Research on the Evolution Trend of Internet Public Opinion under the "Russian Terrorist Attack" Incident

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Abstract: In recent years, the international community frequent emergencies, but also by the Internet users are highly concerned, the public opinion generated from the outbreak of the beginning gradually intensified, and finally gradually dissipated. Therefore, for the government departments, how to appease the negative emotions of netizens and guide and deal with public opinion is particularly important. In this paper, the event of "Russian terrorist attack" on March 23, 2024 is selected as the research object, and all comments under the video with "Russian terrorist attack" as the keyword of station b are obtained by Python crawler. Meanwhile, LDA topic identification and SnowNLP analysis are used to explore the time evolution process of public opinion. Finally, the evolution trend of public opinion is summarized by comparing the change of theme and emotion analysis based on time. This research is helpful for national security departments to monitor public opinion and guide public opinion correctly at a timely time, and is also conducive to analyzing the dynamic trend of public opinion behind major social emergencies. The evolution trend of Internet public opinion will be affected by opinion leaders and government departments. Therefore, in the incubation period and fermentation period of public opinion, public opinion monitoring should be strengthened to avoid the breeding of improper remarks. In the period of public opinion outbreak, we should correctly guide the direction of public opinion, realize the information disclosure, and achieve the transparency of the event report; In the period when public opinion dissipates, preventive measures should be developed to prevent such incidents from happening again, and the quality education of the public should be strengthened.

Keywords: Major social emergencies; Online public opinion; Evolution of public opinion; Leading strategy.

1. Introduction

With the rapid development and widespread adoption of the global Internet, information dissemination has entered a new era. According to the latest data from the International Telecommunication Union (ITU), it is anticipated that by 2023, approximately 5.4 billion people, or 67% of the world's population, will be part of the Internet community. This number has surged by 45% since 2018, indicating that 1.7 billion new users have surpassed the threshold into the digital realm during that period. This monumental transformation has not only significantly reduced the time and space barriers of information transmission but has also propelled social media into a pivotal platform where the public can express emotions, attitudes, and opinions. In this era of information explosion, Internet users worldwide can instantaneously obtain and share news and events from across the globe, creating an unprecedented information-sharing network. However, this rapid dissemination of information is a double-edged sword. While it provides convenience, it also inevitably poses the risk of disseminating false information and misleading content. Such false information often elicits panic and anxiety among the public, which subsequently fuels intense fluctuations in public opinion on social media and, in extreme cases, threatens social stability and national security.

In recent years, the global spread of the novel coronavirus pneumonia epidemic, the geopolitical tensions arising from the Russia-Ukraine conflict, and the humanitarian tragedy of the stampede in Itaewon, South Korea, have all caused profound reverberations in the realm of global public opinion. These events, akin to boulders being cast into a serene lake, have generated ripples that have profoundly influenced public perceptions and emotions. Within this context, conducting in-depth research into the evolutionary trends of public opinion surrounding specific events becomes particularly crucial.

This paper will take the terrorist attack in Russia on March 23rd as an illustrative case and delve into the dynamics of public opinion subsequent to the incident by crawling and analyzing the comment data of netizens on Platform B. This study not only facilitates a deeper understanding of the formation, evolution, and influence mechanisms of public opinion, but also offers valuable reference information for relevant institutions to better guide and manage public opinion, thereby maintaining social stability and national security. Furthermore, the study sheds light on the diversity and complexity of public opinion, revealing the varying levels and perspectives of public awareness regarding national security. Consequently, it holds significant guiding implications for enhancing public awareness of national security. This paper will take the terrorist attack in Russia on March 23rd as an illustrative case and delve into the dynamics of public opinion subsequent to the incident by crawling and analyzing the comment data of netizens on Platform B. This study not only facilitates a deeper understanding of the formation, evolution, and influence mechanisms of public opinion, but also offers valuable reference information for relevant institutions to better guide and manage public opinion, thereby maintaining social stability and national security. Furthermore, the study sheds light on the diversity and complexity of public opinion, revealing the varying levels and perspectives of public awareness regarding national security. Consequently, it holds significant guiding implications for enhancing public awareness of national security. This paper will take the terrorist attack in Russia on March 23rd as an illustrative case and delve into the dynamics of public opinion subsequent to the incident by crawling and analyzing the comment data of netizens on Platform B. This study not only facilitates a deeper understanding of the formation, evolution, and influence mechanisms of public opinion, but also offers valuable reference information for relevant institutions to better guide and manage public opinion, thereby maintaining social stability and national security. Furthermore, the study sheds light on the diversity and complexity of public opinion, revealing the varying levels and perspectives of public awareness regarding national security. Consequently, it holds significant guiding implications for enhancing public awareness of national security.

