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Evaluating the Impact of Internet Users' Emotional Tendencies on Opinion Dynamics through Computer-Assisted Sentiment Analysis of Texts

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Abstract: - Internet communication is characterised by "non-linear flow" and "unorganised aggregation," and computer-assisted text sentiment analysis is an important means of evaluating the impact of netizens' emotions on the dynamics of public opinion. The uncertainty, anonymity, disorder, and blindness inherent in fast-gathering and fast-dispersing Internet communication drive the continuous generation of texts, which has an important impact on public opinion. In order to study this issue in depth, this paper chooses two text types of "popular Weibo" and "popular topics" in Sina Weibo as the object of study and analyses the issue in detail from the two dimensions of agenda construction and agenda setting. In the process of the study, the required text data were collected through Python, and the theoretical assumptions were verified with text analysis methods to explore the influence of text sentiment bias on opinion diffusion, with a view to providing new insights and references for the application of the theory of opinion diffusion and the field of computational diffusion.

Keywords: Computational Communication; Emotional Bias; Public Opinion; Textual Sentiment Analysis

I. INTRODUCTION

Analysing text sentiment through computer-assisted means is an important means of understanding Internet users' emotions. Due to the blindness and fission of emotion transmission in the group behaviour of netizens on the Internet, this leads to the production of a huge amount of comment text in the process of mutual collision, the emotion will be rapidly fermented. As the participation of individuals on the Internet is temporary, the transmission of emotions is highly uncertain. The transmission path of emotions may also be less predictable due to the loose connections between individuals, and clusters of individuals can react strongly to events emotionally. Emotional expression can be found everywhere on the Internet, which lacks rational support and does not end in rational understanding and behaviour, and contains irrational tendencies such as overreaction, paranoia, and fanaticism [1]. Intuitive experience and related research have shown that when Internet users generate Internet communication behaviour around emergencies, there is a clear negative bias in the emotions generated around the text. Negative emotional bias refers to the tendency to emphasise and highlight negative feelings and emotions in the process of understanding, communicating, and producing textual content. Such negative emotions include transient and intense situational and polarising emotions such as "anger," "frustration," and "disgust." The emotions in these texts need to be analysed by computer-assisted means.

In the field of computational communication, the study of the emotional bias of Internet users in Internet communication has a broader social significance. This is because emotional bias in Internet communication not only affects individual behaviour but also directly spreads online public opinion and stimulates social action. So when Internet users publish texts, do they also have emotional bias? Is it easier for netizens to identify with negatively emotionally biassed texts and disseminate the content? The answers to this series of questions are directly related to the dynamic path of public opinion dissemination and diffusion and are of great significance to public opinion research.

II. RESEARCH HYPOTHESIS

Relevant research in neuroscience has shown that the human brain has an obvious negative emotion bias in three areas: perceptual attention, emotional experience, and memory encoding and extraction. First, things that cause negative emotions naturally have a strong ability to attract attention. [2] For example, Smith et al. found in their study that negative pictures are more stimulating neurologically to the visual cortex than positive pictures, which means that negatively biassed content is more capable of attracting attention in the perceptual stage. [3] Mama et al. found that people spend the least amount of time capturing and searching for negative emotional

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content material. [4] Anderson found that the transient disengagement effect of negative emotional content material was weaker, which suggests that negative content is not only prioritised to gain people's attention but also that negative content is prioritised to be processed when a person's attentional capacity is limited. [5] Second, people experience stronger emotions in response to negative stimuli or produce stronger emotions. According to Sun et al.'s experiments, theta wave synchronisation triggered by threatening information content was found to be stronger than pleasant information content. [6] By comparing the stimulation of the hippocampus and amygdala by positive and negative emotional content, Aldhafeeri et al. confirmed that the latter triggered a higher degree of brain activation [7]. Finally, the human brain is also significantly negatively biassed when it comes to the encoding and extraction of memories. Liu et al. found that the amplitude and duration of late positive potentials (LPP) were higher for negatively biased content than for neutral and positive content during the encoding phase of input content. [8] This implies that the brain is more sensitive to the processing of negative emotional stimuli during the memory encoding of information and that negative information can be encoded more deeply. Combining the above findings, this paper proposes a research hypothesis:

H1: Internet users have a more obvious preference for negative emotional texts.

On Sina Weibo, content is presented in two ways. One is Constructing Narrative Topics (CNT). It refers to the constructive process in which multiple actors, such as enterprises, government agencies, platforms, opinion leaders, etc., compete for topics before forming the public agenda. The popular search topic on Weibo is a typical model for constructing topics. Under the influence of multiple factors, such as user interaction, content dissemination, and platform algorithms, Weibo's popular search topics can quickly trigger widespread discussion and draw public attention to specific topics or labels. According to Zhang Kan, the discussion of topics related to online emergencies has an obvious negative emotional bias, and the event will continue to spread with the fermentation of negative emotions and often lead to other events. [9] Zhang Mei et al. found that the proportion of negatively emotionally biassed words in online emergencies was higher than that in other online texts after textual analyses of the source discourse of emergencies on the Internet. [10] Therefore, this study proposes the research hypothesis:

H2a: There is a greater proportion of negatively emotionally biassed texts on the popular topics of Weibo.

