Prediction of Social Mood on Chinese Societal Risk Perception

Yinghong Dong
Educational Science School
Ludong University
Yantai, China

Hao Chen
Department of Social Psychology
Zhou Enlai School of Government
Nankai University
Tianjin, China
Correspondence: hull1919@gmail.com

Xijin Tang
Academy of Mathematics and Systems Science
Chinese Academy of Sciences
Beijing, China

Weining Qian, Aoying Zhou
Software Engineering Institute
East China Normal University
Shanghai, China

***Abstract*—Modern China is exposed to many societal risks in the process of social transformation and globalization. Previous psychological researches have proven that emotion is of importance in individual risk perception. Could the effect apply to large societies? The five social mood time series including happiness, disgust, fear, anger and sadness were obtained by analyzing the text content of daily Sina Weibo using the five basic mood lexicon and term-based matching technique. Then the seven societal risk perceptions including social stability risk, daily life risk, resource & environment risk, public morals risk, government management risk, national security risk and economic & finance risk were gotten by corresponding the public searching behavior on Baidu search engine to the societal risk perception psychologically. Then the correlation between the social moods and societal risk perceptions was investigated by Granger causality analysis and liner regression model. The result found that social moods are predictive of societal risk perceptions but the effect of different kinds of social mood is distinguishing. The four negative moods predict societal risk perceptions positively which means negative social moods increase the public risk perception to societal risk factors. The research manifested that capturing public psychological characteristics on social media was feasible.**

Keywords—Baidu Hot Words; Micro-blog; Social Mood; Societal Risk Perception; China

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I. Introduction

In the process of social transformation and globalization, the modern China is exposed to many kinds of societal risks such as intensive conflicts and disputes, structural poverty and unemployment. These all exert adverse effect on social stability and harmonious [1]. The collective risk perception, a critical component of the social-political context, can fundamentally compel or constrain political, economic and social actions [2]. While researches have consistently proven that the subjective factors, especially emotion is very important in risk perception at the individual level, their relationship on a large scale is costly to assess. Therefore, it is of great theoretical and practical significance to study whether and how the people mood states affect public risk perception to societal risks in China.

The importance of emotion in risk perception was advocated by Zajonc who argued that the first reaction to stimuli was affective reactions occurring automatically and guiding the subsequent risk perception [3]. The dual-process theory proposed that people apprehend information and reality in two fundamentally different ways including rule-based and associated-based processing system [4]. The rule-based system, labeled as analytical, deliberate, verbal and rational, is a cognitive decision making process relying on probability

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calculations, logic and rules, as well as needs for awareness and is relatively slow. The associated-based system is automated decision making system, labeled as intuitive, automatic, natural, narrative and experiential, hence not very accessible to conscious awareness. Analysis is important in some decision-making situations, but the associated-based system remains the most common way to respond to risk or threat, which enables us to survive during the long period of human evolution, even in the modern world. This system links to emotion and transforms uncertain or threaten environment into affective response, which represents risk as feeling [5]. As the same, the affect heuristic theory proposes that people are not rational entirely and the affect is an essential component in risk perception [6]. The stronger the effect of "affect heuristic" on risk perception under time pressure and task complicated. People will underestimate the risk and incline to risk appetite on positive emotion, but overestimate the risk and incline to risk aversion on negative emotion. The perception to hazards has no relation with the objective factors such as the characteristics of risk or happening possibility, but is influenced by psychological factors, especially the dread and unknown [7]. Most of researches reached the consensus that emotion is very important to risk perception on the perspective of individual and small groups. For example, only reading sad or happy news will affect their perception on risk events such as flood and disease [8]. People are more pessimistic when they are sad but more optimistic to the future when they are happy [9]. But different kinds of negative emotion have different effect on risk perception. For instance, people are pessimistic and overestimate the risk factors when they are fear but underestimate the risk when they are angry [10, 11]. Therefore, could the effect of emotion on risk perception on individual apply to societies at large? Does and how the social moods affect their collective risk perceptions?

But how to measure social mood and the collective risk perception? Nowadays, the rise of social computing technologies, generally branded as "web 2.0", has made Internet more open and interactive. A number of user-oriented network or social media websites have emerged rapidly. These text and image information provide the valuable resources and opportunities for the researchers and practitioners to study the individual or collective psychological characteristics.

