# Evolutionary Analysis of Internet Public Opinion on Emergencies and Construction of an Early Warning Mechanism

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## Abstract

**Taking online public opinion on emergencies as the research object, we analyze the theme evolution and sentiment evolution of emergencies by using theme modeling and sentiment analysis techniques on comment data related to emergencies in social media. The results of the analysis are used to establish an early warning mechanism and a reasonable guidance strategy to provide theoretical support and decision-making references for the relevant departments in monitoring public opinion.**

## Keywords

**Emergencies; Theme Evolution; Sentiment Evolution; Early Warning Mechanism.**

## 1. Introduction

The rise of the Internet has changed our perception of the world and shortened the distance between people. The rapid development of self-media platforms has further lowered the threshold for information platforms, resulting in a revolutionary transformation in the production and dissemination of information. Therefore, the role of online public opinion in national stability and social governance is becoming increasingly prominent. The rapid development of the Internet has given Internet users more opportunities to speak out, making them an important channel for public opinion supervision. However, if Internet users cannot distinguish right from wrong and blindly participate, it often leads to online violence and even secondary events. How to make good use of this "double-edged sword", grasp the trend of public opinion, and understand the people's sentiment and opinions is of great significance for controlling the development of public opinion and maintaining social stability.

## 2. Related Research (Literature Review)

### 2.1. Emotion Analysis

Current research on online public opinion sentiment prediction mainly adopts methods such as sentiment dictionaries, machine learning, and deep learning. Among them, [1]Li Ran et al. (2022) constructed a sentiment dictionary, converting sentences into numerical values corresponding to positive, neutral, and negative emotions, and obtained the sentiment tendency of blog posts through summation. Li Tong (2015)[2] took the idea of integrated learning as the guide, constructed the time series features of Weibo sentiment trends, and combined ARIMA, BPNN, and SVM models to predict Weibo sentiment trends. Wu Qinglin et al. (2016)[3] overcame the problem of short text similarity drift by setting thresholds for feature word similarity and increasing the number of related feature words, and tracked and predicted the sentiment change trends of public topics based on Weibo topic clustering, sentiment intensity calculation, and gray model. Huang Ping et al. (2021)[4] used deep learning sentiment classification techniques for university public opinion analysis.

## 2.2. Evolution of Public Opinion

In terms of sentiment evolution and topic evolution, Li Ran et al. (2022)[1] constructed the stages of public opinion evolution, established a system of hot topics reflecting netizens' emotions, and deeply understood the changes in netizens' emotions during the development of public opinion. In addition, Zhang Liu et al. (2019)[5] combined the analysis of user sentiment evolution and the development cycle of public opinion events, dynamically drew a map of sentiment evolution in university public opinion, providing an important reference for the development of public opinion.

# 3. Data Collection and Preprocessing

## 3.1. Text Data Collection

This project crawled four types of emergency events[6], namely sudden public health events, sudden social security events, sudden natural disaster events, and sudden accident disaster events.

Taking sudden public health events as an example, we crawled Weibo comments related to eight topics, including "pneumonia," "cold," "respiratory infection," "influenza A," "influenza A (H1N1)," "influenza," "mycoplasma," and "mycoplasma pneumonia," and obtained the original Weibo addresses and content under each keyword. After preprocessing the comment data, the data volume after deduplication is shown in Table 1.

**Table 1.** Data Crawled by Keywords

| Keywords | Volume (Entries) | Keywords | Volume (Entries) |
|---|---|---|---|
| Pneumonia | 48127 | Influenza A (H1N1) | 961 |
| Cold | 539 | Influenza | 44188 |
| Respiratory infection | 30121 | Mycoplasma | 14563 |
| Influenza A | 11795 | Mycoplasma pneumonia | 5814 |

In terms of sudden social security events, we crawled comment data on topics such as the "high-speed rail beating" incident, the "girl child bitten by a big dog while lying in her mother's arms," and the "Shanghai girl lost on the beach."

For sudden natural disaster events, we collected and organized relevant topics related to the floods caused by Typhoon Doksuri and the snowstorm events in Northeast China. Additionally, we screened data under five keywords from the Chinese corpus of sudden natural disaster events publicly available from Shanghai University, including earthquakes, fires, traffic accidents, terrorist attacks, and food poisoning.

