The Impact of Stakeholder Responses on Netizen Sentiment in Public Opinion Incidents (Postprint)

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Abstract

[Purpose/Significance] Exploring the internal mechanisms of online public opinion evolution can yield deeper insights into the development of public sentiment, facilitating scientific decision-making and guidance for relevant authorities in public opinion incidents. [Method/Process] This study selected blog posts from parties involved in specific public opinion incidents along with corresponding reposts and comments, calculating sentiment scores for comment texts based on a sentiment dictionary. From a time series perspective, it dynamically analyzed changes in sentiment polarity during the evolution of public opinion and the influence of responses from involved parties on netizens' emotions. [Results/Conclusion] The findings indicate that responses from involved parties directly affect the level of attention from netizens; netizens' sentiment polarity is not static during the evolution of public opinion; the content of responses directly influences netizens' emotions, with effective evidence and sincere attitudes helping to mitigate negative emotions in public opinion.

Full Text

The Impact of Responses from Parties Involved on Netizens' Emotions in Online Public Opinion

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Abstract: [Purpose/Significance] Exploring the internal mechanisms of online public opinion evolution can provide deeper insights into the development of public opinion and help relevant units or departments achieve scientific decision-making and guidance during public opinion events. [Method/Process] This study selected blog posts from parties involved in specific public opinion events and their corresponding forwarded comments, calculating sentiment scores of comment texts based on a sentiment dictionary. From a time series perspective, we conducted dynamic analysis of changes in emotional polarity during public opinion development and the impact of party responses on netizens' emotions. [Result/Conclusion] The results indicate that party responses have a direct impact on the level of netizen attention; netizens' emotional polarity is not static during public opinion development; response content directly affects netizens' emotions, and effective evidence and sincere attitudes help alleviate negative sentiments in public opinion.

Keywords: Internet public opinion; party's response; emotional polarity; sentiment analysis

The popularization of the Internet and the widespread use of social media have expanded the scope and speed of public information exchange beyond any traditional media. Increasingly, netizens obtain various types of information, express personal opinions, and participate in public affairs through online platforms such as Weibo, WeChat, and blogs. As the Internet has gradually become an information space for people to acquire information and express their will, government, academic, and social sectors have all attached great importance to online public opinion dissemination. As early as 2004, the Fourth Plenary Session of the 16th Central Committee of the Communist Party of China proposed in the "Decision of the Central Committee of the Communist Party of China on Strengthening the Party's Governance Capacity" [1]: "Establish a mechanism for collecting and analyzing public opinion, firmly grasp the direction of public opinion, and correctly guide social public opinion." This emphasis on guiding social hot issues has produced fruitful results, with online public opinion research continuously expanding and innovating through the close integration of theory and practice.

In light of this, this study collected the main content of blog posts from parties involved in specific online public opinion events and their corresponding forwarded comments. Based on an improved sentiment dictionary, we calculated sentiment scores for comment texts and examined the impact of party responses on changes in netizens' emotions from a time series perspective across multiple dimensions, aiming to gain deeper insights into the internal mechanisms of online public opinion development and evolution.

2 Literature Review

With the popularization of the Internet and the emergence of social media, the general public not only uses social media to exchange information but also influences each other's views and behaviors online. The integration and blending of online and offline, virtual and real [3], constitute a complex public opinion space with the Internet as the main platform. Online public opinion has characteristics of spontaneity, diversity, cross-boundary nature, and conflict, making it not only a key focus of academic research but also a common issue faced by all sectors of society. Meanwhile, different attitudes and viewpoints on specific issues in online public opinion [4], and even opposing viewpoints [5], have gradually attracted researchers' attention. Against this background, sentiment analysis (also known as "opinion mining") has become a challenging topic in public opinion research. The goal of sentiment analysis is to extract and analyze opinions, sentiments, evaluations, attitudes, and emotions expressed by people toward entities and their attributes from text [6]. Sentiment analysis methods are divided into two categories: dictionary-based and statistical analysis. The former mainly conducts sentiment analysis based on the sentiment tendency of words and linguistic knowledge, while the latter discovers and uses sentiment features at the text level. Currently, most general-purpose sentiment dictionaries are manually constructed, primarily by reading large amounts of relevant corpora or using existing dictionaries to manually summarize words with sentiment tendencies, labeling sentiment polarity or intensity to form dictionaries. Famous examples include SentiWordNet, which merges words with the same meaning based on WordNet and assigns corresponding positive and negative scores, allowing users to judge sentiment tendency based on word scores. Common Chinese sentiment dictionaries include HowNet from CNKI, the Dalian University of Technology Chinese Sentiment Lexicon (DUTIR), and the National Taiwan University Sentiment Dictionary (NTUSD). This study will build upon these three Chinese sentiment dictionaries to construct a public opinion sentiment dictionary for specific online public opinion events.

