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The effect of opinion emotion on information dissemination in social networks

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Abstract

When popular topics arise, Internet users typically share their opinions and interact with others on social networking platforms, and the comments generated on social networks contribute to the spread of popular trends. In this paper, we focus on the popular ChatGPT topic and analyze the evolutionary trend of public opinion and the emotional polarity of comments related to ChatGPT on the Weibo and WeChat social media platforms. In this paper, emotions are divided into six categories, the emotions contained in Weibo and WeChat comments are discussed, and the main opinions reflected in each emotion are examined. We expect that our finding will help reveal the relationship between opinion and sentiment.

Keywords: Sentiment analysis, information dissemination, social network

1. Introduction

With the development of social networks, the number of social network users has increased dramatically. At the beginning of July 2022, among the approximately 5.03 billion global Internet users, 4.70 billion use social networks. Social networking has become a preferred way for people to express opinions and sentiments about major events (Son et al., 2019). These users can obtain information, express opinions, and interact with others in a timely manner online using various social media platforms, e.g., WeChat, Weibo, and TikTok. However, users who receive a disproportionate amount of negative information from social media may become increasingly depressed, and those

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who receive more positive information may become more optimistic (Bastick, 2021). In addition, in social media, users' emotions are highly contagious and can be influenced easily (Zhou et al., 2022). Thus, we must carefully consider how sentimental tweets may trigger large-scale sentimental resonance, trigger discourse coordination among social media users, and in turn exacerbate social sentimental imbalances. The accumulation of negative sentiments may cause Internet public opinion incidents and social conflicts (Kwon et al., 2016).

Group polarization refers to a situation in which members' opinion tendencies may be strengthened, catalyzed, and even radicalized in group discussions. The group polarization phenomenon was first proposed by social psychologist James Stoner in 1961 (Stoner, 1961). This phenomenon reflects that people's attitudes and opinions are fermented and catalyzed in group discussions, and sentimental expansion may lead to large-scale group behaviors (Zhou, 2010). Group polarization psychology can promote the group to reach a consensus and improve the core cohesion of the group; however, its negative effects cannot be ignored. It has also been found that online groups are more prone to group polarization than real-world groups (Sia et al., 2002). Thus, in online public opinion events, it is of great practical significance to identify the sentiments in social media and analyze the impact of sentiments on opinions.

Sentiment analysis technology can be utilized to predict the direction of opinion events by analyzing news, comments, and other information on social networks (Liu et al., 2019). Sentiment analysis can be used to predict public opinion on policy-related events, e.g., delaying the retirement age, and it provides support for the formulation of relevant national policies (An et al., 2021). In addition, sentiment analysis can be applied to the judgment and prediction of responses to various emergency situations, e.g., epidemics and hurricanes (Zhang et al., 2020), as well as financial forecasting (Behrendt and Schmidt, 2018).

However, most previous studies only analyzed the emotions behind information dissemination. In other words, the relationship between emotions and opinions has not been investigated extensively. We expect that analyzing the relationship between emotions and opinions will further our understanding of the principles and rules of user opinion dissemination and strengthen guidance of public opinion dissemination.

To address these issues, this paper attempts to analyze the mapping relationship between emotions and opinions. First, the sentiment polarity of Weibo and WeChat comments is analyzed using a dictionary-based sentiment analysis method. Then, we employ a recurrent neural network (RNN) to realize fine-grained classification of Weibo and WeChat comment sentiments. In this study, we categorize the comment emotions into six categories: rationality, positivity, anger, sadness, fear, and surprise. Finally, the correspondence relationship between the emotions and opinions is analyzed.

