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Research Article

Early Cyberspace Emergency Response by Predicting Social-Emotional Security

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With the intensified social conflicts and cyberspace crises, the public is facing the emotional impact and lack of security feelings responding to emergencies. The most recent research only focuses on the influence of discrete emotions, but the induced stressful feeling of emotional security has not been a concern by the government. In this work, we first propose a concept of social-emotional security, evolving from the classical theories of risk society and psychological resilience. Second, we integrate a social-emotional security index measurement method with the proposed three metrics: emotional bias, situational risk, and potential hazard. We also suggest a grading scheme for the emotional regulation strategy with a 0.3 safety valve. Finally, the accuracy is over 78% for detecting the potential risk of emerging events, and the method is feasible in another 30 social safety events with a trend coincidence beyond 63.3%.

1. Introduction

In early 2020, the novel coronavirus pneumonia (COVID-19) threatened human life and health security, then the generated stressful emotions lead to widespread public panic and psychological anxiety. As the anxiety spreads and accumulates, the strong negative emotion evolves into a sense of insecurity and leads to mass incidents, such as seizing medical resources, wild hoarding purchasing of supplies, resisting quarantine measures, and refusing to wear masks, which cause a serious blow to harmony and stability of society [1]. Since emotional security is people's subjective experience reflecting the emotional in response to a sudden emergency, protecting the public's emotional security is a top priority for the government to respond to crises. In a word, the effective means of avoiding crises is timely monitoring and early warning of social-emotional security risks, then accurately guiding social security and stability among the public.

Existing studies focused on the emotion detection and emotion effect on public mental health and social safety, especially anxiety, fear, and anger associated with COVID-19 [2–6]. However, previous discrete emotion studies targeted only on the specific type of emotion, and do not use them for measuring the level of emotional security. Besides this, existing studies have not yet clearly defined the concept of social-emotional security and lack indicators for evaluating this concept. Therefore, the main purpose of this paper is to address (1) how to define social-emotional security, (2) how to measure and monitor the level of the public social-emotional security situation, and (3) how to further enhance the public's emotional security feeling.

To this end, this study proposes the concept of social-emotional security based on two classic theories of risk

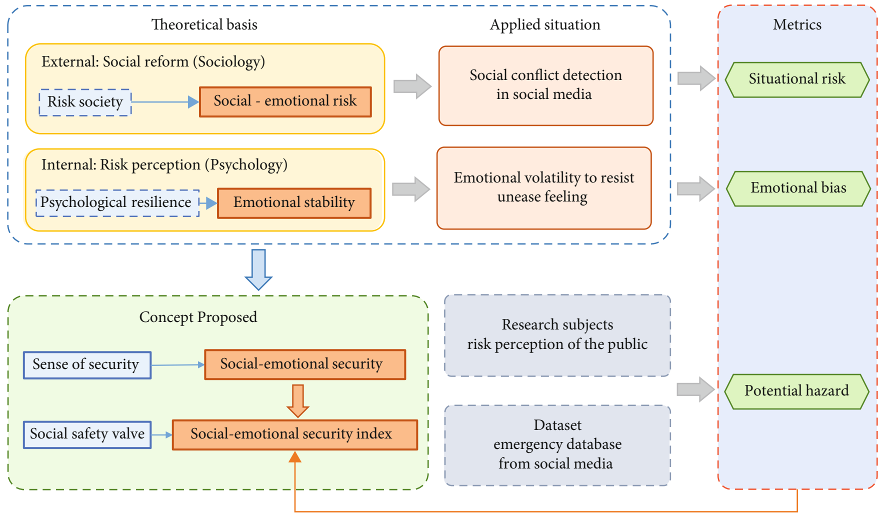

Figure 1: The framework of concept and metrics of social-emotional security.

society and psychological resilience. The framework of the concept and metrics is shown in Figure 1. On the one hand, risk society theory is a basis for measuring environmental risk and hazard levels [7] and also clarifies that emotions usually drive risk perception [8]. On the other hand, psychological resilience theory describes the whole process of overcoming anxiety as people cope with risk [9]. Both theories regard the context of stressful emotions, which coincide with the purpose of this study. However, these two traditional theories do not provide methodologies that can calculate and quantify the level of crisis that the stress triggered people. Furthermore, this study extends the concept of social safety valve into the social-emotional security index that transforms crises to mitigate the harmfulness of emotions to social safety [10].

To provide a timely response to the impact of major public health events on public emotional security, we focus on accurately assessing the level of social-emotional security under the real psychological stress by deep learning models in multidimensional discrete group emotion volatility. Social media has been shown to play a crucial role as a major channel during disease outbreaks [11], so we select Weibo data and use emotional-time series with emotional valence and emotional type obtained from the emotion lexicon. The transformer model [12] is improved for detecting abnormal emotion volatility, and the abnormal emotional valence shows bias. The situational risk is based on the collection of public online interaction behaviors. On this basis, we can determine whether the stressful event is a hazard or not by analyzing the event similarity to the representation of the historical events. The accuracy successfully proves the predictive ability in potential risk beyond 78% for the new stressful event. Then, we expand to other 30 social safety events with these three metrics, and the curve of safety can be consistent with human cognition, as well as reaches 63.3% coincidence.

Our contributions reach one clear concept of social-emotional security, following two classical social and psychological theories, and construct an index system for measuring security index into three aspects: emotional bias, situational risk, and potential hazard.

The remainder of this paper is organized as follows: Section 2 emphasized the relevant theoretical basis and proposed concept and index system. Section 3 describes the social-emotional security index measurement method, and Section 4 reports the experiment results. The discussion and empirical test are presented in Section 5.

