Received December 31, 2019, accepted January 12, 2020, date of publication January 24, 2020, date of current version February 6, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2969270

A Public Psychological Pressure Index for Social Networks

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This work was supported in part by the National Key Research and Development Plan under Grant 2017YFB0803304 and Grant 2017YFB0803305, and in part by the National Natural Science Foundation of China under Grant 61672186, Grant 61872110, Grant 61472108, and Grant 61402149.

ABSTRACT With the worldwide proliferation of social networks, public opinion analysis of data generated by social networks has become an important field of research. Social networks have become a major platform for public opinion formation and diffusion, and analyzing public opinion through social network data plays an important role across numerous fields, including political science, economics, commerce, finance, international trade, public policy implementation and so on. Nevertheless, the corresponding quantitative indexes of public opinion analysis have not yet been developed, and the theoretical foundation underpinning such indexes has yet to be established. How to measure public opinion through social network data is a significant problem in need of the development of a series of quantitative assessment indices and social computing methods that can be used to solve this problem. This paper proposes both the concept of a public psychological pressure index and its calculation method, making it a fundamental work in the field of public opinion analysis. The maximum entropy principle is introduced to the social computing domain in this paper and positions it as the theoretical foundation underpinning such indexes.

INDEX TERMS Information entropy, intelligence and security informatics, public information security, public opinion analysis, public psychological pressure index, social computing.

I. INTRODUCTION

A. THE PUBLIC OPINION AND SOCIAL NETWORKS

With the emergence of Web 2.0 and the accompanying multitude of applications in the field of social networking services, a spiraling number of people are becoming increasingly accustomed to using social networks to acquire information, release messages, and express individual opinions regarding public issues and social events. Unsurprisingly, recognizing that the public opinion analysis of social network data is important, numerous experts and scholars have performed an increasing amount of research in the field [1]–[3].

In 2008, Barack H. Obama became the 44th President of the United States, which is partially attributable to the Obama campaign's excellent social networking strategy, and it helped Mr. Obama defeat John McCain and win the election. The public opinion had played an important role in the national politics [2].

The associate editor coordinating the review of this manuscript and approving it for publication was Vicente Alarcon-Aquino.

Public opinion was born when governments first appeared in human society;government and public opinion are twins. The two brothers—public opinion and human government—have depended on one another, or opposed one another, or helped one another. Their conflicts, confrontations, and mutual assistance have persevered through the various periods of human society [3]–[5].

The practical study of public opinion has a relatively long history in human society, and as long as there have been governments, they have attached great importance to public opinion. Even tyrants must know what the people are thinking, if only to oppress them more effectively [4].

In response to the 9/11 terrorist attacks, the United States government promoted the concept of Intelligence and Security Informatics, which accorded great importance to social computing methods from the field of information content security. This area of research develops intelligent algorithms that process social data scientifically and systematically to improve information gathering and content analysis related to intelligence operation. Financial transaction data, social network data, sales data, locational data, transportation data, electronic travel data and background data that are all generated by individuals in their daily lives can be used by data mining algorithms to analyze potential risks of terrorism and other large-scale events in the name of international, national, and commercial security [6].

The University of Arizona has dedicated a great deal of research to ''intelligence and security informatics (ISI)'' in the service of national security. Similarly, Carnegie Mellon University has performed similar research on events related to public health. Since 2005, the Chinese Academy of Sciences Institute of Automation has conducted ISI research [6], [39], [40].

Public opinion analysis research also belongs to the ISI field. Public opinion has become critical intelligence information in politics, economics, and in trade, finance, policy implementation and so on.

In 2010 Eric and Karrie began to pay attention to how the public emotion affected financial markets [7]. In 2011 Bollen *et al.* published a famous paper in which they apply Twitter mood series to analyze the relationship with the Dow Jones Industrial Average variances [8]. This work is very meaningful for researching the relation between public mood and the state financial market.

During the Arab Spring in 2011 [9], the social networks such as Twitter and Facebook became one of the factors in the social revolution. In particular, the intersection of social network media (including mobile apps) and conventional media (i.e., television, radio, and print) was introduced to the public. When social networks make it easier or more convenient for the public to access information, countries face inevitable social and political consequences [10]. A series of public events organized and announced through social networks led to the outbreaks of mass incidents, and some countries were caught in the political turbulence and societal chaos of these events. In the serious social crisis that ensued, the important social role of public opinion—as expressed through social networks—has come to be realized gradually by the related researchers [9]–[11].

B. THE MEASURING METHODS FOR PUBLIC OPINION

However, measuring people's opinions—and public opinion—is an important problem in this regard. Throughout history, scholars have made great efforts to study these measuring methods [4], [5]. Over the years, many governments have attempted to control and suppress public opinion. Some have gone so far as to establish secret police forces to investigate anyone who opposes the government [3]–[5]. Although the formal academic study of public opinion has only recently been considered, practical research into public opinion has a long history. Over centuries, rulers have developed a variety of methods for acquiring and measuring public opinion data, such as opinion surveys, focus groups, content analysis, telephone surveys and so forth [4], [5].

The emergence of social networks has provided a means for researchers to study public opinion using the massive amounts of data generated by these networks. In 2010, Brendan O'Connor from Carnegie Mellon University and others measured the public mood through performing sentiment analysis from social networks. Acquisition of public opinion information from social networks became a kind of important intelligence information source [11]. Using social network data in the process of public opinion analysis involves many complex interactions between researchers and these data. Quantitative measurement indexes bridge the gulf between them [3], [5], [11]. However, a technical index system has not yet been established. The concept of social computing originated in 1998 and has provided the possibility of solving the problem of quantitatively calculating public opinion [12]–[14]. However, worldwide social networks provide a better source of these data, and the development of these networks has simultaneously assisted researchers who are studying public opinion [1], [2], [11], [14].

Only when people's opinions in the social networks are measured using appropriate technical indexes can the related data processing of public opinion become meaningful. In other words, a quantitative calculation method is the precondition for the task of public opinion analysis [4]–[6].

C. THE WORK IN THIS PAPER

Social computing is one of the basic methods used in social network analysis (SNA). Currently, research into public opinion analysis for social networks is still developing, and the efficiency of public opinion analysis and processing is severely limited due to the absence of a corresponding evaluation index system [14], [15].

In this paper, an attempt to analyze the public mood series is employed to measure the public psychological pressure quantitatively, and the concept of a public psychological pressure index and its calculation method are proposed. In the field of public opinion analysis, this is an important technical index that can represent the status of public psychological pressure in relation to specific social events or topics, thus fulfilling some of the basic tasks of public opinion analysis.

The method for calculating the public psychological pressure index r is also proposed. Beginning from the index, an index system for evaluating public opinion is attempted to be established [3]–[5], [14], [15].

II. RELATED WORK

A. THE HISTORY OF PUBLIC OPINION RESEARCH

Although governments have paid enormous attention to public opinion since their inception—and both government and public opinion share the same long historical relationship with one another—formal academic research in public opinion is relatively new [5], [14], [15].