2. Related Work

2.1. Network public opinion theme analysis related research

Network public opinion, centered on the Internet and specific events, represents a collection of opinions, attitudes, and emotional tendencies of the majority of netizens. Public opinion has always played a pivotal role in society, and its evolutionary direction varies significantly across different environments. The evolution process of online public opinion can be broadly categorized into four stages: latency, fermentation, outbreak, and dissipation. Research methods for analyzing this evolution encompass data visualization, text mining, social network analysis, among others. For instance, Liu, C. et al. [1] utilized LDA thematic modeling technology in conjunction with the SnowNLP emotion classification method, not only quantifying emotion values but also performing spatial visualization, thereby providing a novel perspective on crisis management capabilities. In their study of Wuyi Mountain National Park, Fu, W. and Zhou, B. [2] explored the relationship between humans and nature through the theme exploration and sentiment analysis of online comments, offering suggestions for enhancing the functionality of the national park. Wu, KJ et al. [3] employed multi-source data fusion technology, incorporating LDA and SnowNLP, to demonstrate the feasibility of mining victim information from social media in the case of Typhoon Lekima. AnL et al. [4] examined the differences in topics of interest and their temporal evolution between microblog users and Twitter users in public health emergencies, based on the language used by users and their country of origin. GarciaK et al. [5] utilized Twitter data to calculate and analyze the content of trending topics and their associated emotions among internet users in the United States and Brazil, exploring the reasons behind the content of various topics and their emotional expressions. GorrabA et al. [6] analyzed the similarity of users' followers, topics, and other information using Twitter's spatiotemporal data, and achieved user interest recommendations through cluster analysis.

2.2. Relevant Research on Sentiment Analysis of Online Public Opinion

In the realm of public opinion research, the study of emotions is commonly referred to as emotion computing, opinion mining, or sentiment analysis. This aspect of work directly conveys the emotional polarity, attitudes, and viewpoints of netizens towards public opinion events, thereby elucidating the emotional evolution process of public opinion. Guo, FP et al. [7] combined LDA thematic modeling with BERT technology to deeply analyze the evolution of public sentiment regarding COVID-19 on China's Weibo platform, revealing an overall trend from negative to positive, and thereby providing strong support for the management of public opinion in public health events. Ma You et al. [8] took a novel approach by combining knowledge graphs with the LDA model to effectively extract potential themes and associated information from social media data, thereby enhancing the accuracy and practicality of data analysis. Zhou, ZP et al. [9] focused on the evolution of online public opinion surrounding major accidents, constructing an integrated framework incorporating sentiment analysis and LDA topic extraction. Through actual case studies, they proposed targeted strategies for addressing public opinion, aimed at mitigating the spread of negative emotions and fostering a positive development of public sentiment. Huang et al. [10] highlighted the risks and complexity of public opinion in public emergencies, proposing methods for guiding, controlling, and managing online public opinion from three perspectives: enhancing online public opinion guidance, strengthening online public opinion supervision, and reinforcing legal protection for online public opinion. Zhong Z. [11] utilized SnowNLP to calculate emotions in Baidu Post bar text data and analyzed the temporal evolution characteristics of positive and negative sentiments. Zhang T. et al. [12] took the Typhoon Haiyan event as a case study, exploring the evolution characteristics and distribution patterns of public emotions using microblog spatiotemporal data.

3. Related Theoretical Interpretation

3.1. SnowNLP

SnowNLP, a Python-based Chinese natural language processing (NLP) library, offers a comprehensive suite of functionalities tailored specifically for processing and analyzing Chinese text. Its design philosophy revolves around providing a succinct and user-friendly interface, thereby facilitating the intricate task of Chinese text processing. The theoretical underpinnings of SnowNLP are deeply rooted in NLP and computational linguistics, two interdisciplinary fields that explore the intricacies of effective human-computer communication. NLP, as an academic discipline, delves into the realm of enabling machines to comprehend and interact with human language, drawing upon expertise from linguistics, computer science, and artificial intelligence. Within the context of computational linguistics, researchers strive to develop computational models that can emulate and comprehend the complexities of human language, thereby enhancing the capabilities of computers to process and analyze Chinese text.

Text segmentation: SnowNLP uses dictionary-based segmentation, which is to pre-define a dictionary of various words and then match the text to the words in the dictionary to achieve word segmentation. This method is simple and efficient, but may not handle words or new words that don't exist in the dictionary.

Part-of-Speech (POS) Tagging: POS tagging is a fundamental task in NLP, aiming to identify the grammatical category (e.g., nouns, verbs, adjectives) of each word within a text. SnowNLP employs a statistical approach, utilizing a pre-trained model to assign POS tags to words in the text. This method excels in handling large-scale text data with high accuracy.

SnowNLP provides robust support for Chinese text processing through functionalities such as word segmentation, sentiment analysis, part-of-speech tagging, text classification, and keyword extraction [13]. The following two functionalities are elaborated upon in detail. Text classification involves dividing text into distinct categories based on its content. This process often relies on supervised machine learning models, including naive Bayes and support vector machines, among others. SnowNLP may have employed these models or their variations for implementing text classification. Keyword extraction refers to the process of identifying words or phrases from the text that most effectively represent its thematic content. SnowNLP utilizes algorithms based on TF-IDF (Term Frequency-Inverse Document Frequency) or TextRank to achieve this. These methods account for both the frequency and importance of words within the text, enabling the extraction of the most representative keywords.