2. Theoretical Basis

2.1. Risk Society and Psychological Resilience. The concept of risk society clarifies the issue of human ontological security in society, concerning the security of each individual [13]. Human security is shaken when the scale and potential of hazards in the environment grow [14]. Due to the prevalence of socio-emotional risk, the accumulation of negative emotions in the social situation can cause social change [15]. Then, the level of danger in social situations leads to an atmosphere of “insecurity” in society and culture [7]. On the other hand, negative perceptions dominate in the study of social conflict [16]. Social media increases the uncertainty of social conflict and risk further increasing the difficulty of social risk prevention and control. Therefore, to measure the level of social conflict, we have to assess social security interactions in the social structure. In other words, the concept of risk society emphasizes the danger and the feeling of security of the public in the social environment.

For the public, psychological resilience is the trait that helps people to gain experience and learn to cope with risk in the context of risk perception. This theory first emphasizes the interaction between people and their environment in social behavior, such as Kumpfer [17] proposed the influence of risky environments on personal emotions on mental resilience, and Rutter and Sara [18] claimed that resilience is a phenomenon that arises from the interaction between individuals and their environment. More importantly, the theory highlights emotional stability. Block and Block [19] argued that psychological resilience has the relative stability to eliminate negative emotions during difficult adversity and self-adjust to return to normal. Gooding and Harris [20] argued that the psychological resilience model is based on triggers and experiences that need to be tapped into people's emotional patterns from anxiety to stability. Thus, after sudden environmental stressors bring people to produce reactions [21], human psychological emotions need to be resilient and maintain stable emotions to resist the emergence of insecurity, which means monitoring the emotional volatility in stressful situations is the way to measure security.

Existing theories provide a solid foundation with risk society describing the external force of stressors and psychological resilience focusing on human cognitive stability. Both theories explain real-world situations, but do not define specific social-emotional concepts of security, as well as lack metric evaluations that lack specific measures of guidance. The relative concept includes the sense of security, proposed by Freud [22], which is a prototype around anxiety in a dangerous situation, in the sense of feelings obtained from the release of danger. Thereafter, Coser [10] proposed the concept of social safety valve, pointing out that group interaction is the way to deescalate conflicts. To avoid breaching the boundaries of the social safety valve and triggering a public crisis, it is necessary to eliminate the accumulated discontent and personal resentment, so that the conflict is predictable and controllable.

2.2. Concept and Measurement Metrics. The concept of *social-emotional security* refers to the potential hazard perception, influenced by the emotional bias when the public suffers from the situational risk after the emergence. For different emotional tendencies, the distribution formed by the difference in emotional valence reflects the level of psychological stress in this situation. This emotional valence is the social-emotional security index, which is our extended concept of the safety valve. When the index score is below or equal to a certain value, the event is defined as a significant public emotional safety event; when the index score is in a certain interval, it is defined as a public emotional safety event of concern, and when the index score is above a certain value, it is defined as a safety event. Then, according to the concept and theoretical basis, we construct the specific index metrics depicting the social-emotional safety situation.

Emotional bias depends on the emotional stability in personal experience after an outbreak. Brooks et al. [23] revealed the effect of COVID-19 event intensity on emotions and behaviors to seek psychological safety on mental health. Savolainen [24] argued that the potency of emotions plays an important role in the transmission of online emotion role, with negative emotions such as fear and anger being more controversial and positive emotions being more likely to be embedded in established views. Giri and Maurya [25] noted that positive emotions in the news of the COVID-19 epidemic contribute to resilience. So, simply examining negative effect bias is one-sided, because positive effect also diminishes with dangerous situations, so the full range of compound emotions needs to be monitored simultaneously. At this point, a larger bias after a new event outbreak implies a stressor, and the extent of this bias needs to be quantified. Therefore, the smaller the emotional bias, the more emotionally stable the public will be [19]. The public's original stock of emotions, including emotional state and historical emotions, was formed in response to similar events in the past. The impact of this induced stress and evolved social emotions after an unexpected event can affect the value of situational emotions at the same time.

Situational risk is the cause of public stress reactions under social conflict. Contextual risk is a measure of the impact of the evolution of an emerging event from public concern. Hadjikhani et al. [26] argued that Internet users' emotion generation is a nonlinear dynamic and complex system in coupled with individual cognitive and psychological levels, the media communication level, and the social guidance level. Therefore, the public is in the interactive context of social media, and emotional interactions become the content of the communication. Media platform attributes are obtained from the publishing platform, e.g., Weibo influence calculates the number of account followers and H-factor, and WeChat influence calculates the average number of reads and an average number of supports in the posted historical articles. Yin and Ni [27] used event intensity to measure the impact and influence. Similar to traditional studies, it is necessary to monitor people's online behavior throughout the life cycle of an unexpected event, considering the specific social context, influenced by personal factors, event characteristics, social influence factors, and personal relationship factors [28]. Ning and Lu [29] used the number of tweets in the "popular column" of hot topics, Li et al. [30] used the number of likes of tweets, and Zhang et al. [31] used the number of comments and the number of forwards. Thus, in this study, situational risk refers to the impact of a stressful event, the number of people's attention it attracts, and the number of online engagements it leads to. Needless to say, the longer the public attention, the greater the diffusion effect of the event. All these indicators lead to a greater impact of the event.

Potential hazard means the level of awareness of the danger directly affects the safety of the event. Responding to online public opinion, which is the sum of people's perceptions, attitudes, and emotions about public health emergencies [6], the public takes the path of risk perception through risk information, media, group attitudes, and emotions [32–34]. The potential risk of an emerging stressful event is unpredictable, so it is necessary to compare the similarity of this new event with those historical events.

Therefore, for the COVID-19 pandemic, the measurement of public online behavior and textual content determines the situational risk and impact of stressful events, which provides a solid foundation for the measurement of the socio-emotional security index. Based on the above, the index system includes three levels of indicators, including three level-1 indicators, five level-2 indicators, and ten level-3 indicators. These 18 evaluable indicators constitute the evaluation index system of social-emotional security as shown in Table 1.

Table 1: Social-emotional security index system.