On the other hand, with the continuous development and maturation of machine learning technology, sentiment analysis based on statistical analysis and machine learning has also been applied to public opinion analysis research. T. Mullen et al. [15] combined n-gram with other methods to extract sentiment features from text, finding that this method was more effective than bag-of-words features after stemming. E. Kouloumpis et al. [16] built upon previous n-gram methods, combining three different dimensions of features—"multi-perspective question-answering subjectivity lexicon," "statistics on verbs, adverbs, adjectives, nouns, and other parts of speech," and "positive, negative, and neutral emoticons, as well as emphasis and abbreviations"—to classify sentiment in Weibo texts, achieving good results in Weibo sentiment detection. J. Bollen et al. [17] conducted emotion analysis on tweets, calculating a six-dimensional emotion vector (tension, depression, anger, vitality, fatigue, confusion) on a daily timeline to infer more precise emotional directions of large-scale netizens. K. Liu et al. [18] proposed an opinion target extraction method based on the Word-based Translation Model (WTM), applying WTM to monolingual scenarios to mine the association between opinion targets and opinion words, finding that the WTM model could more accurately capture sentiment for informal large-scale corpora. Wang Xiwei et al. [19] used a Naive Bayes model to conduct sentiment analysis across three dimensions of word frequency, region, and time, finding that users' sentiments toward events tended to be positive. Liao Haihan et al. [20] used the LDA topic model for hotspot mining, displaying the influence of topics at each stage through thematic content and related information under time granularity, demonstrating better effectiveness in public opinion monitoring.

In summary, various research methods for online public opinion have achieved corresponding results. The sentiment dictionary analysis method, based on positive and negative words in linguistics, makes it closer to human emotional cognition. Research data objects are mostly text content published by netizen users, extracting and analyzing emotional features through publicly released text. However, research linking changes in netizens' emotions with the words and actions of parties involved in public opinion is rarely explored. Accordingly, this study selects specific public opinion events, focusing on examining the impact of party responses on changes in netizens' emotions. Based on forwarded comments under parties' Weibo posts, according to an improved sentiment dictionary for the event, and from a time series perspective, we analyze the impact of party responses on netizens' emotions in public opinion events from multiple dimensions and granularities, thereby revealing the influence of party responses on netizens' emotions.

3 Theoretical Foundations

3.1 Sentiment Dictionary and Sentiment Scoring

Sentiment analysis is technically divided into two categories: rule-based (sentiment dictionary) and statistical analysis. The former mainly conducts sentiment analysis based on the sentiment tendency of words and linguistic knowledge, while the latter discovers and uses sentiment features at the text level. Currently, most general-purpose sentiment dictionaries are manually constructed, primarily by reading large amounts of relevant corpora or using existing dictionaries to manually summarize words with sentiment tendencies, labeling sentiment polarity or intensity to form dictionaries. Famous examples include SentiWordNet, which merges words with the same meaning based on WordNet and assigns corresponding positive and negative scores, allowing users to judge sentiment tendency based on word scores. Common Chinese sentiment dictionaries include HowNet from CNKI, the Dalian University of Technology Chinese Sentiment Lexicon (DUTIR), and the National Taiwan University Sentiment Dictionary (NTUSD). This study will build upon these three Chinese sentiment dictionaries to construct a public opinion sentiment dictionary for specific online public opinion events.