Finally, in terms of accident disaster events, we crawled comments on the Sichuan Leshan landslide incident, the roof collapse accident at the Yuecheng Sports Club in Jiamusi City, Heilongjiang Province, and the Yunnan elevator fall incident, obtaining a total of 10,929 comment entries.

## 3.2. Data Preprocessing

The microblogging indices of various public health emergencies, social security emergencies, natural disasters, and accident disasters are obtained, with Sina Weibo serving as the acquisition channel for online public[7]opinion data. A self-compiled web crawler in Python is utilized to gather relevant microblogs on Sina Weibo within each event's period. After undergoing data cleaning, chronological sorting, word segmentation, and stopword removal, the remaining original blog posts become the data for this project.

# 4. Analysis of Public Opinion Evolution

## 4.1. Division of the Lifecycle Stages of Public Opinion

Based on the division of the network lifecycle by Wang Yuefen and Wang Yishan[8], this project divides the lifecycle of four types of emergencies-public health emergencies, social security emergencies, natural disasters, and accident disasters-into latent, outbreak, recurrence, and dissipation stages by combining microblogging indices.

Taking the public health emergency of "influenza A" as an example, its lifecycle of online public opinion is divided into four stages-latent, outbreak, recurrence, and dissipation-based on microblogging indices and microblog comment counts. Specifically: The first stage-latent period: October 27th, 2023 to January 14th, 2024. Following the emergence of the first patient on October 27th, 2023, the number of cases gradually increased, with the first batch of infected individuals appearing at the end of October to early November, followed by a sharp increase until reaching a peak during the outbreak stage. The second stage-outbreak period: January 15th to 17th, 2024. During this brief period, the number of cases surged, reaching a peak in the outbreak stage. The third stage-recurrence period: January 18th to February 8th. Although the number of confirmed cases decreased during this period, there were still a certain number of new cases, and some fluctuations occurred. The fourth stage-dissipation period: February 9th to February 23rd. During this period, the number of confirmed cases gradually decreased, showing an overall downward trend. The lifecycle of public opinion (microblogging) for "influenza A" is illustrated in Figure 1.

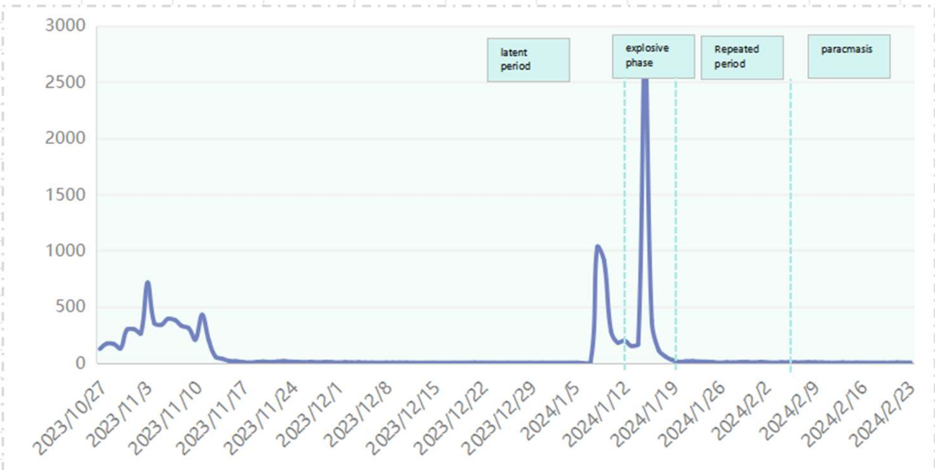


**Figure 1.** Lifecycle of Public Opinion on "Influenza A"

## 4.2. Analysis of Evolution of Public Opinion Themes

### 4.2.1. Methodology or Model (LDA Theme Model based on TF-IDF)

This study utilizes the Latent Dirichlet Allocation (LDA)[9] theme model, drawing on the factual textual data of specific emergency events, to construct a dynamic theme evolution model that explores the stage divisions and topics in social media emergencies, and summarizes the constituent elements of public opinion crises. In each stage, the LDA model is used to extract theme words and obtain the distribution probabilities of keywords corresponding to each theme word. Based on this, a horizontal comparison is made of the theme characteristics obtained in each period to conduct a theme evolution analysis. The theme feature words obtained through LDA theme mining, combined with the TF-IDF word weights and text content, are comprehensively used to select the theme words for each stage of public opinion, summarizing the clustering results of the themes. Through this process, the themes of public

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attention on privacy breaches under the topic are obtained for the latent, outbreak, recurrence, and dissipation stages of the microblog public opinion users.