Level 1	Level 2	Level 3
Emotional bias	Inventory emotion intensity	Public emotional cognition
		A memory of similar events
	Situational emotional valence	Induced event emotion
		Social public emotion
Situational risk	Media influence	Media authority index
		Media platform attributes
	Event influence	Event duration
		Event propagation effect
Potential hazard	Event safety determination	Event similarity
		Safety similarity

3. The Social-Emotional Security Index Measurement Method

To verify the feasibility of the concept of social-emotional security, we propose a social-emotional security index measurement method and demonstrate a public health emergency COVID-19 as an example. The architecture of the proposed method is shown in Figure 2. There are three sections. The first section is the input representation, which extracts the feature vectors and computes emotional temporal from social media content. The second section is the situation awareness model, which facilitates the respective interaction from input, consisting of three modules: (1) emotional bias module, consisting a transformer-based temporal prediction and measured emotion volatility by entropy; (2) situational risk module, assessing the risk event influence among the public; and (3) potential risk module, selecting the security possibility in event similarity. The final section is decision-making, which integrates the former outputs of three metrics and generates the social-emotional security index. We will discuss each section in the following.

3.1. Input Representation. This section performs data processing. The data were collected from the news and opinions issued on Weibo by the news media and the public individuals. The data contains the post content with records of post time and public online behavior in forwards, supports, and comments. The textual content of each individual event E, such as the COVID-19 pandemic event and the Wuhan "lockdown" event, is defined as $E=(E_{t_1}, E_{t_2}, \cdots, E_{t_D})$, where time $t_i=(t_1, t_2, \cdots, t_D)$. Then, we perform feature extraction and load an 8-dimensional discrete emotional lexicon [35] to represent the emotional valence vector in $E_{t_i}=(X_{t_i}^0, X_{t_i}^1, \cdots, X_{t_i}^{j-1})$, where X means the emotional valence, and dimension j is as same as the number of emotion types from expect, joy, love, surprise, anxiety, sorrow, angry, and hate. For the online behavior, the volume of public attention is represented as forwards F_{t_i}, supports S_{t_i}, and comments C_{t_i}. Same processing also carries out for each event, and a large number of events together form a historical events database.

3.2. Situation Awareness Model. The model is a core method addressing three metrics of social-emotional security index. It integrates situation perception and public feelings through the three modules, including the degree of public emotional changes to target event in the emotional bias module, the impact on public online behaviors in the situational risk module, and whether the event is risky in the potential hazard module.

3.2.1. Emotional Bias Module. The emotion bias module is to obtain a bias metric by comparing the emotion valence vectors of two consecutive time points from emerging emergencies. We first follow the attention-based principle of the Transformer network to get emotion valence vectors temporal prediction, then an entropy value is computed to measure the fluctuation degree of the predicted emotion valence vectors at any two continuous time points.

(1) Emotion Valence Vector Temporal Prediction. To perform the temporal prediction mechanism, we refer to a standard Transformer block in [12] an Attentive Module: $\mathrm{AM}(*)$, which is implemented by a multihead attention layer ($\mathrm{MultiHead}(*)$) and a position-wise fully connected feed-forward network layer ($\mathrm{FFN}(*)$). Taking a query matrix Q, key matrix K, and value matrix V as inputs, $\mathrm{AM}(*)$ is defined as follows:

$$\mathrm{AM}(Q, K, V) = \mathrm{FFN}(\mathrm{MultiHead}(Q, K, V)), \tag{1}$$

$$\mathrm{MultiHead}(Q, K, V) = \mathrm{Concat}\left(\mathrm{head}_1, \cdots, \mathrm{head}_{N_{\mathrm{head}}}\right) W^C, \tag{2}$$

$$\mathrm{head}_k = \mathrm{Softmax}\left(\frac{QW_k^Q \left(KW_k^K\right)^T}{\sqrt{d}}\right) VW_k^V, \tag{3}$$

where W^C and W_k^* are learned parameter matrices. We also employed residual connection [36] and layer normalization to each block. As shown in Figure 3, we construct emotional valence vectors $E_{t_{i\longrightarrow i+p+q}} = (E_{t_i}, E_{t_{i+1}}, \cdots, E_{t_{i+p}}, E_{t_{i+p+1}}, \cdots, E_{t_{i+p+q}})$ as a time window from the whole event E. We take $E_{t_{i\longrightarrow i+p}} = (E_{t_i}, E_{t_{i+1}}, \cdots, E_{t_{i+p}})$ as input to encoder after position encoding. To reconstruct the associations between the input sequences, $E_{t_{i\longrightarrow i+p}}$ is mapped to a vector of dimension $(p+1)\times d$ by a linear transformation, and then fed into Attentive Module (Self-Attention) according to the following formula:

$$E_{t_{i\longrightarrow i+p}}^{l+1} = \mathrm{AM}\left(E_{t_{i\longrightarrow i+p}}^{l}, E_{t_{i\longrightarrow i+p}}^{l}, E_{t_{i\longrightarrow i+p}}^{l}\right), \tag{4}$$

where l ranges from 0 to $L-1$, denoting the stacking of L Transformer blocks. After we stack $L(=2)$ Transformer blocks, contextual relevance emotional valence vector $E_{t_{i\longrightarrow i+p}}^{L}$ is obtained. We also take $E_{t_{i+p\longrightarrow i+p+(q-1)}} = (E_{t_{i+p}}, \cdots, E_{t_{i+p+(q-1)}})$ as decoder initial input to reconstruct the self-relations. Note that $E_{t_{i+p\longrightarrow i+p+(q-1)}}$ begins with the last data

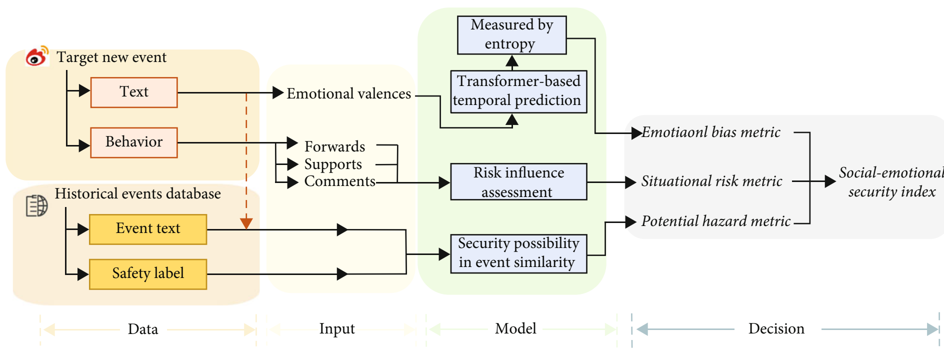

Figure 2: The architecture of social-emotional security index measurement method.