Considering that existing general-purpose sentiment dictionaries have problems such as overly formal vocabulary, inclusion of only words but not phrases, and lack of specific vocabulary for particular events, this study improves upon the comprehensive foundation of HowNet, DUTIR, and NTUSD sentiment dictionaries by adding architectural academic terms such as "fraud," "show drawings," and "CAD," as well as internet slang commonly appearing in blog posts such as "drunk," "convinced," and "speechless," thereby constructing a specialized online public opinion sentiment dictionary for this research. In the study, the dictionary is divided into two aspects: positive sentiment words (pos.weight) and negative sentiment words (neg.weight). Positive and negative sentiment words are identified based on the sentiment dictionary, and sentiment scores are calculated by superimposing scores for sentiment words according to Formula (1):

"Score = pos.weight - neg.weight" Formula (1)

3.2 Party Response and Forwarded Comments

Relevant texts in online public opinion include both published event information and related comment content. Different analysis tasks also select different ranges of text data. This study takes individuals directly involved in public opinion events as direct parties, focusing on examining the impact of statements made by parties on netizens' emotions. Therefore, research data at the text level mainly consists of two parts: statements made by parties and netizen comments. After a party publishes a relevant statement, it triggers related comments from netizens. In response to these comments, subsequent information released by the relevant party can be regarded as the party's response. Since the research work needs to examine the impact of party responses on netizens' emotions, the netizen comment section selects comment texts that contain the party's blog post content, i.e., forwarded comments. The data selection scope for party statements and forwarded comments is shown in Figure 1 [Figure 1: see original paper].

The dashed box in Figure 1 represents the text content of concern in this study. Since forwarded comments contain statements made by the party, they are more persuasive in research on changes in netizens' emotions in response to party responses. Other pure comments or forwards either lack statements made by the party or have no comment content, making it difficult to examine the impact of party statements on netizens' emotions and thus having low research value in this study. Therefore, they are excluded from the data scope of this research. Based on the text within the above scope, sentiment scoring is conducted according to the improved sentiment dictionary, and combined with relevant statements made by the party, multi-granularity and multi-dimensional public opinion sentiment analysis is conducted with the time series as the main thread.

4 Methodology

4.1 Data Collection and Sentiment Scoring

Since the focus of this study is on the impact of party responses to specific events on the emotional polarity of online public opinion, and considering that forwarded comments better reflect netizen users' attention to the party's responses and the impact generated by party responses than ordinary comments, this study selected the specific public opinion event "Jiang Yiyan's Architecture Award" during which the party made multiple responses. Using a self-developed crawler tool, we collected 4 blog posts from the party "@ 江小爬 LOVE" on October 14 (1 post), October 22 (2 posts), and November 21 (1 post) in 2019, along with their corresponding forwarded comments. The collection targets were set as comment text and comment time. This yielded a total of 35,165 forwarded comments under the party's 4 blog posts, with the time span of all forwarded comments being from 20:00 on October 14, 2019, to 0:00 on November 25, 2019.

The research work divided and saved all obtained comment texts by time, then conducted sentiment scoring based on the improved sentiment dictionary for this event. This work first used regular expressions for data cleaning, removing @ mentions, forwarded comment markers, blank information, usernames, emoticons, etc., from comment texts, extracting only the textual comment content, resulting in 14,825 valid messages. The extracted valid information "detailed comment content" and "user comment time" was stored in chronological order. Then, based on the improved sentiment dictionary for this event, effective comments in the event were scored for sentiment to be used for analyzing netizens' emotions in this public opinion event.

4.2 Division of Public Opinion Stages

Since the research work inevitably involves dynamic changes during event development, the time series of forwarded comments is an important factor in the analysis. Netizens' forwarded comments were measured in natural days, and the number of forwarded comments for each natural day was counted, resulting in the time series of forwarded comment quantities shown in Figure 2 [Figure 2: see original paper].

The numbers in Figure 2 represent the number of forwarded comments within each natural day. The data in the figure reveals that although the event lasted a relatively long time on the Internet, the number of forwarded comments on the party's blog posts was not continuous, with even multiple discontinuities appearing. On the other hand, the data also reflects that the number of netizens' forwarded comments has multiple peaks on the date scale. In response to this phenomenon, which differs from common public opinion dissemination patterns, the research work divided the event's public opinion development into 4 stages based on the daily number of forwarded comments (when the number of forwarded comments in a period is significantly larger than in other periods and lasts for a period, that period is considered a relatively special period in the public opinion dissemination process): Incubation period (A: October 14 - October 22, 2019), during which the number of forwarded comments was not large. The party posted photos of visiting architectural designs in Spain, and some netizens raised objections to the party's introduction of architecture in the blog post, believing there were discrepancies in the party's description of historical events, with major V users such as @ 宣和一人 and @ 梦亭 also participating. Outbreak period (B: October 22 - October 26), during which the party continuously posted two blog posts. The first blog post claimed that the party had won the American Architecture Master Award, demonstrating architectural expertise, and the second blog post was a response and statement to previous netizen doubts. The party's response attracted netizens' attention and further questioning, with the number of forwarded comments rising rapidly. At this time, the number of forwarded comments reached its peak, and the speed of public opinion dissemination increased sharply, including demands to show drawings for academic responses. Decline period (C: October 27 - November 20), during which netizens' attention to the event gradually decreased, and the number of forwarded comments dwindled daily. Secondary outbreak period (D: November 21 - November 24), when netizens revealed that the party's award-winning building was an illegal construction, and the party publicly posted an apology blog post, causing the number of forwarded comments to rise again.