2. Related work

2.1 Sentiment analysis

Sentiment analysis is widely used to process text data on the network (Cambria et al., 2017), and it is also used in various other fields, e.g., political forecasting (Ebrahimi et al., 2017), financial forecasting (Xing et al., 2018), and e-tourism (Valdivia et al., 2017). In most application scenarios, sentimental polarity is divided into positive and negative sentiments or neutral and negative sentimental attitudes (Tsugawa and Ohsaki, 2017). However, in reality, the complex inner world of the human mind involves many kinds of sentiments. For example, according to An et al. (2021), the sentiments of public opinion events are divided into seven types, i.e., happy, good, anger, sorrow, fear, sick, and shock. In addition, existing sentiment classification methods are primarily divided into three categories. The first method is the dictionary-based method, which mainly formulates a series of sentimental dictionaries and rules, performs paragraph borrowing and syntactic analysis on the text, calculates the sentimental value, and finally uses the sentimental value as the basis for the sentimental orientation of the given text. For example, Gaikwad and Joshi (2016) found that different words and symbols make different contributions to the sentiment polarity of sentences, and they proposed that weight assignment should be performed to distinguish the influence of these words. The second method is based on machine learning. Most machine learning–based methods transform this problem to a classification task. Zhang et al. (2020) adopted a semi-supervised support vector machine learning method to classify sentiments in microblog texts and revealed how the sentiments of a tweet affect its virality in terms of diffusion volume in the context of an emergency event. The third method is based on deep learning, and the use of deep learning techniques for sentiment analysis has increased in recent years. For example, Konate and Du (2018) applied a deep learning model based on a single-layer convolutional neural network (CNN) to perform sentiment analysis on multilingual text from Facebook. In addition, Li et al. (2021) employed a CNN to construct a network public opinion sentiment analysis model to help governments detect network public opinion.

2.2 Influence of emotions on information dissemination

From a human psychology perspective, people's emotional attitudes have been described in multiple dimensions (Xu et al., 2013). According to Heilman (1997), all primary emotions can be described using two or three factors, including valence, arousal, and motor activation. In addition, physiological arousal is a driver of information dissemination (Berger and Milkman,2012). High-arousal sentiments, e.g., joy, anger, and fear, are more conducive to the dissemination of information than low-arousal sentiments, e.g., sadness (Zhang et al., 2020). It has been demonstrated that opinion is formed under the combined effect of different emotions, and the opinions of agents can be influenced by the emotions of their neighbors (Lian et al.， 2020). Lian and Dong (2022) proposed a sentiment－opinion transformation mechanism, and they analyzed the important role that sentiment plays in opinion dynamics. The impact of Internet users’ emotions on the spread of public opinion has also been studied. The generation of sentiments in public opinion crisis events primarily comes from the cognitive analysis of network information; thus, Lindsay and Norman (2013) established a sentimental arousal model to explain in detail sentimental generation under the cognitive processing system. In addition, Lu et al. (2021) analyzed the influence of users' emotional reactions on communication behavior during the bird flu epidemic. The results demonstrate that Weibo users' emotions affected their communication behavior significantly.

3. Methodology

3.1 Data collection and preprocessing

In this study, we focused on the intelligent dialogue robot model ChatGPT as an example. ChatGPT, which was launched in November 2022, can understand and generate text. It belongs to the text generation modal application model in the Artificial Intelligence Generated Content technology application. ChatGPT users can chat with the AI system in relatively complex areas, e.g., daily life, writing code, copywriting, and solving specific problems. The answers provided by ChatGPT are orderly and professional, and ChatGPT's continuous dialogue ability, strong comprehension, accuracy, and the creativity of its answers made it popular very quickly. By February 2023, the "ChatGPT wave" had swept the Chinese public opinion field, and ChatGPT has attracted high-frequency attention in various other fields, e.g., the Internet and education.

Weibo and WeChat are the two most popular social networking platforms in China. This study utilized a big data crawler system to collect data created through Weibo and WeChat from December 1, 2022 to March 19, 2023 using the keywords “ChatGPT” and “Internet.” In total, 24,250 Weibo comments and 12,797 WeChat comments were obtained. Note that the collected Weibo and WeChat data includes various information, e.g., usernames, titles, comment content, links, and posting time.

The collected data were subjected to preprocessing. Here, we first browsed the Weibo and WeChat data to remove irrelevant data. Then we used the pyltp toolkit (Che et al., 2010) to decompose sentences into words. We removed unnecessary words, e.g., some prepositions that are not helpful for sentiment recognition and sentiment analysis. Finally, we identified and labeled each word with its part of speech.

3.2 Sentiment analysis methods

The sentiment analysis process used in study is divided into two main parts. Initially we analyzed the emotional polarity of the Weibo and WeChat comments, and then we analyzed the fine-grained emotional categories of the Weibo and WeChat comments. The sentiment analysis process is described in the following.