There are two major theoretical approaches to understand the emotional structure. One is the emotional categorical approach. It proposed that there are a small set of basic emotions and complex emotions that are consisted of basic emotions or emotion and cognition [12]. The most widely accepted five kinds of basic emotion are Happiness, Sadness, Fear, Anger and Disgust [13]. The other approach is the dimensional approach, according to which the basic emotions are interrelated in a highly systematic fashion and can be represented by a spatial model rather than being independent with each other [14]. Based on the above two approaches, the traditional way to measure the individual emotion is through self-reporting or opinion-polling using emotional scale or affective adjective checklist. But large surveys of social mood over representative samples of the population are generally expensive and time-consuming to conduct, and cannot measure large-scale population even all. Other indicators such as games [15] and weather condition [16] are indirect assessment which limited their usage to very low degree correlations with the social mood. Recently, the reliable, scalable and early assessments of the social mood are emerged with the big data on Internet and the advancement of sentiment analysis techniques. Significant progress has been made in extracting indicators of the social mood directly from social media and correlating with the meaningful index, such as box office [17] and market prediction [18], disease infection [19] and information dissemination [20], macroeconomic [21] or stock market prediction [22] even emergencies warning [23].

Whereas the concern of risk perception first arose in the mid 1960s, during which experts and lay people often disagreed on how risky various technologies were for producing clean and safe energy and natural hazards. The psychometric paradigm of risk perception is to directly ask people the kinds of acceptable risks and to what extent the risks are acceptable, then gauge people's attitude in relate to a particular risk. For example, the subjects assessed 28 societal risk factors in a 10-point Likert scale on the basis of their dread feeling and occurring possibility and found that the economic crisis and social unrest were the most concerned societal risks in China [24]. However, the predictive value of this methodology is restricted by the design, arrangement of questionnaire, as well as the statistical analysis methods which is difficult to reach consistent result. To overcome the shortcomings of the traditional psychometric paradigm, the researchers constructed a new framework of societal risk indicators based on word association tests. They used the semantic network clustering analysis software CorMap and iView to group associated words into clusters and detected seven main categories of hazards. They were national security risk, economy & finance risk, public morals risk, daily life risk, social stability risk, government management risk and resources & environments risk, and thirty sub-categories in their societal risk indicators [25]. Nowadays, people express themselves freely on a number of user-oriented social media, which offered researchers opportunities to understand societal situations from a new perspective. For example, the searching frequency of word "recession" was correlated with unemployment rate and consumer confidence index (CCI) negatively [26], meaning that the public were pessimistic to economic or finance. The approach utilize people's online searching behavior, which allows for easy gathering of real-time data in a naturalistic setting as well as time series of different societal risks at community or national levels, which grants researchers a novel access to analyze the relationship between the social mood and the collective risk perception.

In this research, we are concerning how the social moods affect public risk perception to Chinese societal risks. The social mood time series were gotten by analyzing the text content of daily Sina Weibo using the Weibo Five Basic Mood Lexicon (Weibo-5BML) and sentiment analysis technique, which included Happiness, Sadness, Fear, Anger and Disgust. While the public risk perception obtained from Baidu search engine based on the hot words including social stability, daily life, resource & environment, public moral, government management, national security and economic & finance. Then

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we used the time series analysis technique to study their relationship of 365 days from November 1, 2011 to October 30, 2012.

II. Data review

A. Generating Social Mood Time Series

We generated the five basic social mood time series including happiness, sadness, anger, fear and disgust based on the Sina Weibo's user generated content (UGC) in three phases. In the first phase, we created the Weibo Five Basic Mood Lexicon (Weibo-5BML) on the basis of emotional categorical approach in psychology. First, we got 448 terms by asking five psychological graduated students to search the synonyms of emotional terms among the basic emotional psychological scales. Then we combined the 1500 emotional terms from Chinese affective words system [27], as well as the Internet folk terminology from micro-blog, such as "屌丝", "你妹" , "吐槽" , "有木有", which were searched by research team members for several days. All of these emotional terms were collected as the initial and raw source of micro-blog emotional lexicon. Then, these terms were simply filtered by removing the ambiguity and overlapping expression. Next, we removed the low frequency emotional terms using the searching engine function of Sina Weibo. At last, we got the initial mood lexicon pool of 2,242 terms. Second, we asked three psychological graduated students to judge discretely to which kind of basic emotions every emotional term belongs in sight of the emotional categorical approach. Then we got 942 terms according to their consistent judgment and deleted the last 10% low frequency terms of each kind. Finally, we got the formal version of the Weibo-5BML with a total of 818 emotional terms, in which Happiness has 306 terms, Sadness has 205 terms, Fear has 72 terms, Disgust has 142 terms, and Anger has 93 terms.