In 1931, D.D.Droba published a paper called ''Methods Used for Measuring Public Opinion'' in which he summarized five types of methods used to measure public opinion [5], [14], [15]. These methods remain the basic approaches to the study of public opinion to this day. In 1962, O.Key expounded on the relationship between public opinion and democracy [13]. In 1973, Mueller [16] published the important paper ‘‘War, Presidents, and Public Opinion’’. In this manner, the critical social role and irreplaceable social function of public opinion have come to be understood gradually [13], [14], [16]. In the present, with the worldwide proliferation of social networks, public opinion research has become even more important to governments, business entities, and so on [1], [2], [16].

B. THE ANALYSIS METHOD OF PUBLIC OPINION

1) SAMPLE SURVEY

The sample survey is a classical analytical method. Surveys are implemented in various ways including face-to-face interviews, telephone interviews, mail, and so on [4], [5], and surveys remain the most important way to learn about public opinion to this day. Some researchers even consider that survey research is the only way to learn about public opinion, and these scholars have devoted almost all their research to this approach. Even in the era of social networks, the survey sample remains the basic method of public opinion research [4], [14], [16]–[18].

2) OTHER QUANTITATIVE METHODS

Two other quantitative methods that differ from survey research—experiments and mail analysis—are introduced in [4].

a: EXPERIMENTS

In his book, Persuasion and Politics, Milburn discusses several laboratory experiments that are relevant to public opinion [17].

b: MAIL ANALYSIS

In ‘‘Mobilizing Public Opinion,’’ Katherine argued convincingly that public opinion can be found by analyzing the letters written to politicians [18].

C. THE ANALYSIS METHOD OF PUBLIC OPINION

In the era of social networks, researchers can acquire far more social data from the Internet, and social computing methods have become the basic method for analyzing public opinion [1], [2], [19].

The history of public opinion analysis shows that the main trend is to develop quantitative calculation methods for public opinion analysis [1], [2], [4], [19]. In 2010, Eric and Karrie began analyze the widespread worry in social networks about the stock market [7]. In 2011, Bollen and others carried out considerable work and attempted to analyze how public mood dimensions affect the financial market [8]. With the development of research on public mood analysis in social networks, the related researchers attempted to extract the Anxiety Index on financial markets from social networks [20].

Currently, analyzing public opinion using social networking data has become the main approach [1], [2].

III. THE PSYCHOLOGICAL PRESSURE

A. THE CONCEPT OF PSYCHOLOGICAL PRESSURE

In 1936, Hans Selye published a famous paper titled ‘‘A Syndrome Produced by Diverse Nocuous Agents’’, subsequently proposing the distinct concept of psychological pressure that ushered in the rapid development of related research [21].

Psychological pressure refers to mental stress that is a kind of syndrome that emanates from a pessimistic mood. Mental stress can be described as a sustained, nervous and comprehensive mental state that develops as an individual responds to stressors in practical living [22]–[24].

Based on the related research of psychological pressure [21]–[25], a clearer definition is as follows:

Psychological pressure is the psychological process by which environmental factors overtax control systems in an individual, thus activating responses whose effects are prolonged and ultimately detrimental to that individual [21]–[23].

Another type of description of psychological pressure is as follows [23], [25]:

Psychological pressure is mental stress that is a kind of syndrome brought about by the pessimistic sentiments.

Consequently, the expression of psychological pressure for people in society is mainly due to some kind of pessimistic mood [21]–[25].

B. THE SOCIAL FUNCTION OF PSYCHOLOGICAL PRESSURE

Psychological pressure is a mental pressure [25], and people in society in a normal mental state need to have a certain psychological pressure. Psychological pressure is a kind of intellectual impetus that has helped people engage in the major sustaining activities and industries of mankind. Moreover, if people lose psychological pressure, then a worsened mental state will occur—emptiness, and it is a kind of unhealthy and dangerous state of mind [21], [22].

With the development of the related research about psychological pressure, its social function has caught the attention of many researchers.

Importantly, normal people in society must master a certain extent of psychological pressure according to the related psychology research [23], [24], which can help them to engage in routine business. However, massive psychological pressure can exert negative effects on social development, and even result in social unrest [9], [10].

C. THE PSYCHOLOGICAL PRESSURE IN SOCIAL NETWORKS

Social networks have become the place where people in society present their comments, which includes many sentiments such as happiness worry, dread, and so on [26]. These sentiments constitute the mapping of public psychological pressure according to social computing [12]. In public opinion analysis, the calculation for the public psychological pressure is a vital task. After the concept of social computing was proposed, the quantitative calculation for the public psychological pressure became possible [15].

Nevertheless, determining how to compute the psychological pressure in social networks is a critical issue. Based on the thinking that underlies social computing, in this paper, a particular computing method for public psychological pressure in social networks is proposed.

IV. THE PUBLIC PSYCHOLOGICAL PRESSURE INDEX FOR SOCIAL NETWORKS

A. THE FORMATION OF PUBLIC SENTIMENTS

With the worldwide adoption of social networking, public opinion can be expressed and formed more rapidly than ever before by users who post their views concerning specific social events or hot topics on social network sites [1], [2]. Such public opinion events may be an important political event such as a presidential election, a natural disaster such as an earthquake, implementation of a national policy (such as health care reform), or a sudden disaster such as environmental pollution, and so on [1], [3], [10]. The formation of public mood is as shown in Fig.1.

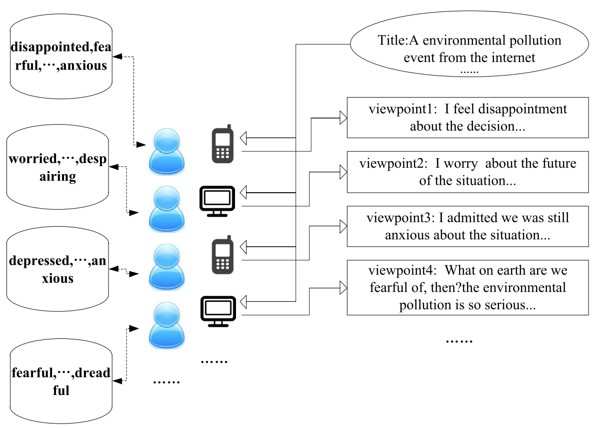

FIGURE 1. The formation of public mood.

In a modern social context, almost every national government is inclined to obtain information regarding public opinion through social networks. In recent years, public opinion analysis of social networks has become an important research field [1], [2], [6], [8], and it has wide applications. In particular, in cyberspace security, public information security is considered part of national security [6], [8]. During the Arab Spring (from 2010 to 2012), the impact of public opinion expressed through social networks shocked the entire world. In fact, during the Arab Spring, people begin to realize the importance of public opinion analysis in the social network era. Thus, it seems as if public opinion has acquired a more critical social role in the Internet era [9], [10].

B. THE PUBLIC PSYCHOLOGICAL PRESSURE IN THE SOCIAL NETWORKS

Fig.1 shows the formation of public sentiments regarding a specific social event in social networks. Individuals' posts on social networks contain a variety of viewpoints, sentiments, attitudes, and so on. Specifically, the rich emotional expressions concerning some social issues objectively reveal the psychological pressures of the public in response to a specific event [22], [23], [25]. Substantial amounts of pessimistic sentiments are expressed in social networks. According to the concept of social computing, these pessimistic sentiments are the map of public psychological pressure in social networks [12], [15].

