	0 AM	4361	Peaceful	2589
	China	16,317	Do it all	4115	Aftershock	2361
	Earthquake Network	16,190	Ya'an Earthquake	4112	Rush	2294
	Official	16,027	Personnel Casualties	3951	Public Security	2276
	Measurement	16,025	Ensure	3394	Rescue	2231

Table 2. *Cont.*

	Words	Word Frequencies	Words	Word Frequencies	Words	Word Frequencies
Maerkang Earthquake	Earthquake	15,934	Measurement	1906	Emergency Response	828
	Sichuan	9779	Earthquake Group	1808	Density	804
	Maerkang	4943	Aba Maerkang	1306	Center	778
	Aba County	4201	Earthquake Warning	1060	Magnitude	771
	Epicenter	4132	Chengdu	1048	Unobstructed	764
	Maerkang County	3494	Depth of Earthquake	1003	Communication	743
	China	2838	Launch	989	Tremors	615
	Earthquake Network	2685	Aftershock	900	Rush to	605
	Official	2019	Crowd	866	Latitude	523
	Divided in	1926	Continuous	843	Longitude	523
Luding Earthquake	Sichuan	571,660	Earthquake Network	90,737	Ganz	13,415
	Earthquake	490,278	Measurement	84,474	Tremors	11,898
	Garze	266,424	Official	73,466	Response	10,960
	Luding Country	265,104	Rescue	72,951	Earthquake Area	9756
	Luding	51,732	Depth of Earthquake	56,458	Journalists	7332
	Divided in	15,061	Epicenter	42,598	Earthquake Relief	7273
	Chengdu	80,344	Rescue Team	27,465	Ya'an	6524
	Command	43,837	Aftershock	21,148	Main Desk	6082
	Launch	35,510	Peaceful	18,349	Emergency Response	5627
	China	14,816	Rescue Force	15,780	Sichuan Province	4186

7. Analysis of Factors That Influence People's Sentiments

According to the behavioral influence model, combined with the individual characteristics of the people, we believe that the changes in people's sentiments are mainly influenced by their regions and official media information. Specifically, when an earthquake occurs, the psychological needs of the people in the affected area are higher than those in non-affected areas due to the devastation caused by the earthquake itself; therefore, the resulting sentiment will be higher than that of the people in other areas. After information is released by official media outlets, people will be affected by their own sentiments to a certain extent after browsing the relevant content. Therefore, we propose two propositional hypotheses based on location and the official media:

Hypotheses 1. *People in the area where the earthquake was located had a higher level of negative sentiments than people in other areas.*

Hypotheses 2. *The microblogging sentiment of the official media positively influenced the changes in people's sentiments.*

Since most of the published microblogs are reprinted microblogs and only provide descriptions of the earthquake disaster, they cannot truly reflect the sentiments of the people. In order to exclude the influences of microblogs without any sentimental value, this paper selects the comments on the post-earthquake microblogs published by "People's Daily" as the data samples for the sentimental analysis. A total of 30 microblogs related to the "Lushan earthquake", the "Maerkang earthquake" and the "Luding earthquake" published by People's Daily, with a total of 28,275 comments, were crawled, and the content unrelated to the earthquake disasters was eliminated by manual means. With the help of the Tencent Cloud natural language processing platform, the sentiment analysis interface is requested (request domain name: nlp.tencentcloudapi.com), the cleaned data mentioned above are encoded and processed, and the sentiment analysis results are expressed as positive, negative and neutral. The results are saved in a dataframe and exported to an Excel spreadsheet.

7.1. Overall Level of Public Sentiment

The proportions of positive, negative and neutral sentiments in the content of each microblog comment were calculated and classified according to the three earthquakes, and the results are shown in Figure 4. Among the comments posted by users, positive sentiments dominated for all three earthquakes, followed by neutral sentiments, and negative sentiments accounted for the smallest proportion. The main reason for this is that the time interval between two of the earthquakes was only 9 days, and the frequent earthquake disasters made people's sentiments change from positive to negative. People's positive sentiments after the Luding earthquake decreased by 5.9% compared with those after the Lushan earthquake.