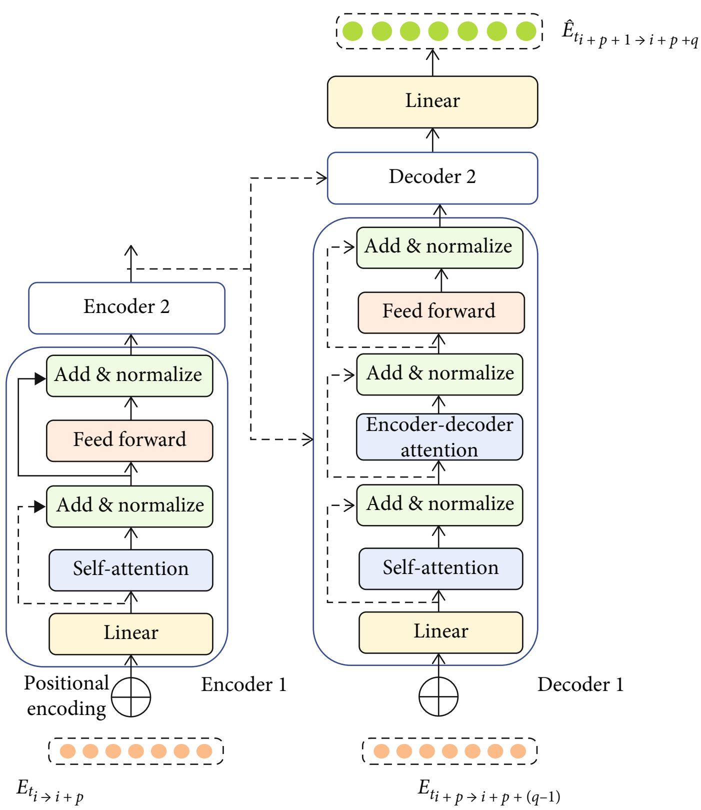

Figure 3: Temporal prediction mechanism in emotional bias module.

point of the encoder input $E_{t_{i\longrightarrow i+p}}$. The decoder Self-Attention is formulated as:

$$E^{l+1}_{t_{i+p\longrightarrow i+p+(q-1)}} = AM\left(E^{l}_{t_{i+p\longrightarrow i+p+(q-1)}}, E^{l}_{t_{i+p\longrightarrow i+p+(q-1)}}, E^{l}_{t_{i+p\longrightarrow i+p+(q-1)}}\right). \tag{5}$$

To predict time series data more accurately, we use Encoder-Decoder Attention to dynamically focus on some inputs closely related to the prediction vector. This is calculated as follows:

$$\widehat{E}^{l+1}_{t_{i+p\longrightarrow i+p+(q-1)}} = \mathrm{AM}\left(E^{l}_{t_{i+p\longrightarrow i+p+(q-1)}}, E^{l}_{t_{i+p\longrightarrow i+p}}, E^{l}_{t_{i+p\longrightarrow i+p}}\right). \tag{6}$$

After stacking $L(=2)$ Transformer blocks, we get a context vector $\widehat{E}_{t_{i+p+1\longrightarrow i+p+q}}$, which is mapped to the target time sequence $\widehat{E}_{t_{i+p+1\longrightarrow i+p+q}}$. Note that we ensure the prediction of time series data points only depends on previous data points by look-ahead masking and one-position offset in our decoder. We employed the MSE loss function to train this transformer-based model by the Adam optimizer [37]:

$$\mathrm{MSE} = \frac{1}{q}\left(\widehat{E}_{t_{i+p+1\longrightarrow i+p+q}} - E_{t_{i+p+1\longrightarrow i+p+q}}\right)^{2}. \tag{7}$$

(2) Emotion Volatility Measured by Entropy. To measure the extent to the emotion volatility at adjacent time points, we introduce a novel entropy to obtain the emotional bias

metric. We first calculate the square of the difference between the predicted value $\widehat{E}_{t_{i+1}}$ and the true value E_{t_i}, as a measure of the emotional value differences for k-dimension:

$$\Delta E^k_{t_i,t_{i+1}} = \left(\widehat{X}^k_{t_{i+1}} - X^k_{t_i}\right)^2, (0 \le k \le j-1). \tag{8}$$

Then, the difference of j-dimensional abnormal emotional valence $\Delta E_{t_i,t_{i+1}} = \{\Delta E^k_{t_i,t_{i+1}}\}_{k=0}^{j-1}$ is obtained by Equation (8) and normalized as shown in

$$P_{t_i,t_{i+1}} = \mathrm{Norm}\left(\Delta E_{t_i,t_{i+1}}\right). \tag{9}$$

Finally, the entropy $h_{t_{i+1}}$ is computed to measure the fluctuation degree at time point t_{i+1}, which is formulated as:

$$h_{t_{i+1}} = H\left(P_{t_i,t_{i+1}}\right), \tag{10}$$

where $H(\cdot)$ represents the entropy of the probability distribution.