Another way of presenting content on Weibo is Presenting Personal Narratives (PPN), which refers to individual users sharing their lives, experiences, opinions, etc. on Weibo and displaying their unique personal narratives through text, pictures, videos, etc. The most representative form of this is the popular Weibo. Popular Weibo is usually determined by a series of interactive indicators and algorithms. The higher the interaction of shares, likes, and comments on a microblog, the more attention and discussion it receives from the public, so that the microblog content will be more likely to get popular recommendations. So is there a negative affective bias in these popular Weibo? According to Baumeister et al., it was found that people give more attention weight to negative emotionally biassed content in both innate bias and acquired experience, and they are also more biassed towards negative things in their actions and decisions. [11] Therefore, this study proposes the research hypothesis:

H2b: There is a higher proportion of negative sentiment-biassed text on popular Weibo.

Bebbington et al. demonstrated that there is a bias towards negative content and an instinct to pass on negative content. [12] Acerbi and Alberto found that negative content was able to receive more shares than neutral content in transmission chain experiments on the sharing behaviour of large anonymous social networks. [13] Liu Cong et al. empirically analysed 24 public events on Weibo and found that the stronger the negative sentiment in Weibo communication, the more forwarding and commenting, while there is no significant correlation between positive sentiment and the number of commenting and forwarding. [14] After analysing the followers in online news through the method of computer-assisted analysis, Dang Minghui found that the degree of negative emotional expression on the Internet is high, while the rate of negative emotional expression is directly proportional to the number of comments. [15] Based on the above research, the text proposes the following research hypotheses:

H3: Individual narrative texts that contain negative affective messages are more likely to be disseminated.

Secondary texts generated around events contain rich emotional energy, and when they are superimposed and collided, they will produce a nuclear fission proliferation effect, making secondary texts spread rapidly on the Internet. On Weibo, does the emotional bias of popular search topics have any influence on the emotional bias of secondary texts? According to Hu Chunjiang and Shan Xuegang, the negative emotional bias of the event itself may trigger the accumulated negative emotions in the network, resulting in a flood of negative emotions and triggering a public opinion crisis. [16] Chen Shuang et al. studied the relationship between emotional bias and the communication behaviour of Weibo users and found that for high emotional arousal Weibo content, the number of forwards and comments on messages carrying positive emotions was significantly higher than the number of negative emotions, while for low emotional arousal Weibo content, there was no significant difference between positive and negative emotions in terms of the number of forwards and comments. [17] All of the above studies have shown that the affective bias of the microblog topic itself is closely related to the affective bias between the secondary narrative texts it can trigger. Therefore, this study proposes the research hypothesis:

H4a:The messages on the popular topics of negative emotions are also skewed negatively. H4b:Messages on popular search topics for positive emotions are also skewed positive.

According to Yu et al., negative emotions are more conducive to communication, and positive emotions are more conducive to mobilisation on the Internet. [18] That is to say, positive emotion-biassed popular search topics can provide cohesion and evoke positive actions. First, positive emotions can promote emotional resonance and emotional connection, making it easier for the public to establish an emotional connection with the subject of the narrative, thus enhancing the content's identity and resonance. Secondly, the positive emotions in individual narratives help to shape the audience's positive attitudes, guiding them to participate more actively in interaction and information dissemination, thus forming a more positive public opinion atmosphere. In addition, positive emotion in narratives can convey warmth, hope, and encouragement, which helps to soothe negative emotions, promote positive emotional healing, and enhance the public's psychological health. Therefore, this study proposes the research hypothesis:

H5: Positive emotions in individual narratives are more significant in guiding public opinion.

On the Internet textual associations are not only reflected in immediate interactions in a co-temporal state but also retrospectively in ephemerality. It follows that research also needs to bring the temporal dimension into scope and analyze whether textual content with different affective biases is retained for different periods of time. Using serial replication, Bebbington et al. arranged for 92 four-person chains to transmit a story containing explicit positive affective events, negative affective events, and ambiguous events. The study was analysed using a mixed-effects model and found that negative affective events were preferentially retained compared to the other two types of events after a period of time had elapsed. [12] Fay et al. also found through their study that information is gradually lost as it spreads from person to person in different social contexts, but negative information is more likely to be retained than positive information. [19] Therefore, this study proposes the research hypothesis:

H6:Pulse opinion events with high impact and long duration have a significant tendency to be negative.

III. Research Design

In terms of the general research design scheme, this paper takes Sina Weibo as the sample source field, and according to the needs of different research hypotheses, it collects two types of text samples, namely, popular search topics and popular Weibo, and collects data indicators such as the number of hot searches, the number of comments, the number of likes, the number of retweets, etc., which are related to them. In Weibo, the number of popular topics, likes, comments, and forwards are important indicators of netizens' preferences, which represent the characteristics of Internet communication in different dimensions (Table 1). After completing the above text data collection, we can subsequently analyse the proportion of texts with different emotional attributes (positive, negative, and neutral) in the hot topics of popular microblogs, as well as the correlation between the texts with different emotional attributes and the number of likes, forwards, and comments, in order to explore the influence of netizens's emotional bias on the diffusion of public opinion.