When researchers analyze public opinion concerning a specific social event such as an environmental pollution event, they want to measure the psychological pressures of the public so that policymakers can take corresponding countermeasures. Consequently, determining how to measure pessimistic public sentiments concerning a social event has become a critical problem, and a corresponding technical indicator is required.

C. PUBLIC SENTIMENT ANALYSIS IN SOCIAL NETWORKS

1) THE RELATED RESEARCH OF PUBLIC SENTIMENT ANALYSIS

Millions of people express their opinions on social networks, making it a valuable data source for the analysis of public sentiment, which has led to the emerging fields of opinion mining and sentiment analysis [27]–[30].

In recent years, a number of studies have explored information retrieval and knowledge discovery from texts using data mining and natural language processing from social networks; they have provided the possibility for us to measure public psychological pressure from social networks [28]–[30]. However, because the related assessment indexes are missing, the efficiency of information analysis and processing for public opinion analysis is severely limited.

2) THE STRUCTURE OF PESSIMISTIC PUBLIC SENTIMENTS

There are nine primary types of moods that represent different degrees of pessimistic sentiments with regard to an incident in social networks: depression, disappointment, fear, worry, panic, anxiety, dread, indignation, and despair.

The classification structure for these pessimistic public sentiments in social network comments is shown in Fig.2

D. THE MATHEMATICAL MODEL OF THE PESSIMISTIC PUBLIC SENTIMENTS

1) THE PROBABILITY THEORY BASIS FOR THE MATHEMATICAL MODEL

According to classical probability theory, real-valued functions defined on the sample space are known as random variables, denoted by X [31].

A set of all possible outcomes of an experiment is known as the sample space of the experiment and is denoted by S.

Suppose that our experiment consists of tossing 3 fair coins. If we let X denote the number of heads that appear, then X is a random variable taking on one of the

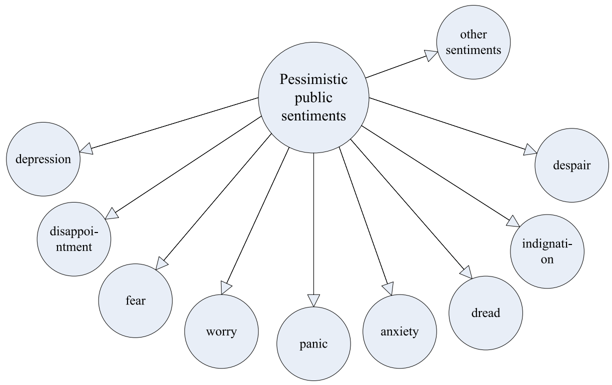

FIGURE 2. The structure of pessimistic public sentiments.

values 0, 1, 2, and 3 with respective probabilities [31].

$$\mathrm{P}\{X=0\} = \mathrm{P}\{(\mathrm{T},\mathrm{T},\mathrm{T})\} = \frac{1}{8},$$
$$\mathrm{P}\{X=1\} = \mathrm{P}\{(\mathrm{T},\mathrm{T},\mathrm{H}), (\mathrm{T},\mathrm{H},\mathrm{T}), (\mathrm{H},\mathrm{T},\mathrm{T})\} = \frac{3}{8},$$
$$\mathrm{P}\{X=2\} = \mathrm{P}\{(\mathrm{T},\mathrm{H},\mathrm{H}), (\mathrm{H},\mathrm{T},\mathrm{H}), (\mathrm{H},\mathrm{H},\mathrm{T})\} = \frac{3}{8},$$
$$\mathrm{P}\{X=3\} = \mathrm{P}\{(\mathrm{H},\mathrm{H},\mathrm{H})\} = \frac{1}{8}.$$

A random variable that can take on at most a countable number of possible values is said to be discrete [31]. For a discrete random variable X, we define the *probability mass function* $p(x)$ of X by

$$p(x) = P\{X = x\} \tag{1}$$

According to Shannon information theory

$$H(X) = -\sum_{x} p(x) \log p(x) \tag{2}$$

The capability of quantitatively calculating the information is an important scientific advance [31]–[33].

2) THE RELATED RESEARCH OF PUBLIC SENTIMENT ANALYSIS

Based on Fig.2, the mathematical model is described as follows.

Assume that the discrete random variable X represents the "pessimistic public sentiments" such that X_1 represents "depression", X_2 represents "disappointment", X_3 represents "fear", X_4 represents "worry", X_5 represents "panic", X_6 represents "anxiety", X_7 represents "dread", X_8 represents "indignation", X_9 represents "despair", X_{10} represents "other sentiments", where $X \sim (X_1, X_2, \ldots, X_{10})$, and $(X_1, X_2, \ldots, X_{10})$ is a multivariate random variable.

Furthermore, assume that the domain of X is U, and the probability distribution is $p(x)$; the domain of $X_1, X_2 \ldots$, and X_{10} are $U_1, U_2 \ldots$, and U_{10}, respectively;and the probability distributions are $p_1(x), p_2(x), \ldots$, and $p_{10}(x)$, respectively.

Therefore, the entropy function H of X as follows can be obtained [32]:

$$H(X) = -\sum_{x} p(x_1, x_2, \ldots, x_{10}) \log p(x_1, x_2, \ldots, x_{10}) \tag{3}$$

Suppose that the entropy of the pessimistic public sentiments in social networks about an incident is r in a single day.

The definition of public psychological pressure index:

The *public psychological pressure* entropy H is an important assessment quantitative indicator for public opinion analysis. According to formula (1), the definition of public psychological pressure index r for social networks is

$$r = H(X) \tag{4}$$

V. THE CALCULATION METHOD OF R

A. THE RELATED RESEARCH

Eric and Karrie analyzed the relation between the worry mood and the stock market, and the Anxiety Index on the financial markets from the social networks was proposed [7]. Bollen *et al.* applied the public mood series to analyze the relation between the Dow Jones Industrial Average (DJIA) [8], [20], and applied the original six individual dimension of mood data to analyze the specific issue. Their works are meaningful for the related research of public mood analysis.

In this paper, the mathematical modeling for pessimistic public sentiments is performed, and the concept of public psychological pressure index r for social networks is subsequently proposed. The index r can be used to measure public psychological pressure in social networks, and it can serve as the universal assessment index for public opinion analysis.

B. THE CALCULATION METHOD BASED ON THE PRINCIPLE OF MAXIMUM ENTROPY

Because $X \sim (X_1, X_2, \ldots\ldots, X_{10})$ according to the mathematical model of the pessimistic public sentiments for Fig.2, the probability distribution function is unknown;therefore, the entropy calculation method is an uncertain issue in social computing.

Here, the procedure for solving the calculation method is as follows.

Suppose that X is a discrete random variable whose range $R = \{x_1, x_2, \ldots, x_n\}$ is finite and countable. Let $p(x_i) = P\{X = x_i\}$; the corresponding probability value is then $p_1, p_2, \ldots, p_i, \ldots, p_n$ and the necessary and sufficient condition is then $p_1 = p_2 = \ldots = p_n = \frac{1}{n}$[33].