Supposing that the social emotion maintains in a stable state during the interval of two consecutive time points $\Delta t = t_{i+1} - t_i$, the distribution of E_{t_i} and $\widehat{E}_{t_{i+1}}$ tend to be the same, and $h_{t_{i+1}}$ tends to be the maximum $h^{\max}_{t_{i+1}} = -\log j$. Therefore, the emotional bias metric at time point t_{i+1} is defined as follows:

$$B_{t_{i+1}} = \frac{h^{\max}_{t_{i+1}} - h_{t_{i+1}}}{h^{\max}_{t_{i+1}}}. \tag{11}$$

3.2.2. Situational Risk Module. The situational risk module is to obtain the situational risk metric by assessing the response of the public online behaviors (i.e., forwards, supports, and comments) on social media. Since it is difficult to obtain the authority and attribute of each releasing media platform, we take event influence into account. When sufficient data is obtained, the weight of media influence can be added to reflect the corresponding effect.

During the period $T_i = [t_1, t_2, \cdots, t_i]$ of the event propagation, the number forwards, supports, and comments are collected at each t_j for each event, denoted as $F_{T_i} = [F_{t_1}, F_{t_2}, \cdots, F_{t_i}]$, $S_{T_i} = [S_{t_1}, S_{t_2}, \cdots, S_{t_i}]$, $C_{T_i} = [C_{t_1}, C_{t_2}, \cdots, C_{t_i}]$, respectively. Next, we take forwards F_{T_i} as an example to estimate the forwards $F_{t_{i+1}}$. The average number of forwards from T_i is shown as:

$$\bar{F}_{T_i} = \frac{\sum_{j=1}^{i} F_{t_j}}{i}. \tag{12}$$

By comparing the number of forwards at each t_j with the average number of forwards $\bar{F}_{T_i}$, we can estimate the number of forwards at $F_{t_{i+1}}$, which is defined as:

$$P_{T_i} = \mathrm{softmax}\left(\left(F_{t_1} - \bar{F}_{T_i}, F_{t_2} - \bar{F}_{T_i}, \cdots, F_{t_i} - \bar{F}_{T_i}\right)\right), \tag{13}$$

$$F_{t_{i+1}} = \sum_{k=1}^{i} P_{t_k} F_{t_k}. \tag{14}$$

Similarly, the supports $S_{t_{i+1}}$ and comments $C_{t_{i+1}}$ can be derived from supports S_{T_i} and comments C_{T_i}, respectively. To comprehensively assess the risk of the $F_{t_{i+1}}$, $S_{t_{i+1}}$, and $C_{t_{i+1}}$ at t_{i+1}, the situation risk metric is obtained by jointly employing the average number of the public online behaviors during the time T_i:

$$R_{t_{i+1}} = \frac{F_{t_{i+1}} + S_{t_{i+1}} + C_{t_{i+1}}}{\left(\bar{F}_{T_i} + \bar{S}_{T_i} + \bar{C}_{T_i}\right) + \left(F_{t_{i+1}} + S_{t_{i+1}} + C_{t_{i+1}}\right)}. \tag{15}$$

3.2.3. Potential Hazard Module. The potential hazard module is to obtain the potential hazard metric by measuring the similarity between the target event E_{tgt} and historical events database $E_{hst} = (E_{hst_1}, E_{hst_2}, \cdots, E_{hst_M})$. Each historical event in E_{hst} contains a short news content and a label represented whether the event is safe or not. The potential hazard metric calculation has three steps. Firstly, we obtain the word vector of each word in event content from a word vocabulary by the word vector training models [38, 39]. We use the cosine function to represent similarity between word w_i and u^k_j, which are from the target event E_{tgt} content and the kth event E_{hst_k} content from events database E_{hst}, respectively.

$$\mathrm{Sim}\left(w_i, u^k_j\right) = \cos\left(w_i, u^k_j\right) = \frac{v_{w_i} \cdot v_{u^k_j}}{\left|v_{w_i}\right| * \left|v_{u^k_j}\right|}, \tag{16}$$

where v_{w_i} and $v_{u^k_j}$ are represented as the word vectors w_i and u_j, respectively.

Secondly, the similarity of the target event E_{tgt} with the kth event E_{hst_k} can be defined as:

$$\mathrm{Sim}\left(E_{tgt}, E_{hst_k}\right) = \sum_{i=1}^{O_w} \sum_{j=1}^{O_u} \mathrm{Sim}\left(w_i, u^k_j\right), \tag{17}$$

where O_w and O_u are represented as the word counts of E_{tgt} and E_{hst_k}, respectively.

Thirdly, we retrieve the word similarity in target event E_{tgt} with that of all historical events E_{hst} with the safety labels and determine the count N of safety events where the similarity is above the threshold (=0.7). Here, we define the potential hazard metric $H_{t_{i+1}}$ is the event similarity Sim_{evt}, which is the average of the sum of word similarity with selected N safety events. It can be evaluated as:

$$H_{t_{i+1}} = \mathrm{Sim}_{evt}\left(E_{tgt}, E_{hst}\right) = \frac{1}{N} \sum_{1}^{N} \left(\mathrm{Sim}\left(E_{tgt}, E_{hst_k}\right) \ge 0.7\right). \tag{18}$$

Table 2: Emotional regulation strategies at different intervals.

Emotional security threshold	$0 \le I < 0.1$	$0.1 \le I < 0.2$	$0.2 \le I < 0.3$	$0.3 \le I < 0.4$	$0.4 \le I < 0.5$
Emotion regulation strategy	Key intervention zone	Safety warning zone	Noteworthy zone	Normal volatility zone	Emotional comfort zone

Table 3: Data description of typical events.

Events	Time coverage	Count
Overall COVID-19 event	Jan. 1, 2020~Feb.18, 2020	1 million
Wuhan “lockdown”	Jan. 1, 2020~Feb.18, 2020	52,560
Shuanghuanglian can inhibit novel coronavirus	Jan. 29, 2020~Feb.8, 2020	7,873

Table 4: The number of different datasets under the pandemic topic.