Table 1: Four Indicators for Measuring Internet Users' Preferences

Norm	Dimension	Dimension Description
Number of popular searches	Trending	Indicates the extent to which the topic is widely followed and discussed on the microblogging platform. When the number of hot searches for a topic rises, it means that it has attracted widespread interest among users.
Number of likes	Favouritism	The number of likes indicates how much users like a topic or piece of content. Topics with a high number of likes usually mean that users agree with, support, or like the content.
Number of comments	Interactivity	Reflects the extent to which users interact with a topic. When a topic attracts the attention and discussion of users, they may express their opinions, views, and suggestions in the comments.
Number of forwards	Degree of transmission	When users find the content of a topic valuable, they can retweet it on their own Weibo, thus spreading the topic to more people. Topics with a high number of forwards usually mean that the topic has a higher spreading influence on social media.

In the sample selection of popular search topics, major public events at home and abroad were taken as the main sampling type, and marketing topic content was excluded as much as possible. In the same type of research in the international communication field, the time span of data collection is conventionally from 3 weeks to 6 weeks, and in this study, a time span of 5 weeks was taken. Three daily time slots were set for collection: 8:00 a.m., 12:00 p.m., and 20:00 p.m.

In terms of research methodology, we have selected the computer-assisted text sentiment analysis method. Text Sentiment Analysis is a research method that analyzes emotional tendencies and sentiment information in text data using computer technology, with the goal of identifying and extracting subjective information [20]. Textual sentiment analysis is widely used in many fields, such as product review analysis, public sentiment monitoring, election prediction, and financial market prediction [21]. The sentiment lexicon chosen to be used in this paper is the Dalian University of Technology Sentiment Vocabulary Ontology Library because it has a better adaptation to online language. After obtaining the textual sentiment data, SPSS software was used to correlate these data results with the number of likes, comments, and other indicative data representing diffusion of communication, to compare the differences between different sentiment categories, to explain the relationship between sentiment and other variables, and to validate the research hypotheses.

IV. Research Findings

A. *Data Analysis of Weibo Popular Search Topics*

In this study, a total of 853 popular Weibo topics were collected and analyzed, of which 197, or 23.1%, were negative sentiment topics. Positive emotional topics account for 410, accounting for 48.1% (Table 2). Among the Weibo topic hot searches, there are more positive emotion topics, which is not consistent with the hypothesis that there is a greater proportion of negative narrative text in the hot search topics, so the hypothesis H2a does not hold.

Table 2: Sentiment Attributes of the Weibo Popular Topics List

Variable	Attribute	Frequency	Percent
Type of emotion	1 negative emotion	197	23.1
	2 neutral emotion	246	28.8
	3 positive emotion	410	48.1

Table 3: Comparison of Distributional Positions of Sentiment Attributes by Topic in the List of Popular Weibo Topics

Variable	Attribute	N	Percentiles			Average rank	H	df	P
			25	50	75				
Number of popular searches	negative emotion	197	23100.0	43800.0	190300.0	343.88	38.382	2	0.000
	neutral emotion	246	24200.0	75900.0	283500.0	414.24			
	positive emotion	410	25700.0	120000.0	293100.0	474.59			
Number of forwards	negative emotion	197	397.0	2174.0	4591.5	551.54	80.456	2	0.000
	neutral emotion	246	144.0	866.5	3255.5	437.71			
	positive emotion	410	103.8	290.0	1530.3	360.73			
Number of comments	negative emotion	197	808.0	1210.0	2217.0	582.49	105.914	2	0.000
	neutral emotion	246	52.0	586.5	1474.3	404.79			
	positive emotion	410	160.8	474.5	788.0	365.61			
Number of likes	negative emotion	197	8793.5	28500.0	79650.0	582.55	142.629	2	0.000
	neutral emotion	246	242.5	1946.0	13675.0	301.23			
	positive emotion	410	3269.5	7570.0	19175.0	427.72			

The number of hot searches, forwardings, comments, and likes of popular Weibo topics in this study showed a significant skewed distribution, so the difference test was conducted using the Kruskal-Wallis H Test, and further multiple comparisons were conducted if differences existed.

The test (Table 3) showed that there was a significant difference in the number of hot searches between different topic sentiment attributes ($H = 38.382$, $P<0.001$), which required multiple comparisons. The results of multiple comparisons (Table 4) showed that there was a significant difference in two-by-two comparisons between topics of different emotional types (Adj. $P<0.001$). Comparison of the average rank (average rank) results showed that positive emotion hot searches > neutral emotion > negative emotion.

Using the same method, it can be seen that: the number of retweets has a significant difference between the emotional attributes of different topics ($H = 80.456$, $P < 0.001$); the number of comments has a significant difference between the emotional attributes of different topics ($H = 105.914$, $P < 0.001$); and the number of likes has a significant difference between the emotional attributes of different topics (H = 142.629, P < 0.001).The comparative mean ranking results showed that in the number of retweets, negative sentiment > neutral sentiment > positive sentiment. In terms of the number of comments, negative emotion > neutral emotion > positive emotion. In terms of number of likes, negative sentiment > positive sentiment > neutral sentiment. Therefore, hypotheses H1 and H3 are partially verified in the test of hot topics.

