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ORIGINAL PAPER

Study on the evolution of online public opinion and government response strategies for the "7–20" extraordinary rainstorm and flooding disaster in Zhengzhou, China

Pu Zhang[1] · Hao Zhang[2] · Feng Kong[1,3]

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Abstract
Disaster-related online public opinion develops rapidly, the actual situation is complex and volatile, and the public opinion environment should be regulated through appropriate guidance. 2021 Zhengzhou 7–20 extraordinary rainstorm and flooding disaster has attracted widespread public attention. In order to analyze the online public opinion triggered by extraordinary rainstorm disasters and propose targeted management measures so as to improve the comprehensive disaster reduction efficiency. This paper collected information about the "Zhengzhou rainstorm" posted on the Sina Weibo platform from July 11 to August 14, 2021. We analyzed the characteristics of related Weibo from two dimensions: sentiment analysis and thematic analysis. The results are as follows: Online public opinion will be generated rapidly and last for a long time; the different emotional colors change at different periods of the disaster; the focus of online public opinion discussion varies at different periods of the disaster. Given this result, the following suggestions are made: the cooperation level between departments should be improved, and an early warning mechanism for public opinion should be established so that once the relevant public opinion is generated, a quick response can be made; a relevant responsibility mechanism should be established to realize that a specific department is responsible for the handling of public opinion in the corresponding section, to realize a scientific and practical normalized control mechanism for public opinion; Relevant departments should improve the openness and transparency of appropriate handling methods, to establish a public opinion control and guidance mechanism. This study has specific significance for improving the level of governance of online public opinion caused by sudden natural disasters.

Keywords Disaster public opinion · Major natural disasters · Zhengzhou rainstorm · Emergency management · Natural language processing

✉ Feng Kong
kongfeng0824@foxmail.com

1 College of Humanities and Development Studies, China Agricultural University, Beijing, China

2 College of Information and Electrical Engineering, China Agricultural University, Beijing, China

3 Center for Crisis Management Research, Tsinghua University, Beijing, China

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1 Introduction

In the context of climate change, rainstorms and floods are frequent in China and are prone to secondary risks (Kong 2019). In the context of the mobile Internet, social media platforms play the role of information dissemination in public events (Alshehri et al. 2013; Bai and Yu 2016; Dong et al. 2021b). The information itself often covers the emotional color of the information publishers themselves, so if it is not controlled and allowed to develop wildly, it is likely to cause substantial public opinion pressure and adversely affect society's long-term stability (Bird et al. 2014; Chen et al. 2022a; Dwibhasi et al. 2015). In sudden public events, Internet speculation, rumors, and Internet violence are likely to form a negative public opinion (Zhao et al. 2022; Zhou and Jing 2020; Zhou 2022). Once the Internet opinion environment is out of control, it will seriously affect social stability and negatively affect the image and credibility of the government (Mollema et al. 2015; Zhong 2021). The in-depth development of the network society boosts the dissemination of public opinion on the network of emergencies (Deng et al. 2016). To maintain the harmony and stability of society and to calm the public's anxiety, it is urgent to deal with the dissemination of public opinion on the network of emergencies in a timely and effective manner (Dong et al. 2021a; Han and Wang 2022). Given this, it is of great practical significance to realize effective management of the Internet public opinion caused by unexpected events to achieve long-term social stability and stable economic development.

Social network public opinion, especially disaster-related public opinion, is important for studying disaster risk perception. The public's emotional perception of disasters is important for disaster risk perception (Castaños and Lomnitz 2009). Some scholars consider the dissemination of information and the characterization of the public's response to risk as the main determinants of the nature and severity of the risk (Renn 2008). The academic community has developed well-accepted social media-related online opinion analysis methods (Geng et al. 2021; Ma et al. 2014; Mei et al. 2019). First, obtain the text or comments posted by users and then classify them into topics, calculate sentiment analysis, and determine the temporal trends of sentiment. At the present stage, the research on natural disaster-related online public opinion is primarily focused on two aspects: one aspect is the direct text information mining based on user-generated content (UGC) to analyze its time series of public opinion characteristics, which has been widely applied in China (Li et al. 2022; Liu et al. 2022b; Xu et al. 2020). And some foreign universities have also conducted related researches. Another aspect is to combine public opinion data and geographic data (Jain and Katarya 2019; Kraft et al. 2020), thus realizing multi-dimensional analysis in time and space, and such methods are less applied at home and abroad compared with the former (Guo et al. 2022; Tang et al. 2022; Xu et al. 2019).

What are the evolutionary features of the public opinion on the Internet triggered by this rainstorm disaster? What topics do these characteristics indicate in terms of the population's focus in the disaster emergency management process? What are the implications for government departments and others to improve disaster emergency management? Those issues are of great significance for modernizing governance capacity and ensuring the prosperity and stability of society. In order to answer the above questions, the analysis is carried out according to the following logical framework. In brief, we first analyzed the emotional characteristics of online public opinion triggered by the rainstorm disaster using the emotional color analysis module based on the BERT fine-tuning model. Next, we used the keyword co-occurrence semantic network knowledge graph technique with TF-IDF algorithm as the core to map the thematic focus of the public discussion. On this basis, by analyzing the characteristics of public opinion, we sort out the features of disaster-related public opinion and summarize the corresponding governance suggestions.

2 Data and methodology

In this paper, by collecting the data of text and release time of the Weibo related this disaster, we use a machine learning method based on the BERT fine-tuning model for text sentiment analysis (Cui et al. 2021; Devlin et al. 2018). It also combines the temporal and spatial change trends for visualization and presentation and then analyzes the change trends of public opinion associated with this disaster. In addition, we used a knowledge graph technology based key co-occurrence word sense network to analyze the thematic changes of related Weibo during this disaster. The logical structure of our study is shown in Fig. 1 below. This research is of practical significance for sorting out the evolutionary features of the online public opinion triggered by this disaster. Through the relevant analysis of public opinion data related to a specific disaster, we can derive certain change patterns. Furthermore, we can provide particular suggestions and inspirations for relevant departments to make public opinion control decisions.

2.1 The basic information of "7–20" extraordinary rainstorm and flooding disaster

Henan Province suffered an extraordinary rainstorm and flooding disaster in late July 2021, severely affecting Zhengzhou City. Between 8:00 a.m. on the 17th and 8:00 a.m. on the 23rd, the cumulative rainfall in Zhengzhou City amounted to 5,590 km^2 above 400 mm and 2,068 km^2 above 600 mm. In the process, some meteorological stations' cumulative surface rainfall observation data amounted to 993.1 mm, with the most vital hourly point in Zhengzhou City rainfall amounting to 201.9 mm (Chen et al. 2022b). After collecting and organizing the relevant data released by the Henan Provincial Meteorological Bureau and other meteorological observation department, the precipitation in Zhengzhou City from July 18 to July 23 is shown in Fig. 2 below (Su et al. 2021; Wang et al. 2022).

The disaster caused 14,786,000 people affected, 398 people dead or missing, and direct economic losses of 120.6 billion RMB (about 17 billion US dollars). While the disaster has caused significant loss of life and property, it has also attracted widespread attention from netizens. Only during the period from July 20 to August 1, the topics related to the Zhengzhou Rainstorm became one of the most talked about topics on Weibo more than 20 times and caused much discussion among the public. The content posted by the Weibo account "CCTV News" alone has been read more than 1 billion times. News messages on the Weibo platform labeled "Henan rainstorm" have been read more than 330 million times. In addition, several radio and television organizations, including the China Central Television (CCTV), have made frequent reports on related topics.