In the second phrase, we generated five social mood time series on the basis of Weibo-5BML. We crawled and analyzed minute texts in micro-blogs like twitter using a transparent approach named term-based matching technique, which matches the emotional terms used in each tweet against the emotional lexicon [28]. The Weibo-5BML could capture a variety of naturally occurring mood terms in Weibo tweets and map them to their respective social mood dimensions. First, we computed the score of each term that matched the Weibo-5BML as the fraction of tweets containing it each day. Then we averaged the quantity over all words linked to that particular emotion which means that the higher frequency of a word will have a larger impact on the mean value of each emotion. At last, we obtained five basic social mood daily time series from November 1, 2011 to October 30, 2012.

In the third phase, we validated the social mood time series by comparing the mood time series to fluctuations recorded and labeled by the vital social events and the traditional festivals in China. This method was widely used in sentiment analysis [29]. For example, the conflict of Diaoyu Islands between China and Japan was dramatically at the critical moment in 2012. On September 10, the Japanese government announced to buy the Diaoyu's southern and northern islands to implemate the so-called nationalization, and would finish the relevant procedures the next day, which seriously violated the territorial sovereignty of China. The Chinese government and people opposed the behavior, marched throughout the country, and lanched anti-Japanese activities including some aggressive and radical behaviors. In the present analysis, we found angry emotion was rising from September 10 and spiked on September 16, which the suspects were surrendered who smashed the Japanese car in Xi'an, and September 18 of "9.18 incident" anniversary in 2012. The happiness wasn't high from September 10 until the mid-Autumn day of September 30. But during the period of Golden Week from October 1 to 7, people were not happy as been thought, even a little sad, fearful and disgusted due to the congestion, chaos, and unpredictable accidents.

B. Measurement of public societal risk perceptions

Researchers from Chinese Academy of Sciences extracted the public risk perception daily time series from November 1, 2011 to October 30, 2012 by corresponding the public searching behavior on Baidu search engine to societal risk perception for the first time. Baidu is the biggest Chinese search engine worldwide, whose news portal site presents 10-20 hottest query words (Baidu Hot Words) of news automatically updated every 5 minutes. Tang automatically discerned the Baidu Hot Words into 7 risk categories including national security risk, economy & finance risk, public morals risk, daily life risk, social stability risk, government management risk and resources & environments risk mentioned above and improved the accuracy further manually. She assigned different scores from 20 to 1 according to the word's hourly rank by crawling the hottest search words hourly and got a daily list of hot words normally around 30-70, together with their frequencies and accumulated hot scores. The societal risk perception indicators are validated ecologically by corresponding to significant influences of the major social events on Chinese people during the past several years. For instance, the risk perception dropped during the London Olympic Games as most hot words were about sports but not relevant to risks, which manifests the societal risk perception indicators are the excellent thermometer of Chinese society [30].

III. Results

In this section, we are concerned with the question whether variations of the social moods correlate with changes of the public societal risk perception. To answer the question, we apply the econometric technique of Granger causality analysis to the daily time series produced by Weibo-5BML vs. the level of seven kinds of societal risk perception. The Granger causality analysis rests on the assumption that if a variable X causes Y then changes in X will systematically occur before changes in Y. We will thus find the lagged values of X will exhibit a statistically significant correlation with Y. Correlation however does not prove causation but one time series has predictive information about the other or not. In the second phase, we created the liner regression model in which the social moods are individual variables and societal risk perceptions are dependent variables to count the exact

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predictive value of social moods to every kind of societal risk perceptions.

A. Prediction of social moods to social stability risk perception

Based on the results of our Granger causality in table I, we found that all social moods except happiness have significant causal relations with social stability risk perception. The sadness has the Granger causality relation with the social stability risk perception for lags ranging from 1 to 3 days. The disgust has the Granger causality relation with it for lags 1 and 2 days, while the fear and anger are the Granger causality of it only lags 1 day.