Table 4: Multiple Comparison Results

Variable	Sample 1-Sample 2	H	S.E.	Std. H	Adj. P
Number of popular searches	negative emotion-neutral emotion	-70.361	23.556	-2.987	0.008
	negative emotion-neutral emotion	-130.712	21.358	-6.120	0.000
	neutral emotion-positive emotion	-60.351	19.869	-3.037	0.007
Number of forwards	positive emotion-neutral emotion	76.977	19.870	3.874	0.000
	positive emotion-negative emotion	190.804	21.359	8.933	0.000
	neutral emotion-negative emotion	113.827	23.556	4.832	0.000
Number of comments	positive emotion-neutral emotion	39.180	19.870	1.972	0.146
	positive emotion-negative emotion	216.880	21.359	10.154	0.000
	neutral emotion-negative emotion	177.700	23.557	7.544	0.000
Number of likes	neutral emotion-positive emotion	-126.491	19.870	-6.366	0.000
	neutral emotion-negative emotion	281.324	23.557	11.942	0.000
	positive emotion-negative emotion	154.833	21.359	7.249	0.000

B. Analysis of Popular Weibo Data

A total of 21,357 popular Weibo events were collected in this study, which were analysed and found to include 7,040 negative sentiments accounting for 33.0% and 8,446 neutral sentiments accounting for 39.5%. Positive sentiment: 5871 articles, accounting for 27.5% (Table 5). Among them, the proportion of neutral sentiment is higher, which is inconsistent with hypothesis H2b, so hypothesis H2b is not valid.

Table 5: Sentiment Attributes of Popular Time on Weibo Home Page

Variable	Attribute	Frequency	Percent
emotional property	1 negative emotion	7040	33.0
	2 neutral emotion	8446	39.5
	3 positive emotion	5871	27.5

The analysis results show that the number of forwards, comments, and likes of popular Weibo shows an obvious skewed distribution, and the Kruskal-Wallis H test is used for the comparison of the distribution of multiple independent samples. If there is a significant difference in the overall, then further multiple comparisons will be made. Since the Kruskal-Wallis H test is not sensitive to the shape difference of multiple overall distributions, the test hypothesis H_0 is the same location of multiple overall distributions in practical applications. The opposing alternative hypothesis H_1 is that multiple aggregate distribution locations are not all the same, and multiple comparisons are required.

The results of the multiple comparisonsanalysis showed that as far as the difference in the ranking of the number of retweets among the types of affective attributes is concerned, the statistic H=663.039 with P<0.001 (Table 6), rejects the null hypothesis, which states that there is considered to be a significant difference in the location of the distribution of the number of retweets among the types of affective attributes. The results of multiple comparisons (Table 7) show that there is a significant difference between the two comparisons between different emotion types (Adj. P<0.001). The mean ranked results of the comparisons showed that negative emotions > neutral emotions > positive emotions. Similarly, it can be seen that there is a significant difference in the distribution position of the number of comments and the number of likes in different popular Weibo sentiment attributes (P<0.001). A comparison of the mean rankings shows that, in terms of the number of comments, negative emotion > neutral emotion > positive emotion. In terms of the number of likes, negative emotion > positive emotion > neutral emotion. Therefore, hypotheses H1 and H3 were verified in the test of Weibo Popular. Therefore, hypotheses H1 and H3 are valid.

Table 6: Comparison of the distribution position of each sentiment attribute in Weibo Popular

Variable	Attribute	N	Percentiles			Average rank	H	Df	P
			25	50	75				
Number of forwards	negative emotion	7040	43.0	343.5	2111.0	12164.0	663.039	2	0.000
	neutral emotion	8446	23.0	113.0	587.5	10263.6			
	positive emotion	5871	11.0	64.0	652.0	9496.0			
Number of comments	negative emotion	7040	54.0	234.0	1077.8	11912.8	440.768	2	0.000
	neutral emotion	8446	33.0	128.0	505.0	10266.1			
	positive emotion	5871	19.0	115.0	500.0	9795.0			
Number of likes	negative emotion	7040	740.0	5922.0	20000.0	12204.5	1444.409	2	0.000
	neutral emotion	8446	171.0	909.0	4206.0	8712.7			
	positive emotion	5871	554.0	5016.0	16300.0	11678.5			

Table 7: Multiple Comparison Results

Variable	Sample 1-Sample 2	H	S.E.	Std. H	Adj. P
Number of forwards	positive emotion-neutral emotion	767.552	104.752	7.327	0.000
	positive emotion-negative emotion	2667.975	108.957	24.487	0.000
	neutral emotion-negative emotion	1900.424	99.489	19.102	0.000
Number of comments	positive emotion-neutral emotion	470.081	104.756	4.487	0.000
	positive emotion-negative emotion	2117.845	108.961	19.437	0.000
	neutral emotion-negative emotion	1647.764	99.493	16.562	0.000
Number of likes	neutral emotion-positive emotion	-2965.799	104.762	-28.310	0.000
	neutral emotion-negative emotion	3491.853	99.499	35.095	0.000
	positive emotion-negative emotion	526.054	108.967	4.828	0.000

C. Validation of the correlation between Sentiment Attributes of Popular Search Topics and Sentiment Attributes of Messages

In this study, 186 hot topics were analyzed, and the first 100 messages were taken for each hot search, resulting in a total of 18,600 messages. Among them, there are 93 negative emotion topics and 93 positive emotion topics, both of which have 9300 messages, respectively. There are 5,554 negative emotion messages, accounting for 59.7%, 1,518 neutral emotion messages, accounting for 16.3%, and 2,228 positive emotion messages, accounting for 24.0%. In the positive emotional topics, there are 1206 negative emotional messages, accounting for 13.0%, 2347 neutral emotional topics, accounting for 25.2%, and 5747 positive emotional topics, accounting for 61.8% (Table 8). That is to say, the proportion of negative emotion messages is higher in negative emotion topics, and the proportion of positive emotion messages is higher in positive emotion topics.