Proof: Because $\sum_{i=1}^{n} p_i = 1$, according to the Lagrange multiplier, we attempt to solve the probability distribution under the maximum entropy constraint condition $\sum_{i=1}^{n} p_i = 1$,

$$F(p_1, p_2, \ldots, p_n) = -\sum_{i=1}^{n} p_i \ln p_i + \lambda \left(\sum_{i=1}^{n} p_i - 1 \right)$$

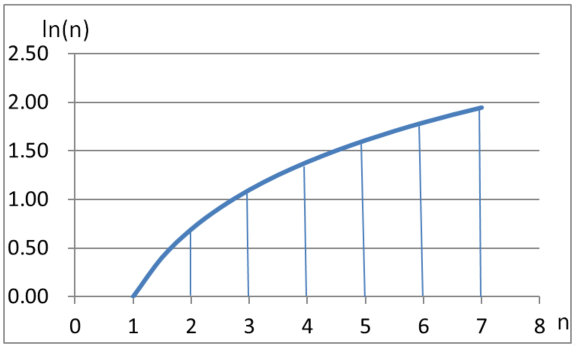

FIGURE 3. The monotonic behavior of the entropy function $H(x) = \ln(n)$.

Based on the necessary condition for obtaining the maximum,we take the partial derivative of p_i to obtain the equation set.

Thus, we would have

$$\frac{\partial F}{\partial p_i} = -\ln p_i - 1 + \lambda = 0, \quad i = 1, 2, \ldots, n.$$

To solve this, $p_i = exp\,(\lambda - 1)$, and p_i is a constant.

According to the constraint condition $\sum_{i=1}^{n} p_i = 1$, we know that $np_i = 1$; that is, $p_i = 1/n$.

Therefore, the entropy function would be

$$H(x) = -\sum_{i=1}^{n} \left(\frac{1}{n}\right) \ln\left(\frac{1}{n}\right) = \ln(n)$$

The conclusion is that

$$H(x) = \ln(n) \tag{5}$$

The entropy calculation formula for multidimensional random variables is similar to that of a one-dimensional random variable.

The calculation of the social event information content is a maximum entropy problem in which the constraint condition is $\sum p(x_1, x_2, \ldots, x_n) = 1$. Consequently, its entropy function form is similar to that of a one-dimensional random variable in which the information entropy value can be any positive number.

When the entropy function is maximized, the joint probability distribution is the uniform probability distribution [33].

$$\begin{aligned} H&(X_1, X_2, \ldots, X_n) \\ &= -\sum_{x} p(x_1, x_2, \ldots, x_n)\, logp\,(x_1, x_2, \ldots, x_n)\,, \\ &= -logp\,(x_1, x_2, \ldots, x_n) \end{aligned}$$

therefore,

$$H(X) = -\sum_{x} p(x_1, x_2, \ldots, x_n)\, logp\,(x_1, x_2, \ldots, x_n)$$

According to maximum entropy theory, entropy is derived as follows.

Suppose that q_i represents the number of times of X_i after obtaining the values. When X_i obtains its value from its value domain once, $q_i = 1$, as shown in Table 1.

TABLE 1. Values of subvariables.

X_i	X_1	X_2	……	X_n
q_i	q_1	q_2	……	q_n

In other words,the entropy function of social multidimensional random variables can be described by the following formula

$$H(X_1, X_2, \ldots, X_n) = \log\left(\prod_{i=1}^{n} q_i\right) \tag{6}$$

According to formula (4), the calculation formula of public psychological pressure index r for social networks is

$$r = \log\left(\prod_{i=1}^{10} q_i\right) \tag{7}$$

Here, $n = 10$.

VI. EXPERIMENTS AND RESULTS

Here,9 typical public events are selected that occurred within a brief timespan in China with the calculation of the corresponding public psychological pressure index of each.

The experimental data show the variations of the public psychological pressure over 30 days. Moreover, the public psychological pressure indexes of different types of events can be compared with one another.

A. THE DATA USED IN THE EXPERIMENTS

From July 2012 to August 2012, a number of important public events occurred that garnered a certain amount of attention in Chinese social networks. These events are listed in Table 2.

TABLE 2. Public events.

Sequence number	Event	Time
1	The 7/21 rainstorm in Beijing.	2012.7.21
2	Japan began the procedure to nationalize the Diaoyu Islands.	2012.7.24
3	A Japanese company discharged carcinogenic sewage into Nantong city, Jiangsu Province.	2012.7.25
4	Sansha city in Hainan Province unveiled a plaque.	2012.7.25
5	Nanshan milk powder was found to contain strong carcinogens in Hunan province.	2012.7.25
6	A flight was forced to make an emergency landing because of a smoking engine.	2012.7.25
7	Neusoft Group's trade secrets were leaked.	2012.7.25
8	The public prosecution of the Bogukailai criminal case began.	2012.7.27
9	A 3.3-magnitude earthquake occurred in Dali, Yunan Province.	2012.7.27

The corresponding social media comments concerning these events were collected from social networks over a 30-day period. There are 285,876 public comments in the text corpus. These comments tended to be highly integrated and

TABLE 3. Event 1.

Time(day)	No.1	No.2	No.3	No.4	No.5	No.6
Number	1572	1795	1837	1936	1846	2305
…	…	…	…	…	…	…
Time	No.25	No.26	No.27	No.28	No.29	No.30
Number	441	382	321	309	331	341

TABLE 4. The classification rules.

Mood category template	Feature elements
Depression_mod	{'哎(ai)', '郁闷(depressed)', '咋这样(why such)', '真够呛(really tough)', '难过(sad)','啥素质(poor qualities)','唉(ai)','丢人(shame)', '真差(really bad)', '差劲(the synonym of 'bad')', '啥人性(the synonym of 'bad')', '真垃圾(the synonym of 'bad')', '真次(the synonym of 'bad') ',…}
Disappointment_mod	{'不尽如人意(unsatisfactory)','有待提高(should improve)',不行(not good)','这样不行(the synonym 'not good')','失望(Disappointed)','真不行(really not good)','够呛(the synonym of 'not good')','质量不行(poor quality)','品质低(the synonym of 'poor quality ')','素质差(the synonym of ' poor quality ')',…}
Fear_mod	{'我怕(I'm afraid)','恐怕(fear)',我怕会(be afraid to)','唯恐(the synonym of ' fear ')','担心(worry)',' 难过极了(very sad)','够呛(the synonym of 'not good')','完了(the synonym of 'not good)' ,…}
Worry_mod	{'令人担忧(most worrying)','不容乐观(not optimistic)','怕是(worry about)','担心(worry)','会受批评的(will be criticized)','忧虑情绪(get worry)','感到忧虑(feel worried)',…}
Panic_mod	{'大吃一惊(amaze)','令人惊讶(surprise)','惊恐万分(terrified)','头要炸了(the synonym of 'amaze')','超级郁闷(super upset)','咋成这样了(the synonym of 'amaze')','我的妈呀(the synonym of 'amaze')','令人头疼(the synonym of 'amaze')'…}
Anxiety_mod	{'情绪焦虑(anxious)','心急如焚(the synonym of 'anxious')','让人昏倒(the synonym of 'anxious')','狂晕(the synonym of 'anxious')','憋闷(the synonym of 'anxious')','无语(the synonym of 'anxious')','低劣透顶(the synonym of 'anxious')','感到难过(feel terrible)',…}
Dread_mod	{'可怕(dread)','恐惧(the synonym of 'dread')','惧怕(the synonym of 'dread')','令人心怕(feel dreadful)','恐慌(the synonym of 'dread')','惊慌失措(the synonym of 'dread')','头疼(the synonym of 'dread')','恐怖(the synonym of 'dread')','感到恐怖(dreadful)','惊骇(the synonym of 'dreadful')','令人惊骇(the synonym of 'dreadful')',…}
Indignation_mod	{'义愤填膺(indignant)','激于义愤(the synonym of 'indignant')','令人气愤(the synonym of 'indignant')','愤慨(the synonym of 'indignant')','极其气愤(the synonym of 'indignant')','令人发指(the synonym of 'indignant')',…}
Despair_mod	{'绝望(desperate)','彻底完了(all up)','输定了(must lost)','崩溃(collapse)','无法忍受(unbearable)','难受死了(the synonym of ' unbearable ')','没希望(beyond hope)','灭绝人性(inhuman)',…}