Topics	Count in 1 million	Count in hot and public opinion events	Event count in 410 hot events
Pandemic news and data report	146,117	201,524	17
Medical care was on the front line	175,402	160,684	53
Nation- and local-issued policy measures	114,613	155,428	109
Public protection initiative	146,855	128,347	48
Scientific breakthroughs and knowledge dissemination	139,804	127,130	148
Peripheral symptoms cause inner anxiety	129,257	110,971	28
Be objective in daily life	147,952	115,916	7

3.3. Decision-Making. To this end, we propose the method of social-emotional security index $I_{t_{i+1}}$ at the predicted time t_{i+1}, after we obtain three metrics of index system in:

$$I_{t_{i+1}} = \frac{R_{t_{i+1}} * H_{t_{i+1}}}{B_{t_{i+1}}}. \tag{19}$$

From the perspective of emotional security, we provide an emotional regulation grading scheme with a five-level emotional security threshold (safety valve) in Table 2. This scheme concisely and clearly describes the public’s cognitive feelings about emergencies. And we suggest that the interval above 0.3 is the emotional security level.

4. Experiment and Results

4.1. Datasets. Since there is no open dataset about Chinese public safety to verify the proposed method objectively, truthfully, and effectively, we first use 2 million COVID-19 Weibo events as an example with 410 hot events and 52 public opinion events tagged. Each event data includes text content, comment content, safety label, forwards volume, comments volume, supports volume, and issued time. We get the total number of posts and calculate emotional tendency and valence accordingly. As space limited, we take three incidents as examples to describe in detail. The data description is shown in Table 3.

The first line is the open dataset of COVID-19, covering the period from Jan. 1, 2020, to Feb.18, 2020, with the data volume of 1 million, describing the overall situation during the pandemic. The other two are subevents of hot events and public opinion events related to COVID-19, namely, subevents, which crawled through Weibo API. The time coverage is determined by the event duration and crawled quality. Two typical subevents, the Wuhan “lockdown” and Shuanghuanglian (a kind of Chinese medicine) that can inhibit novel Coronavirus, were selected for demonstration in this study because the Wuhan lockdown event played a crucial role in the containment of the epidemic and also was one of the most influential events affected public emotions during the epidemic. The Shuanghuanglian inhibition event was particularly typical in that it instantly boosted public confidence during the most serious period of the epidemic. We use the 7 pandemic topics [35] to label the safety events. Details are shown in the following Table 4.

4.2. Results

4.2.1. Emotional Bias Metric. When it comes to the emotional bias metric, we use subevent Wuhan “lockdown” to show the result. The transformer-based temporal prediction model found that anger, joy, expect, and hate are four abnormal emotion types. So, we choose these four to calculate the emotional bias. The emotional bias metric B are shown in Table 5 following the date.

From the calculated original emotion valence, it can be seen that the valences of different emotions are also in different threshold ranges. We select the four abnormal volatility and calculate the overall four emotional changes through

Table 5: The abnormal emotion bias in Wuhan "lockdown" event.

Date	Anger	Joy	Expect	Hate	Emotional bias B
2020/1/21	0.2228	0.2823	0.4603	0.0344	0.3998
2020/1/22	0.1791	0.3279	0.3649	0.1278	0.3721
2020/1/23	0.2529	0.2837	0.4105	0.0528	0.1065
2020/1/24	0.2242	0.3406	0.3630	0.0719	0.2545
2020/1/25	0.2767	0.2727	0.4142	0.0362	0.2924
2020/1/26	0.2531	0.2737	0.4212	0.0518	0.4082
2020/1/27	0.2765	0.3140	0.3521	0.0573	0.7152
2020/1/28	0.3850	0.2342	0.3394	0.0412	0.6419
2020/1/29	0.3165	0.2481	0.3709	0.0643	0.8568
2020/1/30	0.3424	0.2559	0.2871	0.1144	0.8762

each emotion on each day. More obviously, the news of the Wuhan "lockdown" was released on Jan 23, so the emotional bias decreased significantly. On Jan 29, multiple media report warm sun shines on Wuhan city, and citizens prayed for blessings, which also contributed to a rise of emotional bias.

4.2.2. Situational Risk Metric. The measurement of situational risk metric is mainly depending on the statistics of multiple variables, including the number of Weibo posts, the number of comments, forwards, and supports, etc. As the Wuhan lockdown affected the huge volatility of social-emotional security at then, we take this as an example. The results are shown in Figure 4.

From the two curve trends in Figure 4, the situation risk metric line is consistent with the Baidu Index, which is a famous trend indicator that describes the popularity of public opinion with a keyword search scale in verification. The coordinate axis on the left (0-0.8) is the calculated situational risk metric, and the coordinate axis of the Baidu Index is on the right, which is from 0 to 450,000. It can be found that the calculation method depicts the situational risk within a relatively fixed numerical range and avoided the sharp increase and fall caused by the simple quantitative accumulation in the traditional index research. This adaption better reflects the integrity of event evolution.

4.2.3. Potential Hazard Metric. We use these three selected events as examples to show the potential hazard metric performance among the 410 historical events database. The results of the experiment are shown in Table 6, where the type of topic is corresponded, and the number of events with safety labels included. From the calculated metric H result, there is no doubt that the event "Shuanghuanglian can inhibit novel coronavirus" makes the public feel safer and has the highest value of potential risk metric.

5. Discussion

This study proposes an effective concept of social-emotional security and achieves the goal of accurately depicting public emotional volatility in COVID-19-related events. In practice, the experiment carries out completely around the

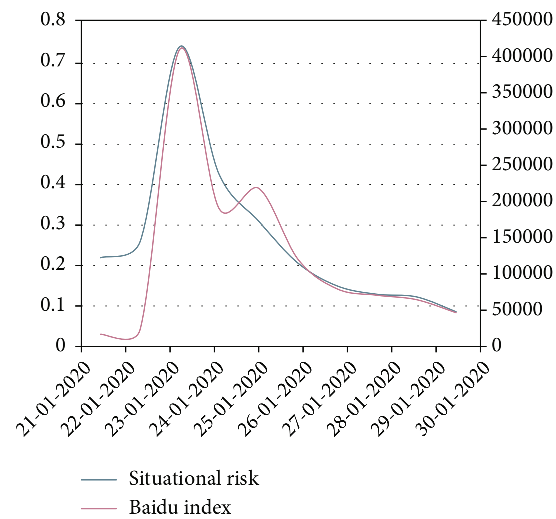

Figure 4: The consistency between situational risk and Baidu Index.