Table 8: Sentiment Attributes of Messages in Hot Topics with Different Sentiment Attributes

Popular Search Emotional Attributes	Message Emotional Attributes	Frequency	Percent
negative emotion	negative emotion	5554	59.7
	neutral emotion	1518	16.3
	positive emotion	2228	24.0
positive emotion	negative emotion	1206	13.0
	neutral emotion	2347	25.2
	positive emotion	5747	61.8

The Kruskal-Wallis H-test was further used to test the difference between secondary replies and number of likes among different message sentiment attributes in different popular search topic sentiment attributes, and further multiple comparisons were made if there were significant differences. The results (Table 9) of the analysis show that there is a significant difference between different message sentiment attributes in secondary replies in negative sentiment topics ($H = 830.538$, $P<0.001$), and the results of multiple comparisons (Table 10) show that there is a significant difference in both comparisons between different message sentiment attributes (Adj. $P<0.001$), and the results of the comparison of the average rankings show that: positive sentiment>negative sentiment>neutral sentiment messages; Similarly, it can be seen that the number of likes in the negative topic attributes shows a significant difference between different message emotional attributes ($H = 786.873$, $P<0.001$), and then the results of multiple comparisons and comparisons of the average ranking results show that: negative emotion>positive emotion>neutral emotion;

In the positive sentiment topic, there was a significant difference in secondary responses between different message sentiment attributes (H = 906.554, P<0.001). Comparison of the average ranking results shows that: negative emotion>positive message>neutral message; the number of likes is significantly different among different message emotional attributes (H = 1355.919, P<0.001), and comparison of the average ranking results shows that: positive emotion>negative message>neutral message. Therefore, hypothesis H4a and hypothesis H4b are valid.

Table 9: Comparison of the Distribution Positions of Emotional Attributes of Messages in Popular Search Topics with Different Emotional Attributes

Variable	Topic Emotional Attributes	Message Emotional Attributes	N	Percentiles			Average rank	H	df	P
				25	50	75				
secondary reply	negative emotion	negative emotion	5554	45.0	157.5	521.0	4782.6	830.538	2	0.000
		neutral emotion	1518	3.0	16.0	165.0	2954.2			
		positive emotion	2228	52.0	299.5	1599.0	5476.8			
	positive emotion	negative emotion	1206	41.8	335.0	2323.0	5361.7	906.554	2	0.000
		neutral emotion	2347	8.0	35.0	197.0	3216.1			
		positive emotion	5747	70.0	209.0	701.0	5087.1			
number of likes	negative emotion	negative emotion	5554	721.5	3725.5	14200.0	5143.7	786.873	2	0.000
		neutral emotion	1518	15.0	186.5	2606.0	2966.3			
		positive emotion	2228	296.3	1180.0	12100.0	4568.6			
	positive emotion	negative emotion	1206	220.8	975.0	7867.5	4022.8	1355.919	2	0.000
		neutral emotion	2347	56.0	294.0	3260.0	3073.2			
		positive emotion	5747	1245.0	5208.0	18500.0	5426.4			

Table 10: Multiple Comparison Results

Variable	Popular Search Emotional Attributes	Sample 1-Sample 2	H	S.E.	Std. H	Adj. P
secondary reply	negative emotion	neutral emotion-negative emotion	1828.402	77.754	23.515	0.000
		neutral emotion-positive emotion	-2522.596	89.347	-28.234	0.000
		negative emotion-positive emotion	-694.194	67.325	-10.311	0.000
	positive emotion	neutral emotion-negative emotion	2145.633	95.120	22.557	0.000
		neutral emotion-positive emotion	-1870.979	65.767	-28.448	0.000
		neutral emotion-negative emotion	274.654	85.035	3.230	0.004
number of likes	negative emotion	neutral emotion-positive emotion	-1602.316	89.352	-17.933	0.000
		neutral emotion-negative emotion	2177.435	77.758	28.003	0.000
		positive emotion-negative emotion	575.119	67.329	8.542	0.000
	positive emotion	neutral emotion-positive emotion	-2353.176	65.769	-35.780	0.000
		neutral emotion-negative emotion	949.602	95.122	9.983	0.000
		negative emotion-positive emotion	-1403.574	85.037	-16.505	0.000

D. A Data Analysis of the Role of Positive Emotions in Guiding Public Opinion

In this study, we capture the Weibo comments related to controversial Weibo hot topics with neutral sentiment bias and calculate the number of likes, comments, and forwards obtained by the Weibo statements with positive sentiment and negative sentiment, respectively. The proportion of positive emotions was analysed, as was the number of likes, comments, and forwards that positive emotions were able to obtain. The study obtained a total of 48 hot topics with neutral sentiment bias and 4,800 messages; among them, 1,585 (33.0%) were negative sentiment messages, 2,220 (46.3%) were neutral sentiment messages, and 995 (20.7%) were positive sentiment messages (Table 11). That is to say, the proportion of neutral emotion messages is higher, followed by negative emotion messages, and the least positive emotion messages.