TABLE I. GANGER CAUSALITY CORRELATION OF SOCIAL MOODS VS. SOCIAL STABILITY RISK PERCEPTION

Lag	1day	2days	3days	4days	5days
Sadness	0.007**	0.020*	0.038*	0.054	0.110
Happiness	0.298	0.615	0.722	0.850	0.911
Fear	0.018*	0.058	0.098	0.130	0.227
Disgust	0.050*	0.039*	0.082	0.102	0.119
Anger	0.031*	0.089	0.096	0.023	0.046

a. The statistical significance (p-values) is for testing the bivariate Granger causality correlation between the lagged values of 5 different basic social moods from 1 to 5 days and the 7 different Chinese societal risk perceptions.

b. *p-value < 0.05; **p-value < 0.01

The original model uses only 1 day lagged value of social stability risk perception for prediction (called the null model M0). Then we created the liner regression models of sadness, fear, disgust and anger to social stability risk perception separately on the basis of Granger causality analysis (called the predictive model M1, M2, M3 and M4). The result of the regression analysis is shown in table II, the predictive accuracy increased by 1.26% adding 1 day lagged values of sadness which is the most. The predictive accuracy significantly increased by 0.67% adding 1 day lagged values of disgust which is the least. The regressive coefficients of four negative social moods to Chinese social stability risk perception are all positive (*B*>0).

TABLE II. LINER REGRESSION RESULT FOR SOCIAL MOODS OF SADNESS, FEAR, DISGUST AND ANGERVS. SOCIAL STABILITY RISK PERCEPTION.

Model	variable	R^2 (%)	$\triangle R^2$ (%)	B	t
M0	social stability risk (-1)	36.44		0.604	14.405**
M1	sadness(-1)	37.70	1.26*	0.115	2.702**
M2	fear(-1)	37.41	0.97*	0.100	2.370*
M3	disgust(-1)	37.11	0.67*	0.083	1.965
M4	anger(-1)	37.25	0.81*	0.091	2.169*

c. R^2 is the predictive accuracy of Chinese societal risk perception combining the lagged value of 1 day of the corresponding societal risk perception and the lagged values of 1 day of different social mood according to the Granger causality result. $\triangle R^2$ is the increasing predictive accuracy adding the lagged value of social mood respectively and their statistical significance. *B* is the regressive coefficients of every kind of social mood to Chinese societal risk perception. *T*-test is for testing the statistical significance of the liner model.

d. *p-value < 0.05; **p-value < 0.01

B. Prediction of social moods to daily life risk perception

According to the results of our Granger causality in table III, we can reject the null hypothesis that the social mood time series do not predict the daily life risk perception. However, this result only applies to the social mood-disgust. The other four social moods do not have significant causal relations with daily life risk perception.

TABLE III. GANGER CAUSALITY CORRELATION OF SOCIAL MOODS VS. DAILY LIFE RISK PERCEPTION

Lag	1day	2days	3days	4days	5days
Sadness	0.176	0.373	0.531	0.679	0.735
Happiness	0.171	0.370	0.606	0.329	0.473
Fear	0.572	0.652	0.511	0.611	0.632
Disgust	0.028*	0.078	0.202	0.261	0.225
Anger	0.392	0.376	0.560	0.267	0.379

e. *p-value < 0.05

We make disgust independent variable to predict the daily life risk perception. The original model uses only 1 day lagged value of daily life risk perception for prediction (called the null model M0), while adding 1 day lagged value of disgust for predictive model M1. The result of regression analysis is shown in table IV. The regression coefficient of disgust to daily life risk perception is positive and increases the predictive accuracy by 0.86% significantly ($p<0.05$).

TABLE IV. LINER REGRESSION RESULT FOR SOCIAL MOOD OF DISGUST VS. DAILY LIFE RISK PERCEPTION.

Model	variable	R^2 (%)	$\triangle R^2$	B	t
M0	daily life risk (-1)	35.22		0.592	14.030**
M1	disgust(-1)	36.08	0.86*	0.093	2.200*

f. *p-value < 0.05; **p-value < 0.01

C. Prediction of social moods to government management risk perception

From the table V of the results of our Granger causality, we observed that the social moods-happiness, fear and anger don't have causal relation with the government management risk perception. While both sadness and disgust are the Granger causality of government management risk perception lagging 1 day and 2 days.

TABLE V. GANGER CAUSALITY CORRELATION OF SOCIAL MOODS VS. GOVERNMENT MANAGEMENT RISK PERCEPTION

Lag	1day	2days	3days	4days	5days
Sadness	0.004**	0.013*	0.056	0.089	0.092
Happiness	0.602	0.164	0.217	0.115	0.200
Fear	0.066	0.209	0.418	0.577	0.709
Disgust	0.017*	0.036*	0.103	0.174	0.185
Anger	0.915	0.869	0.995	0.814	0.773

g. *p-value < 0.05; **p-value < 0.01

The original model uses only 1 day lagged value of government management risk perception for prediction (called the null model M0), while adding 1 day lagged value of sadness and disgust for predictive model M1 and M2 separately. The result of regression analysis is shown in table

VI. The regression coefficients of sadness and disgust to government management risk perception are positive. The sadness is more predictive than disgust and the predictive accuracy increases by 1.75% significantly adding 1 day lagged value of it ($p<0.01$).