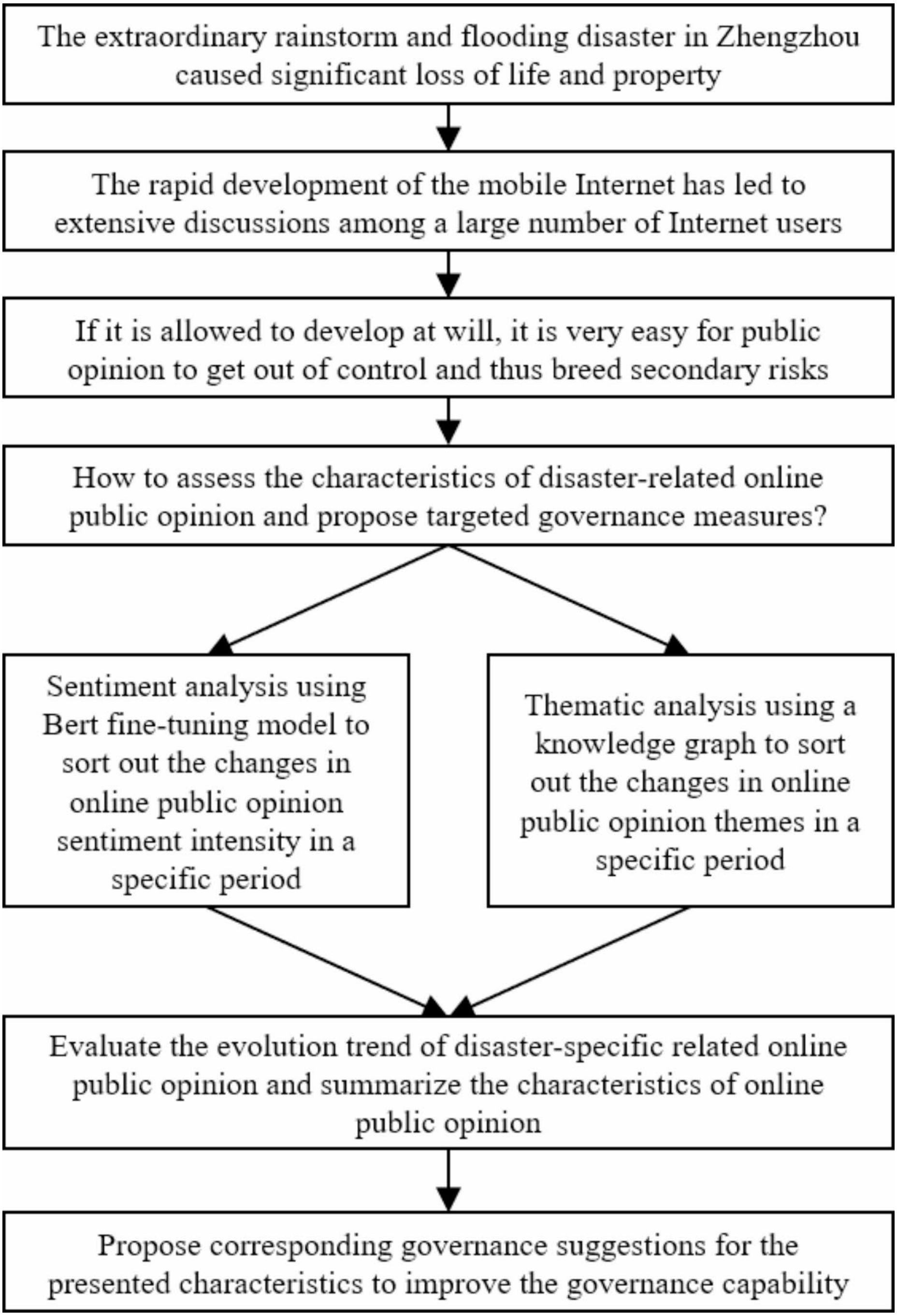

Fig. 1 The logical framework of this paper

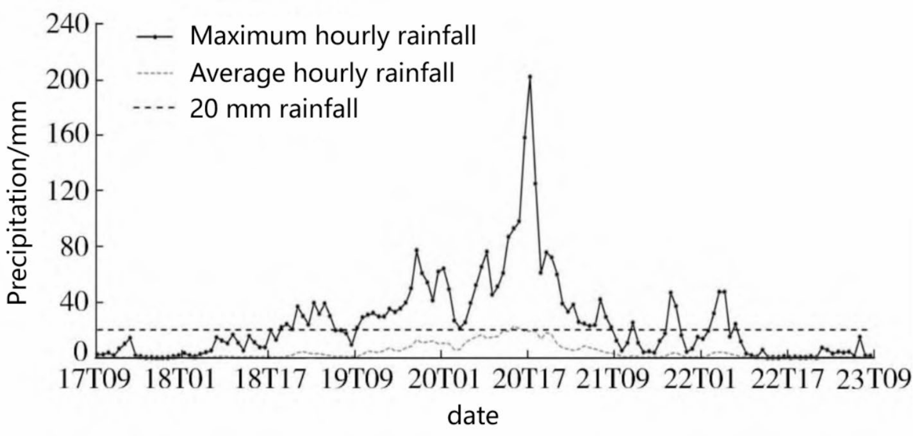

Fig. 2 The precipitation in Zhengzhou City from July 18 to July 23

2.2 Data collection and pre-processing

2.2.1 Data crawling and data cleaning

Firstly, we rely on the crawls-based crawler program to collect 50 Weibo each time by simulating users to search for the relevant content of Weibo with specific keywords (Zhengzhou rainstorm). We categorize the release time of relevant Weibo into three periods based on emergency management theory. We then visualized the data distribution and user retweets and comments. Next, we used the user IDs in the crawled Weibo to backfill the user region information, and all districts and counties were unified into prefecture-level cities. The number of Weibo posted in different prefecture-level cities was counted to evaluate the posting of related topics in each province and city. Since the text of the crawled Weibo contains many useless characters, such as "@XXX" and "#XXX," We deleted them one by one. After removing the non-Chinese characters and the related content after the @ sign, we realized preliminary cleaning. For the existence of emoji, since the emoji itself contains a specific emotional meaning, it cannot be deleted directly. To address this issue, the "emoji switch" library is used to replace the emoji with Chinese characters.

2.2.2 Time distribution of related Weibo

The data were collected with "Zhengzhou rainstorm" as the core keyword. A series of Weibo posted on the Sina Weibo platform from July 11, 0:00 to August 14, 24:00 were collected. The data mainly includes the content of the text of the Weibo, the time of posting, user ID, and other essential information. After crawling, a total of 63,899 related information was obtained.