The basic principle of Snow NLP sentiment analysis is as follows [14]: Assuming there are two categories of sentiment analysis: positive evaluation (c1) and negative evaluation (c2). Each comment comprises a textual space containing n independent words, denoted as w1, w2, ..., wn. The conditional probabilities of a comment belonging to the positive evaluation P(c1|w1, ..., wn) and the negative evaluation P(c2|w1, ..., wn) are calculated separately using the naive Bayes formula. The calculation formula can be expressed as:

$$P(c_i|w_1,...,w_n) = \frac{P(w_1,...,w_n|c_i)P(c_i)}{P(w_1,...,w_n)} \tag{1}$$

And according to the law of total probability, P(B) = P(B|A)P(A) + P(B|A')P(A'), P(w1, ..., wn) can be expressed as:

$$\begin{aligned} & P(w_1,...,w_n) \\ & = P(w_1,...,w_n|c_1) + P(w_1,...,w_n|c_2)P(c_3) \end{aligned} \tag{2}$$

The formula can then be converted to:

$$\begin{aligned} & P(c_i|w_1,...,w_n) \\ & = \frac{P(w_1,...,w_n|c_i)}{P(w_1,...,w_n|c_1)P(c_1) + P(w_1,...,w_n|c_2)P(c_2)} \end{aligned} \tag{3}$$

3.2. LDA analysis

The LDA model is grounded on two central probability distributions: the document-topic distribution, which characterizes the probability of occurrence of each topic within a document [15]. This distribution mirrors the document's representation in the topic space, elucidating how the document is a blend of multiple topics. The second is the topic-term distribution, which quantifies the likelihood of each term appearing within a given topic. This distribution unveils the lexical signature of each topic, specifying which words contribute to its composition.

It is assumed that both the document-topic distribution and the topic-term distribution follow the Dirichlet distribution, which is a multivariate continuous probability distribution suitable for describing the distribution of probability vectors. The inference process of the LDA model involves estimating the parameters of the document-topic distribution and the topic-term distribution by observing text data and utilizing Bayesian inference [16]. This process encompasses complex mathematical operations and statistical methods, including Gibbs Sampling or Variational Bayesian Inference. These algorithms iteratively update the parameter estimates to maximize the likelihood or posterior probability of the document, yielding a topic structure that best aligns with the data distribution. From the inference process of the LDA model, the topic distribution of each document and the lexical distribution of each topic can be derived. Such distribution information can be harnessed to identify potential themes within the text data.

Sampling from the Dirichlet distribution with parameter α generates the topic distribution θi corresponding to document di. The topic Zi,j for the j-th word in document i is sampled from the multinomial distribution θi. Subsequently, the word distribution for topic Zi,j is generated by sampling from the Dirichlet distribution with parameter β. Finally, the word Wi,j is generated based on the multinomial distribution corresponding to topic Zi,j.

Among these, the parameters α, β, and the number of topics K are typically specified in advance. In the diagram, vector edges represent dependencies, rectangles signify repetitions, and the letters M, N, K are used to indicate repetitions, with the number of repetitions denoted within the rectangles. Consequently, to generate a document, the conditional probability formula for the occurrence of each word in the document is as follows:

$$\mathrm{per}plexity(D) = \exp\left[-\frac{\sum_{d=1}^{M}\log(P(w)_d)}{\sum_{d=1}^{M}Nd}\right] \tag{4}$$

The probability of each word appearing in each document is denoted as P(w|d); the frequency of each word occurring in each topic is represented by P(w|z); and the probability of each topic appearing in each document is indicated by P(z|d). Given a text collection, a 'document-word' matrix can be constructed by segmenting each text into words and calculating the word frequency of each word across all texts. The LDA topic model leverages a three-layer structure of 'document-topic-word' to infer the topics of documents with a certain probability.

$$p(w) = p(z|d) * p(w|z) \tag{5}$$

4. Research Framework and Method

4.1. Research framework

This paper takes the 'Russian terrorist attack' incident as an illustrative case to delve into the evolutionary trends of public opinion and temporal dynamics surrounding major international emergencies. The research framework is designed to uncover the propagation patterns of such events, as well as the dynamic shifts in sentiment and thematic content on social media, through rigorous systematic data analysis.

In this paper, Python crawler technology was employed to obtain comment data related to the event from Bilibili (abbreviated as B-station) [17], which served as a rich source of material for subsequent analysis. Following data acquisition, rigorous cleaning, preprocessing, and word segmentation were conducted to ensure the accuracy and analyzability of the dataset. Subsequently, the processed data were subjected to in-depth analysis utilizing SnowNLP and LDA techniques. SnowNLP facilitated the calculation of the public's emotional sentiment towards the 'Russian terrorist attack' event, whereas the LDA topic model illuminated the salient topics of public interest and the evolutionary trends of these themes [18]. By contrasting the emotional scores and topic distributions across different time periods, we gained a clear understanding of the outbreak, propagation, decline, and stabilization phases of public opinion, as well as the shifting emotional tendencies and focal points of public attention within each phase.

This study not only offers valuable insights into the propagation patterns of major international emergencies on social media but also serves as a reference for governments, media outlets, and the public in managing public opinion. By monitoring and analyzing the dynamics of public opinion on social media, governments can promptly adopt effective countermeasures to uphold social stability. The media, on the other hand, can leverage these data to more precisely grasp the public's areas of concern and emotional leanings, thereby enhancing the relevance and communication efficacy of their news reports. Moreover, by gaining access to these analytical outcomes, the public can adopt a more rational perspective towards events and articulate their viewpoints and aspirations with greater clarity.