### 4.2.2. Analysis of Theme Evolution Stages

Construct a bag-of-words model, count word frequencies, and generate word clouds, Based on the preprocessed microblog text data, the LDA theme analysis model is used to analyze each period. To determine the most suitable number of themes, parameters are adjusted and the LDA model is trained based on theme perplexity and coherence metrics. Finally, we obtain the distribution and probabilities of themes in the documents. Through the segmentation of the overall document by time period, we obtain comment data for the four stages and identify the themes that have garnered public attention in each stage. The theme scores for each period are shown in Tables 2-5:

**Table 2.** Theme Word Scores for the Latent Period

| Serial Numbe | Category 0 | Theme Score | Category 1 | Theme Score | Category 2 | Theme Score | Category 3 | Theme Score |
|---|---|---|---|---|---|---|---|---|
| 1 | Pneumonia | 0.030 | Children | 0.029 | Influenza A | 0.015 | Hospital | 0.020 |
| 2 | Illness | 0.029 | Influenza | 0.020 | Body | 0.015 | Influenza B | 0.018 |
| 3 | Mycoplasma | 0.027 | Mycoplasma | 0.014 | Face Mask | 0.014 | Doctor | 0.015 |
| 4 | Community | 0.016 | COVID-19 | 0.012 | Influenza Vaccine | 0.013 | Virus | 0.010 |
| 5 | Children | 0.015 | seltamivir | 0.012 | Feeling | 0.013 | Influenza A | 0.008 |
| 6 | Infection | 0.011 | Vaccine | 0.011 | Vaccine | 0.008 | Teacher | 0.008 |
| 7 | School | 0.010 | Slightly | 0.010 | Specific Drug | 0.007 | Immunity | 0.007 |
| 8 | Symptoms | 0.010 | Effect \| | 0.009 | Health and Wellnes | 0.005 | Nose | 0.007 |

**Table 3.** Theme Word Scores for the Outbreak Period

| Serial Numbe | Category 0 | Theme Score | Category 1 | Theme Score | Category 2 | Theme Score |
|---|---|---|---|---|---|---|
| 1 | Influenza B | 0.022 | Face Mask | 0.023 | Influenza A | 0.035 |
| 2 | Hospital | 0.021 | Body | 0.021 | Oseltamivir | 0.034 |
| 3 | Symptoms | 0.021 | Children | 0.013 | Virus | 0.016 |
| 4 | Influenza A | 0.021 | COVID-19 | 0.009 | Vaccine | 0.013 |
| 5 | Sufud | 0.017 | Doctor | 0.009 | Feeling | 0.011 |
| 6 | Sisters | 0.012 | Epidemic | 0.008 | Mycoplasma | 0.009 |
| 7 | Throat | 0.009 | Feeling | 0.008 | Community | 0.007 |
| 8 | Life | 0.007 | Infection | 0.008 | Sick | 0.007 |

**Table 4.** Theme Score in Recurrence Period

| Serial Numbe | Category 0 | Theme Score | Category 1 | Theme Score | Category 2 | Theme Score |
|---|---|---|---|---|---|---|
| 1 | Aosi | 0.012 | Influenza A | 0.012 | Hospital | 0.027 |
| 2 | Doctor | 0.009 | Friend | 0.011 | COVID-19 | 0.018 |
| 3 | Child | 0.008 | Body | 0.009 | Cause of Illness | 0.014 |
| 4 | Influenza A | 0.008 | Feeling | 0.008 | Hormone | 0.009 |
| 5 | Fever Reducer | 0.008 | Symptom | 0.008 | Adult | 0.009 |
| 6 | Influenza B | 0.007 | Hour | 0.006 | Nausea | 0.008 |
| 7 | Body | 0.007 | Throat | 0.006 | Vaccine | 0.007 |
| 8 | Sore Throat | 0.007 | Influenza B | 0.006 | Virus | 0.007 |

