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The Implication of Negative Emotional Comments on the Evolution of Online Public Opinion: Exampled with Sina Weibo

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Abstract: Negative comment messages tend to have stronger emotional energy among the Internet and have an important impact on the evolution of online public opinion. This study analyzes the influence of negative comments on individual perceptions and group emotions of Internet users based on the sample of comment discourse of events that are hotly searched on Sina Weibo. The results of the study show that the performance characteristics of negative comments differ for international news, social news, and entertainment discussion topics. Reviews of negative emotional attributes received more comments, rally more social sentiment and stimulate the transmission of sentiment. And negative emotion comments involving other events in the past can stimulate Internet users' memories and construct the collective memory of the Internet. The study facilitates the understanding of the impact of negative emotional comments on the cognitive psychology of Internet users in online public opinion and provides a reference for scientific understanding of online social psychology.

1. Introduction

Online public opinion is a research hotspot in cross-cutting fields, and different disciplines have different perspectives and methodological preferences in studying online public opinion. The field of journalism and communication focuses on the influence of opinion leaders on the expression of opinions on the Internet [1]. Qualitative research method is used to analyze the case process of network public opinion. Linguistics pays close attention to linguistic phenomena on the Internet and maps the collective psychology in online society through statistical analysis of semantic [2]. Sociology and information science mostly analyzes the evolution pattern of online public opinion by means of data analysis and simulation modeling [3,4]. However, the above studies on online public opinion have ignored the important vector of psychological mechanisms. Online public opinion is the general reflection of users' psychology, and the process of change of public opinion give expression to the transformation of users' psychology. The influence of psychological factors on online public opinion can be divided into two levels [5]. The first one is individual psychological cognition, which involves users' cognitive processing of information [6]. For example, the process of users' own emotional reactions after being influenced by others' information [7], and how users react when faced with information they do not agree with. The second dimension is group-level emotional contagion. This requires examining interpersonal and intergroup psychological relationships in online public opinion [8]. This relationship has a dynamic and interactive feature [9], and is influenced by various factors such as the group identity, shared behavior, and so on [10]. The process of occurrence of emotional infection at the group level is more complex than at the individual psycho-cognitive level. In the current study, it has been found that the group psychology of users shows "emotion cycles" [11] and "collective effervescence"[12]. Psychological mechanisms of negative attributes play an important role in both individual user psychological perception and group emotional infection [13,14]. In the evolution of online public opinion, negative emotion attribute text will continuously extend throughout the Internet text field, forming transmitted emotions in the process of text interaction and causing widespread emotional infection. on the Internet, negative emotions are presented in the form of texts, which are usually expressed in the form of text comments, pictures and emojis. For the textual analysis of negative emotions in online public opinion, a common approach is to collect text data by computer and perform a general analysis. This requires grabbing data through Python, obtaining text published by network users and building a sample library of text, then analyzing the text corpus based on the word2vec model, mapping the text content processing to vector operations in K-dimensional vector space, and finally matching scores of emoticons, degree adverbs, and negation words through the sentiment vocabulary ontology library to calculate the negative sentiment intensity [15]. The advantage of this text mapping approach is that it can be calculated for a large amount of text, reflecting an overall clustering feature and trend. However, its problem is that the text mapping approach can only statistically analyze the surface meaning of a text, but cannot interpret the text in the context. In fact, the meaning of a text does not exist in isolation; it is closely related to the society and culture and the context. This is merely a way to capture and calculate text words, which cannot read out the deeper meanings such as metaphors and ironies in the text, nor can it really analyze the user psychology behind the text in the context of culture. The process of vector conversion of text by computer also inevitably causes damage to the original text context and misinterprets the real emotion behind the text, which makes it difficult to analyze online public opinion. In order to cope with these problems, this research adopts a qualitative textual interpretation method to analyze the text. In the text sampling of user comments in popular search topics on Sina Weibo, the researcher analyzes the real meanings of the texts in conjunction with the contextual background and encodes the sentiment attributes of the texts, and then explores the influence of negative sentiment texts on online public opinion by analyzing the association among the texts with negative sentiment attributes and other variables. Although this method increases the workload of data collection, it can analyze the sentiment attributes in texts more accurately in combination with the context, reduce the possible errors in the analysis, and obtain results that are more in line with the actual situation. To this end, answers were sought for the following research questions:

1). How do the characteristics and expressions of negative sentiment comments differ for different categories of topics?

2). Do comments with negative sentiment stimulate the spread of negative sentiment to a greater extent?

3). Do negative sentiment comments that relate to other related events in the past stimulate more discussion? Do such texts sustain the collective memory of the Internet?