According to the actual occurrence of this disaster, noticeable rainfall had begun to occur on July 18th, and on July 24th, the urban functioning of Zhengzhou City had been basically restored. Thus we regarded this stage as the mid-disaster period. Since there is very little discussion related to the pre-disaster period, we collected data related to the seven days prior to the disaster and divided it into pre-disaster periods. Considering the above together, we took July 18 as the starting time node of the disaster; July 24 as the ending time node of the disaster. The release time of the relevant Weibo posts was divided into three periods: the pre-disaster period (July 11–17), the mid-disaster period (July 18–24), and the post-disaster period (July 25-August 14). Based on the time series analysis of the crawled data, the number of Weibo during the "Zhengzhou rainstorm" disaster was obtained (Fig. 3). We found that the number of related Weibo before the disaster was tiny. The number of related Weibo rose steeply with the sudden occurrence of the disaster. It decreased in the late stage of the disaster, and the hotness also gradually declined.

2.2.3 Spatial distribution of related Weibo

According to the statistics of Weibo posted in different regions, the top 10 cities are shown in Table 1. It can be found that among the top 10 cities, except for Zhengzhou and Xinxiang, which were severely affected, all other cities are large cities with large populations, such as Beijing, Shanghai, Guangzhou, and Shenzhen.

We analyzed 63,899 Weibo crawled by program and found that 47,945 Weibo had 0 forwardings, 10,643 Weibo had 1 ~ 10 forwardings, 5,311 Weibo had 11 ~ 51 forwardings, 458 Weibo had 51 ~ 100 forwardings, and 890 Weibo had more than 100 forwardings. Based on the number of Weibo replies, we categorized them into four zones. After performing the statistics, the distribution of the data is shown in Table 2 below.

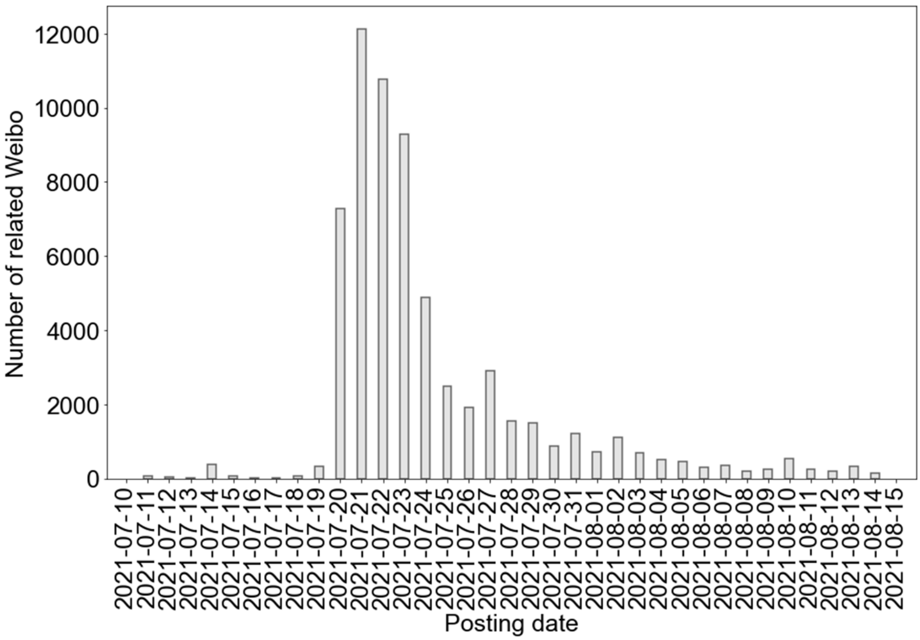

Fig. 3 Number of Weibo posts related to the "Zhengzhou rainstorm" period

Table 1 Details of the top ten cities posts Weibo related to the "Zhengzhou rainstorm"

City	Number of Weibo	Percentage/%
Zhengzhou	4 974	10.67
Beijing	3 636	7.80
Chengdu	2 197	4.71
Shanghai	1 767	3.79
Xinxiang	1 449	3.11
Hangzhou	1 392	2.99
Chongqing	1 261	2.70
Shenzhen	1 132	2.43
Guangzhou	1 103	2.37
Nanjing	1 054	2.26

Table 2 Percentage of forwarding of "Zhengzhou rainstorm"-related Weibo

Number of forwarding	Number of Weibo	Percentage/%
0	47,945	75.03
1~10	12,251	19.17
11~50	2355	3.69
51~100	458	0.72

2.3 Research Methodology

Further combing through the existing studies reveals that: relying on the stage division theory of emergency management, a phased analysis of disaster-triggered online public opinion can better assess the relevant characteristics of online public opinion (Coetzee and Van Niekerk 2012; Kim and Hastak 2018; Wang et al. 2020). This study mainly constructs the evaluation method of public opinion analysis from 2 dimensions: the sentiment and thematic changing trend. Firstly, we crawl many Weibo related to the "Zhengzhou Rainstorm". Then we perform data cleaning on the crawled data. After removing useless characters, we uses the machine learning method based on the BERT fine-tuning model to analyze and determine the sentiment tendency of each Weibo text. We organize and downscale the temporal information and then achieves the analysis on time series. The Weibo posts at different times of the same day are grouped into one day, and then the time series can be analyzed. On the basis of completing these two analyses, we characterize the results. We next use the keyword co-occurrence knowledge graph technique based on the TF-IDF algorithm to process the three sets of Weibo texts after grouping them according to different periods. The analysis allows us to derive the clustering of Weibo text topics in different time periods. Through these characterizations, we are able to identify the evolutionary characteristics of the online public opinion triggered by this disaster and sort out the corresponding experience of online public opinion management. The specific technical framework is shown in Fig. 4.

2.4 Sentiment analysis based on the BERT fine-tuning model

BERT, known as Bidirectional Encoder Representation from Transformers, is an unsupervised pre-trained language model for natural language processing tasks (Devlin et al. 2018). The model is widely used in natural language processing, including sentiment analysis, named entity recognition, and other fields. Since the corpus of this study is Chinese text, the

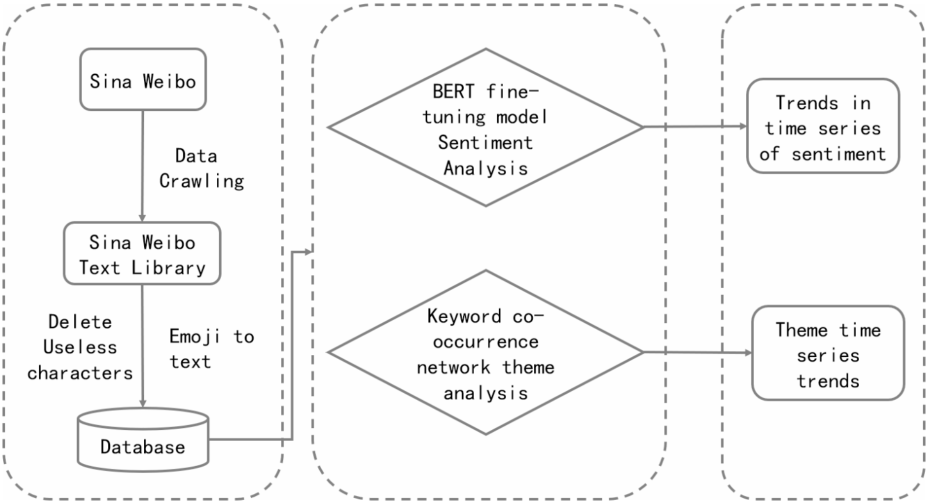

Fig. 4 Framework of this research

BERT-WWM fine-tuning model is used, which has a high accuracy for sentiment tendency judgment of Chinese text (Cui et al. 2021). After processing, each Weibo text is assigned a sentiment score from 0 to 1. The closer the score tends to 0, the more pronounced the negative sentiment is; the closer it tends to 1, the more pronounced the positive sentiment is; when it tends to 0.5, it is usually considered neutral.