TABLE VI. LINER REGRESSION RESULT FOR SOCIAL MOODS OF SADNESS AND DISGUST VS. GOVERNMENT MANAGEMENT RISK PERCEPTION.

Model	variable	R^2 (%)	$\triangle R^2$ (%)	B	t
M0	government management risk (-1)	25.00		0.500	10.984**
M1	sadness(-1)	26.75	1.75**	0.133	2.937**
M2	disgust(-1)	26.17	1.17*	0.109	2.395*

h. *p-value < 0.05; **p-value < 0.01

D. Prediction of social moods to economy & finance risk perception

Based on the results of our Granger causality in table VII, we observed that sadness and disgust both have the Granger causality relation with the economy & finance risk perception for lags ranging from 1 to 3 days. The fear has the Granger causality relation with it for lags ranging from 1 to 5 days. The other two kinds of social moods don't have significant causal relations with economy & finance risk perception.

TABLE VII. GANGER CAUSALITY CORRELATION OF SOCIAL MOODS VS. ECONOMY & FINANCE RISK PERCEPTION

Lag	1day	2days	3days	4days	5days
Sadness	0.004**	0.013*	0.034*	0.133	0.242
Happiness	0.783	0.757	0.681	0.885	0.966
Fear	1.70 e-05**	6.80 e-05**	0.000**	0.002**	0.006**
Disgust	0.001**	0.005**	0.018*	0.079	0.054
Anger	0.174	0.143	0.242	0.244	0.405

i. *p-value < 0.05; **p-value < 0.01

The original model uses only 1 lagged value of economy & finance risk perception for prediction (called the null model M0). Then we created the liner regression models of sadness, fear and disgust to economy & finance risk perception separately on the basis of Granger causality analysis (called the predictive model M1, M2 and M3). The result of the regression analysis is shown in table VIII, the predictive accuracy significantly increased by 3.44% adding 1 day lagged value of fear which is the most ($p<0.01$). The regression coefficients of three social moods are all positive.

TABLE VIII. LINER REGRESSION RESULT FOR THE SOCIAL MOODS OF SADNESS, FEAR AND DISGUST VS. ECONOMY & FINANCE RISK PERCEPTION

Model	variable	R^2 (%)	$\triangle R^2$ (%)	B	t
M0	economy & finance risk (-1)	31.14		0.558	12.796**
M1	sadness(-1)	32.71	1.57**	0.126	2.900**
M2	fear(-1)	34.58	3.44**	0.187	4.358**
M3	disgust(-1)	33.06	1.92**	0.139	3.212**

j. *p-value < 0.05; **p-value < 0.01

E. Prediction of social moods to national security risk perception

From the table IX of the results of our Granger causality, we can reject the null hypothesis that the social mood time series do not predict the national security risk perception. However, this result only applies to the social mood-happiness and anger. The anger has the Granger causality relation with the national security risk perception for lags ranging from 1 to 5 days while the happiness is the Granger causality of it only lagging 1 day.

TABLE IX. GANGER CAUSALITY CORRELATION OF SOCIAL MOODS VS. NATIONAL SECURITY RISK PERCEPTION

Lag	1day	2days	3days	4days	5days
Sadness	0.382	0.460	0.654	0.737	0.768
Happiness	0.039*	0.075	0.143	0.215	0.165
Fear	0.495	0.804	0.718	0.703	0.768
Disgust	0.581	0.823	0.915	0.966	0.765
Anger	0.003**	0.001**	0.012*	0.026*	0.049*

k. *p-value < 0.05; **p-value < 0.01

Then we created the liner regression model which happiness and anger are independent variables. The original model uses only 1 lagged value of national security risk perception for prediction (called the null model M0) and adding happiness or anger to national security risk perception separately (called the predictive model M1 and M2). The result of the regression analysis is shown in table X. The regression coefficient of happiness is negative but anger is positive, and the predictive accuracy significantly increased by 1.56% adding 1 day lagged value of anger ($p<0.01$).