traditional with abundant emotional coloring. For example, the number of comments collected over 30 days for Event 1 is shown in Table 3.

B. THE IMPLEMENTATION OF THE CLASSIFICATION ALGORITHM

To finish the text classification task, the corresponding 9 text classification feature templates must be constructed based on the classification rules.

The Chinese language has its own outstanding characteristics. The social networking users present their viewpoints using some sentiment words, interjection, modal particles, or colloquial language [34]. The text-trained corpus is the text comments in Chinese social networks. The rule acquisition is executed according to the trained corpus and the domain expert knowledge, as shown in Table 4 .

The classification algorithm is implemented based on these rules in Table 4, and this kind of supervised classification method has merits in mass data processing [1], [28]. The rule-based classification algorithm uses a set of "if...Then..." statements to combine these rules to form the execution structure, as follows in Fig.4 [35], [36].

$$
\begin{aligned}
&if \cdots then \cdots\\
&elseif \cdots then \cdots\\
&\cdots\\
&elseif \cdots then \cdots\\
&else \cdots
\end{aligned}
$$

FIGURE 4. The execution structure of the rule-based classification algorithm.

TABLE 5. The comments about the Event 1.

Sequence number	Social networks comments
…	…
0636	"哎，某些人在这次暴雨灾难中的表现令人气愤，其作法使国人极度愤慨，趁火打劫的作法简直让人无语，其素质简直让人疯掉；同时支持国家政府在这一事件中的态度，这才是大国风范，众志成城，共度难关，同时保持发展才是硬道理，加强基础设施建设，不要再让人失望，避免类似悲剧再次发生。"
…	…
0920	"真让人崩溃，城市下场雨，竟然淹死这么多人，更让人无法忍受的是人的素质，令人发指，不去救人，反而趁机涨钱，宰客。灾害是很可怕，但没人性更可怕。要是中国人都这样，那这个民族就没希望了。反而一些农民工让人看到了希望，参与到救灾中，必须赞扬一下！"
…	…
1325	"下大雨就能淹死人，北京这城市排水系统也太差了，比这更差的是北京的出租车司机，本来应该抓紧救人，他们却涨价，这人品素质真够呛，有待提高，唉,担心。差劲，最近总下雨，恐怕还会出事故"
…	…

```
>>> str
'哎    某些  人  在  这次  暴雨  灾难  中  的  表现  令人  令人气愤  人气  气
愤    心情  郁闷    其  作法  使  国人  人极  极度  愤慨    趁火打劫  打劫
 的  作法  简直  让  人  无语    其  素质  简直  让  人  疯  掉    同时  支
持  国家  家政  政府  在  这  一事  事件  中  的  态度    这  才  是  大国  国
风  风范    众志成城  志成  成城    共度  难关    同时  保持  发展  才  是
 硬道理  道理    加强  基础  基础设施  设施  建设    避免  类似  悲剧  再次
 再次发生  发生'
```

FIGURE 5. The word segmentation for comment 0636 of event 1.

```
>>> text_need_match
['哎', '某些', '人', '在', '这次', '暴雨', '灾难', '中', '的', '表现', '令人', '令人气愤', '人
气', '气愤', '心情', '郁闷', '其', '作法', '使', '国人', '人极', '极度', '愤慨', '趁火打劫', '
打劫', '的', '作法', '简直', '让', '人', '无语', '其', '素质', '简直', '让', '人', '疯', '掉',
'同时', '支持', '国家', '家政', '政府', '在', '这', '一事', '事件', '中', '的', '态度', '这', '
才', '是', '大国', '国风', '风范', '众志成城', '志成', '成城', '共度', '难关', '同时', '保持',
'发展', '才', '是', '硬道理', '道理', '加强', '基础', '基础设施', '设施', '建设', '避免', '类似
', '悲剧', '再次', '再次发生', '发生']
```

FIGURE 6. The list data type for comment 0636 of event 1.

```
>>> part_of_Depression_mod
['哎', '郁闷', '咋这样', '真够呛', '难过', '啥素质', '唉', '丢人', '真差', '差劲', '啥人性', '
真垃圾', '真次', '…']
```

FIGURE 7. The part of depression_mod.

The comments about the Event 1 "The 7/21 rainstorm in Beijing." on Day 1 are listed in Table 5, and the English versions are listed in the Appendix.

First, the natural language processing system based on Python 3 is built [37]. The social networks comments are divided into words using the jieba module, as shown in Fig.5.

Second, the list data type can be obtained, as shown in Fig.6.

Third, the "text_need_match" list is matched with the mood category templates in Table 4.

The classification algorithm is executed as follows.

Algorithm 1 Rule-Based Classification Algorithm

1: construct the classification rule
2: build the Rule set R
3: Read in text dataset C_i ($1 \leq i \leq n$)
4: Read in Rule set R_j($1 \leq j \leq m$)
5: For the text i in sets C_i
  For R_j in R
    If text i accord with Rule j
      If score > r
      the text i in Rule j
    build category(k)
6: Output the category(k) ($1 \leq k \leq \sum j$+1)
7: Return

The loop pattern matching operation is performed with the "Mood category template" in Table 4. After the three comments (sequence numbers: 0636, 0920, and 1325) are processed by the classifier, the corresponding match items can be obtained, as listed in Table 6.

TABLE 6. The pattern matching items.

Mood category	the items
X_1: depression	'哎', '唉','差劲'
X_2: disappointment	'失望'
X_3: fear	'恐怕','够呛'
X_4: worry	'担心'
X_5: panic	
X_6: anxiety	
X_7: dread	'可怕', '可怕'
X_8: indignation	'令人气愤' , '愤慨', '令人发指'
X_9: despair	'灭绝人性', '崩溃'
X_{10}: other sentiments	

The rule-based classifier has a better cover rate and accuracy rate; the cover rate and the accuracy rate of the rule-based classifier in the corpus are listed in Table 7.