The sentiment analysis process is divided into four steps as follows: firstly, the cleaned Weibo is processed by the BERT fine-tuning model according to the three periods of the disaster, and then the sentiment score of each Weibo is obtained. The visualization is carried out using a Python-related mapping library to present the distribution of sentiment tendency in different periods. To further analyze the temporal change characteristics, the initial scores were subtracted by 0.5 so that the positive sentiment scores were all positive and the scores of negative sentiment were all negative, which were then distributed on both sides of 0. The Weibo are grouped according to their posting dates, and then the Weibo scores that showed positive sentiment colors were added for each day. The negative scores were also added up to assess sentiment intensity.

2.5 Thematic analysis based on the semantic network of keywords

Keyword co-occurrence semantic network (Montemurro and Zanette 2013; Wang et al. 2015) refers to the mapping of simple words into a complex network to discover the connection between words in line with natural linguistic properties, which in turn provides help to achieve better text analysis. In addition, keyword co-occurrences can somehow be considered the same related topic, thus clustering the classification of topics covered by the text and determining the proportion of different topics. In this paper, we extract word frequency relationships by TF-IDF (Term Frequency-Inverse Document Frequency) algorithm (Aizawa 2003). When there are different words with the same word frequency in a document, the algorithm can distinguish the importance of these words to the document. After using the above algorithm to find the keyword situation in each stage of the Weibo body, a keyword co-occurrence semantic network can be established by connecting the keywords into a network according to the co-occurrence relationship. Since the text of the Weibo is in Chinese, we first need to do word separation, and the word separation tool we use is the “Jieba” library.

3 Sentiment analysis of related Weibo

Due to the impact of climate change, extreme rainstorm disasters have occurred frequently in China in recent years (Shi et al. 2017). The extraordinary rainstorm in Zhengzhou, as the most serious rainstorm and flooding disaster event in China in recent years, has caused serious loss of life and property. Affected by the negative effects brought by the disaster, many netizens posted destructive remarks on social media platforms, which also brought serious challenges to the governance of the online public opinion environment (Wang 2023). In general, except in the case of particularly severe torrential rainfall and flooding, most people’s online statements about flooding are more positive (Ma 2021). In this context, it is of great practical significance to explore the emotional color of online public opinion of this disaster and to compare it with online public opinion of similar disasters in order to improve the effect of comprehensive disaster reduction and the ability of online public opinion management.

Sentiment analysis, also known as opinion mining, is a typical application of text analysis in the field of natural language processing, and can be used to analyze the emotional attitudes, positive and negative situations embedded in people’s opinions about products, events, services and other content (Ravi and Ravi 2015). Depending on the sentiment analysis task, it can be further classified into subjective and objective analysis, positive and negative sentiment polarity analysis (dichotomous classification), and multi-sentiment classification. In general, sentiment classification is done using a machine learning approach based on feature classification (Drus and Khalid 2019). The emotional intensity color of the Weibo text can reflect people’s attitude towards the events related to the Zhengzhou rainstorm. It has considerable practical significance to rely on partial data to assess the overall environment of online public opinion (Wu and Cui 2018). The larger the proportion of negative statements, the more negative the overall public opinion environment is. In this study, emotional intensity was classified into five levels. The specific classification criteria and representative texts are shown in Table 3 below.

Table 3 Emotional intensity values correspond to emotional tendencies

Emotional intensity score	Emotional Tendencies	Typical corpus
[0,0.2)	Strongly Negative	Geez, that’s too bad.
[0.2,0.4)	Negative	So much rain, so scary.
[0.4,0.6)	Neutral	The weather station issued a weather warning.
[0.6,0.8)	Positive	Trust the government!
[0.8,1.0]	Strongly Positive	Come on, it’s going to get better!

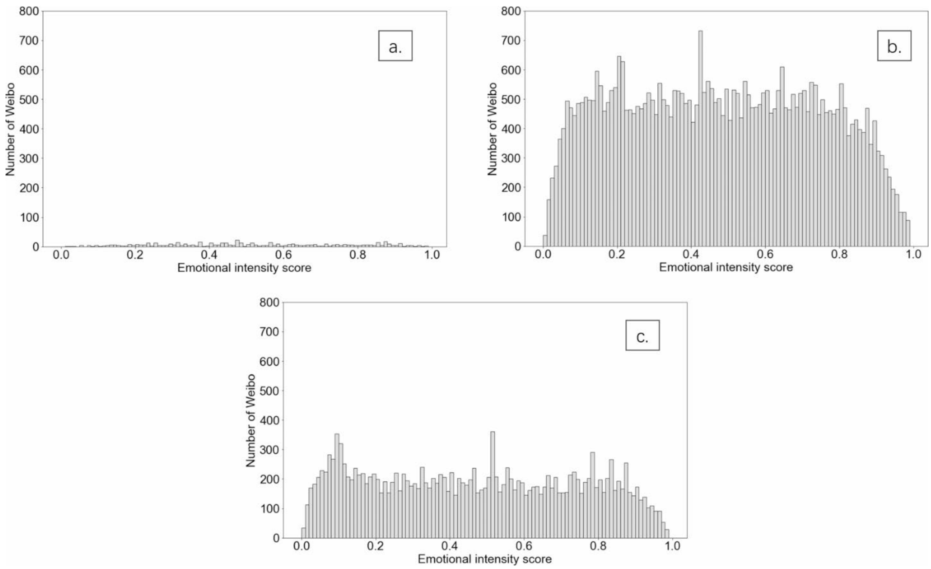

Fig. 5 Distribution of emotional intensity scores in the pre-disaster period (a), mid-disaster period (b), and post-disaster period (c)

Table 4 Distribution of disaster-related Weibo sentiment intensity in the pre-disaster period

Emotional intensity score	Emotional Tendencies	Number of Weibo	Percentage/%
[0,0.2)	Strongly negative	62	10.06
[0.2,0.4)	Negative	141	22.89
[0.4,0.6)	Neutral	169	27.44
[0.6,0.8)	Positive	123	19.97
[0.8,1.0]	Strongly Positive	121	19.64

3.1 Pre-disaster period

We used the BERT fine-tuning model to evaluate the sentiment color of related Weibo posts in the pre-disaster period. The results are shown in Fig. 5(a). The distribution of emotional intensity was a normal distribution, and the data distribution was sparse because there were fewer relevant data in the pre-disaster period. The most concentrated number of Weibo points appear close to neutral emotions, which is in line with the usual plain perception of the rainstorm.

In order to make the results more intuitive, we counted the percentage of the number of Weibo in each emotional intensity range, and the obtained results are shown in Table 4. This table shows that during the pre-disaster period, most people posted storm-related Weibo texts with a neutral emotional color. There are relatively few texts with obvious emotional colors, and the percentage of texts with positive colors is higher than those with negative emotional colors. This result is consistent with the general emotional perception of rainstorms in the hot summer.