**Table 5.** Theme Score in Remission Period

| Serial Numbe | Category 0 | Theme Score | Category 1 | Theme Score | Category 2 | Theme Score |
|---|---|---|---|---|---|---|
| 1 | Feeling | 0.035 | Nasal Mucus | 0.042 | Ginger | 0.025 |
| 2 | Influenza B | 0.035 | Antibiotics | 0.041 | Lantern | 0.025 |
| 3 | Influenza A | 0.035 | Anti-inflammatory Drugs | 0.041 | Cough Relief | 0.025 |
| 4 | Hospital | 0.021 | Eyes | 0.021 | Fever | 0.024 |
| 5 | Grandmother | 0.010 | Resistance | 0.020 | Days | 0.024 |
| 6 | Urticaria | 0.007 | Feeling | 0.008 | Years Ago | 0.009 |
| 7 | My Heart | 0.007 | Weight | 0.008 | Feeling | 0.009 |
| 8 | Rainy Weather | 0.005 | Pneumonia | 0.006 | Weight | 0.007 |

By analyzing the theme scores of the four stages (latent period, outbreak period, recurrent period, and remission period), we can gain a deeper understanding of people's concerns and changing needs regarding the disease at different stages. In the latent period, the theme scores are mainly concentrated on disease-related topics such as pneumonia, illness, and Mycoplasma, indicating that people are paying attention to the potential risks and transmission routes of the disease before getting sick. Special attention is given to symptoms, preventive measures (such as wearing masks), and treatment methods (such as hospitals and doctors).During the outbreak period, themes such as Influenza B, masks, and Influenza A score highly, reflecting the widespread concern caused by the outbreak and spread of the disease. People begin to focus on the severity of the epidemic, the importance of personal protective measures, and attention to symptoms and coping strategies.

In the recurrent period, themes like Aosi, Influenza A, hospitals, and COVID-19 continue to receive attention, possibly indicating repeated or worsened cases of the disease. People are paying more attention to the causes, symptom changes, and treatment effects of the disease in order to find more effective treatment methods and prevention strategies.Finally, in the remission period, themes like feeling, Influenza B, and Influenza A score higher, indicating that symptoms are gradually improving or disappearing. People start to focus on physical sensations, medication, dietary adjustments, and other aspects during the recovery process to ensure a smooth recovery.

Taken together, the theme scores across these four stages can guide epidemic management and health education efforts. These data can assist in formulating key measures such as scientific prevention and control, timely medical attention, and scientific conditioning to better respond to disease outbreaks and protect public health and safety.

## 4.3. Analysis of Public Opinion Emotional Evolution

### 4.3.1. Analysis of Sentiment Orientation of Network Public Opinion Data

Using a domain-specific emotional dictionary[10] built based on domain emotional dictionaries to capture emotional information in reviews. Then, a deep learning model is adopted to perform feature learning and sentiment prediction on review texts. By combining domain emotional dictionaries with deep learning methods for sentiment analysis[[11], we predict the sentiment value of reviews and judge their sentiment orientation.

Through text mining and word cloud visualization, we can initially define the keywords that appear frequently in public opinion events, and further analyze text features. This article combines the domain emotional dictionary and deep learning method to classify the emotional content of online user reviews, which can further explore the impact of online user emotional evolution on the spread of public opinion. By combining the analysis of user emotional evolution and the development cycle of public opinion events, we can dynamically display the changes in emotions, thereby comprehensively understanding the development of public opinion on sudden public health events and the law of users' emotional changes.

Based on the analysis of public opinion emotional characteristics, in the "influenza A" event, positive emotions accounted for 37.6%, negative emotions accounted for 30.9%, and neutral emotions accounted for 31.3%. The proportion of positive emotions among netizens towards this event is relatively high. Most netizens did not show excessive panic towards the event and their attitude was relatively positive. They hoped to overcome influenza A as soon as possible and maintain good health.