Combined with the party's information behavior, we can preliminarily find that each time the party publishes a blog post, it stimulates the subsequent number of forwarded comments to varying degrees. If we infer from this that the party's response behavior is the main factor stimulating public opinion development and propose that the party should remain evasive or silent in public opinion events, it would obviously be somewhat arbitrary. Different response content from the party may lead to different impact effects. What kind of impact the party's response has on netizens' emotions requires deeper analysis. In the specific research work, we calculated the overall sentiment score of netizens in the event and the sentiment scores for each stage based on forwarded comment texts, analyzing changes in netizens' emotions during public opinion development based on absolute score values and score proportions. On this basis, combined with the timing and content of party responses, we tracked changes in the number of forwarded comments and emotional polarity on the time series, focusing on analyzing the impact of party response content on netizens' emotional polarity.

5 Results

5.1 Dynamic Analysis of Emotional Polarity

The research work calculated the sentiment scores of netizens' forwarded comments based on the sentiment dictionary established earlier, using Formula (1). The total emotional score for the entire event's public opinion process was -11,519, meaning that netizens' forwarded comments showed extreme negativity throughout the entire public opinion cycle. However, as previously discovered, the number of netizens' forwarded comments varied significantly across different public opinion stages (see Figure 2). The research work further counted positive and negative scores separately according to the four stages of public opinion development, obtaining the sentiment scores for different stages of the event as shown in Figure 3 [Figure 3: see original paper].

The data in Figure 3 reveals that although forwarded comments in the incubation period had both positive and negative tendencies, the overall sentiment score was positive (-33 + 179). During the outbreak period, netizens' negative emotions continued to grow and accumulate (the cumulative negative sentiment score for this stage was -16,668). Although there were still forwarded comments with positive tendencies, the overall emotional polarity of this stage turned sharply downward, with a score of -9,365 (-16,668 + 7,303). During the decline period, the event gradually faded, the number of forwarded comments decreased, and the negative score dropped to -478, narrowing the gap between positive and negative tendencies. However, after the party published the 4th blog post, the number of netizens' forwarded comments increased rapidly again, and public opinion development entered a secondary outbreak period. The overall sentiment score for this stage was -2,117 (-8,424 + 6,307), with negative emotions once again occupying a clear advantage. Although the data in Figure 3 reflects differences in emotional polarity across stages (overall sentiment scores fluctuating between positive and negative), the influence of the absolute number of forwarded comments prevents accurate grasp of netizens' emotional fluctuation trends. The research work further analyzed the proportion of emotional polarity across different stages (relative quantities), obtaining the changes in emotional polarity proportions during public opinion development as shown in Figure 4 [Figure 4: see original paper].

Figure 4 shows that the proportions of positive and negative emotions also change with public opinion development. In the incubation period, the number of forwarded comments was small (see Figure 2), with positive emotions accounting for 84%, far higher than negative emotions (16%). This indicates that netizens were generally appreciative or supportive of the party's blog post content. As public opinion developed into the outbreak period, the emotional tendency suddenly changed, with the proportion of negative emotions rising significantly (70%), reaching the peak of negative emotions, while the proportion of positive emotions decreased to 30%, reversing their positions. In the subsequent decline period (8,566 comments) and secondary outbreak period (5,803 comments), the number of forwarded comments plummeted, with even zero comments on some natural days (see Figure 2). During this stage, the proportion of negative emotions declined (62%) while the proportion of positive emotions increased (38%), narrowing the gap between the two. In the secondary outbreak period, although the number of forwarded comments increased again, the gap between negative emotion proportion (57%) and positive emotion proportion (43%) further narrowed, with emotional polarity gradually trending toward balance. This phenomenon indicates that during public opinion event development, although cumulative sentiment scores are related to the number of forwarded comments, the proportion of emotional polarity is not directly related to comment quantity. That is, while the number of forwarded comments can reflect netizens' attention to the event, it cannot fully explain the reasons for changes in netizens' emotional polarity.