Table 5 Distribution of disaster-related Weibo sentiment intensity in the mid-disaster period

Emotional intensity score	Emotional Tendencies	Number of Weibo	Percentage/%
[0,0.2)	Strongly negative	8 501	19.00
[0.2,0.4)	Negative	10 078	22.52
[0.4,0.6)	Neutral	10 162	22.71
[0.6,0.8)	Positive	9 903	22.13
[0.8,1.0]	Strongly Positive	6 103	13.64

Table 6 Distribution of disaster-related Weibo sentiment intensity in the post-disaster period

Emotional intensity score	Emotional Tendencies	Number of Weibo	Percentage/%
[0,0.2)	Strongly negative	4 314	23.66
[0.2,0.4)	Negative	3 775	20.70
[0.4,0.6)	Neutral	3 656	20.05
[0.6,0.8)	Positive	3 669	20.12
[0.8,1.0]	Strongly Positive	2 822	15.47

3.2 Mid-disaster period

We performed the same process for Weibo posts in the mid-disaster period, and the results are shown in Fig. 5(b). The emotional intensity scores in the mid-disaster also showed a normal distribution, with the highest frequency of occurrence at a point close to 0.4, with a slight bias toward negativity.

We use the same operation to group the assigned text, and the results are shown in Table 5. Looking at the chart, it can be seen that there are almost 20,000 relevant texts with a clear negative tone, while the number of positive texts is about 16,000. It can be assumed that negative emotions dominate in this phase. This phenomenon is significant since serious safety accidents in the subway have led to casualties and panic in the public's minds. As a result, many people have begun to make negatively colored statements.

3.3 Post-disaster period

We performed the same process for Weibo posts in the post-disaster period, and the results are shown in Fig. 5(c). The distribution of affective intensity values in this period showed a distinct difference from the previous period. It is characterized by peaks appearing in both negative and neutral emotions.

The data from the post-disaster period were processed, and the results are shown in Table 6. The graph shows that there are still more than 8,000 Weibo statements with a strongly negative color, which is still more than those with a positive emotional color. Compared with the mid-disaster stage, the overall distribution of sentiment colors did not change much in this stage, but the event fervor showed a significant decline. This phase still shows a wave of negative sentiment among the public due to the announcement of the property damage and other related circumstances of the Zhengzhou rainstorm-related events. However, the texts of cheering and encouragement still appear in large numbers.

3.4 Comparative analysis of the distribution of emotional intensity in three periods

Comparing the data of the above period, it can be found that the distribution of emotional intensity values is mainly concentrated around neutral emotion. Texts showing extreme emotional coloration are rare, but they change as disasters evolve. Further, there was a significant increase in Weibo that showed serious negative emotional overtones as the disaster progressed. It increased from 10.06 to 19.00% and finally reached 23.66%. This indicates that if online speech is not guided and negative speech is allowed to ferment, it is highly likely to breed a negative public opinion environment. This harms social stability.

4 Temporal change characteristics of the emotional color of Weibo

4.1 Trends in the pre-disaster period

We grouped the Weibo classified in the pre-disaster period according to the sentiment intensity score and calculated the sum of positive sentiment intensity for each day. Then the same operation was performed for the negative sentiment intensity. The results are shown in Fig. 6 (Period A). The results show that people were not too concerned about the "Zhengzhou rainstorm" in the pre-disaster stage. There was only a tiny climax of concern on July 14 due to the local rainfall in Zhengzhou.

4.2 Trends in the mid-disaster period

The Weibo posts in the mid-disaster period were grouped, and the cumulative intensity of emotional color for each day is shown in Fig. 6 (Period B). The results showed that as the disaster continued to fester, the intensity of emotion fluctuated dramatically. Both positive

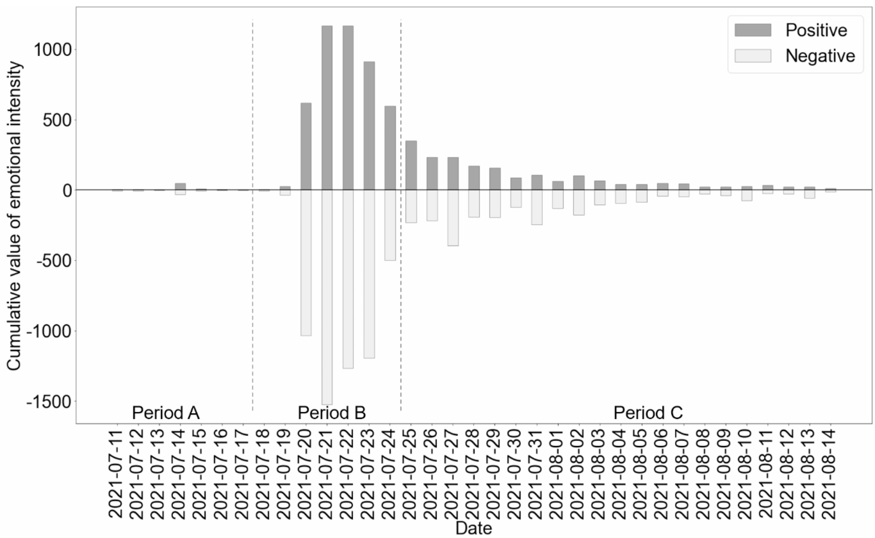

Fig. 6 Cumulative Time Series of Emotional Scores in the pre-disaster period

and negative emotions began to change significantly and showed a trend of increasing and decreasing. The single-day cumulative intensity of positive sentiment peaked on July 22, while negative sentiment peaked on July 21. This is also in line with the massive coverage that began on July 20 with the Zhengzhou rainstorm, and the popularity continued as the disaster continued to be reported; the event's popularity gradually decayed as people's fatigue with the same event gradually increased.

4.3 Trends in the post-disaster period

The Weibo posts in the post-disaster period were grouped, and the cumulative intensity of emotional color for each day is shown in Fig. 6 (Period C). As the post-disaster work continues, the single-day cumulative value of emotional intensity shows a decreasing trend. Some anomalous time points were related to disaster-related information released by the government after checking. On July 27, there was a spike, which was verified to be due to the large number of people who were saddened by the massive news coverage of the 14 people killed on Metro Line 5. On August 2, the Henan Provincial Government Information Office held a press conference to announce the disaster's extent. A large number of casualty figures again led to more negative sentiment in the statements.

5 Thematic analysis of disaster-related Weibo

Relying on the knowledge graph technology based on the keyword co-occurrence semantic network, we can quickly analyze the topics posted by Internet users in a specific period (Lou and Qiu 2014). By comparing the hot situations discussed by netizens in the three periods, targeted plans can be made to improve the effect of channeling online public opinion. This thematic feature analysis consists of the following steps: firstly, the complete sentence is split into single words suitable for processing using jieba splitting, and then the most important 200 keywords are extracted in combination with TF-IDF algorithm, so as to build a keyword semantic network graph, which in turn presents the hot topics focused on by these related Weibo (Zhiliang et al. 2019). Depending on the relevance of the keywords, two to five distinct topic clusters are usually presented. By manually summarizing the sections with strong correlation, we can assess the corresponding topic focus.