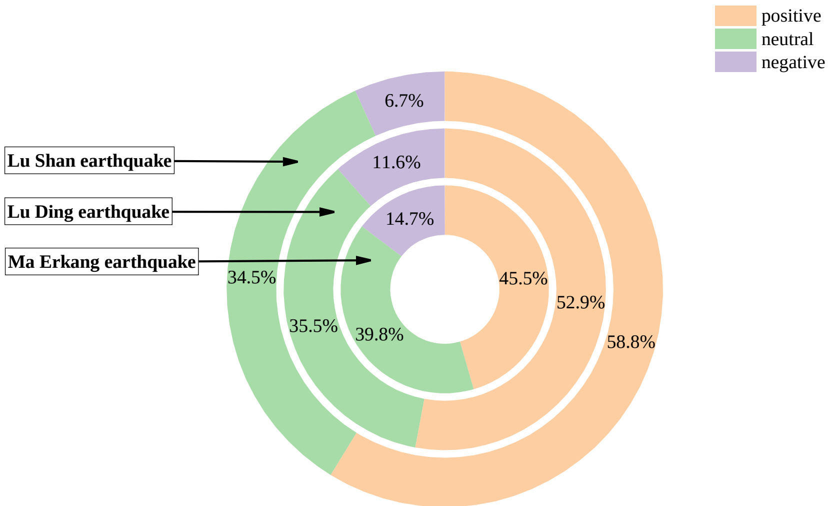


Figure 4. Sichuan earthquake sentiment scale map.

7.2. Regional Influence on Public Sentiment

In order to investigate the main sources of the three types of sentiments of people after the earthquakes, this paper classifies the provinces where people commented on microblogs in the three earthquakes into Sichuan and non-Sichuan regions, and it collates the number of people's sentiments according to the different regions. The smaller the value, the more negative the sentiment, and the larger the value, the more positive the sentiment; a value above 0.5 is regarded as positive sentiment, a value below 0.5 is regarded as negative sentiment, and a value equal to 0.5 is regarded as neutral sentiment. For example, a value of 0 indicates extreme negative emotions, and a value of 1 indicates extreme positive emotions [23]. This paper demonstrates the changes in the sentiments of the people in Sichuan and those of the people in other regions, as shown in Figure 5, where microblogs 1–16 indicate the people's sentiments of the Luding earthquake, microblogs 17–27 indicate the people's sentiments of the Lushan earthquake, and microblogs 28–30 indicate the people's sentiments of the Maerkang earthquake.

Overall, the number of sentiment values above 0.5 was 16 in Sichuan and 23 in the other regions, with positive sentiments accounting for more than 50% of the total sentiment, indicating that the overall average sentiment of the public was positive. By region, in Sichuan, people's sentiment values were generally lower than those in the other regions due to the impact of the earthquake disaster. By earthquake, the average sentiment values between the people in Sichuan and those in the other regions regarding the Lushan earthquake were about 0.5 and 0.61, respectively, and the average sentiment values between the people in Sichuan and those in the other regions regarding the Maerkang earthquake were about 0.29 and 0.55, respectively. The level of sentiment in Sichuan was significantly lower than that in non-Sichuan regions; the average sentiment in Sichuan regarding the Luding earthquake was closest to that in other regions, with a difference of about 0.08. A comparison of sentiment by region revealed that the sentiment values of the people in the provinces where the affected areas were located regarding the three earthquakes were generally lower than those of the people in the other regions and that people's sentiments were influenced by the region where the earthquake occurred, supporting Hypothesis 1.