2. Research Design

In this study, the popular search topics on Sina Weibo were used as the sampling objects, and the topics were divided into three categories: international news, social news, and entertainment news, and coded according to A\B\C respectively. For each category, four topics were selected, and topics that are likely to generate controversial opinions were chosen as much as possible to avoid the situation that all opinions are biased to one side. For each topic, the first 20 user comments were sampled and then coded according to the specific textual context. The specific coding process follows the following guidelines:

(1) The texts were recorded as C (Critical), N (Neutral), and P (Positive) according to their sentiment attributes. It is important to note that the coding of affective attributes is based on the news text. If the text of a commentary contains a negative meaning of the news text, whether this negativity is expressed in the form of strong condemnation or in the form of a joke or a picture metaphor, it is categorized as "Critical". At the same time, this categorization of emotional attributes is not rigid; some commentary texts are not directly dissatisfied with the content of the news text, but with the events or social environment related to the news text, which will also be categorized as "Critical".

(2) Texts need to be labeled as Y (Yes) if they involve comments about past events, and N (No) if they do not.

(3) Depending on the specific presentation, the comments can be classified into T (Text), E (Emoji), and P (Picture). Their encoding methods are shown in Table 1.

Table 1: Encoding of the relevant variables

Comment on emotional attributes	Whether the comments involve past events	Hot search theme classification	The form of the comment
N(Neutral) C(Critical) P(Positive)	Y(Yes) N(No)	A= International news B= Social news C= Entertainment news	T(Text) E(Emoji) P(Picture)

After completing the encoding of the above attributes of the comment text, the following relevant values of the comment text are also recorded: (1) the number of replies from other users under the comment text, which represents the degree of attention the text has attracted. (2) The number of “likes” from other users under the comment text, which represents the degree of approval of the text. (3) The number of user interactions in the replies to the comments, which represents the intensity of the discussion generated by the text. These values indicate the impact of negative sentiment texts on online public opinion at multiple levels. The complete data collection process is shown in Figure 1.

After completing the collection of text data, the data will be analyzed from the following perspectives. Firstly, the overall data will be analyzed descriptively to calculate the percentage of negative comments, neutral comments, positive comments, and comments involving past events in the total sample, and the number of “likes” they received, the number of replies, and the number of user interactions in the replies will be calculated separately. Secondly, the characteristics and expressions of negative sentiment comments of different topics are analyzed differently, and I calculate which topic has more negative sentiment comments among the three types of topics. Which topics receive more replies, “likes” and discussions. Thirdly, a correlation analysis was conducted for each variable indicator to analyze the correlation between the emotional attributes of comments and variables such as number of comments, number of “likes”, and number of interactions in replies. Fourthly, a cross-tabulation analysis is conducted on the variables of topic categories, number of replies, number of “likes”, and number of interactions for negative comments involving past events to explore how the negative comments involving past events have influenced online public opinion.