- First, a sentiment dictionary was constructed. In this study, we employed a dictionary-based approach to sentiment analysis of opinions expressed in the Weibo and WeChat comments. Based on the Chinese emotional vocabulary ontology library of Dalian University of Technology (Xu et al., 2018) combined with the characteristics of corpus texts, we expanded the dictionary of emoticons, the dictionary of Internet terms, the dictionary of event-specific words, the dictionary of single-character emotional words, and the dictionary of commonly used modal particles to form the final emotional dictionary.
- Second, we performed sentiment polarity classification. Here, we calculated the sentiment value by comparing the number of positive and negative sentiment words in the target sentence. For example, assume that the number of positive words in a comment is $SumPos(d_i)$, and the number of negative words is $SumNeg(d_i)$. Then, the formula to calculate the final sentiment value $P(d_i)$is expressed as follows.

$$P(d_i) = SumPos(d_i) - SumNeg(d_i)$$

When $P(d_i) > 0$, the final sentiment polarity of the comment is positive, and when$P(d_i) < 0$, the final sentiment polarity is negative. When $P(d_i) = 0$, the final sentiment polarity is neutral.

- Third, we classified the fine-grained sentiments. To the best of our knowledge, only a few studies have investigated fine-grained sentiments. Ekman's six-category emotion classification system has fairly prominent influence (Yang and Wang, 2019). As mentioned previously, in this study, we focus on six emotion categories: rationality, positivity, anger, sadness, fear, and surprise. A long short-term memory (LSTM) network (Hochreiter and Schmidhuber, 1997) was selected as the textual sentiment classifier. Note that an LSTM network is an implementation of an RNN that circumvents some of the main problems with RNNs (Pascanu et al., 2013), Such as gradient disappearance.

Each individual unit module in the LSTM network consists of an internal memory cell, an input gate, a forget gate, and an output gate. All gate structures are composed of a feedforward network layer and an activation function. The feedforward network layer mainly consists of a series of weights to be learned. For the given input data x_t at the current moment and the implicit encoding h_{t-1} at the previous moment, the input gate, forget gate and output gate encode them through their respective parameters to obtain the output i_t、$f_t$and $o_t$of the three gate structures respectively. On this basis, the implicit encoding h_t of the current moment is finally obtained by further combining the internal memory unit information $c_{t-1}$of the previous moment.

The LSTM model are shown in Figure 1 as followed.

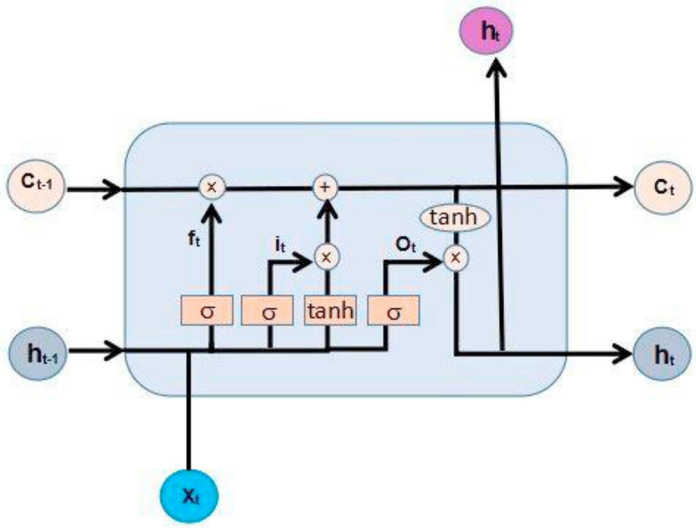

Figure 1. The LSTM model

The required conformance and its meaning in LSTM are shown in Table 1 below:

Table 1. The symbols of LSTM model

symbol	Content description or operation
x_t	Input data at time t
i_t	The output of the input gate: $i_t = sigmoid(W_{xi}x_t + W_{hi}h_{t-1+}b_i)$ (W_{xi}, W_{hi} and b_i are the parameters of the gate)
f_t	The output of the forget gate： $f_t = sigmoid(W_{xf}x_t + W_{hf}h_{t-1+}b_f)$ (W_{xf}, $W_{hf}$$and$ b_f are the parameters of the forget gate)
o_t	The output of the output gate： $o_t = sigmoid(W_{xo}x_t + W_{ho}h_{t-1+}b_o)$ (W_{xo}, $W_{ho}$$and$ b_o are the parameters of the output the gate)
c_t	The output of the internal memory cell: $c_t = f_t \otimes c_{t-1} + i_t \otimes \tanh(W_{xc}x_t + W_{hc}h_{t-1+}b_c)$ W_{xc}, $W_{hc}$$and$ b_c are the parameters of the internal memory cell. The input gate i_t controls how much information flows into the current moment internal memory unit c_t, and the forget gate controls how much information in the previous moment internal memory unit c_{t-1} can be accumulated into the current moment internal memory unit c_t
h_t	Implicit encoding h_t of input data at time t： $h_t = o_t \otimes \tanh(c_i)$ $= o_t \otimes \tanh(f_i \otimes c_{t-1} + i_t \otimes \tanh(W_{xc}x_t + W_{hc}h_{t-1+}b_c))$ Input gate, forget gate and output gate information i_t, f_t, o_t participate together to get h_t
$\otimes$	Multiply the corresponding elements of two vectors by bits

When the input data x_t at the current time t in the given sequence data and the implicit encoding h_{t-1} at the previous time, the following formula can be used to calculate the internal memory unit information and implicit encoding according to Table 1 and Figure 1.

The output of the input gate: $i_t = sigmoid(W_{xi}x_t + W_{hi}h_{t-1+}b_i)$

The output of the forget gate: $f_t = sigmoid(W_{xf}x_t + W_{hf}h_{t-1+}b_f)$

The output of the output gate: $o_t = sigmoid(W_{xo}x_t + W_{ho}h_{t-1+}b_o)$

The output of the internal memory cell: $c_t = f_t \otimes c_{t-1} + i_t \otimes \tanh(W_{xc}x_t + W_{hc}h_{t-1+}b_c)$

Implicit encoding h_t of input data at time t : $h_t = o_t \otimes \tanh(c_i) = o_t \otimes \tanh(f_i \otimes c_{t-1} + i_t \otimes \tanh(W_{xc}x_t + W_{hc}h_{t-1+}b_c))$

Since the range of sigmoid function is between (0,1), the three gate structures of input gate, forgetting gate and output gate use the linear mapping function of sigmoid to play the role of information control gate. In internal memory unit and implicit coding, tanh function is used, whose range is (-1,1), so that it can increase and decrease in information integration.

4. Results and discussion

4.1 Evolution trend of public opinion

- The Weibo and WeChat comment trends in terms of event-related keywords are shown in Figures 2 and 3, respectively. By comparing the results shown in Figures 1 and 2, we can observe that the number of comments about ChatGPT on Weibo and WeChat fluctuated at a low level from December 10, 2022 to January 28, 2023. The ChatGPT topic did not spread quickly on either Weibo or WeChat. However, on January 31, 2023, the number of related comments on Weibo increased rapidly and reached a peak on February 8, 2023. Then, the public opinion attention declined rapidly; however, it rose slightly on March 17, 2023. On January 28, 2023, the number of WeChat comments increased rapidly and reached a peak on February 9. Since then, relevant public opinion attention has continued to fluctuate. Nonetheless, the ChatGPT topic continued to exhibit strong topic attraction.