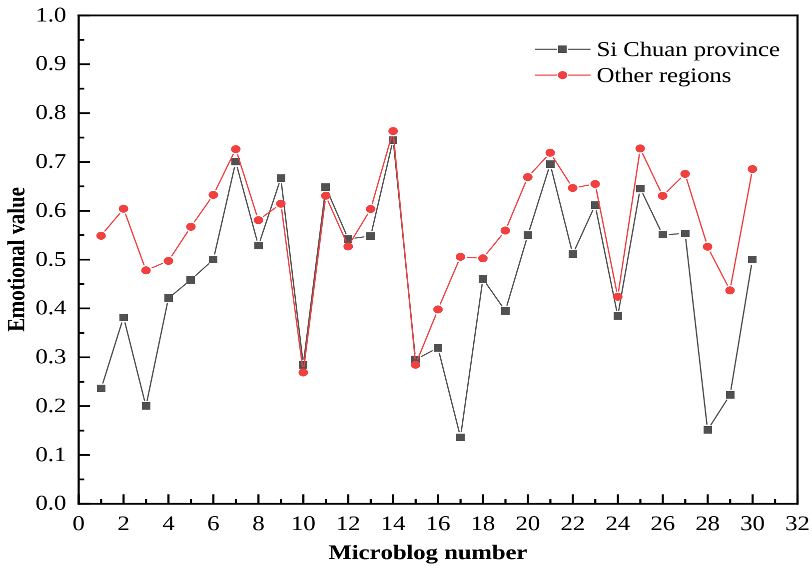


Figure 5. Regional Sentiment Comparison Chart.

7.3. The Influence of Official Media on Public Sentiment

According to the regional sentiment comparison, it can be seen that there is no specific pattern of sentiment change between the people in Sichuan and those in the other regions, and positive sentiment and negative sentiment are shown interchangeably. In order to explore the influencing factors of the changes in people's sentiment values, this paper firstly identified the sentiments of the microblogs released by the official media and conducted a correlation analysis by combining the overall sentiment value, Sichuan's sentiment value and the other regions' sentiment values; Table 3 shows the results of the descriptive statistics of the variables, and Table 4 shows the results of the correlation analysis of the variables.

Table 3. Descriptive statistics.

Variable	N	Mean	SD	Min	p25	p50
Office-Emo	30	0.1	0.66	−1	0	0
Overall-Emo	30	0.54	0.14	0.27	0.42	0.57
Si Chuan-Emo	30	0.46	0.17	0.14	0.32	0.5
Other-Emo	30	0.57	0.12	0.27	0.5	0.59

Table 4. Correlation analysis.

Variables	Office-Emo	Overall-Emo	Si Chuan-Emo	Other-Emo
Office-Emo	1.000			
Overall-Emo	0.551 ***	1.000		
Si Chuan-Emo	0.435 **	0.892 ***	1.000	
Other-Emo	0.592 ***	0.952 ***	0.741 ***	1.000

Note: *** indicates $p < 0.01$, ** indicates $p < 0.05$, * indicates $p < 0.1$.

As can be seen in Table 3, the mean values of the national sentiment, Sichuan's sentiment and other regions' sentiment are all below the middle value, indicating that most of the people's sentiment shows a low degree, with a mean value of 0.46 in the Sichuan region, which indicates that most of the people have negative sentiment; the results in Figure 5 also confirm this conclusion. From the analysis results shown in Table 4, it can be seen that the changes in people's sentiment in general, in the Sichuan region and in the other regions show a significant positive effect with the sentiment of the published microblogs, and when official microblogs present positive sentiment, the level of people's sentiment improves, verifying Hypothesis 2. In a comparison, the sentiment of official microblogs is found to have the greatest degree of influence on other regions and the lowest degree of influence on Sichuan. The reason for this might be that the people in Sichuan were themselves affected by the disaster and, at the same time, received more extensive information about it, so the factors affecting the sentiments of the people in this region are more complex. The other regions receive relatively single information and rely more on microblogs to deliver disaster information. Therefore, after the earthquake, when there are casualties or other negative scenarios, official media outlets should promptly release microblog content with positive emotions, for example, showing the progress of relief work and heart-warming moments of rescue, in order to enhance the positive sentiments of the public and, thus, control the risk of generating public opinion.