TABLE 7. The cover rate and accuracy rate.

cover rate		73.3%
accuracy rate		70.2%

Subsequently, the data in corpus for these comments were processed.

C. THE CALCULATION AND ANALYSIS OF PUBLIC PSYCHOLOGICAL PRESSURE INDEX R

The statistical totals of the pessimistic public sentiments on Day 1 for event 1 are shown in Table 8.

Thus, the public psychological pressure r1 of the public Event 1 on the first day can be calculated as follows according to formula (5).

TABLE 8. Pessimistic public sentiments on day 1 for Event 1.

X	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
q_i	786	846	935	772	857	1056	895	1047	668	1

$$\begin{aligned} r_1 &= \ln(q_1\, q_2 \ldots q_9\, q_10) \\ &= \ln(786^*846^*935^*772^*857^*1056^*895^*1047^*668^*1) \\ &= 60.87 \end{aligned}$$

Similarly, the values of the public psychological pressure index r_1 over 30 days are shown in Table 9.

TABLE 9. The public psychological pressure index of Event 1.

Time(day)	No.1	No.2	No.3	No.4	No.5	No.6
r_1	60.87	62.09	61.73	62.35	62.38	63.71
…	…	…	…	…	…	…
Time	No.25	No.26	No.27	No.28	No.29	No.30
r_1	49.85	49.77	49.47	49.03	49.29	49.42

Thus, the public psychological pressure indexes of all the public events can be calculated from Event 1 to Event 9, as shown in Table 10.

TABLE 10. The public psychological pressure index of 9 events.

Time(day)	No.1	No.2	No.3	No.4	No.5	No.6
r_1	60.87	62.09	61.73	62.35	62.38	63.71
r_2	68.58	70.90	73.57	70.06	74.89	68.57
r_3	53.54	54.89	56.36	54.24	52.63	50.05
r_4	49.65	50.35	51.01	48.36	47.05	45.67
r_5	50.31	50.21	50.93	49.37	48.77	48.01
r_6	49.47	48.72	43.09	37.74	29.02	23.41
r_7	43.62	41.72	37.12	35.03	29.58	23.32
r_8	64.66	65.74	65.02	67.79	69.51	67.36
r_9	42.78	42.03	35.95	31.45	23.75	19.28
…	…	…	…	…	…	…
Time(day)	No.25	No.26	No.27	No.28	No.29	No.30
r_1	49.85	49.77	49.47	49.03	49.29	49.42
r_2	61.63	61.06	59.05	58.91	58.36	58.88
r_3	40.82	41.02	40.93	40.21	39.78	40.61
r_4	35.05	34.05	34.83	33.66	34.83	33.40
r_5	38.63	38.31	38.22	37.11	37.56	37.26
r_6	17.69	13.38	17.36	17.76	17.22	13.51
r_7	15.27	12.16	15.13	15.82	12.32	13.23
r_8	63.83	62.86	63.94	62.52	63.57	62.54
r_9	10.43	13.57	12.25	10.63	12.67	13.85

Using those data, the tendency of public psychological pressure over 30 days can be described, as shown in Figs.8–10.

The r values for Event 1, Event 2, and Event 8 are shown in Fig. 8, making them easy to compare. Notably, they have similar tendencies.

Event 1, "*the rainstorm that occurred on 7/21 in Beijing*"—was one of the worst natural disasters that China experienced in 2012. Some 79 people died in the storm:approximately 10,660 houses collapsed,1.602 million

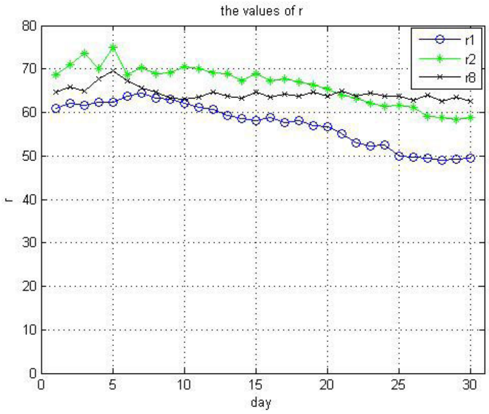

FIGURE 8. The r values for event 1, event 2, and event 8.

people were affected by the disaster, and the economic losses reached 11.64 billion CHY.

Analysis of the data from social network comments showed that the public experienced high psychological pressure (r_1) from this event.

Event 2, "*Japan started the procedure to nationalize the Diaoyu Islands*" is a significant international relations event that attracted wide attention—particularly because the Japanese Prime Minister, Yoshihiko Noda, claimed that if the Diaoyu Islands were attacked he would consider using Japan Self-Defense Forces. This announcement regarding the Diaoyu Islands led to widespread comments on social network sites. The result of calculating the public psychological pressure index r_2 illuminates the situation. After Yoshihiko Noda publicly presented his political views, the r_2 value reached its maximum.

As Fig.9 shows, the values of r_3, r_4, and r_5 over 30 days corresponding to Event 3, Event 4, and Event 5, respectively, are similar, and the tendencies of r_3, r_4, and r_5 are also similar.

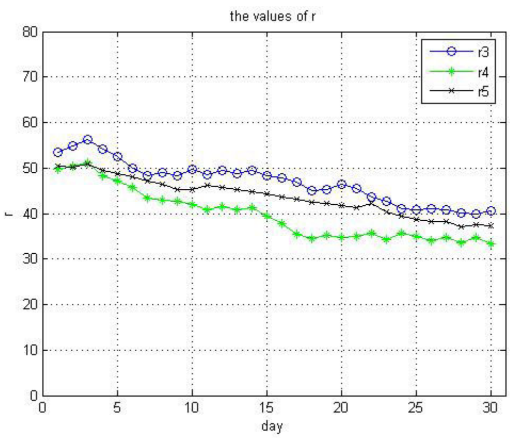

FIGURE 9. The r values for event 3, event 4, and event 5.

Event 3 "*A Japanese company discharged carcinogenic sewage into Nantong city, Jiangsu Province*" was a public health event that involved the release of carcinogenic substances into the public sewage system. Such pollution events are among the most sensitive public topics. However, the event involved only one small city (Nantong), whose national influence is quite limited. Therefore, the corresponding values of the public psychological pressure index, r_3, are medium, as shown in Fig.9.

Event 8 "*The public prosecution of the Bogukailai criminal case*" is a famous trial that also attracted wide attention. In response, the public exhibited an even higher psychological pressure index.

Event 4, "*Sansha city in Hainan Province unveiled a plaque*" was a public event that involved important international relations, specifically, the political situation in the South China Sea. The public exhibited a certain level of psychological pressure, and the values of r_4 are shown in Fig.9.

Event 5 "*Nanshan milk powder was found to contain strong carcinogens in Hunan province*" is similar to Event 3. The r_5 values represent the psychological pressure shown by the public for this specific public health event, as shown in Fig.9.