5.2 Impact of Party Responses on Netizens' Emotional Polarity

The research work further examined the relationship between content published by parties involved in public opinion and netizens' emotional polarity. The direct party "@ 江小爬 LOVE" published a total of 4 blog posts throughout the public opinion event, located at the front end of the incubation period, outbreak period, and secondary outbreak period, respectively, triggering subsequent forwarded comments. The study extracted high-frequency words from forwarded comment texts in these three stages and corresponded them with the direct party's blog post content, with results shown in Table 1 :

Table 1: Direct Party's Blog Post Content and High-Frequency Comment Words and Sentiment Changes

Stage	Number of Comments	Party's Blog Post Theme Content	High-Frequency Comment Words (Top 10)	Cumulative Sentiment Score
Incubation Period (A)	167	The party visited architectural works in Spain, introducing the life and achievements of architect Gaudi	like (23), architecture (22), sister (20), teacher (15), love (11), Barcelona (10), text (10), good-looking (8), beautiful (8), art (8)	146
Outbreak Period (B)	8,566	1. Sharing information about the party winning the American Architecture Master Award; 2. Thanking the party's design team; 3. Responding to netizen doubts; 4. Proposing the party's years of public welfare experience to refute fraud claims	architecture (1,423), design (872), professional (657), client (575), teaching support (420), persona (402), designer (395), academic (283), drawings (277), questioning (262)	-9,365

Stage	Number of Comments	Party's Blog Post Theme Content	High-Frequency Comment Words (Top 10)	Cumulative Sentiment Score
Secondary Outbreak Period (D)	5,803	1. Apologizing for recent events; 2. Returning to the original aspiration, returning to being an actor, being a simple person	apology (886), sincere (447), cheer up (410), actor (317), like (269), PR (233), teaching support (221), design (198), house (170), architecture (162)	-2,117

In the incubation period, the party's blog post theme content was about sharing personal knowledge in architecture and building momentum before winning the award. High-frequency words (Top 10) in forwarded comments during this stage included many positive words such as "like," "good-looking," and "beautiful." Although some netizens questioned the party's architectural knowledge, negative words did not enter the top 10 high-frequency word set. At this time, netizens held a relatively positive attitude (146) toward the event, reflecting that when the content did not involve winning awards, netizens' emotions were relatively calm and objective, showing envy and support for the party's simple sharing.

After the party continuously published two blog posts announcing award information and responding to previous doubts, public opinion entered the outbreak stage. The party's blog post theme content included award information, responses to doubts, and public welfare experiences, attempting to demonstrate architectural expertise from professional and personality perspectives to respond to netizens' doubts. However, failing to provide conclusive evidence of substantive participation in architectural design work triggered more professional-level questions about architecture. Professional vocabulary such as "design," "client," "academic," and "drawings" entered the Top 10 high-frequency word set. Meanwhile, the party's extreme statements and responses ("If everyone thinks everything can be faked…, then please join in! After all, I do look quite like an award presenter") caused netizens' negative emotions to explode rapidly, with the cumulative sentiment score reaching -9,365 and the overall emotional polarity reversing, making "questioning" a high-frequency word in this stage.

After this, public opinion development entered a decline period, and attention to the event gradually cooled. On November 7, netizens revealed that the party's award-winning villa had not obtained planning approval and was illegally expanded. On November 18, the Beijing Municipal Commission of Planning and Natural Resources responded to the report. However, the netizens' report and the relevant department's response did not cause obvious changes in the number of forwarded comments (see data from November 7 to November 19 in Figure

2), with most netizens maintaining a wait-and-see attitude. However, the exposure of relevant information facilitated the party's information behavior. On November 22, the party sincerely apologized for previous immature behavior and extreme statements ("I want to apologize to society. Due to improper personal behavior, I have become the focus of public opinion, occupying social resources. The whole event looks like a joke. I enjoyed those untrue high moments. People are prone to get carried away when complacent. Returning to the original aspiration, returning to authenticity, returning to being an actor is a lesson for me personally"). This was followed by another wave of forwarded comment peaks, but the high-frequency word set included positive words such as "sincere" and "cheer up," with the cumulative sentiment score falling back to -2,117 and the emotional trend of public opinion gradually moving toward equilibrium.