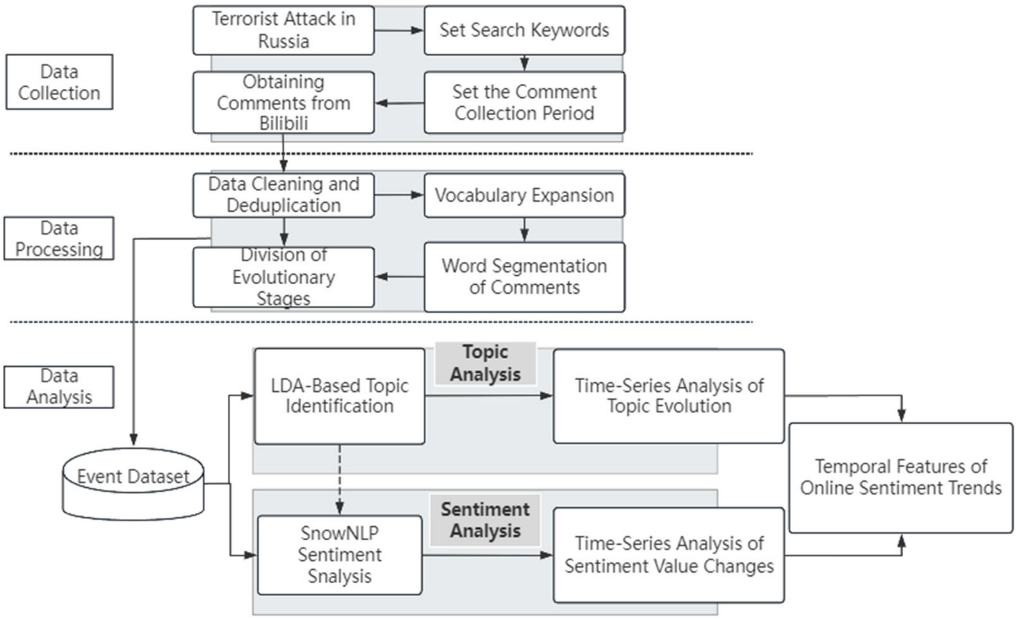

Figure 1. Research framework

4.2. Research methods and steps

4.2.1. Data acquisition and processing

To profoundly dissect the public opinion storm ignited by the "Russian Terrorist Attack" incident in cyberspace, this paper meticulously selects the temporal node and contextual backdrop for the study. On March 23, 2024, a terrorist attack occurred within a concert hall in Moscow, Russia, leading to the tragic loss of over a hundred innocent lives. This event sparked immense global attention. Given its grave consequences and extensive societal implications, this paper selects this incident as the focus of our research, aiming to offer valuable insights to relevant authorities through an in-depth analysis of the ensuing network public opinion.

In the data acquisition phase, this paper employs Python crawling technology to search for videos featuring the keyword "Russian terrorist attack" on the Bilibili platform, and subsequently collects all comments posted beneath these videos within the period spanning from March 23, 2024 to April 1, 2024. These comment data encompass information such as the names of commenters, the precise timestamps of the comments, and the detailed content of the comments, thereby providing an abundant source of raw material for subsequent analysis.

In the data processing stage, this paper meticulously cleansed and preprocessed the vast amount of raw data. We eliminated duplicate comments to ensure the accuracy of our analysis, and rigorously inspected and complemented missing data, aiming to ensure that each data point effectively supports the research objectives of this paper. Following this, we conducted stopword removal to exclude words devoid of substantive meaning. Through this series of processing steps, we ultimately obtained a dataset comprising 77,642 comments, which undoubtedly serves as a solid foundation for subsequent in-depth analysis. As shown in

Table **1**.

Table 1. Comment content information sheet

	ID of the commenter	Name of the Commenter	Time of Comment	Content of the Comment
0	577830568	森林里的小鱼精	March 25, 2024	在人多的地方飙车属于危害公共安全，必须刑事拘留留案底才对，因为对他人生命造成威胁了
1	701237491	朴秀今天吃什么	March 25, 2024	“当你在莫斯科看到彩虹六号COSER”
2	1094036150	新鲜的鸽子汤	March 25, 2024	原世界和平
3	502175011	仓鼠一哥	March 25, 2024	在屋里也不安全
4	6900235	时晴时雨_	March 25, 2024	这些恐怖分子是真该死啊，为了100w卢布(7.9wRMB),干下这种罄竹难书的恶行，真该凌迟...

In the course of data analysis, this paper employs techniques such as LDA topic identification and SnowNLP sentiment analysis to conduct a profound exploration and excavation of these emotionally charged and opinionated comments. By contrasting the discussion topics and emotional trajectories across different time frames, the paper endeavors to unravel the inherent logic and influencing factors driving the evolution of online public opinion. Through rigorous scientific analysis and concise summarization, we are able to discern the developmental trends of public opinion and provide pertinent and practical recommendations for relevant authorities. According to the data set after complete data processing, this paper manually divides the public opinion cycle into four stages, as shown in Table 2.

Table 2. Periodic table of public opinion

Stage	Time
Outbreak Stage	March 23, 2024—March 24, 2024
Spread Stage	March 24, 2024—March 28, 2024
Decline Stage	March 28, 2024—March 31, 2024
Stable Stage	March 31, 2024—April 1st, 2024

Finally, based on the comment frequency and the categorized public opinion cycle, a graph of the public opinion cycle and comment frequency is produced, as depicted in Figure 2. This graph allows for a general overview of the speed of propagation of public opinion over time, as well as the magnitude of changes in its popularity.