COVID-19 outbreak, so the features are all in the same vector space. Besides, the loaded emotion lexicon is also built for COVID-19, so the result of measurement is more consistent with the real world in human cognition. However, there are lacking specific evaluation metrics to reflect the accuracy of trend prediction quantitatively; we also apply it to other different types of safety events to validate the social-emotional security computing method.

As shown in Figure 5, we only highlight these two dimensions, and the emotion regulation strategy uses the gradient from red (danger) to green (safety) to reflect the social-emotional security.

At the initial stage of the epidemic in January 2020, the public did not fully perceive the risk, so the relevant search volume in situational risk was not high. However, after a large number of public opinion events were released, it began to rise significantly in the middle and late January and remained stable. In terms of emotions, they were a more sensitive in response to the situational risk. The public emotions dropped significantly after reports of unexplained infections found in Wuhan in the early, but rose rapidly after

Table 6: The performance of the potential hazard metric.

Events	Topics	The number of safety label	Metric H
Overall COVID-19 event	Pandemic news and data report	4	0.21
Wuhan "lockdown"	Nation- and local-issued policy measures	42	0.34
Shuanghuanglian can inhibit novel coronavirus	Scientific breakthroughs and knowledge dissemination	77	0.87

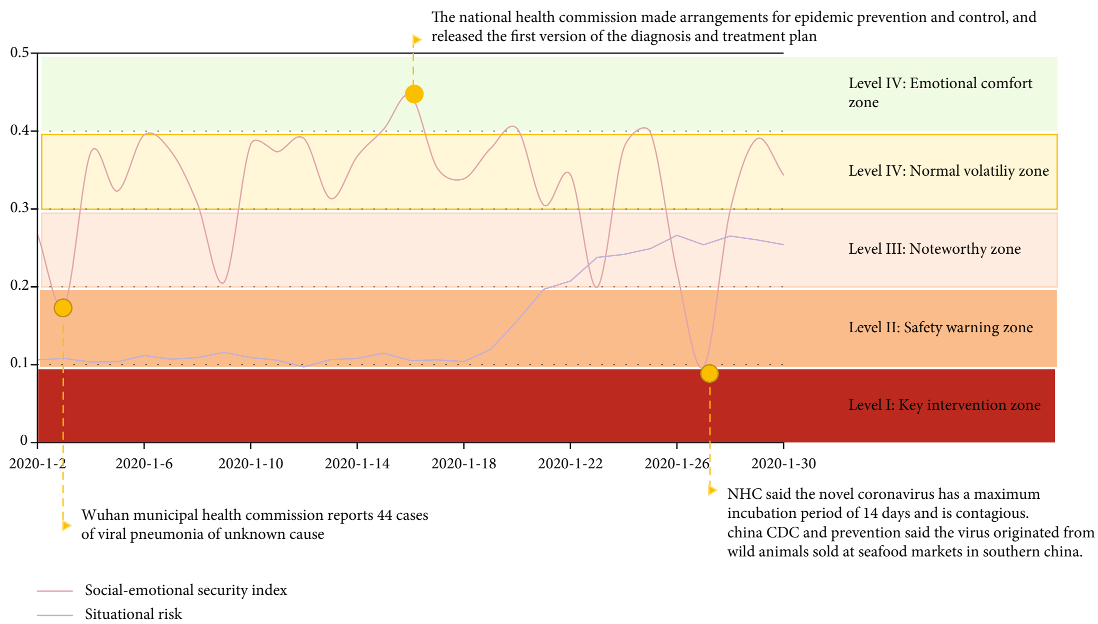

Figure 5: Social-emotional security index in overall COVID-19 event.

the country introduced relevant epidemic prevention measures. The volatility curve fully reflects that the public is apparently to the emotional changes and will respond quickly after acquiring information. This is also the reason why we focus on the emotional security of the whole society rather than using the situational risk alone to observe.

Then, the subevent is the lockdown of Wuhan. As a result of the large number of people infected and outflow, the whole country fell into panic. As shown in Figure 6, on January 23, the news was released that Wuhan would lockdown from midnight on January 24. As can be seen, the search volume increased significantly after the information was released, but the public emotions were still panicked. Therefore, the release of the lockdown news further aggravated the decline of public safety. Because the data was collected from the whole nation and did not have regional attributes, the emotional fluctuations of those people who were not in Wuhan are not heavy. On January 29, when the situational risk of the event gradually disappeared, the range of social-emotional security returned to the normal range.

It should be noted here that because the data is calculated and presented for a single event, the situational risk and emotional security index only reflect the situation of the event itself within this time interval. On the other hand, our proposed method can capture social emotions and validates by the fact that the social-emotional security index was monitored all about 0.2 on January 23 in Figures 5 and 6, while the data inputs are from different datasets.

As for the event of Shuanghuanglian can inhibit novel coronavirus, as shown in Figure 7, the instant situational risk rose as soon as it was reported on January 31, but public opinion fell back two days later immediately. Under the continuous tension of public emotions, this news undoubtedly rapidly improved their emotional security, reaching beyond the normal "comfort" level, and continued to stabilize at a high level of safety during the public offline shopping situation.

This also confirms that our method effectively perceives the public's response from a perspective of social-emotional security. Unlike most studies that focus on situational risk, the social-emotional security index provides a more comprehensive and accurate identification of potential risk, as well as the impact of an unexpected event on the public's emotional security.