The research work further integrated the number of forwarded comments in Figure 2 with the daily sentiment scores of forwarded comments and the party's responses across multiple dimensions, obtaining the impact of party responses on netizens' emotional polarity as shown in Figure 5 [Figure 5: see original paper].

In Figure 5, the size of the circles represents the number of forwarded comments on that day, the line represents the trend of netizens' sentiment scores, and the dashed lines mark the response behaviors of direct or indirect parties. The figure shows that after the direct party (@江小爬 LOVE) published the first blog post of the event (visiting works, introducing architects), the sentiment score of forwarded comments was above the emotional baseline, with moderate netizen attention and relatively strong positive emotions. When the direct party continuously published the 2nd and 3rd blog posts (award information, responding to doubts, public welfare experience, refuting fraud) as responses, the sentiment score of forwarded comments was directly pulled below the emotional baseline. Since the 2nd and 3rd blog posts were published near or at night (17:05 and 21:44 respectively), the number of forwarded comments surged further the next day, and the sentiment score fell to its lowest point. After a period of time, netizen attention gradually decreased, the number of forwarded comments gradually diminished, and the sentiment score gradually moved toward the emotional baseline, then fluctuated around it. After the direct party published the 4th blog post (apology), it once again attracted netizens' attention, with the number of forwarded comments surging again. The sentiment score first fell below the baseline, then rose above it, and finally approached the emotional baseline. Combining the direct party's response timing and sentiment scores of forwarded comments in Figure 5, and further considering the direct party's relevant blog post content in Table 1, we find that the direct party's responses and their content have a direct impact on netizens' emotions. Responses lacking strong evidence and with extreme wording cannot suppress netizens' negative emotions, while sincere apologies are more likely to gain public understanding.

At the same time, during the public opinion outbreak period (October 22 - October 26), the indirect party (the American Architecture Master Award organizer) also responded to the direct party's award on October 24 at 11:39. The main content was "We believe excellent architecture is the result of team collaboration and should not examine each design team member or client's individual contribution level. The project won the award because of the team's excellent design, and the award was given to the entire company and team." In response to the indirect party's statement, @ 新浪娱乐 created an online vote. Figure 5 marks the timing of the indirect party's response and shows the voting results in a pie chart. The voting results showed that among the 254,000 netizens who participated, more than one-third of voters (B: 37.0%) believed that making suggestions does not represent participation in design and directly rejected the indirect party's response in the face of explanations without evidence of work contribution; 30.3% (A) of voters were relatively calm, proposing that the party show drawn drawings as evidence, otherwise not recognizing the indirect party's response; and less than one-third of voters (C: 32.7%) found the indirect party's response convincing. In fact, the average sentiment score per comment on October 23 was -1.088 (total daily score / number of comments that day), while the average sentiment score on October 24 decreased to -1.244. Obviously, after the indirect party issued the statement, netizens' negative emotions were not effectively alleviated, and at the level of average sentiment scores, they even became more severe.

Through the above analysis, we can find that netizens' emotional polarity is closely related to the content of direct party responses. Without considering party responses (before each response occurs), although the number of forwarded comments gradually decreases over time (the circle area in Figure 5 shrinks), netizens' emotional polarity does not change. After the party issues a response, the number of forwarded comments surges and triggers changes in netizens' emotional polarity. In this event, the party's initial simple sharing behavior triggered mixed positive and negative forwarded comments, but positive emotions dominated; high-profile award announcements and extreme response statements not only failed to eliminate the small amount of previous doubts but instead provoked more professional-level questions, overturning the dominant position of positive emotions and making negative emotions dominant; after the party's sincere apology, although the number of forwarded comments increased again, the proportion of positive emotions gradually rebounded, the proportion of negative emotions gradually decreased, and netizens' emotions gradually moved toward balance. Whether from direct or indirect parties, empty explanations or statements without evidence cannot gain netizens' recognition nor help alleviate netizens' negative emotions. At the same time, the proportion of negative emotions further decreased (see Table 1, Figure 5). This result indicates that in public opinion events, real and strong evidence materials and positive and sincere attitudes can more easily gain public understanding and recognition than strong wording or irrelevant evidence, providing a new perspective for public opinion guidance and emotional relief.