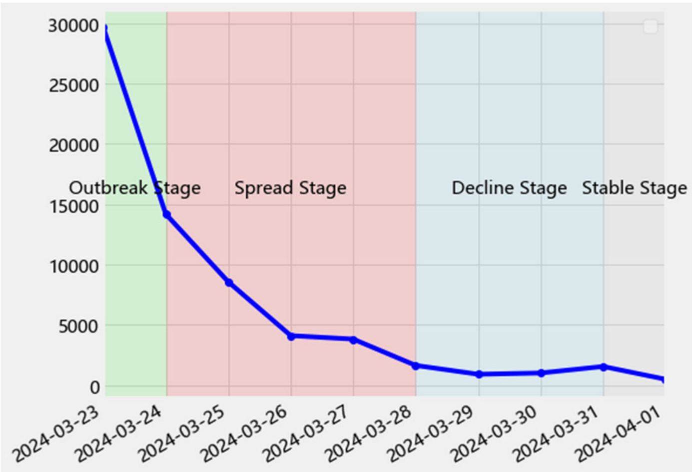

Figure 2. Public opinion cycle and comment frequency chart

4.2.2. Affective computing

When delving into the evolution trends of public opinion surrounding major emergencies, this paper employs the internationally significant event of "the Russian terrorist attack" as a case study, comprehensively analyzing the development process of public opinion dynamics from a temporal perspective. This research not only scrutinizes the event itself but also delves into the dynamic shifts in public emotions and focal points of attention, offering a distinctive lens for comprehending and addressing the public opinion ecology of comparable events. The SnowNLP sentiment score calculation relies on the naive Bayes classification algorithm, which, through training on labeled positive and negative sentiment data, enables the model to predict the sentiment orientation of text and quantify it into a sentiment value. Given that the SnowNLP algorithm presupposes the independence of textual feature words, this paper utilizes this algorithm to compute the sentiment orientation within user comments, thereby uncovering the temporal trends in public sentiment changes [20]. The sentiment value ranges from [0,1], with 0 signifying the most negative sentiment and 1 indicating the most positive sentiment [21]. As detailed in Table 3, descriptive statistical information pertaining to the sentiment values across various evolutionary stages is presented. Through this methodology, we are able to articulate the evolution patterns of public sentiment within the network public opinion landscape of emergencies with clarity.

Table 3. Descriptive statistics of emotion values in each evolutionary stage

Stage	Positive Rate	Neutral Rate	Negative Rate	Sentiment Average
Outbreak Stage	0.630248	0.020060	0.349691	0.612568
Spread Stage	0.627339	0.015981	0.356680	0.609881
Decline Stage	0.657860	0.014884	0.327256	0.630360
Stable Stage	0.623323	0.011569	0.365109	0.599283

4.2.3. Subject recognition

At present, the most widely applied methods for topic identification include LDA (Latent Dirichlet Allocation) and PLSA (Probabilistic Latent Semantic Analysis), among others. These methods are extensively utilized in research on network public opinion topic recognition. LDA thematic analysis delves deeply into the latent themes within the text, uncovering the focal points of public concern and hot topics of discussion.

In the current Internet environment, online public opinion analysis holds paramount importance in comprehending the focus and hotspots of public discourse. As a pivotal technology within public opinion analysis, topic recognition delves into the underlying themes embedded within textual data, offering robust support for public opinion monitoring and decision-making processes. Among the myriad of topic recognition methodologies, Latent Dirichlet Allocation (LDA) has garnered widespread adoption owing to its distinctive advantages [22]. LDA facilitates the automatic identification of textual themes by positing that each document is a conglomeration of multiple topics, with each topic manifested as a probability distribution over a vocabulary. This paper employs the LDA method to identify the themes within the textual data pertaining to a specific network public opinion event, thereby providing an insightful analysis of the topic characteristics that evolved across various stages of the event [23].

As depicted in Table 4, during the outbreak stage, the public's primary concern centered on avoiding conflict and facilitating negotiations between parties, reflecting an initial interest in the incident. Upon entering the dissemination phase, as the event gained widespread attention, the public's focus shifted towards themes such as terrorist attacks and international relations, with detailed narratives and specifics of the incident gradually coming to light. As the heat of the event gradually dissipated during the declining phase, the public's attention shifted towards international opinions and speculations about the event, while also expressing a yearning for peace. Finally, in the stabilization stage, the themes converged primarily on event speculation and international public opinion, with the public's interest in the event stabilizing. Through the application and analysis of the LDA method in this network public opinion event, it is evident that LDA can effectively discern the latent themes within the textual data, and these themes are intimately tied to the actual progression of the event. This finding not only validates the efficacy of LDA in the context of network public opinion topic identification but also furnishes a practical foundation for further investigations into the utilization of alternative topic identification methodologies within the realm of network public opinion analysis.