Table 11: Distribution of Message Sentiment Attributes

Variable	Attribute	Frequency	Percent
Message Emotional Attributes	1 negative emotion	1585	33.0
	2 neutral emotion	2220	46.3
	3 positive emotion	995	20.7

The Kruskal-Wallis H-test was further used to test the difference between different popular search topic sentiment attributes in terms of secondary replies and the number of likes among different message sentiment attributes, and further multiple comparisons were made if there was a significant difference. The results of the analysis (Table 12) show that there is a significant difference in secondary replies among different message sentiment attributes ($H = 639.989$, $P<0.001$), and multiple comparisons are needed. The results of multiple comparisons (Table 13) showed that there was a significant difference in both comparisons between different message sentiment attributes (Adj. $P<0.001$). The mean-ranked results of the comparisons showed that negative emotion > positive emotion > neutral emotion.

There was a significant difference in the number of likes between different message sentiment attributes ($H = 654.382$, $P<0.001$), requiring multiple comparisons. The results of multiple comparisons showed that there was a significant difference in the number of likes among different subgroups (Adj. $P<0.001$). When comparing the mean rankings, the results revealed that negative affect > positive affect > neutral affect.

Table 12: Comparison of Distribution Positions of Different Message Sentiment Attributes

Variable	Message Emotional Attributes	N	Percentiles			Average rank	H	df	P
			25	50	75				
secondary reply	negative emotion	1585	108	467	1627	3002.09	639.989	2	0.000
	neutral emotion	2220	16	74	230	1876.03			
	positive emotion	995	72	252	642	2612.36			
number of likes	negative emotion	1585	1742	9828	27850	3016.96	654.382	2	0.000
	neutral emotion	2220	160	885.5	4573.5	1873.58			
	positive emotion	995	886	4468	13000	2594.6			

Table 13: Multiple Comparison Results

Variable	Sample 1-Sample 2	H	S.E.	Std. H	Adj. P
secondary reply	neutral emotion-positive emotion	-736.331	52.867	-13.928	0.000
	neutral emotion-negative emotion	1126.067	45.569	24.711	0.000
	positive emotion-negative emotion	389.736	56.049	6.954	0.000
number of likes	neutral emotion-positive emotion	-721.221	52.869	-13.642	0.000
	neutral emotion-negative emotion	1143.584	45.570	25.095	0.000
	positive emotion-negative emotion	422.364	56.050	7.535	0.000

Conclusion: Among the controversial popular search topics, the sentiment percentage of messages: neutral > negative > positive. The correlation between messages and the number of re-replies to discussions is significant: the number of replies to negative messages > the number of replies to positive messages > the number of replies to neutral messages, and the correlation between messages and the number of likes is significant: the number of likes to negative messages > the number of likes to positive messages > the number of likes to neutral messages. Therefore hypothesis H5 does not hold.

E. An Analysis of Emotional Bias in Pulsatile Public Opinion Events

This study analysed a total of 304 pulsed opinion events, of which there were 232 negative emotions, accounting for 76.3%, 50 neutral emotion topics, accounting for 16.4%, and 22 positive emotion topics, accounting for 7.2%; the proportion of emotions in pulsed events was negative > neutral > positive (Table 14).

Table 14: Distribution of Emotional Attributes

Variable	Attribute	Frequency	Percent
Topic Emotional Attributes	1 negative emotion	232	76.3
	2 neutral emotion	50	16.4
	3 positive emotion	22	7.2

The Kruskal-Wallis H-test was further used to test the difference between the number of secondary replies and likes in different popular topic sentiment attributes among different message sentiment attributes, and further multiple comparisons were made if there was a significant difference.

Among them, there was a significant difference in the amount of discussion between different event emotion attributes ($H = 67.96$, $P<0.001$)(Table 15), and the results of multiple comparisons (Table 16) showed that there was a significant difference in two-by-two comparisons between emotion attributes of different topics (Adj. $P<0.001$) and that negative emotions were significantly higher than positive and neutral emotions ($P<0.001$), whereas the difference between positive and neutral emotions was not significant ($P> 0.05$). Upon comparison of the mean ranking results, the number of discussions on the emotional attributes of different events showed that: the amount of negative emotion discussions > the amount of neutral emotion discussions > the amount of positive emotion discussions.

There was a significant difference in the number of key query words between different event emotion attributes ($H = 55.186$, $P<0.001$), and the results of multiple comparisons showed that the number of significant query words for negative emotion was significantly higher than that of neutral emotion and positive emotion ($P<0.001$), whereas the difference in the number of query words for positive emotion and neutral emotion was not significant ($P > 0.05$). The comparative average ranking results showed that the number of query words for different event emotion attributes: the number of negative emotion query words > the number of neutral emotion query words > the number of positive emotion query words.

Table 15: Comparison of Distribution Positions of Topics with Different Emotional Attributes

Variable	Attribute	N	Percentiles			Average rank	H	Df	P
			25	50	75				
Number of discussions	negative emotion	232	87000	244500	892750	175.41	67.96	2	0.000
	neutral emotion	50	19500	30500	109750	86.87			
	positive emotion	22	4552	8392	35750	60.07			
Number of key search terms	negative emotion	232	3	4	9	172.81	55.186	2	0.000
	neutral emotion	50	1	1	3	96.57			
	positive emotion	22	1	1	1.25	65.43			

Table 16: Multiple Comparison Results

Variable	Sample 1-Sample 2	H	S.E.	Std. H	Adj. P
Number of discussions	positive emotion-neutral emotion	26.802	22.488	1.192	0.700
	positive emotion-negative emotion	115.341	19.609	5.882	0.000
	neutral emotion-negative emotion	88.539	13.705	6.460	0.000
Number of key search terms	positive emotion-neutral emotion	31.138	22.290	1.397	0.487
	positive emotion-negative emotion	107.379	19.436	5.525	0.000
	neutral emotion-negative emotion	76.240	13.584	5.612	0.000

Conclusion: Among the pulsatile public opinion events, the distribution of sentiment bias for the event itself is: negative > neutral > positive. The significance of the correlation between the emotion of the event and the amount of discussion: negative > neutral > positive, and the significance of the correlation between the emotion of the event and the number of keyword queries: negative > neutral > positive. Therefore, hypothesis H6 is valid.