6 Conclusion and Discussion

This study addressed the issue of the impact of party responses on netizens' emotional polarity in public opinion events. Based on an improved sentiment dictionary, we calculated sentiment scores for forwarded comments of blog posts from parties involved in specific public opinion events. According to the number of forwarded comments, we divided online public opinion development into four stages: incubation period, outbreak period, decline period, and secondary outbreak period, and combined these with party response content to analyze the changing characteristics of netizens' emotional polarity. Based on the above analysis results, the research work preliminarily draws the following conclusions:

6.1 Party Responses Have a Direct Impact on Netizens' Attention Level

The time series of forwarded comment quantities during the public opinion period shows that when the party involved in public opinion publishes a blog post, it attracts netizens' attention, but this attention gradually fades over time; however, when the party publishes another blog post making a response, it stimulates a new round of growth in forwarded comment quantities (see Figures 2 and 5). This result indicates that in online public opinion events, the reactions of parties involved play an important role in public opinion development. While netizens pay attention to the development process of the event, they pay more attention to the words and actions of the parties themselves regarding the event.

6.2 Netizens' Emotional Polarity Is Not Static During Public Opinion Development

Most previous studies examined public opinion events as a whole, focusing on netizens' emotional tendencies toward a public opinion event. This study found that after segmenting the public opinion cycle according to the number of forwarded comments, netizens' emotional polarity differed throughout the public opinion development period. The incubation period was generally in a positive mood, but in the outbreak period, it turned sharply downward to show extremely negative emotions, with emotional polarity reversing (see Figure 3). In addition, the proportions of positive/negative emotions in each stage were also different (see Figure 4). This result indicates that for online public opinion monitoring and analysis, it is necessary to conduct more fine-grained examinations, as general summary may ignore or omit important information.

6.3 Party Response Content Directly Affects Netizens' Emotional Polarity

The analysis found that party responses not only affect the number of netizens' forwarded comments but also have a direct impact on netizens' emotional polarity. Analysis combining party responses (including direct and indirect parties) shows that extreme justifications and unsubstantiated exonerations do not help suppress netizens' negative emotions; on the contrary, sincere apologies instead gain some public understanding to a certain extent, and the number of forwarded comments grows again while the proportion of negative emotions further decreases (see Table 1, Figure 5). This result indicates that in public opinion events, real and strong evidence materials and positive and sincere attitudes can more easily gain public understanding and recognition than strong wording or irrelevant evidence, providing a new perspective for public opinion guidance and emotional relief.

Combining party responses with changes in netizens' emotional polarity can provide new perspectives for understanding the characteristics and patterns in the development of online public opinion. The relationship between party responses and netizens' attention level and emotional polarity discovered in this study can help relevant units or departments gain deeper information and insights during public opinion events and provide reference for public opinion decision-making and guidance. The study also has certain limitations. Since this study is an exploratory study on the impact of party responses on netizens' emotional polarity, and different public opinion events require different sentiment dictionaries, the research work only analyzed a single specific event with party responses during public opinion development. Future research work will further select more public opinion events with party responses, conduct deeper analysis from broader perspectives, more dimensions, and finer granularity, to more comprehensively explore and reveal the characteristics and patterns of online public opinion evolution and development.

References

[1] The Fourth Plenary Session of the 16th Central Committee of the Communist Party of China. Decision of the Central Committee of the Communist Party of China on Strengthening the Party's Governance Capacity [N]. People's Daily, 2004-09-27(1).

[2] Xu Xin, Zhang Chengzhi, Li Wenjing. Review and Prospect of Domestic Online Public Opinion Research [J]. Information Studies: Theory & Application, 2009, 32(3): 115-120.

[3] Tian Yilin, Teng Guangqing. Analysis of Network Key Information Affecting Offline Derivative Behaviors [J]. Information Studies: Theory & Application, 2016, 39(10): 80-85.

[4] Mulder K. The dynamics of public opinion on nuclear power: Interpreting an experiment in the Netherlands [J]. Technological Forecasting & Social Change, 2012, 79(8): 1513-1524.

[5] Kim K, Young M B, Narae K. Online news diffusion dynamics and public opinion formation: A case study of the controversy over judges' personal opinion expression on SNS in Korea [J]. The Social Science Journal, 2015, 52(2): 205-216.