5.1 Thematic analysis of the pre-disaster period

The 616 texts in the body of Weibo classified as the pre-disaster period were divided into words, the 200 keywords with the highest word frequency were taken out, and a semantic network graph was constructed. Finally, 5844 connecting lines were formed, which could lead to the results shown in Fig. 7. The semantic network diagram presents three distinct panels, indicating the existence of three distinct themes at this stage. The first panel shows purple color, accounting for 44%. Its content is mainly about the issuance of weather warnings by relevant departments in Henan and the description of some rain conditions, which can be summarized as disaster-causing factors. The second panel shows orange color with 40.5%. The main content is the situation at the time of the storm and the impact on the

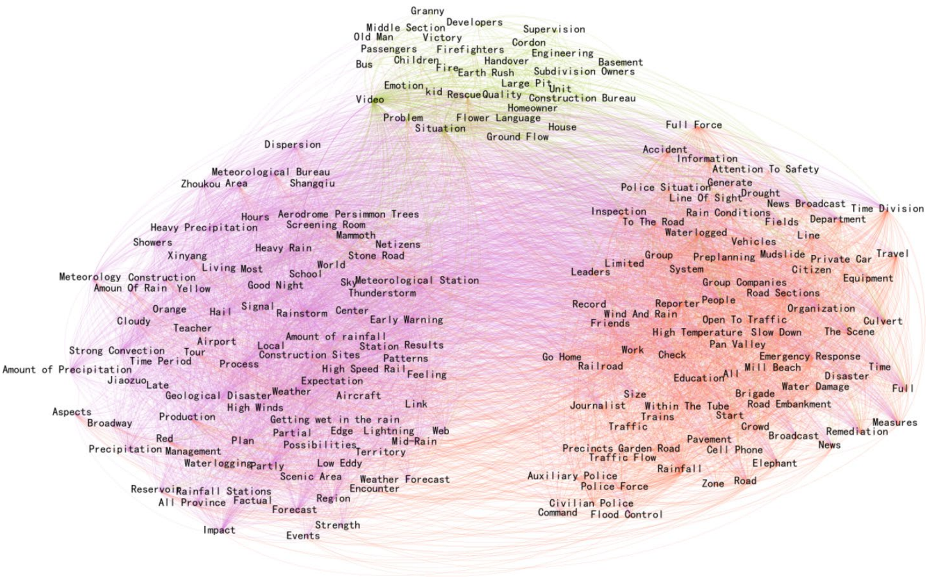

Fig. 7 Pre-disaster semantic network diagram

environment and infrastructure. The third panel shows green color with 15.5%. The main content is the response to the rainstorm and the aftermath.

5.2 Thematic analysis of the mid-disaster period

The same method was adopted to construct a semantic network graph for the 44,747 Weibo posts in the mid-disaster period. 18,523 connecting lines were formed, and the results can be obtained, as shown in Fig. 8. Observation of this graph reveals the presence of three distinct panels, indicating the existence of three distinct themes in this period. The first part is the orange panel which accounts for 56.5% of the total. The main content includes the situation of the disaster and the relevant staff carrying out rescue work. The second section is the blue panel, which accounts for 26.5% of the total. The main contents are the disaster-causing factors, such as the large amount of precipitation that caused the disaster and the damage to life and property caused by the disaster. The third section is the green section, which accounts for 17% of the total. The main content is the disaster situation in specific areas, such as airports, railway stations, etc.

5.3 Thematic analysis of the post-disaster period

The same method was adopted to construct a semantic network graph for the 18 536 Weibo posts in the post-disaster period. The 200 keywords formed 16,837 connection lines, and the results are shown in Fig. 9. Three distinct segments are present, indicating the existence of three distinct themes in this period. First, the purple portion of 70% of the total. There are flooding disasters in many places, and the whole country is enthusiastic about helping and actively assisting in disaster relief. The second is the orange portion of 17% of the

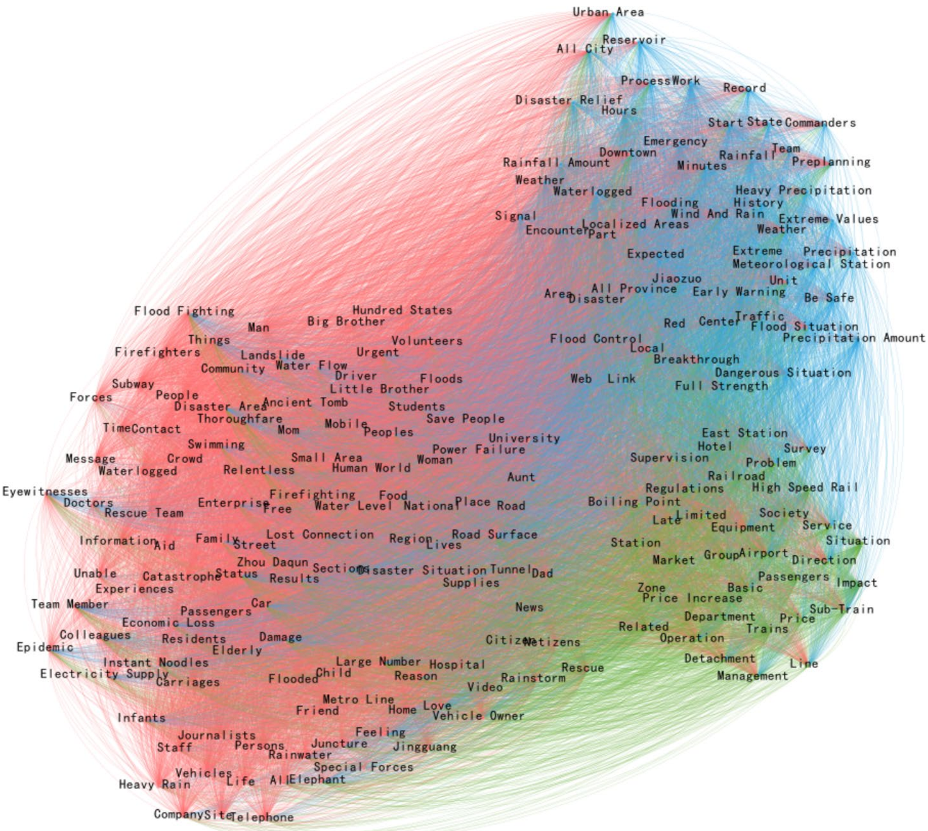

Fig. 8 Mid-disaster semantic network diagram

total. Some areas are still experiencing heavy precipitation, and departments at all levels are making good emergency plans to prevent dangerous situations from happening again. For example, Metro Line 5, Jingguang Expressway, and other accident areas. Third, the green portion of 13% of the total. It mainly includes disaster situations in specific regions and exemplary deeds that emerged during the relief process.

5.4 Comparative analysis of the distribution of themes in the three periods

Further statistics on the thematic clustering of the three periods and a summary of the thematic outline of each cluster can be obtained, as shown in Table 7 below. It can be observed that the focus of the population keeps changing as the disaster period continues to progress. In the early period of a disaster, people's attention is mainly focused on the causative factors and disaster losses; in the middle period of a disaster, people focus on disaster response, rescue and relief, and disaster losses; in the late period of a disaster, people focus on the situation and losses, and specific cases of rescue and relief. Accordingly, in order to better channel online public opinion, we should make targeted plans for different periods of disasters.