Figure 2. Quantity trend of Weibo comments on event-related keywords

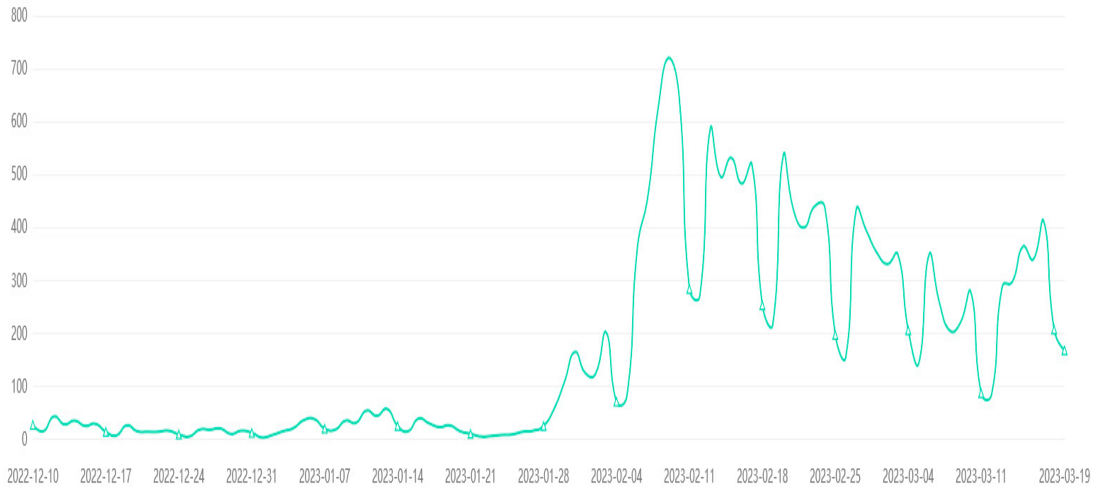

Figure 3. Quantity trend of WeChat comments on event-related keywords

4.2 Comment sentiment polarity

As shown in Figure 4, there were 10,691 positive comments (83.55%), 887 neutral comments (6.92%), and 1,219 negative comments (9.53%) in the WeChat comments about ChatGPT. As can be seen, most WeChat users maintained sufficient rationality and restraint relative to ChatGPT, and their comments primarily represented an attitude of learning and embracing. In terms of negative comments, a small number of netizens expressed concern about the iteration of "ChatGPT" in the Internet field and the work of AI replacing people.

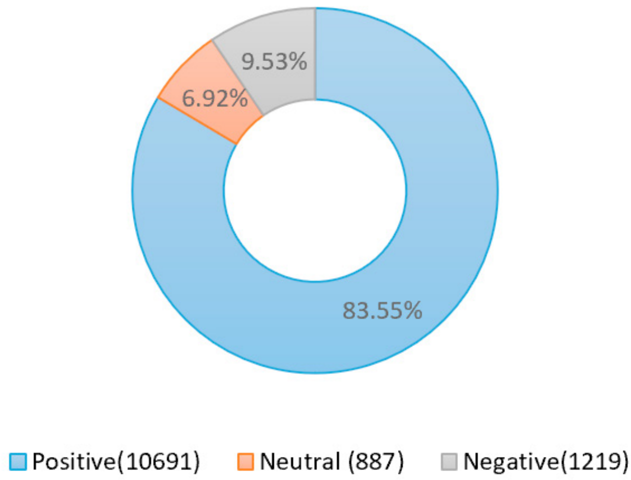

Figure 4. Proportion of sentiment polarity of WeChat comments

The sentiment polarity of the Weibo comments is shown in Figure 5. As can be seen, we identified 16,305 positive comments (67.24%), 857 neutral comments (3.53%) and 7,088 negative comments (29.23%) in the Weibo comments about ChatGPT. On Weibo, more than two-thirds of users held positive views of ChatGPT. Compared with WeChat, the negative comments on Weibo were more diverse, and they expressed Concerned about whether domestic Internet companies can develop the most advanced technology of ChatGPT.