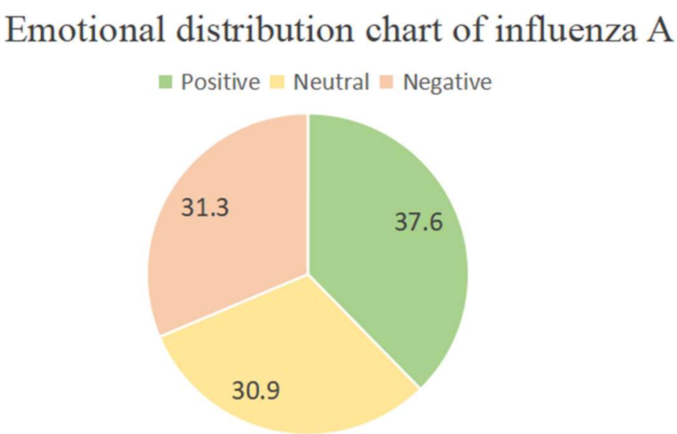


**Figure 2.** Overall Sentiment Proportion of "Influenza A"

### 4.3.2. Analysis of Emotional Evolution Stages

During the influenza A event from October 27, 2023 to February 23, 2024, netizens' emotions underwent four stages of change: latent period, outbreak period, recurrent period, and remission period. In the latent period, positive emotions accounted for 36%, neutral emotions accounted for 31%, and negative emotions accounted for 33%, mainly manifesting as worry and fear. In the outbreak period, positive emotions accounted for 42%, neutral emotions accounted for 31%, and negative emotions accounted for 27%. Netizens showed a positive and optimistic attitude and hoped for a quick resolution of the event. In the recurrent period, neutral emotions accounted for 43%, positive emotions decreased to 31%, and negative emotions accounted for 26%. Netizens shared methods to alleviate symptoms and hoped for an early end to the event. In the remission period, neutral emotions accounted for 41%, positive emotions slightly decreased to 32%, and negative emotions accounted for 27%. Netizens hoped for a peaceful conclusion to the event. Overall, netizens' emotional changes shifted from worry to calmness, with fewer negative emotions and a dominant positive and optimistic attitude.

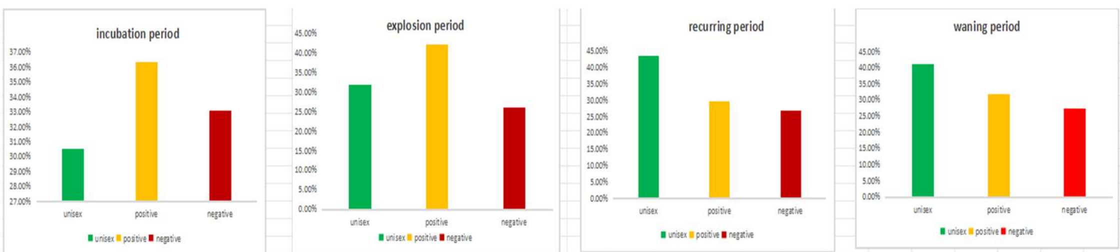


**Figure 3.** Sentiment Proportion of "Influenza A" in Each Period

Dividing the "influenza A" event into cycles and analyzing emotional evolution provides practical reference for public opinion regulatory authorities to understand the trend of public opinion on emergencies in real-time and take timely control measures during the public opinion cycle.

# 5. Establishment of an Early Warning Mechanism

## 5.1. Construction of the Early Warning Mechanism

The implementation of an early warning mechanism[12] can detect information in advance, facilitating timely response to risks. To build an early warning mechanism applicable to this study, comments on various emergencies on Weibo were selected and emotional indicators were categorized. By reviewing relevant literature on early warning mechanisms, a solution was derived with the following specific steps:

(1) Select events and crawl comment content from relevant platforms. Categorize emotions into three directions: positive, neutral, and negative, and quantify them as 1, 0, and -1, respectively.

(2) Calculate the weights of the three emotional directions corresponding to comments for each event.

(3) Calculate the emotional index for each event.