V. Analysis of Results

Taking Sina Weibo as the sample source, this study collected two types of text samples, namely, Weibo Hot Topics and Popular Weibo, and collected their related data such as number of hot searches, number of comments, number of likes, number of forwards, etc., and measured the emotional polarity and emotional intensity of the texts through the method of textual sentiment analysis with a view to exploring the influence of netizens' emotional bias on the diffusion of public opinion. The main findings are summarised and analysed as follows:

First, Internet users have a more obvious preference for negative emotion texts. This suggests that negatively emotionally biassed text content is more likely to be liked, forwarded, and commented on, and that Internet users have a more pronounced preference for negatively emotional text, a finding that is consistent with the findings of cognitive science. This finding is consistent with the findings of cognitive science. This may be due to the fact that the brain has a cognitive bias towards negative emotions at the level of cognitive preference, i.e., more attention is given to negative emotional content. It may also be because Internet users may be more willing to pay attention to and discuss negative affective texts because they are in different real-life contexts, they have different views and positions, and there are information gaps in their perceptions of each other in textual interactions.

Second, there is no significant bias in the share of negative narrative texts in the initial texts of Internet-disseminated hot topics and popular Weibo tweets. This suggests that positive emotions are more likely to get a higher number of searches. The reason for the above results may be related to the agenda-setting mechanism of the Weibo platform and the framing effect of opinion leaders. Because the topics of Weibo popular searches need to take into account factors such as the amount of topic discussion, freshness, interactivity, etc., as well as agenda setting based on a series of factors such as social values, public order and morality, and public opinion orientation, this may lead to a more positive sentiment bias in Weibo popular searches. At the same time, as many popular Weibo tweets are directly sourced from influential opinion leaders, sharing content with negative sentiment may lead to controversy and negative impact, which may damage the reputation of the opinion leaders. Therefore, these opinion leaders may be more inclined to post content with positive or neutral sentiment, which helps to maintain image and influence and reduce controversy and negative impact.

Third, in Internet users' individualized narrative texts, information with negative emotions can be disseminated more. This may first be because texts with negative emotions tend to have novel, unexpected, and shocking contents, which are more likely to arouse people's interest in dissemination. Secondly, messages with negative emotions may be controversial, and controversy tends to lead to more discussion and attention. People may be more willing to engage in discussions, comment, and share controversial content, which increases the dissemination of texts with negative emotions. Again, messages with negative emotions may relate to social issues, cautionary tales, etc. This emotional resonance may motivate people to participate more actively in the discussion, sharing, and dissemination of these messages.

Fourth, the emotional bias of the related texts on the hot topics matches the emotional nature of the initial topics, with negatively emotional topic messages favouring the negative direction and positively emotional topic messages favouring the positive direction. This mechanism of emotion triggering and dissemination can lead to the formation of perceptual aggregation of a series of similarly emotional texts on social media. Topics with negative emotions may be more likely to trigger negative emotions associated with them, thus attracting more emotionally resonant messages. Similarly, topics with positive emotions may attract positive emotional resonance, resulting in messages that are skewed positive.

Fifth, positive sentiment texts do not have a significant guiding effect on public opinion diffusion. Although messages on positive hot topics are also biassed in the positive direction, the highest number of likes, comments, and forwards on Weibo speeches with a neutral sentiment tendency is negative sentiment bias, which suggests that positive sentiment bias does not have a significant role in guiding public opinion in the positive direction. Poor diffusion of information may mean that information cannot spread quickly and affect a large number of people, and different people's perceptions of the same information are inconsistent, which may also lead to difficulties in forming consensus, making it difficult to achieve the goal of public opinion guidance.

Sixthly, there is a clear negative sentiment bias in the case of high-impact, long-lasting pulse events. The study analyses the proportion of topics with various emotional tendencies in the one-year-long pulse and the relationship between the emotional bias of public opinion topics and the indicators of "discussion volume" and "keyword query number," and finds that most of the pulse events are negatively emotionally biassed, and the discussion volume and keyword query number of the negatively emotionally biassed events are significantly higher compared to the neutral and positive emotions. It is found that chakra events are mostly negatively biased, and the discussion volume and keyword query count of negatively biased events are significantly higher compared with those of neutral and positive emotions. This may first be due to the fact that the human brain has evolved to be more prone to noticing and remembering negative situations, helping people make better decisions in the face of potential threats. This negative affective bias makes it more likely that negative events will dominate people's thinking, thus allowing them to remain out of attention and discussion of these events over a longer period of time as well. Furthermore, there is a tendency in the media frame to track negative affective times that have been controversial, as these events are more likely to garner attention and resources. This also tends to lead to greater exposure to negative affective events, which increases the amount of discussion and keyword queries.