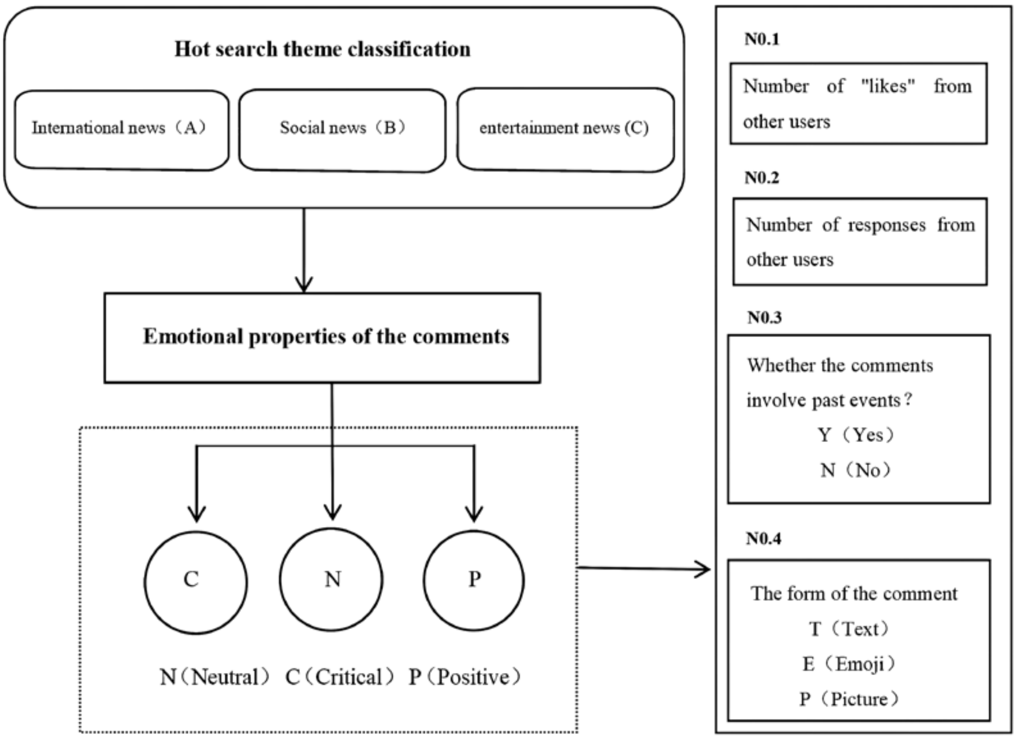

Figure 1: The process for the data collection

3. Results and Discussion

3.1 A Basic Description of the Study Findings

The study was divided into three categories, each category has selected 4 topics, a total of 12 topics. Each topic selected the top 20 comment texts, totaling 240 comment texts. According to Table 2, the most important comments are negative emotions, including 105, or 43.75%, then positive emotions, 84, or 35.00%, and only 51, or 21.25%. In terms of the number of comments, 218 were 10,000 or less, or 90.83%, followed by 1,001-2,000, and 13, accounting for 5.42%. In terms of interactions, 50 or less, 214, accounting for 89.17%, followed by 101-150, 16, accounting for 6.67%. In terms of “likes”, mainly 5000 or below, 166, accounting for 69.17%, followed by 5001-25000, 39, accounting for 16.25%. For past events, most of the comments were not involved, including 207 articles, or 86.25%, and only 33 articles, or only 13.75%.

In terms of discussion intensity, the discussion intensity value in this study = number of user interactions / comment responses in comment responses * 100%. In the analysis results, values in the range 0% -20% represent "Not intense"; 21% -40% range represents "Relatively not intense"; 41% -60% range represents "Commonly"; 61% -80% range represents "Relatively intense"; 81% -100% range represents "Intense". In terms of the specific results, most of the comments were not intense. In terms of hot search topics, 82, accounting for 34.17%, were mainly followed by international news and social news, with 79, respectively, accounting for 32.92%. In terms of the main forms of comments and replies, 208 are mainly words, accounting for 86.67%, followed by pictures, 23, accounting for 9.58%; the least is facial expressions, only 9, accounting for 3.75%.

Table 2: Fundamental state (N=240)

Theme		Frequence	Percentage (%)	Accumulative perception (%)
Emotional attributes of the comments	Neutral	51	21.25	21.25
	Critical	105	43.75	65.00
	Positive	84	35.00	100.00
Reply number of comments	1000 and less	218	90.83	90.83
	1001-2000 Times	13	5.42	96.25
	2,001-3,000 times	3	1.25	97.50
	3001-4000 times	2	0.83	98.33
	4001-5000 times	2	0.83	99.17
	More than 5,000 times	2	0.83	100.00
The number of interactions	50 Times and below	214	89.17	89.17
	51-100 Times	5	2.08	91.25
	101-150 Times	16	6.67	97.92
	151-200 Times	5	2.08	100.00
The number of "likes"	5000 and less	166	69.17	69.17
	5,001-25,000 times	39	16.25	85.42
	By 25,001-45,000 times	7	2.92	88.33
	45001-65000 times	9	3.75	92.08
	65,001-85,000 times	5	2.08	94.17
	More than 85,000 times	14	5.83	100.00
Whether the comments involve past events	No	207	86.25	86.25
	Yes	33	13.75	100.00
The degree of discussion	Not intense	206	85.83	85.83
	Relatively not intense	22	9.17	95.00
	Commonly	8	3.33	98.33
	Relatively intense	1	0.42	98.75
	Intense	3	1.25	100.00
Hot search theme classification	International news	79	32.92	32.92
	Social news	79	32.92	65.83
	Entertainment news	82	34.17	100.00
The form of the comment	T(Text)	208	86.67	86.67
	E(Emoji)	9	3.75	90.42
	P(Picture)	23	9.58	100.00

3.2 For three Different Themes, the Characteristics and Expression Mode of the Comment Text are Different

In the difference analysis, the univariate difference analysis (ANOVA) was mainly used to explore the group differences between the three themes. We found that the total number of responses to comments was different for different topics. It can be seen from Table 3: (1) there are significant differences in the response number of comments to different hot search topics ($P < 0.001$), and the response number of entertainment news comments was the highest, with an average of 623.82; followed by social news, with an average of 359.77; and then international news, with an average of 99.09. (2) The number of "likes" in different hot topics is significantly ($P < 0.001$), and the highest responses in entertainment news comments, with an average of 30438.93, followed by social news, with an average of 8806.49, and then international news, with an average of 2271.84. This phenomenon is mainly because entertainment news has a tradition of fans to improve the comment data for their idols, so entertainment news has the highest number of comments and thumb up comments. Social news topics are closer to the lives of netizens, so the number of replies and "likes" for comments are higher than those of international news.