Fig. 10 shows that the values of r_6, r_7, r_9 over 30 days have similar tendencies.

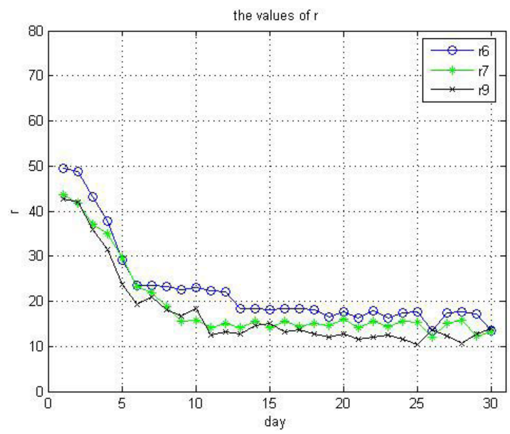

FIGURE 10. The r values for event 6, event 7, and event 9.

The trend of r_6 based on Event 6 is similar to r_7, which is based on Event 7. The influential scopes of the two events are not wide, and the results are also not serious.

Event 9 was one of the natural disaster events of China in 2012, but there were no casualties in the earthquake event, and losses in this small earthquake were minor. Accordingly, public psychological pressure is not particularly great, as shown in Fig.10.

When a serious public event such as "*North Korea's third nuclear test*" (January 24,2013) occurs, the public psychological pressure index r may be greater than the r for other events that occur during the same period, as shown in Fig. 10. As Fig.11 shows, the public psychological pressure index r_{10} remained very high throughout the 30-day study period.

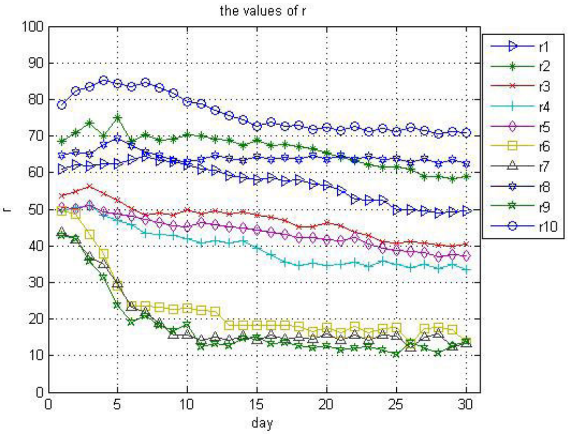

FIGURE 11. Comparison of *r* values for events 1–10.

Using a graph of the psychological pressure indexes for the 10 events over 30 days, it can be seen that the changing trends of r belong to distinctly different types of events, as shown in Fig.11.

When the values of the public psychological pressure index r of a public event remain high over an extended period of time, the relevant government agencies or companies must have a way to address these challenging crises to avoid even more serious consequences. In particular, mass public protests such as parades, demonstrations, public assemblies, and so on should be prevented from occurring; otherwise, the societal losses can become serious.

During the Arab Spring [9], [10], a series of public events promoted through social networks led to outbreaks of mass public protests and resulted in further collapses of the governments in many countries [10], [15].

D. ANALYSIS OF COMPUTATIONAL ACCURACY

The computational accuracy of the corresponding calculation method is very important. Here, the experimental data of event 1 in the dataset are selected, as shown in Table 1. The total number of comments about event 1 is 1,871 in the first day, and the first sampling is 1,572. Because the sampling is based on a random algorithm and some strict rules, at every time point, the sample varies.

The collected dataset is sampled 10 times, as shown in Table 11 . According to formula 5, calculation of the 10 samplings is done. The results of the computation are shown in Table 11.

To describe the computational accuracy of the numerical characteristics of the computation results shown in Table 12, the mathematical statistics method is applied.

Suppose $\bar{r}$ is the value of expectation, and δ is the maximum deviation. Here,

$$\bar{r} = \frac{r_{10} + r_{11} \ldots + r_{19}}{10}, \quad and\ \delta = \max_{0 \le i \le 9}(|r_{1i} - \bar{r}|).$$

The following formula can show the computational accuracy m of the corresponding calculation method,

$$m = \frac{\delta}{\bar{r}}\% \tag{8}$$

TABLE 11. The public psychological pressure index of Event 1.

Time (days)	No. 1	No. 2	No. 3	No. 4	No. 5	No. 6
r_{10}	60.87	62.09	61.73	62.35	62.38	63.71
r_{11}	61.09	62.43	61.82	62.56	62.76	63.92
r_{12}	60.62	62.16	61.65	62.16	62.24	63.59
r_{13}	60.67	61.95	61.53	62.17	62.25	63.66
r_{14}	60.74	62.13	61.57	62.22	62.31	63.68
r_{15}	61.05	62.42	62.06	62.63	62.71	63.96
r_{16}	60.64	61.82	61.62	62.54	62.63	63.72
r_{17}	61.07	62.35	61.93	62.54	62.68	63.93
r_{18}	60.73	62.16	61.87	62.30	62.27	63.52
r_{19}	61.06	62.37	62.03	62.54	62.62	63.82
…	…	…	…	…	…	…
Time (days)	No. 25	No. 26	No. 27	No. 28	No. 29	No. 30
r_{10}	49.85	49.77	49.47	49.03	49.29	49.42
r_{11}	50.03	50.01	49.74	49.33	49.43	49.66
r_{12}	49.73	49.72	49.25	48.83	49.09	49.23
r_{13}	49.78	49.79	49.38	48.93	49.08	49.24
r_{14}	49.62	49.63	49.29	48.91	49.17	49.53
r_{15}	50.08	50.03	49.63	49.28	49.44	49.63
r_{16}	49.66	49.68	49.24	48.89	49.14	49.33
r_{17}	50.03	50.03	49.81	49.24	49.45	49.64
r_{18}	49.63	49.71	49.23	48.83	49.33	49.23
r_{19}	50.02	50.01	49.67	49.24	49.43	49.51

TABLE 12. $\bar{r}$, δ, m of Event 1 in 30 Days.

Time (days)	No. 1	No. 2	No. 3	No. 4	No. 5	No. 6
$\bar{r}$	60.85	62.19	61.78	62.40	62.49	63.75
δ	0.23	0.24	0.28	0.23	0.27	0.23
m	0.38%	0.39%	0.45%	0.37%	0.43%	0.36%
…	…	…	…	…	…	…
Time (days)	No. 25	No. 26	No. 27	No. 28	No. 29	No. 30
$\bar{r}$	49.84	49.84	49.44	49.05	49.29	49.42
δ	0.24	0.21	0.21	0.22	0.21	0.22
m	0.48%	0.42%	0.42%	0.45%	0.43%	0.44%

Here, the computational accuracy is analyzed based on the computation results. In the calculation, the sampling is based on a stricter selected condition. The computational accuracy is $99.29\% \le \theta \le 99.64\%$, and the calculation has a better accuracy.