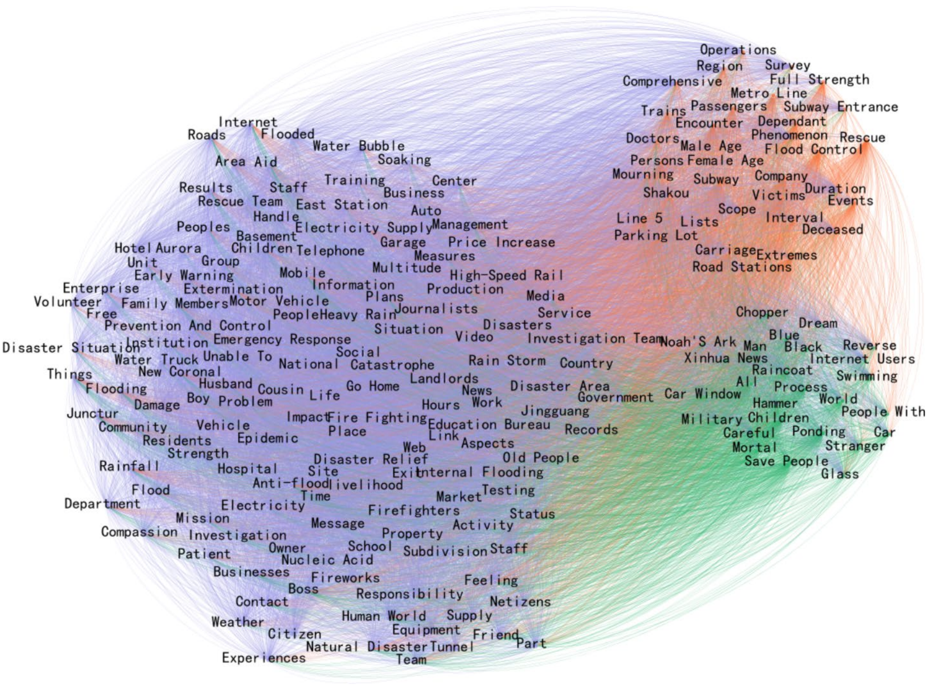

Fig. 9 Post-disaster semantic network diagram

Table 7 Changes in theme clustering in three periods

Period of disaster	Theme Overview	Color	Percentage/%
Pre-disaster	Disaster Warning, Disaster-causing factors	Purple	44
	Disaster Status, Disaster Damage	Orange	40.5
	Disaster response, Emergency rescue	Green	15.5
Mid-disaster	Disaster Status, Emergency rescue	Orange	56.5
	Disaster-causing factors, Disaster Damage	Blue	26.5
	Status of disasters in specific areas	Green	17
Post-disaster	Disaster Status, Disaster Damage	Purple	70
	Specific disaster events	Orange	17
	Specific rescue exemplary deeds	Green	13

6 Discussion

6.1 Characteristics of Online Public Opinion

In the context of the high popularity of the mobile Internet, more and more ordinary people can use online media platforms to express their views on frequent natural disasters. Coupled with the suddenness and destructiveness of natural disasters, the destructive power of online public opinion caused by disasters is even more astonishing (Al-Saggaf and Simmons 2015; Li et al. 2020). This makes the governance of disaster public opinion a critical issue that cannot be ignored in comprehensive disaster reduction (Böhmelt 2020; Miles and Morse 2007; Shi et al. 2022). If the government fails to respond to disaster-related online public opinion in a timely and appropriate manner, it is very likely to lead to secondary disasters, thus causing more significant social risks and even a loss of government credibility. The research in this paper explores public perceptions of events at different times of the day, which provides some support for government guidance (Zhang et al. 2024). It also helps to provide a reference for subsequent guidance of public opinion on rainstorm and flooding disasters in the context of the frequent occurrence of rainstorms and floodings (Ardaya et al. 2017).

The Zhengzhou 7–20 extraordinary rainstorm disaster has indeed caused a public opinion event with a long duration, widespread and considerable impact on the Weibo platform. We have conducted a systematic analysis of this online public opinion using sentiment analysis and thematic analysis methods. Based on the results, we consider that the network public opinion triggered by this extraordinary rainstorm and flooding disaster presents the following three characteristics.

(1) Public opinion was generated unusually quickly and reached a climax within a short period and lasts for an extended period, and the heat shows a repeated trend. The number of related Weibo exceeded 6,000 on July 20, the day of the massive precipitation, and peaked on July 21 after only one day of fermentation. The number of related Weibo exceeded 12,000 in a single day. This shows that when a disaster occurs, there is a ripple effect, and the public's attention is quickly focused on the causative factors, the process, and the disaster's consequences. Since public opinion began to appear on July 20, the heat remained high, and a small climax appeared again on July 27. According to the news released by the relevant departments of Zhengzhou City, the city resumed its operation on July 24. However, the related topics' heat and emotional tendencies did not level off until August 10. This reflects that natural disasters can cause frequent public concern for a certain period after they occur, thus making public opinion appear repeated (He et al. 2019).

(2) As the disaster process evolves, the emotional color of netizens' disaster-related discussions will shift, and the whole public opinion environment is extremely likely to be negative. Since major disasters often accompany significant loss of life, many people are often immersed in grief. Coupled with the complexity of the existing mobile Internet environment, Internet rumors occur from time to time (Yin et al. 2021). Some of the news exaggerating human casualties or economic losses spread uncontrollably during special periods, which can easily lead to further deterioration of the public opinion environment. Compared to the extraordinary rainstorm and flooding disasters that have occurred in China in recent years, the proportion of negative sentiment in this Internet opinion is remarkably higher (Zhang et al. 2023).

(3) The focus of online public opinion at different periods of a disaster varies. In the pre-disaster period, people are still keen on discussing the causative factors and the damage caused by the disaster. In the mid-disaster period, people focus on the specific disaster situation and the post-disaster emergency relief work. In the post-disaster period, people start to pay more attention to the significant incidents in a particular disaster. It can be found that disaster-related online public opinion is not invariable, and different responses are needed for different stages of disasters (Dong et al. 2022).

6.2 Governance advice

With the popularization of mobile Internet worldwide, the response to Internet public opinion has become a global problem. Since natural disasters occur inevitably, the Internet public opinion that accompanies them is also difficult to eliminate. In the face of public opinion on the Internet, we cannot just delete posts and let things go. Reasonably channeling online public opinion and creating a positive online environment is of positive significance for improving the effectiveness of disaster recovery and reducing the psychological trauma caused by disasters to people (AlQahtany and Abubakar 2020). Since the world today generally faces the problem of unbalanced development, there are often many direct or potential social contradictions. The combination and interaction of the widespread existence of social contradictions and Internet public opinion can easily make Internet public opinion a hotbed for the birth of social instability. We must be deeply aware that disaster-related online public opinion has different characteristics at different stages. We can realize scientific management and achieve good governance by taking corresponding guidance measures in a targeted manner.

The research results show that public opinion caused by sudden major natural disasters represented by heavy rainfall and floods is often characterized by abnormally rapid generation, long duration, and extremely prone to forming a negative public opinion environment. In order to reasonably channel public opinion, it is important to minimize messages with negative emotional colors and to respond to people's concerns (Karami et al. 2020). In order to minimize the adverse effects, this paper puts forward three recommendations in response to this situation.