Table 4. Theme feature distribution in each stage

Stage	Topic Number	Keywords of the Topic	Overview of the Topic"
Outbreak Stage	1	美国、平民、冷静、局势、避免、安息	Avoid conflict
	2	历史、谈判、双方、克制、莫斯科、制暴	Negotiations
	3	默哀、保佑、恐怖、爱国、希望、沉重	Rest in peace for the deceased
	4	逝者、可怕、浪漫、音乐 、惋惜、无情	Rest in peace for the deceased
	5	邻国、紧张、电影、情报、普京、大哭	International public opinion
Spread Stage	1	情报、乌克兰、恐袭、偷袭、歹徒、英雄	Gangster terrorist attack
	2	美国、雇主、奖金、乌克兰、支持、良心	International public opinion
	3	美国、中国、大使馆、视频、武器、人群	Country relations
	4	新闻、卖命、武器、音乐会、俄罗斯、恐袭	The event passed
	5	袭击、扫射、补枪、真凶、训练、素质	Event details
Decline Stage	1	问题、国安局、袭击、警察、国家、平民	International public opinion
	2	军事、美国、客观、指示、媒体、散布	International public opinion
	3	美国、剧情、保佑、国家、武力、大选	Speculation of event
	4	国家、支持、和平、战争、歹徒、边境	Longing for peace
	5	组织、诡异、安息、和平、拥抱、袭击	Gangster terrorist attack
Stable Stage	1	美国、情报、散布、恐怖、俄罗斯、策划	Speculation of event
	2	乌克兰、残忍、专业、和平、悲痛、素养	Rest in peace for the deceased
	3	美国、大使馆、诱导、卖命、乌克兰、收钱	Speculation of Event
	4	美国、武器、指使、声明、乌克兰、行动	Speculation of event
	5	西方、人权、美国、反派、策划、差距	International public opinion

5. Research Result

5.1. Time evolution of emotion

Figure 3 illustrates the variations in social emotional values across different stages. It is evident that, in the context of major public emergencies, the social emotional values generally exhibit an upward trend over time, signifying a growing positivity in societal sentiment as the situation unfolds. This trend can be attributed to gradual psychological adaptation. Initially, in the aftermath of a terrorist attack, the public possesses limited knowledge about the cause, sequence, and aftermath of the incident, fostering intense feelings of anxiety, fear, and anger. Consequently, during the initial and dissemination stages, the public discourse is dominated by expressions of concern, fear, and anxiety. However, as time progresses, the public acquires an increasing amount of information about the terrorist attack, enabling a clearer understanding of its nature and implications. This, in turn, leads to a gradual alleviation of anxiety and fear. Furthermore, with the gradual clarification of the incident's development trajectory and the specifics of its handling, coupled with effective public relations efforts, the communication landscape stabilizes, and societal emotions shift towards positivity.Thus, the data presented in Figure 3 underscores the fact that the evolution of public emotional values across various stages of a terrorist attack mirrors the transformation of social psychological states.

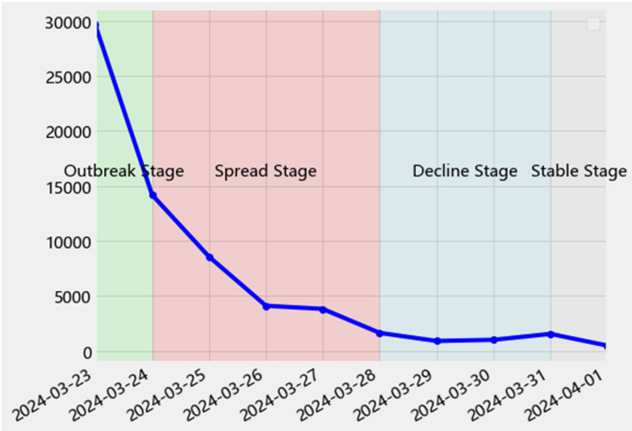

Figure 3. Affective temporal evolution map

5.2. Dynamic time evolution of the theme

Figure 4 provides a clear depiction of the evolutionary trajectory of online public opinion in response to the 'Russian Terrorist Attack' incident, visually elucidating the primary discussion foci among the public and the temporal shift in thematic emphasis throughout the event.

During the outbreak phase of the incident, online public opinion primarily centered on "avoiding conflict" and "negotiations between the parties", reflecting the public's aspiration for a peaceful resolution to such incidents, while also voicing concerns about the potential adoption of hardline measures by both sides. At this stage, the issue of "granting peace to the deceased" also garnered widespread attention, expressing condolences for the innocent victims. As the incident further escalated, online public opinion transitioned into a period of dissemination. During this time, netizens delved into the "course" and "details" of the incident, attempting to uncover the truth. Additionally, "international opinion" and "the dissemination period" emerged as hot topics of discussion, highlighting the extensive attention and influence the event garnered within the international community. Upon entering the stabilization phase, online public opinion began to rationalize and stabilize. Netizens started to scrutinize the incident from a more macroscopic perspective, focusing on its implications for "interstate relations" and the trajectory of bilateral ties post-incident. Simultaneously, the call for "peace" gradually intensified, mirroring the public's yearning for a stable and peaceful international environment. In the latter stages of the incident, online public opinion entered a period of decline. At this juncture, public interest in the event gradually waned, and discussions tapered off. Nevertheless, this does not signify that the incident's impact has vanished altogether; rather, it may persist in the public's memory in some form, potentially influencing future international relations and regional stability.

It is evident that the evolution of online public opinion constitutes a dynamic process, influenced by a multitude of factors, such as the nature of the event, its progression, the international environment, and the psychological state of the public [24]. Consequently, when confronted with similar incidents, it is imperative that we closely monitor the evolving trends of online public opinion, promptly adopt effective measures to steer public discourse towards a positive trajectory, and thereby uphold social stability and harmony.