TABLE X. LINER REGRESSION RESULT FOR SOCIAL MOODS OF HAPPINESS AND ANGERVS. THE NATIONAL SECURITY RISK PERCEPTION.

Model	variable	R^2 (%)	$\triangle R^2$ (%)	B	t
M0	national security risk (-1)	36.77		0.606	14.509**
M1	happiness(-1)	37.51	0.74*	-0.087	-2.067*
M2	anger(-1)	38.33	1.56**	0.132	3.020**

l. *p-value < 0.05; **p-value < 0.01

F. Prediction of social moods to resource & environments risk perception

According to the results of our Granger causality in table XI, we observed that all kinds of social moods except anger don't have causal relation with the resources & environments risk perception.

TABLE XI. GANGER CAUSALITY CORRELATION OF SOCIAL MOODS VS. RESOURCES & ENVIRONMENTS RISK PERCEPTION

Lag	1day	2days	3days	4days	5days
Sadness	0.068	0.235	0.421	0.380	0.118
Happiness	0.895	0.114	0.221	0.137	0.229
Fear	0.053	0.171	0.192	0.269	0.256
Disgust	0.079	0.210	0.366	0.363	0.492
Anger	0.037*	0.054	0.010**	0.021*	0.032*

m. *p-value < 0.05; **p-value < 0.01

We make anger independent variable to predict the resources & environments risk perception. The original model uses only 1 day lagged value of resources & environments risk perception for prediction (called the null model M0), while adding 1 day lagged value of anger for predictive model M1. The result of regression analysis is shown in table XII. The regression coefficient of anger to resources & environments risk perception is negative and increases the predictive accuracy by 0.7% significantly ($p<0.05$).

TABLE XII. LINER REGRESSION RESULT FOR THE SOCIAL MOOD OF ANGER VS. RESOURCES & ENVIRONMENTS RISK PERCEPTION.

Model	variable	R^2 (%)	$\triangle R^2$ (%)	B	t
M0	resources & environmens risk (-1)	41.85		0.647	16.142**
M1	anger(-1)	42.55	0.7*	-0.084	-2.091*

n. *p-value < 0.05; **p-value < 0.01

G. *Prediction of social moods to public morals risk perception*

We observed that all kinds of social moods don't have causal relation with public morals risk perception from the Granger causality analysis in table XIII.

TABLE XIII. GANGER CAUSALITY CORRELATION OF SOCIAL MOODS VS. PUBLIC MORALS RISK PERCEPTION

Lag	1day	2days	3days	4days	5days
Sadness	0.311	0.551	0.807	0.903	0.490
Happiness	0.431	0.473	0.518	0.678	0.782
Fear	0.988	0.347	0.605	0.731	0.701
Disgust	0.836	0.173	0.321	0.475	0.557
Anger	0.770	0.544	0.683	0.676	0.677

Based on the above results, we found that social moods have predictive effect on societal risk perception, but different kinds of social moods can predict different categories of societal risk perception. We described the most important social mood to every kinds of societal risk perception and mapped the relation of social moods with societal risk perception in Fig. 1. We found that the negative social mood-sadness, anger, fear and disgust are more important predictors of Chinese societal risk perceptions.

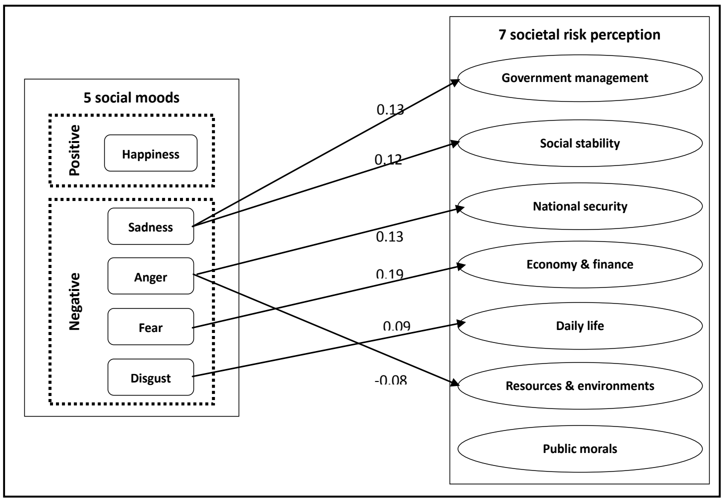

Fig. 1. The predictive effects of five social moods on seven Chinese societal risk perceptions