Table 3: The difference in the number of comments and "likes" (N=240)

	Theme	N	Mean value	Standard deviations	F	P
Reply number of comments	International news	79	99.09	289.312	7.554	0.001
	Social news	79	359.77	514.019		
	Entertainment news	82	623.82	1345.719		
The number of "likes"	International news	79	2271.84	5305.795	21.840	0.000
	Social news	79	8806.49	16120.664		
	Entertainment news	82	30438.93	45580.712		

According to Table 4, the most popular comments on entertainment news are text forms (N=58), followed by pictures (N=22) and emoji (N=2). But on entertainment news topics, the pictures gets the most replies (M=1048.95) and "likes" (M=47334.55). Most of the picture comments on the entertainment news are the idol photos posted by the fans, while other fans will like them, and the photos are mostly from the idols' praise to the fans. At the same time, it can be found that the user interaction times in the reply of entertainment news picture comments is less (M=8.95), which is also because this kind of picture comments are all praise of idols and do not really form a topic of communication.

Table 4: Comments and "likes" for entertainment News (N=82)

	The form of the comment	N	Mean value(M)	Standard deviations	F	P
Entertainment theme	T(Text)	58	3.00	0.000		
	E(Emoji)	2	3.00	0.000		
	P(Picture)	22	3.00	0.000		
Reply number of comments	T(Text)	58	464.33	1073.044	2.526	0.044
	E(Emoji)	2	572.50	809.637		
	P(Picture)	22	1048.95	1889.118		
The number of interactions	T(Text)	58	9.14	26.124	3.705	0.043
	E(Emoji)	2	55.00	77.782		
	P(Picture)	22	8.95	26.841		
The number of "likes"	T(Text)	58	25072.48	38961.438	3.437	0.030
	E(Emoji)	2	214.00	292.742		
	P(Picture)	22	47334.55	58546.849		

Figure 2 shows that international news are mainly negative comments, accounting for 22.50%, and a few positive comments, only 5 articles, accounting for only 2.08%. Social news is mainly negative comments, 46, accounting for 19.17%; a small positive comment, only 13, accounting for 5.42%. Entertainment news was dominated by positive comments, with 66 articles, accounting for 27.50% overall.

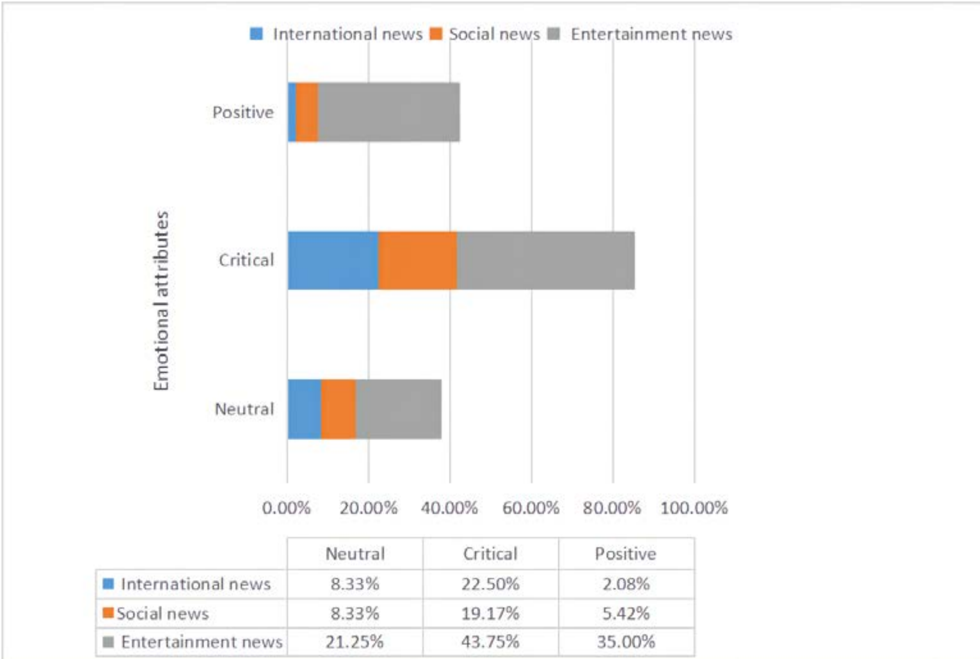

Figure 2: Differences in the emotional attributes of hot search topics (N=240)