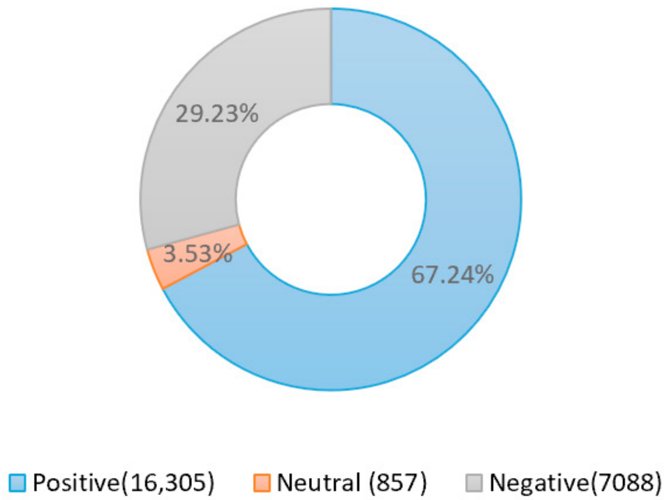

Figure 5. Proportion of sentiment polarity of Weibo comments

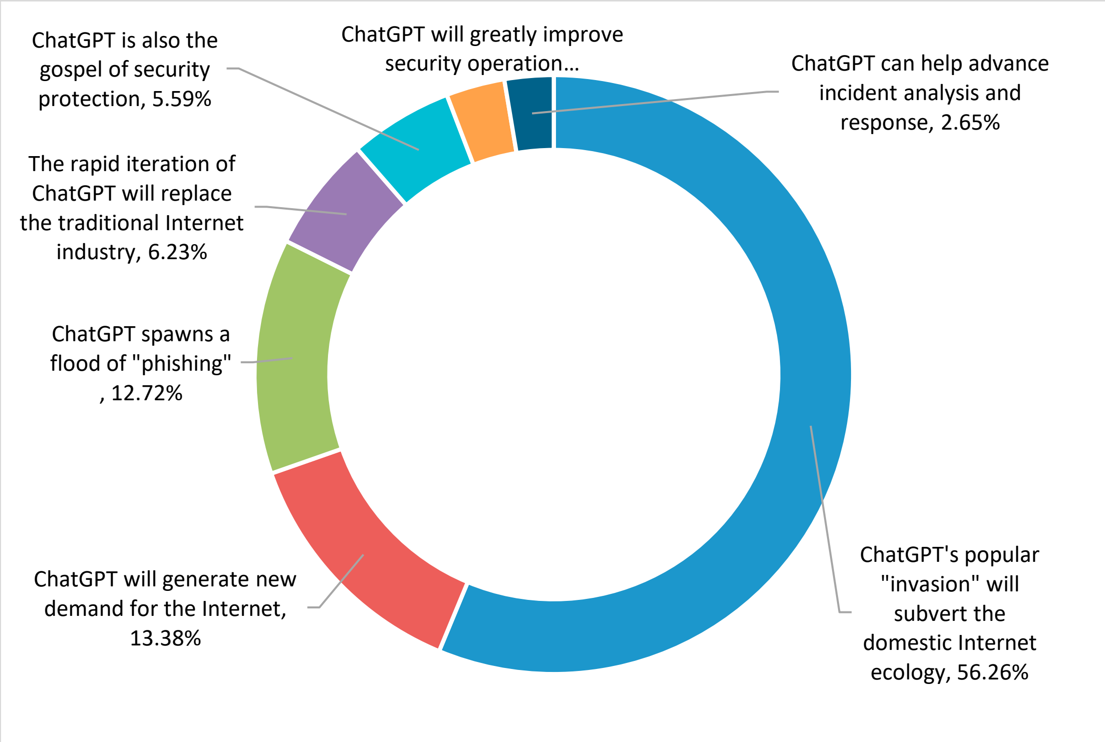

Figure 6. Major opinions about ChatGPT on Weibo and WeChat

The most common opinions about ChatGPT on Weibo and WeChat are shown in Figure 6, which primarily focused on the prospect of ChatGPT being applied to the Internet field and the iterative subversion of the domestic Internet industry, as well as concerns about the development of the domestic Internet industry.

4.3 Mapping analysis of emotions and opinions

The emotions derived from the opinions about ChatGPT on Weibo and WeChat were divided into six categories, as shown in Figure 7. As can be seen, most users exhibited rational (67.11%) and positive (13.64%) attitudes, and they looked forward to the prospect of ChatGPT and its application in the Internet field in the future and were even eager to try it. However, a small number of user comments demonstrated negative sentiments, e.g., anger (7.80%), sadness (4.72%), fear (4.47%), and surprise (2.26%). We suspect that these users, although motivated to follow established trends, may be hostile to new things, thereby leading to irrational sentimental tendencies.