E. THE COMPUTATION OF THE Z-SCORE

Johan Bollen, Huina Mao, and Xiaojun Zeng proposed a method to calculate the index z-scores in their famous paper "Twitter Mood Predicts the Stock Market", and they attempted to predict financial market trends [8]. A very important academic viewpoint in their paper is that critical social intelligence information can be obtained through the analysis of social data from social networks and other social data sources. After obtaining the data dimension, they applied the normalization method to make all time series fluctuate around a zero mean [8], [20]. This data processing method has its merits, and it is useful for subsequent contrast experiments in their paper.

In this paper, a calculation method of the public psychological pressure index for social networks is proposed. The experiments in this work show that the calculation method

TABLE 13. The Z-Scores of the public psychological pressure index of 9 events.

Time (day)	No. 1	No. 2	No. 3	No. 4	No. 5	No. 6
z-score(r_1)	0.84	0.64	0.39	1.12	-0.53	0.81
z-score(r_2)	1.08	0.61	0.51	-0.42	1.74	0.95
z-score(r_3)	0.82	0.34	0.55	0.53	0.14	-0.42
z-score(r_4)	0.86	0.68	0.54	0.17	0.03	-0.08
z-score(r_5)	0.87	0.64	0.48	0.09	0.05	0.00
z-score(r_6)	1.07	0.96	0.62	0.12	-0.72	-0.72
z-score(r_7)	1.07	0.86	0.51	0.23	-0.01	-0.34
z-score(r_8)	0.83	0.61	0.34	0.79	1.83	0.60
z-score(r_9)	1.10	1.00	0.58	0.06	-0.42	-1.26
…	…	…	…	…	…	…
Time (day)	No. 25	No. 26	No. 27	No. 28	No. 29	No. 30
z-score(r_1)	-0.64	-0.41	-0.40	-1.43	-0.23	1.19
z-score(r_2)	0.36	0.47	-0.66	-0.42	-0.64	0.92
z-score(r_3)	-0.59	0.09	0.68	-0.78	-1.47	0.91
z-score(r_4)	0.43	-0.91	0.42	-0.92	1.43	-0.72
z-score(r_5)	-0.35	-0.20	0.20	-1.10	-0.02	-0.35
z-score(r_6)	0.58	-2.35	0.56	0.99	1.04	-0.83
z-score(r_7)	0.36	-1.55	0.61	1.41	0.92	-0.22
z-score(r_8)	0.47	-1.15	1.16	-0.49	1.06	0.03
z-score(r_9)	-1.42	1.53	0.08	-1.33	0.28	1.69

in this paper is a better method for calculating the public psychological pressure index for social networks.

The z-scores can describe the relative fluctuation degree of one data dimension within a sliding window of k days before and after the particular date.

The z-score of time series X_t, denoted Z_{X_t}, is defined as [9]:

$$Z_{X_t} = \frac{X_t - \bar{x}(X_{t\pm k})}{\sigma(X_{t\pm k})} \tag{9}$$

where $\bar{x}(X_{t\pm k})$ represents the mean, and $\sigma(X_{t\pm k})$ represents the standard deviation of the time series within the period $[t-k, t+k]$. Here, $k = 3$ is selected, and the time period is a week (this is a reasonable selection, and the sliding window is relatively wider). The z-scores of the public psychological pressure index of 9 events are calculated, as shown in Table 13.

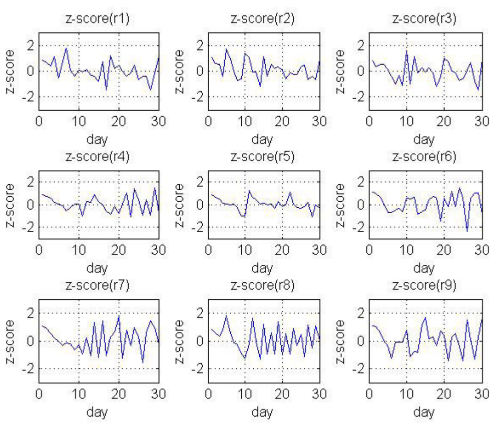

FIGURE 12. Comparison of z-score values for r1–r9.

The resulting time series are shown in Fig.12. Nevertheless, the index z-scores can only describe limited measurement characteristics and fluctuations. Meanwhile, single-dimension measurement data cannot represent the complex uncertainty in the social computing problem as well; an objective implementation of new and more reasonable computing methods is needed [38].

VII. CONCLUSION

This paper proposes a concept for a new evaluation index for public opinion analysis along with the method to calculate the index.

Based on the results of experiments, the public psychological pressure index is a critical technical indicator that has both theoretical and practical value, and it can be widely used in online public opinion analysis or used to construct a more comprehensive social computing model.

In addition, other evaluation indexes for public opinion analysis can continue to be proposed in future research such as a topic controversy, a negative mood index and so on.

APPENDIX

See Table 14.

TABLE 14. The comments about event 1.

Sequence number	**Social networks comments (in English)**
…	…
0636	“哎，某些人在这次暴雨灾难中的表现令人气愤，其作法使国人极度愤慨，趁火打劫的作法简直让人无语，其素质简直让人疯掉；同时支持国家政府在这一事件中的态度，这才是大国风范，众志成城，共度难关，同时保持发展才是硬道理，加强基础设施建设，不要再让人失望，避免类似悲剧再次发生。”
0636(**in English**)	“Alas, the behavior of some people in this storm disaster is infuriating; its behavior makes the people extremely indignant; the behavior of taking advantage in the calamity is speechless; the quality of these people is driving men mad; At the same time, we should support the attitude of the national government in this incident. This is the style of a great country. We should work together to overcome difficulties and maintain development. We need to strengthen infrastructure so that no one will be disappointed and similar tragedies will not happen again.”
…	…
0920	“真让人崩溃，城市下场雨，竟然淹死这么多人，更让人无法忍受的是人的素质，令人发指，不去救人，反而趁机涨钱，宰客。灾害是很可怕，但没人性更可怕。要是中国人都这样，那这个民族就没希望了。反而一些农民工让人看到了希望，参与到救灾中，必须赞扬一下！”
0920(**in English**)	“Indeed, let a person collapse; an urban rainfall runoff in the city can unexpectedly drown so many people, but the quality of some people more, lets me feel unbearable, how heinous! Not to save people, but take the opportunity to raise prices, to overcharge the guests. Disasters are terrible, but inhumanity is more terrible. If all Chinese are like this, there is no hope for this nation. In contrast, some migrant workers let people see the hope, participate in the relief, and must be praised!”
…	…
1325	“下大雨就能淹死人，北京这城市排水系统也太差了，比这更差的是北京的出租车司机，本来应该抓紧救人，他们却涨价，这人品素质真够呛，有待提高，唉,担心。差劲，最近总下雨，恐怕还会出事故。”
1325(**in English**)	“Heavy rain can drown people; this city drainage system of Beijing is too bad; the Beijing taxi drivers are worse than this, and they should have rushed to save people, but they raise prices. Such character and quality is really too bad, and needs to improve; alas, worry. Suck, it's been raining a lot lately. I'm afraid there will still be an accident.”
…	…

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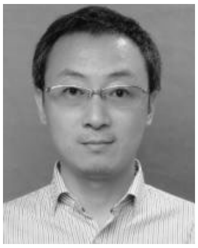

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