According to the above data analysis, the number of comments and "likes" in the popular searches of entertainment topics are the highest, and the proportion of picture comments is also the highest, while the real topic communication between users in the comments reply is small, which is obviously different from international news and social news. The reason for this phenomenon is that the entertainment news is greatly influenced by the fan culture. In order to promote the idol, Fans will try to make positive comments, and do not let the negative comments appear at the top of the topic comments, to achieve the purpose of beautifying the image of the idol. In order to show their identity, fan groups need to gain identity in the network. Identity is the prerequisite for fan aggregation, the cornerstone of fan consumption and cultural participation, and the source of cohesion in fan communities. Therefore, fans need to consciously construct a new identity in the online space and shape a new self and corresponding interpersonal relationships. In order to enhance this identity, fans need to constantly comment favorably on their idols and defend their comments, thus demonstrating their identity in the group. Thus, in entertainment news, there is a large number of fans controlling comments and praising idols. International news accounts for the largest proportion of negative emotions in international news, and the number of replies and "likes" in the comments is less than that of social news topics, which shows that users have relatively little controversy about international news, and many show relative silence and show a relatively unified negative emotional tendency. Although the number of comments and "likes" in social news is less than that of entertainment news, its data comes from spontaneous discussion by users, rather than the group behavior of fan organizations like entertainment news. The negative emotion of social news is also more serious, and the number of comments and "likes" data are higher than that of international news, indicating that social news will have more attention and discussion than international news.

3.3 The Higher the Number of Negative Emotions Texts, the More the Number of Comments and "Likes" are obtained, Stimulating the Spread of Negative Emotions

In order to explore the relationship between the comment emotion and the number of replies, "likes", and the number of interactions, the Pearson correlation coefficient analysis was used in this study. According to Table 5: (1) there is a significant correlation between the number of comments and "likes" ($p < 0.01$); this indicates that the emotional attributes affect the number of comments and the number of "likes". The number of comments and replies was significantly and positively correlated with the number of "likes" ($p < 0.01$), which indicates that the more frequent the number of replies was, the more the number of "likes" was received accordingly.

Table 5: Correlation analysis (N=240)

Variable	Emotional attributes of the comments	The degree of discussion	Reply number of comments	The number of "likes"
Emotional attributes of the comments	1			
Reply number of comments	0.209^{**}	-0.113	1	
The number of interactions	0.009	-0.031	0.293^{**}	
The number of "likes"	0.339^{**}	-0.133^{*}	0.645^{**}	1

Explanatory note: $^{*}p<0.05$; $^{**}p<0.01$

Table 6: Difference analysis among the three types of hot search topics

Hot search theme classification	Variable	Emotional attributes of the comments	N	Mean value(M)	Standard deviations	F	P
International news(N=79)	Reply number of comments	Neutral	20	21.60	35.875	1.475	0.235
		Critical	54	136.78	343.683		
		Positive	5	2.00	4.472		
	The number of "likes"	Neutral	20	199.30	184.471	3.057	0.050
		Critical	54	3247.41	6192.870		
		Positive	5	25.80	33.996		
Social news(N=79)	Reply number of comments	Neutral	20	192.65	431.775	5.117	0.008
		Critical	46	326.24	515.045		
		Positive	13	434.15	480.102		
	The number of "likes"	Neutral	20	1110.60	1361.207	6.477	0.003
		Critical	46	13972.98	19503.423		
		Positive	13	2364.92	3719.732		
Entertainment news(N=82)	Reply number of comments	Neutral	11	74.273	147.505	2.229	0.014
		Critical	5	671.000	1439.281		
		Positive	66	643.636	1441.853		
	The number of "likes"	Neutral	11	8693.182	26357.470	3.011	0.050
		Critical	5	655.000	1422.239		
		Positive	66	36319.576	47944.034		

According to Table 6, there is no significant difference between the number of comments and the emotional attributes of the comments in international news ($p > 0.05$), but the number of negative "likes" is significantly higher than positive ($p < 0.05$). This shows that in the international news, people mainly express their recognition of the negative emotional comments in the way of "likes".

In social news, the number of negative comments was more than positive comments, and the number of negative comments was significantly higher than positive comments (p <0.05), but the number of responses to positive comments was significantly higher than negative comments. In entertainment news, there were more positive comments than negative comments, and positive comments were significantly higher than positive comments. But the number of negative comments was significantly more positive than positive comments (p <0.05). Here, a new assumption is made: will there be a one-sided siege of the minority opinion in social news and entertainment news?

According to Figure 3, the discussion of international news is mainly not intense, including 71 articles, accounting for 29.58% of the total, followed by 7, accounting for 2.92%. Entertainment news is also mainly not intense, with 80 articles, accounting for 33.33% of the total. The social news is also not intense, 55, accounting for 22.92% of the total. But the discussion of social news is higher than that of international news and entertainment news.