(4) Classify the emotional index into three levels: positive emotion (Level III), neutral emotion (Level II), and negative emotion (Level I).

## 5.2. Classification of Early Warning Levels

(1) Select events and take the public health emergency of "influenza A" as an example. Establish corresponding early warning strategies for the four cycles as follows:

(a) Latent period: Identify potential public opinion risks based on emotional analysis during this stage.

(b) Outbreak period: Continuously monitor discussions and opinions related to specific topics on mainstream media, social media, online forums, and other platforms. Develop emergency response plans, clarify the handling procedures and responsibility assignments for various public opinion events, and prepare for responding to unexpected public opinion events.

(c) Recurrent period: Timely track the development and changes of public opinion and monitor the reactions and attitudes of various parties. Develop emergency response plans, clarify the handling procedures and responsibility assignments for various public opinion events, and prepare for responding to unexpected public opinion events.

(d) Remission period: Evaluate the effectiveness of handling public opinion events, summarize lessons learned, and timely adjust and improve the early warning mechanism and response strategies. Strengthen follow-up management of public opinion events and promptly follow up on related issues and feedback.

Among the crawled comment content, emotions are categorized into three directions: positive, neutral, and negative, and quantified as 1, 0, and -1, respectively. Based on the emotional dictionary, the comment content for the four periods of the "influenza A" event is emotionally quantified: if a vocabulary appears in the positive dictionary, it is assigned a value of +1; if it appears in the negative dictionary, it is assigned a value of -1; if it does not appear, it is assigned a value of 0.

(2) Calculate the weights of the three emotional directions corresponding to comments for each event. After determining the emotional quantification values, it is necessary to calculate the weights of the emotional tendencies for the four periods of the "influenza A" event. Determine the weight of each indicator, calculate the word frequency of positive, negative, and neutral words within each stage, and record them as P, N, and M, respectively. Then, obtain a

comprehensive evaluation of the document by subtracting the weight of negative words from the weight of positive words and adding the weight of neutral words. The emotional weight values for the four stages are shown in Table 6 below. The weight proportions in Table 7 indicate that emotions within the public opinion stage are dominated by neutral emotions. Combined with the results of topic analysis, during the latent period of public opinion, netizens focused on "prevention and management of children and community infectious diseases," resulting in neutral emotional aggregation. During the outbreak period, intense discussions surrounded the topic of "influenza management and influenza A prevention in hospitals," generating more positive feedback emotions. During the remission period, the public focused on epidemic prevention and control, expressing more positive emotions, and discussions became more peaceful. The proportion of positive emotions increased, and the proportion of neutral emotions also gradually increased.

**Table 6.** Emotional Weight Proportions for Different Stages of Public Opinion

| Sentiment Phases | Positive Words | | Neutral Words | | Negative Words | |
|---|---|---|---|---|---|---|
| | Number/Entry | Weight/% | Number/Entry | Weight/% | Number/Entry | Weight/% |
| Latency | 3023 | 36.30 | 2536 | 30.50 | 2750 | 33.20 |
| Explosion | 1372 | 42.20 | 1039 | 31.80 | 850 | 26.00 |
| Recurrence | 60 | 29.70 | 88 | 43.50 | 54 | 26.90 |
| Subsidence | 7 | 31.80 | 9 | 40.90 | 6 | 27.30 |
| Total | 4462 | 35.00 | 3672 | 36.65 | 3660 | 28.35 |

(3) Adopting a sentiment analysis method based on machine learning, the Snow NLP model of natural language processing in Python is utilized to calculate the sentiment scores of microblog comments on the "Influenza A" event. The sentiment indices of each event in different stages of public opinion are calculated, and the emotions of Internet users are analyzed.

By calling the sentiment classification method under Python, the sentiment score of the text can be obtained, ranging from 0 to 1. If the score is greater than 0.6, the sentiment is relatively positive; if the score is less than 0.5, the sentiment is relatively negative; if the score is between 0.5 and 0.6 (inclusive), the sentiment is neutral.