IV. DISCUSSION

As we enter into the Web 2.0 era, new media offers people opportunities to publicly express opinions, and has attracted many researchers to get images of societal situations by making use of those free expressions. In this paper, we obtained the social moods from Sina Weibo on the emotional structure theory, and got the societal risk perceptions from Baidu search engine making using of the public searching behavior. By matching the social mood and societal risk perception time series against the vital social events, we found the social media is effective in capturing the public psychological characteristics. Then we examined the relation of social moods with the societal risk perception, which indicates different kinds of social mood can predict different kinds of societal risk perception, specifically, positive mood-happiness can't predict all kinds of societal risk perception, while the other four negative moods predict societal risk perception positively, meaning negative social moods increase the level of risk perception to societal risk factors except the resources & environments risk perception. Moods may increase the availability of mood-congruent information as its informational and directive functions. First, the mood may increase the availability of similarly valenced events in memory which make people use their momentary affective state as information relevant to making various kinds of judgments. In addition, moods may direct one's attention to specific classes of information in an attempt to sort out the plausible causes for such feelings, but the directive effect of different valenced affective states is distinguishing. Negative mood may motivate people to seek reasonable explanations to reduce their unpleasantness, whereas the positive mood simply don't demand any explanation [31].

Our research makes valuable contribution to both computational science and social science. First, we highlight the vast information of social mood and social cognition based on social network services (SNS). We obtain a useful micro-blog mood lexicon on the basis of emotional structure theory and argue that sentiment analysis of minute text corpora (such as Weibo) is efficiently obtained via a term-based approach that requires no training or machine learning. Then, the relationship of social mood and societal risk perception is systematically studied based on the theory of cognition and emotion but not using data to explain data. Second, we complied the big data and information science technology into traditional social science research to make comprehensive understanding the human psychological and behavioral characteristics from both micro and macro level. We present a reliable, scalable and early assessment of the social mood, having some offset for large survey which is expensive and time consuming to conduct or other indicators which can't measure social mood directly. Then we study the psychological attitude from searching behavior while the

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traditional research only speculated them based on sample with the limitation of manpower, material and resources. In addition, the psychological characteristics could be directly obtained using the massive information of Internet or social network, while traditional research mainly relied on one-time, self-reported data which isn't so real because of social desirability and other subjective effects.

Of course, there are many limitations in our paper and does not acknowledge a lot of important factors which need further research. First, although both the number of users and the popularity and influence of Sina Weibo are increasing rapidly, the main stream of micro-blog users are still the highly educated and young people. What extent to which these users on behalf of the general public is still debatable. Second, the data of social moods and societal risk perception are from different network platform. The users of those two website are not same entirely which may influence the accuracy of research. Third, we don't examine other factors influencing risk perception such as gender, age and personality traits et.al, so the relationship between social moods and societal risk perceptions isn't causality but correlation. Whatever, we only focus on the effect of different kinds of emotion to Chinese societal risk perception on the basis of emotional categorical approach. However, the emotional dimensional approach, rather than being independent, these basic emotions are interrelated in different dimensions including valence, arousal and dominance [32]. The prediction of emotional dimensions to Chinese societal risk perception needs to study further.

References

[1] C. F. Yang, "The jurisprudential interpretation of risk society," Law and Social Development, vol. 6, pp. 106–114, 2011. (in Chinese)

[2] A. Leiserowitz, "Climate change risk perception and policy preferences: the role of affect, imagery, and values," Climatic Change, vol. 77, pp. 45–72, 2006.

[3] R. B. Zajonc, "Feeling and thinking: preference need no inferences," American Psychologist, vol. 35, pp. 151–175, 1980.

[4] S. Epstein, "Integration of the cognitive and psychodynamic unconscious," American Psychologist, vol. 49, pp. 709–724, 1994.

[5] P. Slovic, and E. U. Weber, "Perception of risk posed by extreme events," Risk Management Strategries in an Uncertain World Conference, NY: Palisades, 2002.

[6] P. Slovic, M. Finucane, E. Peters, and D. G. MacGregor, "Rational actors or rational fools: implications of the affect heuristic for behavioral economics," The Journal of Socio-economics, vol. 31, pp. 329–342, 2002.

[7] E. Peters, and P. Slovic, "The role of affect and worldviews as orienting dispositions in the perception and acceptance of nuclear power," Journal of Applied Social Psychology, vol. 26, pp. 1427–1453, 1996.

[8] E. J. Johnson, and A. Tversky, "Affect, generalization, and the perception of risk," Journal of Personality and Social Psychology, vol. 45, pp. 20–31, 1983.