VI. CONCLUSION

This study explores the important influence of sentiment bias on opinion diffusion in the Weibo field through computer-assisted analysis. By collecting text samples of Weibo hot topics and popular Weibo tweets, combining the number of hot searches, number of comments, number of likes, number of forwards, and other data, and applying textual sentiment analysis methods, the impact of sentiment bias on the diffusion of public opinion was investigated, which provides useful insights into understanding the role of netizens's sentiment bias in the diffusion of public opinion. Meanwhile, although the above study provides some valuable conclusions, sentiment analysis accuracy still needs improvement. Artificial intelligence can assist future research in conducting more accurate analyses of the impact of netizens' emotions on public opinion generation.

REFERENCES

[1] S. Srivastava, M. K. Sarkar and C. Chakraborty, "Machine Learning Approaches for COVID-19 Sentiment Analysis: Unveiling the Power of BERT," in *IEEE Annual Computing and Communication Workshop and Conference* Las Vegas, NV, USA,pp.92-97,2024.

[2] P. Rozin and E. B. Royzman, "Negativity bias,negativity dominance, and contagion," Personality and Social Psychology Review, vol. 5, pp. 296-320, 2001.

[3] N. K. Smith, J. T. Cacioppo, J. T. Larsen, and T. L. Chartrand, "May I have your attention please:Electrocortical responses to positive and negative stimuli," Neuropsychologia, vol. 42, pp. 171-183, 2003.

[4] Y. Mama, M. S. Ben-Haim and D. Algom, " When emotion does and does not impair performance: A Garner theory of the emotional Stroop effect," Cognition & Emotion, vol. 27, pp. 1340-1352, 2013.

[5] A. K. Anderson, " Affective influences on the attentional dynamics supporting awareness," Journal of Experimental Psychology: General, vol. 134, pp. 258-281, 2005.

[6] J. Sun, B. Sun, B. Wang, and H. Gong, " The processing bias for threatening cues revealed by event-related potential and event-related oscillation analyses," Neuroscience, vol. 203, pp. 91-98, 2012.

[7] F. M. Aldhafeeri, I. Mackenzie, T. Kay, J. Alghamdi, and V. Sluming, "Regional brain responses to pleasant and unpleasant IAPS pictures: Different networks," Neuroscience Letters, vol. 512, pp. 94-98, 2012.

[8] Y. Liu, H. Huang, M. McGinnis-Deweese, A. Keil, and M. Ding, "Neural substrate of the late positive potential in emotional processing," The Journal of Neuroscience, vol. 32, pp. 14563-14572, 2012.

[9] K.Zhang, "Study on the Happening， Evolution and Responding Countermeasures to Network Emergency in China," Innovation Science and Technology, vol. 5, pp. 43-47,2015.

[10] M.Zhang, S.H.Ding, G.F. Liu,Y.Z. Xu,X.Y.Fu,W.Zhang and Z.Q.Xin,"Negativity bias in emergent online events: Occurrence and manifestation ," Acta Psychologica Sinica, vol. 53, pp. 1361-1375, 2021.

[11] R. F. Baumeister, E. Bratslavsky, C. Finkenauer, and K. D. Vohs, "Bad is stronger than good," Review of General Psychology, vol. 5, pp. 323-370,2001.

[12] K. Bebbington, C. MacLeod, T. M. Ellison, and N. Fay, "The sky is falling: Evidence of a negativity bias in the social transmission of information," Evolution and Human Behavior, vol. 38, pp. 92-101, 2017.

[13] A. Acerbi, "From Storytelling to Facebook Content Biases When Retelling or Sharing a Story," HUMAN NATURE-AN INTERDISCIPLINARY BIOSOCIAL PERSPECTIVE, vol. 33, pp. 132-144, 2022.

[14] C.Liu, G.Y.Xie and A.X.Wan, "relationship between microblog emotion and diffusion across different user types：An empirical study based on 24 public events," Journalism & Communication, vol. 9, pp. 92-106, 2015.

[15] M.H.Dang, "Frame Effect of the Negative Emotion Expression Based on Computer-assisted Content Analysis of Online News Comments," Journalism & Communication, vol. 24, pp. 41-63, 2017.

[16] C.J.Hu and X.G.Shan, "Nationwide 'onlookers': online public opinion highlights the social 'pain points'," in China Education Daily, 2011/2/14.

[17] S.Chen, M.J.Zhou and J.X.Zhang, "The influence of the emotional valence and arousal degree of microblog information on information dissemination," in Summary of abstracts of the 15th National Academic Conference on Psychology, pp. 472, 2012.

[18] G.M.Yu, X.M.Geng and J.B.Pan, The development of public opinion in China: theory, evolution of The Times and practical application. Beijing: People's Daily Press, pp. 84,2021.

[19] N. Fay, B. Walker, Y. Kashima, and A. Perfors, "Socially Situated Transmission: The Bias to Transmit Negative Information is Moderated by the Social Context," Cognitive Science, vol. 45, 2021.

[20] E. M. Mercha, H. Benbrahim and M. Erradi, "Heterogeneous text graph for comprehensive multilingual sentiment analysis: capturing short-and long-distance semantics.," PeerJ Computer Science, vol. 10, 2024.

[21] G. Huang and X. Xu, "Emotional Computing Technology Applications in Information Systems Security and Their Risk Prevention," Applied Mathematics and Nonlinear Sciences, vol. 9, 2024.