**Table 7.** Sentiment Values of Different Public Opinion Phases

| Public Opinion Phase | Sentiment Value |
|---|---|
| Latency | 0.4737672181921908 |
| Explosion | 0.664991045418926 |
| Recurrence | 0.6649910454189244 |
| Subsidence | 0.5365894286184176 |

From the above table, it can be seen that during the outbreak and recurrence periods, the emotions of Internet users are mostly positive and optimistic. Despite the troubles and challenges brought by the Influenza A virus, people have demonstrated amazing adaptability and a spirit of unity.

(4) To set the Early Warning level for online public opinion, we need to comprehensively consider international practices, relevant institutional regulations in China, and the development trends of online public opinion. By combining the calculated sentiment indices, we can categorize the Early Warning levels for online public opinion into three grades: positive sentiment (Grade III, non-routine), neutral sentiment (Grade II, warning level), and negative

sentiment (Grade I, critical level). These grades will be represented by yellow, orange, and red colors, respectively.

Yellow Level (Grade III): When the score is greater than 0.5. Public opinion emerges, but domestic Internet users have a low level of attention towards it. The spread is slow, and the impact of public opinion is limited to a small scope, with no potential for conversion into behavioral public opinion. Overall, residents are in an optimistic and upward emotional state.

Orange Level (Grade II): When the score falls between 0.4 and 0.5 (inclusive). Domestic Internet users have a relatively high level of attention towards the public opinion. The spread is moderate, and the impact is limited to a certain extent, without the potential for conversion into behavioral public opinion. Overall, residents are in an objective and calm emotional state.

Red Level (Grade I): When the score is less than 0.4. Internet users have a high level of attention towards the public opinion. The spread is rapid, and the impact has diffused to a wide range, with the potential for conversion into behavioral public opinion. Overall, residents are in a state of agitation and unrest.

Based on the sentiment indices derived from topic comments, the warning levels for the following eight sudden public events are determined. The experimental results are presented in the table below.

**Table 8.** Determination of Warning Levels for Sudden Public Health Events

| Serial Number | Event | Sentiment Index | Warning Level |
|---|---|---|---|
| 1 | Pneumonia | 0.44767845850986676 | Orange Level |
| 2 | Cold | 0.274443171919885 | Red Level |
| 3 | Respiratory Infection | 0.334082872480589 | Red Level |
| 4 | Influenza A | 0.44767845850986676 | Orange Level |
| 5 | Influenza A Virus | 0.421874597530976 | Orange Level |
| 6 | Influenza | 0.44767845850986676 | Orange Level |
| 7 | Mycoplasma Pneumonia | 0.5678383114913966 | Yellow Level |
| 8 | Mycoplasma | 0.5360497463434882 | Yellow Level |

From the above table, we can draw the conclusion that the warning level for influenza and respiratory infections is red, so the official Weibo should focus on reminding the public to strengthen protective measures in their daily lives, especially for influenza and respiratory infections. Such classification also helps the government and relevant departments to understand the public's emotional changes in time, take corresponding measures to guide public opinion, stabilize social order, and improve the efficiency of public crisis management.

Overall, through emotional analysis of online public opinion on public emergencies and the establishment of an early warning mechanism, timely and accurate information feedback can be provided to the government and the public, helping them better respond to various emergencies and reduce possible losses. At the same time, it is also an important measure to promote the construction of an information-based society and improve the level of public crisis management.

## 6. Conclusion

This project used web crawler technology to crawl and analyze Weibo comments on four types of emergencies. Taking the "influenza A" as an example of public health emergencies, the emotional and thematic evolution of online public opinion was studied in depth. Emotional evolution analysis revealed the changes in netizens' emotional tendencies during different periods of public opinion, gradually shifting from concern and fear to optimism and positivity.

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Thematic evolution analysis demonstrated the evolution of netizens' concerns, ranging from disease-related topics to personal protection, treatment strategies, and then to recovery and social impact.

In addition, the project also established an early warning mechanism, dividing emotional indicators and calculating weights, as well as using machine learning for emotional analysis to set the early warning level of online public opinion, providing decision support for relevant departments. In summary, this project comprehensively utilized various technical means to conduct an in-depth analysis of online public opinion on emergencies, providing a useful reference for public opinion monitoring and response.

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