8. Conclusions and Insights

8.1. Conclusions

The Lushan, Maerkang and Luding earthquakes selected for this research all occurred in the Sichuan region, and they occurred relatively close in time, causing casualties and bringing serious economic losses to the local people. Meanwhile, the Lushan earthquake is located in the Longmenshan Fault Zone; the Maerkang earthquake occurred in the Songgang Fault Zone; and the Luding earthquake occurred in the Xianshui River Fault Zone. Of the above three earthquakes, the Luding earthquake was the most destructive, caused the most serious damage and received the most public attention. Microblogs currently represent one of the most important vehicles for reflecting public opinion, and analyses of disaster-related microblog texts are of great significance for researching public opinion. Therefore, we crawled the posting data of microblogs after the three earthquakes and the comments of microblogs posted by official media outlets based on Sina Weibo to describe the spatial and temporal characteristics of a number of people's microblogs posted 144 h after the earthquakes and to analyze the differences in people's attention affected by space and time. We crawled the content of people's comments under the microblogs released by official media outlets and identified the comment sentiment with the help of the Tencent Cloud natural language processing platform, and, thereafter, we classified the analysis of people's sentiment and explored the influencing factors of the changes in people's sentiment. The main conclusions are as follows:

(1) Examining the statistical results regarding the number of microblogs, microblog users paid high attention to the three earthquakes and published and retweeted a lot of information related to them. People published the most microblogs about and paid the highest attention to the Luding earthquake, followed by the Lushan earthquake, while the lowest in the Maerkang earthquake. The number of aftershocks, the severity of secondary disasters and the scope of social influence will all lead to an increase in the number of microblogs and an increase in attention; otherwise, the number of microblogs will show a decreasing trend. In the spatial characteristics, the people's attention is not only closely related to the areas where earthquakes occur and historical disasters are frequent, but also influenced by labor migration, the coastal areas are also in the forefront of attention, and the three earthquake microblogging areas are mainly concentrated in Sichuan, Guangdong and Jiangsu and Zhejiang.

(2) Examining the characteristics of the microblogs, the word "earthquake" appeared the most frequently in the microblogs after the earthquakes. "Lushan", "Maerkang", "Sichuan", "Luding" and other words indicating geographical location were also among the top most frequently used words, while other high-frequency words, such as "casualties", "depth of earthquake", "earthquake network" and "aftershock" were closely related to the three earthquakes.

(3) From the viewpoint of the change in sentiment, the positive sentiment of the people in Sichuan was higher than the negative sentiment for all three earthquakes, among which the positive sentiment of people after the Maerkang earthquake decreased by 13.3% compared with the Lushan earthquake, and the positive sentiment of people after the Luding earthquake decreased by 5.9% compared with the Lushan earthquake. Through a comparison by region, we observed that the sentiment value of the people

in Sichuan was generally lower than that of the people in the other regions and that people's sentiment has a close relationship with the region that they are in. Through a correlation analysis of official sentiment and public sentiment, we found that the change in public sentiment was not only affected by the disaster itself but that it was also influenced, to a certain extent, by the microblogs released by the government and other official departments, showing a positive and significant influence. Therefore, determining how to grasp public opinion dynamics and releasing positive information in a timely manner are important aspects of public opinion guidance.

8.2. Insights

The smooth and orderly development of online public opinion is of great significance to the long-term stability of the country. If it is allowed to develop freely, it may lead to a large negative trend of public opinion and even cause a complete loss of control of public opinion. Facing the characteristics and problems of Internet public opinion in the new media era, we should consider disaster public opinion management countermeasures from multiple angles and levels. (1) In the Internet era, when an earthquake occurs, it is key that the public opinion monitoring department monitors the microblogs posted in quake-stricken provinces, as well as in Guangdong, Jiangsu and Zhejiang. (2) The relevant departments should focus on the content of microblogs posted 2h after the earthquake to understand the dynamic changes in the disaster area and to understand the psychological needs of the people. (3) The management of the public opinion of disasters is also particularly important for earthquake prevention and mitigation work, as the sentiment of official microblogs can positively influence the psychological emotions of people, so the relevant departments should first grasp the initiative of public opinion and release information regarding quake-resistant and warm-hearted events at the right time to reduce panic, effectively guide people's speech and promote the harmonious and stable development of society.

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