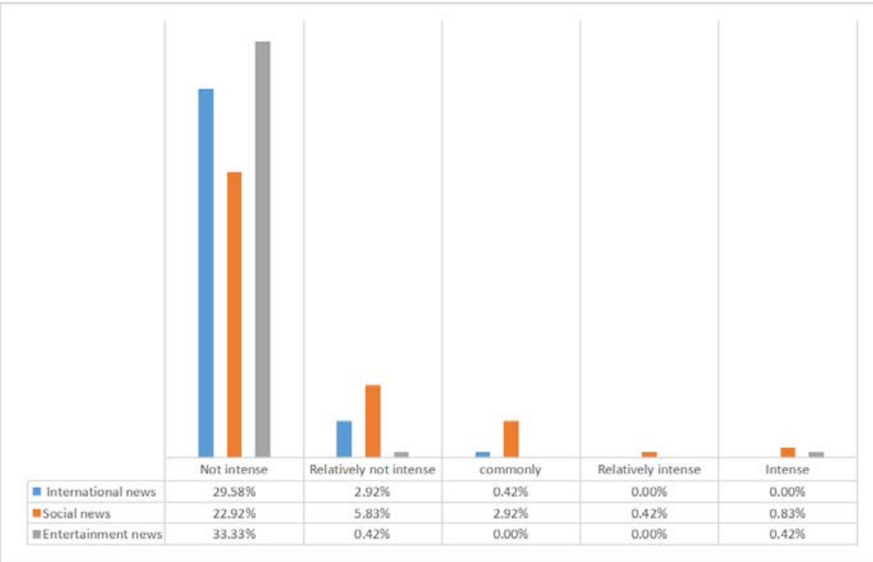

Figure 3: Discusses the intensity analysis (N=240)

According to Table 7, the number of comment replies and the number of "likes" differed significantly (p<0.001) in terms of the form of the replies. The number of comment replies and the number of "likes" differed by comment form. The form of Emoji had no comment replies (M=0) and the number of "likes" was also the lowest among the three forms (M=209), which implies that there is no way to get sufficient discussion by commenting with Emoji alone.

Table 7: Difference analysis of comments and reply forms (N=240)

Variable	The form of the comment	N	Mean value(M)	Standard deviations	F	P
Reply number of comments	T(Text)	208	268	669.55	8.687	0.000
	E(Emoji)	9	0	0.67		
	P(Picture)	23	1008	1855.91		
The number of "likes"	T(Text)	208	11174	24671.93	15.484	0.000
	E(Emoji)	9	209	240.91		
	P(Picture)	23	45440	57917.66		

These research data show that the emotional attributes of the comments have an impact on both the number of comments answered and the number of "likes" received. In international news and social news, negative emotional comments get more replies and "likes". In the social news, the discussion in the comments is the most intense, which shows that in the social news, the negative emotional comments will stimulate the spread of the negative emotions more. In entertainment news, positive comments will get more replies and “likes” because fans need to beautify their idols.

3.4 Social News has the Most Comments about Past Related Events, and It is Mostly Negative

The cross-analysis between topic categories and the number of comments involving past events revealed the most social news involving past events, including 16, or 6.67% of the total, followed by international news, or 3.75%, and finally, entertainment news, accounting for 3.33% (Figure 4). Negative comments on past events were mostly 25 comments, accounting for 10.42% of the total, followed by 7 positive comments, accounting for 2.92% (Figure 5).