(1) Establishing a sound public opinion early warning mechanism. Only by establishing effective response mechanisms can we discover the generation of online public opinion, make an early warning in time, and then realize scientific disposal of online public opinion. Only through the timely discovery of public opinion hotspots can potential social crisis events be nipped in the bud, and social governance costs can be minimized. The level of inter-departmental cooperation should be improved so that once the relevant public opinion arises, various departments can cooperate efficiently, thus realizing the corresponding quick treatment of disaster public opinion.

(2) Establishing a sound mechanism for normalized control of public opinion. Internet public opinion is intense and sudden, but the response measures for Internet public opinion should be long-term and consistent. A relevant responsibility mechanism should be established to realize that a specific department is responsible for handling public opinion in the corresponding section and for realizing a scientific and effective normalized control mechanism for public opinion. In turn, the positive environment of the online community should be promoted, and the uncontrolled spread of anxiety and panic due to misleading, wrong

information should be avoided to cause negative social impacts. This is important to ensure the social environment's overall stability and the governance capacity's modernization.

(3) Establishing a sound public opinion control and guidance mechanism. The occurrence of unexpected events is inevitable, and the next occurrence of online public opinion is also inevitable. However, correct and effective guidance and mitigation can primarily reduce the adverse effects brought by negative online public opinion. Relevant departments should promptly find and explain the unstable factors in public opinion and improve the openness and transparency of appropriate handling methods to stop potential risks in the first place. At the same time, they should actively promote the dissemination of positive information and guide positive public opinion to become the main body of online public opinion. Since ordinary netizens are the most significant main force in receiving and disseminating relevant information in sudden natural disasters, it is necessary to strengthen guidance. The Party and the government should actively voice out to grasp the right to guide online public opinion. In particular, online public opinion should be targeted according to the different stages of the disaster.

6.3 The implications of this study

Considering the different characteristics of online public opinion triggered by major disasters during different periods, we suggest focusing on different directions accordingly.

In the pre-disaster period, the following steps are crucial for effective public opinion control mechanism: Firstly, Utilizing public opinion monitoring tools and social media analysis software to conduct real-time monitoring and data collection of keywords related to disasters. And establish a monitoring system that covers traditional media, online media, and social media to gather information from multiple channels. Establishing an early warning mechanism to promptly detect potentially alarming information is important. In addition, the government department also should develop crisis response plans tailored to different types of disasters, including detailed measures for public opinion management, information release, and crisis public relations.

During the mid-disaster period, the focus shifts to guiding and responding to public opinion: Timely release of authoritative information through official channels to guide public opinion and curb the spread of rumors. Establish specialized public opinion response teams to analyze and respond to negative public opinions, actively guiding public sentiment. Strengthen communication and cooperation with media and social media platforms to ensure accurate information dissemination and reduce the spread of false information. Conduct crisis public relations activities, such as holding press conferences and conducting interviews, to provide authoritative information and increase public trust.

In the post-disaster period, the focus is on information recovery, ongoing management, and continuous improvement: Proactively disclose the accident handling process and results, carry out information recovery and repair efforts, and restore public confidence. Release explanatory statements regarding hot topics to guide the public in properly understanding the situation and alleviate panic emotions. Continuously monitor relevant public opinion after the disaster to understand public concerns and ensure ongoing management and guidance of public opinion. Summarize the entire public opinion management process, identify issues, and improve management mechanisms to continuously enhance the ability and level of disaster public opinion response.

6.4 The contributions of this study

The research significance of this paper is as follows: (1) It enriches the application of machine learning and knowledge mapping in the field of online public opinion research of emergencies through the sentiment analysis method based on BERT and the theme analysis method based on keyword semantic network analysis; (2) It provides a certain reference basis for the relevant departments to analyze the changes in the development of online public opinion of specific emergencies, and also provides certain theoretical guidance to the relevant departments for the subsequent formulation. It also provides some theoretical guidance for the relevant departments to formulate and introduce corresponding online public opinion governance methods; (3) analyzes the characteristics of online public opinion on Weibo platforms triggered by this major natural disaster in a more systematic way, which is of some reference significance for the improvement of the monitoring and assessment mechanism of online public opinion as well as the governance mechanism of online public opinion.

Compared with similar existing studies, this paper has two innovations: (1) the sentiment analysis adopts a time-based cumulative analysis to compare the sentiment of Weibo in three stages before and during the disaster (Liu et al. 2022a); (2) the keyword co-occurrence semantic network is used to analyze the thematic evolution of the Weibo related to the Zhengzhou rainstorm, which enriches the study of the online public opinion triggered by this major disaster (Kim and Hastak 2018).

6.5 The limitations and future studies

The research method has some limitations. Although the machine learning method used in this study has a high accuracy rate for sentiment analysis (about 95% for general tasks), the possibility of errors is inevitable, which makes the results of the analysis of the data have certain flaws. Additionally, the keyword co-occurrence algorithm used for topic clustering still requires manual summarization and classification after visualization, which demands a high level of discipline literacy and related knowledge from researchers, making it difficult to extend to other fields.

Another limitation is the source of empirical data. This study primarily uses the "Zhengzhou rainstorm" data from the Weibo platform as the research source. The Weibo platform cannot comprehensively cover public opinion data across the entire online social media landscape, resulting in some limitations. Due to the constraints of the Sina Weibo platform and account permissions, it is not possible to collect all public posts, further restricting the study's scope.

Furthermore, the geographic tags in the Weibo data we collected are very limited, making it challenging to conduct a regional assessment of public opinion differences effectively. As a result, we are currently unable to evaluate the differences in responses between those who experienced the flood in Zhengzhou and those who did not. This is an important aspect that we recognize needs further exploration.

In the subsequent research, it is essential to address the issue of communication in crisis management more comprehensively. This includes integrating the prediction and prevention of crisis information to enhance the effectiveness of crisis management practices. Additionally, we will focus on obtaining more geographically detailed data to facilitate regional assessments of public opinion differences, which will help in understanding the varied responses of people inside and outside the affected areas.

7 Conclusion

As a sudden natural disaster with a significant impact, the “7–20” extraordinary rainstorm and flooding disaster has essential research value. We collected more than 60,000 Weibo texts related to this disaster on the Sina Weibo platform to analyze the characteristics of this online public opinion. A sentiment analysis method based on the BERT fine-tuning model was used to evaluate the time-series changes in online public opinion sentiment intensity. Subsequently, a knowledge graph technique based on a keyword co-occurrence semantic network was used to analyze the thematic changes of this online public opinion. Based on summarizing the characteristics of this online public opinion, we put forward some targeted suggestions for the governance of online public opinion. This study has some implications for analyzing the evolutionary characteristics of online public opinion caused by major sudden natural disasters. It also has some reference value for modernizing governance capacity.

The paper’s main findings are as follows: (1) Online public opinion caused by disasters can climax quickly and last for extended periods; (2) The emotional color profile of disaster-induced online public opinion changes over time; (3) The hotspots of disaster-related online opinion will change over time. Therefore, we should take targeted measures to reduce the negative impact of disaster-induced online public opinion on society.

The analysis of this characteristic led us to the following enlightenment: (1) Establish an early warning mechanism for network public opinion to achieve rapid response to network public opinion; (2) Establish a normalized public opinion management mechanism to realize daily management of online public opinion; Establish a reasonable public opinion channeling mechanism to provide targeted channeling according to the characteristics of public opinion at different stages.

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Declarations

Conflict of interest The author declares that no conflict of interest exists.

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