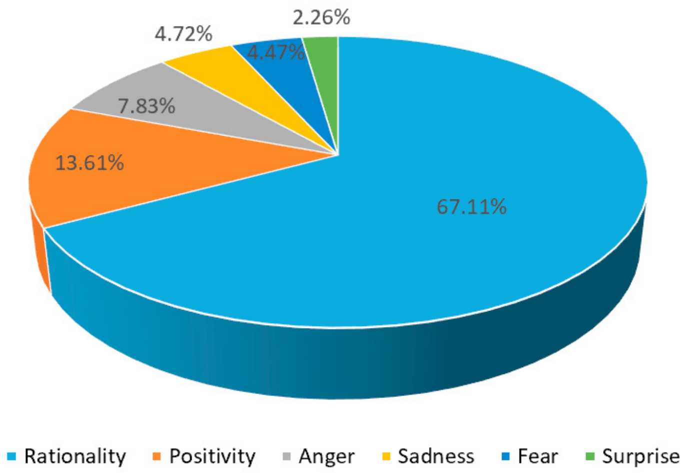

Figure 7. Emotions of opinions about ChatGPT on Weibo and WeChat

As shown in Figure 6, rationality is the largest emotion (61.77%). The people holding this type of opinion have relatively objective and rational attitudes toward ChatGPT and maintain sufficient confidence in their own position, and they believe that Internet practitioners should embrace the trend actively. The main point of these opinions was that ChatGPT will generate new demand outlets for the Internet. The segmentation point of this opinion is described as follows. First, ChatGPT will become a new outlet in the Internet industry, and it should be viewed rationally and given sufficient investment (35.62%). Second, Baidu company's "Wen Xin Yi Yan" is a good start, and other domestic Internet companies should actively follow up (21.58%). Third, ChatGPT will bring new opportunities to the Internet industry (9.91%).

The second emotion is positivity, which accounted for 13.64%. Such opinions have a positive attitude toward the introduction of ChatGPT and are eager to bring AI to the Internet industry. The main point of this opinion is that the AI ChatGPT can promote incident analysis and response. The segmentation point of this opinion is described as follows. First, ChatGPT is another outlet in the Internet industry, and will bring about changes (6.53%). Second, ChatGPT will bring more thinking to the Internet industry. This is an epoch-making change (4.27%). Third, the domestic Internet industry is too conservative, and trying and embracing ChatGPT can bring a better future (2.84%).

The third emotion is anger, which accounted for 7.80%. This type of opinion is more conservative and represents resistance and rejection of new things. The main point of this opinion is that ChatGPT will spawn a phishing flood. The segmentation point of this opinion is summarized as follows. First, ChatGPT will replace traditional Internet code farmers, which will bring another round of unemployment (3.26%). Second, ChatGPT replacing human beings must be resisted; otherwise, we will all become slaves of AI in the future (2.28%). Third, with the rapid rise of ChatGPT, Baidu company's "Wen Xin Yi Yan" launched in China is much weaker than ChatGPT (2.26%).

The fourth emotion is sadness, which accounted for 4.72%. This type of opinion is more pessimistic than anger and exhibits a great deal of negative sentiment. The main point of this opinion is that ChatGPT's popular “invasion” will subvert the domestic Internet ecology. The segmentation point of the opinion is summarized as follows. First, the invasion of ChatGPT is irreversible, and the domestic Internet will usher in a new round of reshuffle (2.53%). Second, ChatGPT is growing too fast, and domestic Internet development has lagged far behind the times (1.28%). Third, the milestone of ChatGPT will replace 5G, which will eventually have an incalculable impact on the Chinese Internet industry (0.91%).

The fifth emotion is fear, which accounted for 4.47%. This opinion is fraught with extreme aversion and lash out at anything insensitive. The main point of this opinion is that ChatGPT's rapid iteration will replace the traditional Internet industry. The segmentation point of this opinion is summarized as follows. First, ChatGPT will eventually replace the traditional Internet industry, which will be an inevitable tragedy (2.16%). Second, AI will bring huge innovations, which will result in a rapid widening of the gap between the rich and poor, and class division is inevitable (1.57%). Third, ChatGPT has infiltrated every aspect of our lives. If we cannot resist, we will be replaced until we perish (0.74%).

The sixth emotion is surprise, accounting for 2.26%. Related opinions do not have sharp sentimental expression. Instead, they represent an outstanding perception of new things. The main point of this opinion is that ChatGPT is also helpful for Internet security protection. The segmentation points of this opinion described as follows. First, the impact of ChatGPT on the Internet industry is positive and worthy of recognition (1.24%). Second, my country's Internet companies will lose this outlet; however, this is not a bad thing (0.53%). Third, we need to watch the impact of AI in the Internet field, and not make any evaluation at present (0.49%).

5. Conclusion

In this study, we analyzed the evolutionary trend of public opinions about ChatGPT on the Weibo and WeChat social media platforms. Then, the main sentiment polarity of comments found on Weibo and WeChat is analyzed using a dictionary-based sentiment analysis method. Besides, we used a recurrent neural network (RNN) to analyze the granularity of emotions, divided the emotions expressed in public opinion into six categories, and analyzed the proportion of six emotions in public opinion and the main viewpoints contained in each emotion. This study will help us to understand the relationship between emotions and opinions, and provide an effective reference for future research.

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