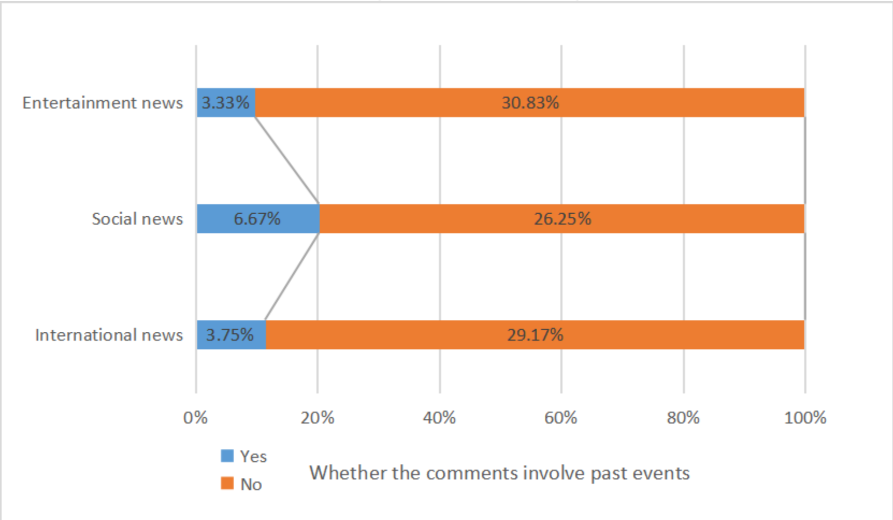

Figure 4: Differences in comments involving past events across different topics

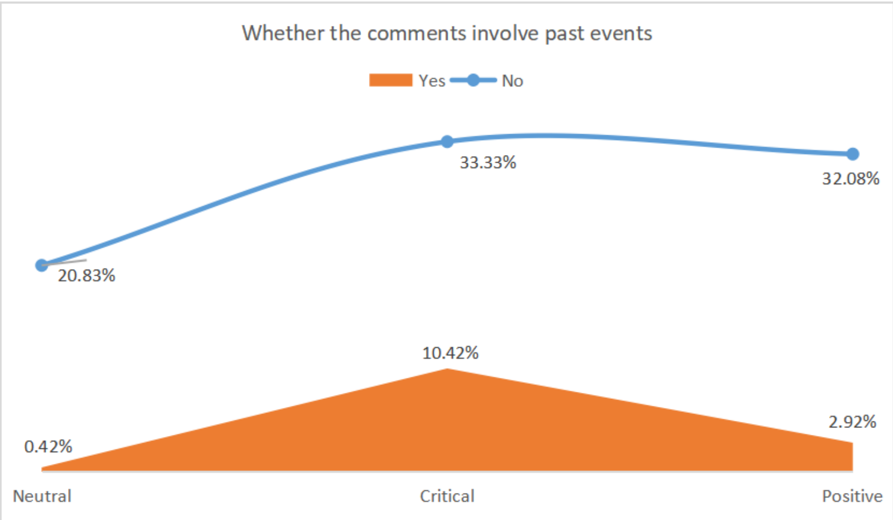

Figure 5: Emotional attributes of the comments involving past events

In comments about past events, the number of intra-reply interactions varied significantly in hot search topics ($p < 0.05$). Specifically, comments on social news topics were relatively high, with an average of 34.13, followed by entertainment news with an average of 19.50, and the lowest on international news with an average of 6.78 (Figure 6).

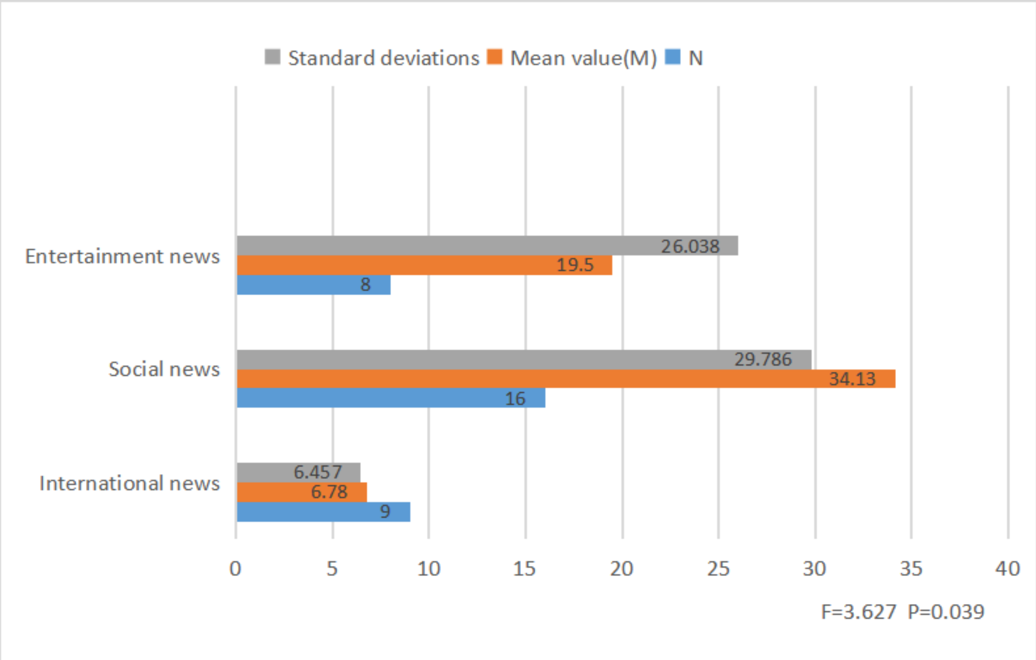

Figure 6: Hot search topic differences for the number of interactions (N=33)

Overall, the comments related to the past are the most easily involved in the social topics, and the emotions of these past-related comments are mostly negative. Moreover, in the social news, the number of interactive discussions involved in the past comments and responses is relatively high. This shows that the social topic holds the Internet's collective memory.

3.5 When Opinions are One-Sided in Social and Entertainment Topics, Minority Opinions that Violate the Mainstream can Lead to Heated Discussion.

According to Table 8, among the three types of hot search topics, international news and social news are mainly negative comments, with a few positive comments; entertainment news is mainly positive comments, with a few negative comments.