6. Method Validation for Extended Events

To further verify that the index system of social-emotional security indicators is more universal, we apply the method to other 37 hot events from January to October 2020, including positive events and negative events. The event list

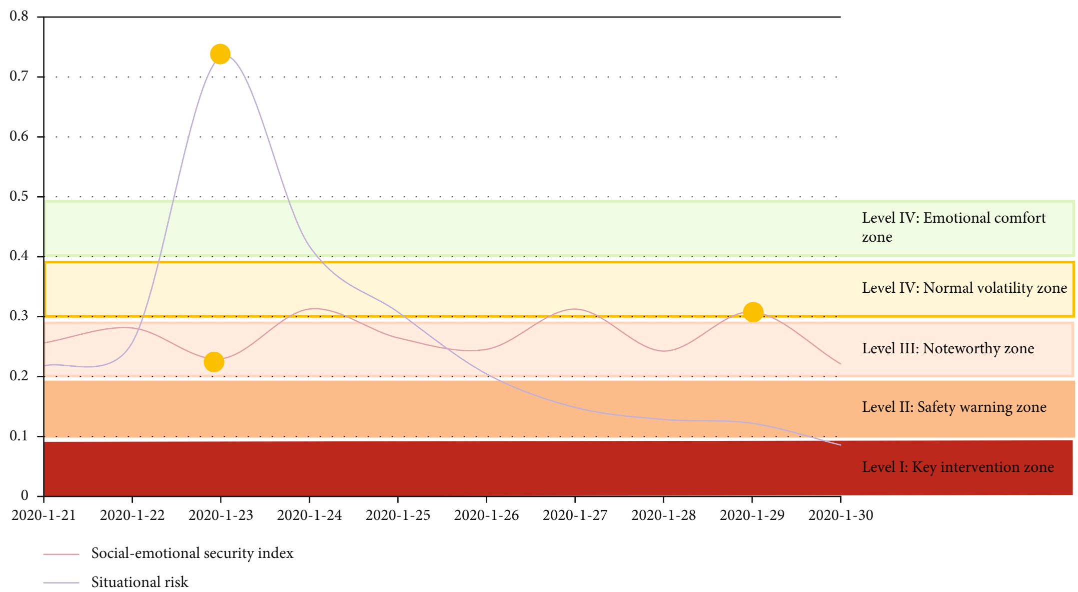

FIGURE 6: Social-emotional security index in Wuhan lockdown subevent.

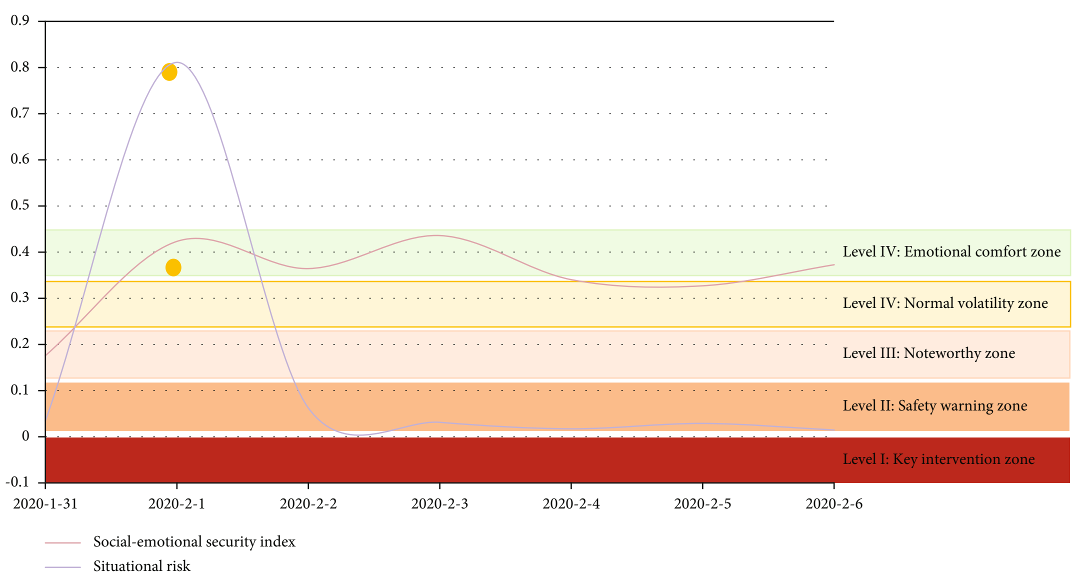

FIGURE 7: Social-emotional security index in Shuanghuanglian inhibition subevent.

includes "primary school students winning the prize for cancer research," "the national safety law of Hong Kong was issued," "the scientific researchers of the Chinese Academy of Sciences resigning collectively," and "the regulations on the administration of permanent residence of foreigners triggered a heated debate." Similarly, each event includes text content, comment content, forwarding volume, comment volume, support volume, and the total number of posts. After screening and cleaning, 30 events are selected for expanding experimental verification. We have invited three experts in the same field to label whether the event is with potential safety or not, and we only determine the safety label when all three experts believe that the event affects emotional security to the public.

In the experiment of verifying the social-emotional security index, the accuracy of the method is excellent. The trend prediction accuracy of 19 events is lifting to 63.3% (19/37), while in monitoring COVID-19-related emergencies, the accuracy reaches 90%.

7. Conclusion

The current frequency of public safety incidents has led the public to be more concerned about environmental safety and their health than ever before. Therefore, we need to monitor and defuse safety risks timely, as well as reduce the negative impact on the public. Based on this motivation, we propose the concept of social-emotional security from two classical theories of risk society and psychological resilience and construct an index system to measure public safety with three core metrics in emotional bias, situational risk, and potential hazard. The proposed social-emotional security concept and index measurement method are validated by the actual major public health emergency COVID-19. The validation results show that the trend of emotional security is in line with the actual situation. We also apply the method to other hot events, and the predicted trend could still reach 63.3% consistency although we do not have sufficient data and features of the events.

Moreover, we suggest a five-scheme emotional regulation for social-emotional security with the 0.3 threshold. In future work, we will extend our method to more safety domains to continuously improve the performances of theories, methods, and intervention strategies, so as to promote the social stability.

Data Availability

The data can be found here: https://www.datafountain.cn/competitions/423, accessed on 3 March 2020.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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