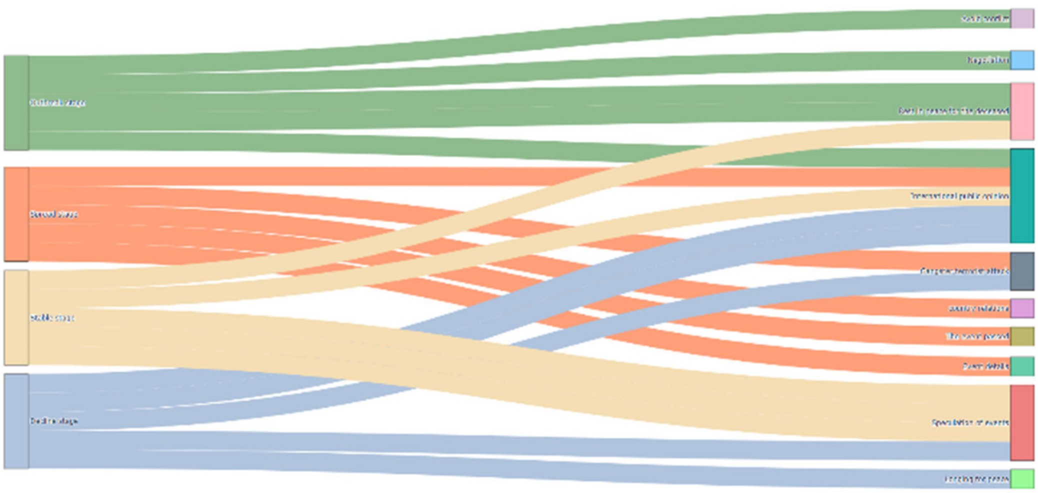

Figure 4. Each stage theme word evolution Sankey diagram

6. Conclusion Countermeasures and Prospects

This paper, taking the "Russian Terrorist Attack" incident that occurred on March 23, 2024 as a case study, delves into the temporal evolution process of online public opinion amidst major social emergencies. By employing LDA topic modeling and SnowNLP sentiment analysis techniques, this research uncovers the entire lifecycle of public opinion, spanning from its inception, through fermentation and outbreak, to eventual dissipation. Furthermore, it illuminates the shifts in the public's focal points of attention and the patterns of emotional fluctuations throughout this process. This paper sheds light on the evolutionary laws and underlying mechanisms of online public opinion surrounding the "Russian Terrorist Attack" event, offering a novel perspective and methodology for comprehending network public opinion. Consequently, it holds significant reference value for the monitoring and guidance of public opinion in future similar incidents.

In terms of subject matter, over time, the focus of public attention has shifted from the event itself to an in-depth discussion of the underlying causes, effects, and the government's response measures. Particularly during the fermentation and outbreak stages of public opinion, topics such as the government's coping strategies, concerns over social security issues, as well as sympathy and support for the victims, emerged as prominent points of discussion. The public's concern over the "Russian Terrorist Attack" gradually evolved from centering solely on the event to encompassing its underlying causes, impacts, and the government's subsequent actions. This transition underscores the public's deepening understanding of the event and their heightened expectations of government intervention. Regarding emotions, this study observes notable fluctuations in public sentiment as the event progressed. At the inception of public opinion, amidst a scarcity of information and uncertainty, the public mood was predominantly tense and anxious. As the event unfolded and information trickled in, emotions gradually stabilized. Following the government's implementation of effective countermeasures, a degree of positivity emerged. Nevertheless, in the dissipation phase of public opinion, the lingering effects and aftermath of the incident continued to evoke a certain level of sensitivity among the public.

Based on the above findings, this study offers a decision-making reference for stakeholders including governments, enterprises, and investors in terms of public opinion judgment and regulation. Specifically, the government should enhance the monitoring and guidance of online public opinion, promptly address societal concerns, and ensure transparency and openness of information [25]. Furthermore, the following recommendations are provided for national security departments in monitoring and guiding public opinion during major social emergencies: During the incubation stage of public opinion, strengthen information gathering and monitoring to promptly grasp the public's concerns and emotional shifts. In the fermentation phase, intensify supervision and filtering of inappropriate remarks to prevent the dissemination of rumors and negative sentiments. During the outbreak period, actively steer public opinion, enhance information openness and transparency, thereby bolstering public trust in the government. In the dissipation stage, formulate effective preventive measures to prevent the recurrence of similar incidents, and strengthen public education to improve their discernment and response capabilities regarding online public opinion.Additionally, this study underscores the pivotal role of opinion leaders in the evolution of public opinion. The opinions and actions of opinion leaders frequently shape public viewpoints and emotions. Consequently, in monitoring and guiding public opinion, special heed should be paid to the activities of opinion leaders, fostering communication and collaboration with them to jointly uphold the healthy and orderly development of cyberspace.

In addition, this study exhibits certain limitations. Firstly, the data is solely sourced from the Bilibili platform. Future research could incorporate data from additional social media platforms to undertake multi-modal data analysis, thereby gaining a more comprehensive understanding of public opinion. Secondly, the approach to text analysis necessitates further innovation, particularly in enhancing fine-grained analysis, to enrich and refine the outcomes.

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Reference

[1] Liu C, Tian Y, Shi Y, et al. An analysis of public topics and sentiments based on social media during the COVID-19 Omicron Variant outbreak in Shanghai 2022[J]. Computational Urban Science, 2024, 4(1): 19.