However, it can be seen from Table 9 that: (1) in international news, the number of comments and the number of interactions within the replies are still mainly negative comments, with the average value of 136.78 and 4.65 respectively. Therefore, there is no heated discussion of the minority opinions on international news topics. (2) In the social news, the number of comments ($p < 0.01$) and the number of interactions within the reply ($p < 0.001$) was significantly different in the comment emotions, and mainly positive comments, with the average value of 735.54 and 142.15, respectively. Therefore, in terms of social news topics, there is a heated discussion of a few opinions. (3) In entertainment news, the number of comments ($p < 0.05$) and the number of in-time interactions in response ($p < 0.001$) was significantly different in comment emotions, mainly negative comments, with the average values of 1571.20 and 118.20, respectively. Therefore, in terms of entertainment news topics, there is a heated discussion of a few opinions.

According to the above data analysis, when there are one-sided opinions in social topics and entertainment topics, the minority opinions that violate the mainstream will cause heated discussion, which is mainly due to the siege and opposition to the people who hold the opposite opinions. In social topics and entertainment topics, this public opinion pressure is more obvious, while in international news, the contrary opinion is more acceptable.

Table 8: Subject differences in the number of interactions (N=240)

Subject number	User interaction interaction interaction interactions in the reply of comments 50 Times and below	51-100 Times	51-100 Times	51-100 Times	Total
1	10 4.17%	3 1.25%	5 2.08%	2 0.83%	20 8.33%
2	17 7.08%	1 0.42%	1 0.42%	1 0.42%	20 8.33%
3	20 8.33%	0 0.00%	0 0.00%	0 0.00%	20 8.33%
4	19 7.92%	0 0.00%	1 0.42%	0 0.00%	20 8.33%
5	16 6.67%	0 0.00%	4 1.67%	0 0.00%	20 8.33%
6	14 5.83%	1 0.42%	4 1.67%	1 0.42%	20 8.33%
7	20 8.33%	0 0.00%	0 0.00%	0 0.00%	20 8.33%
8	20 8.33%	0 0.00%	0 0.00%	0 0.00%	20 8.33%
9	18 7.50%	0 0.00%	1 0.42%	1 0.42%	20 8.33%
10	20 8.33%	0 0.00%	0 0.00%	0 0.00%	20 8.33%
11	20 8.33%	0 0.00%	0 0.00%	0 0.00%	20 8.33%
12	20 8.33%	0 0.00%	0 0.00%	0 0.00%	20 8.33%
Total	214 89.17%	5 2.08%	16 6.67%	5 2.08%	240 100.00%

Table 9: The intense discussion phenomenon among the minority opinions

Theme	Variable	Emotional attributes of the comments	N	Mean value(M)	Standard deviations	F	P
International news (N=79)	Reply number of comments	Neutral	20	21.60	35.875	1.475	0.235
		Critical	54	136.78	343.683		
		Positive	5	2.00	4.472		
	The number of interactions	Neutral	20	1.55	2.800	3.293	0.042
		Critical	54	4.65	6.519		
		Positive	5	0.00	0.000		
Social news (N=79)	Reply number of comments	Neutral	20	192.65	431.775	5.117	0.008
		Critical	46	326.24	515.045		
		Positive	13	735.54	472.891		
	The number of interactions	Neutral	20	19.10	43.335	73.669	0.000
		Critical	46	26.57	29.468		
		Positive	13	142.15	16.960		
Entertainment news (N=82)	Reply number of comments	Neutral	11	74.27	147.505	2.229	0.014
		Critical	5	1571.20	935.860		
		Positive	66	643.64	1441.853		
	The number of interactions	Neutral	11	2.18	3.710	1178.558	0.000
		Critical	5	118.20	7.294		
		Positive	66	3.36	5.161		

4. Conclusion

This paper analyzes the impact of negative emotional comments on the evolution of online public opinion by sampling three types of popular search topics on Sina Weibo. The results of the study showed different effects of negative emotional comments. In international news and social news, negative emotion comments account for the majority. The entertainment news theme has the collective positive comment behavior of the fan organizations. In the international news and social news topics, the negative comments will get more replies, forming a negative emotional preference in the field of Internet public opinion. At the same time, other past events will be more involved in the social news, and such comments involving other events in the past are mostly negative emotional preference, which can gather more attention and reply. This suggests that comments on past events in social topics will stimulate the intertextuality mechanism of texts and maintain the collective memory in the Internet field to some extent. This study also found that when the opinions in social topics and entertainment topics are obviously identical, as a minority opinion will trigger a heated discussion, forming a pressure on the online public opinion field of the minority opinions. The problem of network public opinion is complex. Taking negative emotional comments in the network as the entry point can provide some ideas for us to understand the generation and evolution of online public opinion. However, as this study is manual text sampling and interpretation coding, the sample size is limited, and there is some randomness. In the future research, we can try to include more influencing factors in the design of the research framework, and combine the two methods of computer collection text and manual interpretation to cross-verify the results, so as to form more cognition of the evolutionary mechanism of network public opinion.

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