[6] Liu Bing. Sentiment Analysis: Mining Opinions, Sentiments, and Emotions [M]. Beijing: China Machine Press, 2017: 1-26.

[7] Turney P D, Littman M L. Measuring praise and criticism: Inference of semantic orientation from association [J]. ACM Transactions on Information Systems, 2003, 21(4): 315-346.

[8] Taboada M, Brooke J, Tofiloski M. Lexicon-based methods for sentiment analysis [J]. Computational Linguistics, 2011, 37(2): 267-307.

[9] Zhong Minjuan, Wan Changxuan, Liu Dexi. Construction of a sentiment dictionary for product reviews based on association rule mining and polarity analysis [J]. Journal of the China Society for Scientific and Technical Information, 2016, 35(5): 501-509.

[10] Zhang Haitao, Liu Yashu, Zhang Xiaohui, et al. Research on topic discovery based on modularity and netizen emotion fluctuation: Taking the "China-US trade friction" topic on Sina Weibo as an example [J]. Library and Information Service, 2019, 63(4): 6-14.

[11] Zhang Peng, Cui Yanchen, Lan Yuexin, et al. Sentiment analysis and guidance strategies for microblog emergencies based on grounded theory and dictionary construction [J]. Modern Information, 2019, 39(3): 122-131, 143.

[12] Jiang Jingui, Yan Siqi. Research on microblog public opinion evolution based on the interaction of topics and emotions: Taking the "Red Yellow Blue child abuse incident" as an example [J]. Information Science, 2018, 37(12): 118-123.

[13] An Lu, Wu Lin. Analysis of emergency microblog public opinion evolution integrating topic and sentiment features [J]. Library and Information Service, 2017, 61(15): 120-129.

[14] Wang Renwu, Song Jiayi, Chen Chuanbao. Research on the application of Word2vec-based sentiment analysis in brand cognition [J]. Library and Information Service, 2017, 61(22): 6-13.

[15] Mullen T, Nigel C. Sentiment analysis using support vector machines with diverse information sources [C]//Empirical Methods in Natural Language Processing. Barcelona: Association for Computational Linguistics, 2004: 412-418.

[16] Kouloumpis E, Wilson T, Moore J D. Twitter sentiment analysis: The good the bad and the OMG! [C]//International Conference on Weblogs and Social Media. Barcelona: AAAI Press, 2011: 450-453.

[17] Bollen J, Mao H, Pepe A. Modeling public mood and emotion: Twitter sentiment and socio-economic phenomena [C]//International Conference on Weblogs and Social Media. Barcelona: AAAI Press, 2011: 538-541.

[18] Liu K, Xu L, Zhao J. Opinion target extraction using word-based translation model [C]//Empirical Methods in Natural Language Processing. Stroudsburg: Association for Computational Linguistics, 2012: 1346-1356.

[19] Wang Xiwei, Zhang Liu, Wen Qing, et al. Research on user sentiment evolution of network public opinion in mobile environment based on Bayesian model: Taking the "Chinese women's volleyball championship at Rio Olympics" topic on Sina Weibo as an example [J]. Journal of the China Society for Scientific and Technical Information, 2018, 37(12): 1241-1248.

[20] Liao Haihan, Wang Yuefen, Guan Peng. Topic mining and viewpoint identification of different disseminators in the microblog public opinion dissemination cycle [J]. Library and Information Service, 2018, 62(19): 77-85.

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Abstract: [Purpose/significance] Exploring the internal mechanism of Internet public opinion evolution can gain deeper insights into public opinion development and help relevant units or departments achieve scientific decision-making and guidance in public opinion events. [Method/process] This paper selected the blog posts of parties in specific public opinion events and their corresponding forwarded comments, calculating the sentiment scores of comment texts based on a sentiment dictionary. From a time series perspective, dynamic analysis was conducted on the changes in emotional polarity during public opinion development and the impact of party responses on netizens' emotions. [Result/conclusion] The results show that party responses have a direct impact on the level of netizen attention; the emotional polarity of netizens during public opinion development is not static; response content directly affects netizens' emotions, and valid evidence and sincere attitudes help alleviate negative sentiments in public opinion.

Keywords: Internet public opinion; party's response; emotional polarity; sentiment analysis

Note: Figure translations are in progress. See original paper for figures.