[2] Fu W, Zhou B. Theme Exploration and Sentiment Analysis of Online Reviews of Wuyishan National Park[J]. Land, 2024, 13(5): 629.

[3] Wu K, Wu J, Li Y. Mining typhoon victim information based on multi-source data fusion using social media data in China: a case study of the 2019 Super Typhoon Lekima[J]. Geomatics, Natural Hazards and Risk, 2022, 13(1): 1087-1105.

[4] AnL, YuC, LinX, etal. Topical Evolution Patternsand Temporal Trends of Microblogson Public Health Emergencies: An Exploratory Study of Ebolaon Twitterand Weibo [J].OnlineInformation Review, 2018, 42(6):821－846.

[5] GarciaK, BertonL. Topic Detectionand Sentiment Analysisin Twitter Content RelatedtoCOVID-19 from Braziland the USA [J]. Applied Soft Computing, 2021, 101:107057.

[6] GorrabA, KboubiF, JaffalA, etal. Twitter User Profiling Model Based on Temporal Analysis of Hashtagsand Social Interactions [M]. Lecture Notesin Computer Science, 2017: 124-130.

[7] Guo F, Liu Z, Lu Q, et al. Public Opinion About COVID-19 on a Microblog Platform in China: Topic Modeling and Multidimensional Sentiment Analysis of Social Media[J]. Journal of Medical Internet Research, 2024, 26: e47508.

[8] You M A, Kun Y U E, Zi-chen Z, et al. Extraction of social media data based on the knowledge graph and LDA model[J]. Journal of East China Normal University (Natural Science), 2018, 2018(5): 183.

[9] Zhou Z, Zhou X, Chen Y, et al. Evolution of online public opinions on major accidents: Implications for post-accident response based on social media network[J]. Expert Systems with Applications, 2024, 235: 121307.

[10] Huang HL.Transmission of Network Public Opinion for Public Emergency inNetwork Medias [C]. 2nd International Conference on Education, Sports, Artsand Management Engineering, 2017, 123: 1090-1093

[11] ZhongZ. Internet Public Opinion Evolutioninthe COVID-19 Eventand Coping Strategies [J]. Disaster Medicineand Public Health Preparedness, 2020, 15(6):21-23.

[12] ZhangT, ChengC. Temporaland Spatial Evolutionand Influencing Factors of Public Sentimentin Natural Disasters—A Case Study of Typhoon Haiyan [J]. ISPRSinternational Journal of Geo-Information, 2021, 10(5):299.

[13] Xie T, Yang Y, Li Q, et al. Knowledge graph construction for intelligent analysis of social networking user opinion[C]//Advances in E-Business Engineering for Ubiquitous Computing: Proceedings of the 16th International Conference on e-Business Engineering (ICEBE 2019). Springer International Publishing, 2020: 236-247.

[14] Lu K, Wu J. Sentiment analysis of film review texts based on sentiment dictionary and SVM[C]//Proceedings of the 2019 3rd international conference on innovation in artificial intelligence. 2019: 73-77.

[15] Lei H, Wang H, Wang L, et al. An Analysis of the Evolution of Online Public Opinion on Public Health Emergencies by Combining CNN-BiLSTM+ Attention and LDA[J]. Journal of Computer and Communications, 2023, 11(4): 190-199.

[16] Li X, Ling M, Luo C. Public opinion evolution in social networks based on latent Dirichlet allocation and sentiment analysis[C]//International Conference on Algorithms, High Performance Computing, and Artificial Intelligence (AHPCAI 2023). SPIE, 2023, 12941: 586-593.

[17] Lu K, Wu J. Sentiment analysis of film review texts based on sentiment dictionary and SVM[C]//Proceedings of the 2019 3rd international conference on innovation in artificial intelligence. 2019: 73-77.

[18] Wu Y. Sentiment Analysis of Yaya Event of Giant Panda in the United States based on LDA Topic Model[C]//SHS Web of Conferences. EDP Sciences, 2023, 178: 01002. [19] Lu K, Wu J. Sentiment analysis of film review texts based on sentiment dictionary and SVM[C]//Proceedings of the 2019 3rd international conference on innovation in artificial intelligence. 2019: 73-77.

[19] Lu K, Wu J. Sentiment analysis of film review texts based on sentiment dictionary and SVM[C]//Proceedings of the 2019 3rd international conference on innovation in artificial intelligence. 2019: 73-77.

[20] Media Bias against Foreign Firms as a Veiled Trade Barrier: Evidence from Chinese Newspapers[J]. SUNG EUN KIM.American Political Science Review,2018(4)

[21] Topological evolution of the internet public opinion[J]. Ying Lian;;Xuefan Dong;;Yijun Liu.Physica A: Statistical Mechanics and its Applications,2017

[22] Leveraging cross-media analytics to detect events and mine opinions for emergency management[J]. Wei Xu;;Lingyu Liu;;Wei Shang.Online Information Review,2017

[23] A Multichannel Biomedical Named Entity Recognition Model Based on Multitask Learning and Contextualized Word Representations[J]. Hao Wei;;Mingyuan Gao;;Ai Zhou;;Fei Chen;;Wen Qu;;Yijia Zhang;;Mingyu Lu;;Yin Zhang.Wireless Communications and Mobile Computing,2020