[9] W. F. Wright, "Mood effects on subjective probability assessment," Organizational Behaviour and Human Decision Processes, vol. 52, pp. 276–291, 1992.

[10] J. S. Lerner, and D. Keltner, "Beyond valence: toward a model of emotion-specific influences on judgment and choice," Coginitve & Emotion, vol. 14, pp. 473–493, 2000.

[11] J. S. Lerner, and D. Keltner, "Fear, Anger and risk," Journal of Personality and Social Psychology, vol. 81, pp. 146–159, 2001.

[12] P. Ekman, and W. C. Friesen, "Constants across cultures in the face and emotion," Journal of Personality and Social Psychology, vol. 2, pp. 124–129, 1971

[13] M. J. Power, and T. Dalgleish, Cognition and emotion from order to disorder. U.K: Psychology Press, 1997.

[14] J. A. Russell, "A circumplex model of affect," Journal of Personality and Social Psychology, vol. 39, pp. 1161–1178, 1980.

[15] A. Edmans, D. Garca, and O. Noril, "Sports sentiment and stock returns," Journal of Finance , vol. 62, pp. 1967–1998, 2007.

[16] D. Hirshleifer, and T. Shumway, "Good day sunshine: stock returns and the weather," Journal of Finance, vol. 19, pp. 1009–1032, 2003.

[17] S. Asur, and B. Huberman, "Predicting the future with social media," Proceedings of the 2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology, Toronto, 2010.

[18] D. Gruhl, R. Guha, R. Kumar, J. Novak, and A. Tomkins, "The predictive power of online chatter," In ACM, New York, 2005.

[19] H. Choi, and H. Varian, "Predicting the present with Google trends," Economic Record, vol. 88, pp. 2–9, 2012.

[20] J. Bollen, B. Goncalves, G. C. Ruan, and H. N. Mao, "Happiness is assortative in online social network," Artificial Life, vol. 17, pp. 237–251, 2011.

[21] J. Bollen, A. Pepe, and H. N. Mao, "Modeling public mood and emotion: Twitter sentiment and social–economic phenomena," In ICWSM, North Carolina: Raleigh, 2010.

[22] Y. H. Dong, H. Chen, W. N. Qian, and A. Y. Zhou, "Micro–blog social moods and Chinese stock market: the influence of emotional valence and arousal on Shanghai composite index voulme," International Journal of Embedded System, vol. 7, pp. 148–155, 2015.

[23] T. Lansdall–Welfare, V. Lampos, and N. Cristianini, "Effects of the recession on public mood in the UK," Proceedings of the 21st International Conference Companion on World Wide Web, France: Lyon, 2012.

[24] X. F. Xie, and L. C. Xu, "The study of public risk perception," Psychological Science, vol. 6, pp. 723–724, 2002.(in Chinese)

[25] R. Zheng, K. Shi, and S. Li, "The influence factors and mechanism of societal risk perception," Proceedings of the First International Conference on Complex Science: Theory and Applications, Springer, pp. 2266–2275, 2009.

[26] H. N. Mao, S. Counts, and J. Bollen, "Computational economic and finance gauges: polls, search, & Twitter," In Behavioral Finance Meeting, CA: Stanford, 2011.

[27] Y. N. Wang, L. M. Zhou, and Y. J. Luo, "The pilot establishment and evaluation of Chinese affective words system," Chinese Mental Healthy Journal, vol. 22, pp. 608–612, 2008. (in Chinese)

[28] B. O'Connor, R. Balasubramanyan, R. B. Routledge, and A. N. Smith, "From tweets to polls: link text sentiment to public opinion time series," Proceedings of the International AAAI Conference on Weblogs and Social Media, DC: Washington, 2010.

[29] J. Bollen, H. N. Mao, and X. J. Zeng, "Twitter mood predicts the stock market," Journal of Computational Science, vol. 2, pp. 1–8, 2011.

[30] X. J. Tang, "Applying search words and BBS posts to societal risk perception and harmonious society measurement," Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics, UK: Manchester, pp. 2191–2196, 2013.

[31] N. Schwarz, and G. L. Clore, "Mood, misattribution, and judgments of well-being: Informative and directive functions of affective states," Journal of Personalty and Social Psychology, vol. 45, pp. 513–523, 1983.

[32] Mehrabian A, Pleasure–Arousal–Dominance: a general framework for describing and measuring individual differences in temperament. Current Psychology, vol. 14, pp. 261–292, 1996.

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