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ORIGINAL RESEARCH

Research on the Evolution Trend of Group Psychological Security Risks Under Public Health Emergencies: Mining and Analysis Based on Social Media Data

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Background: In the digital age, people's attitudes and psychological security towards public health emergencies will be shared. Similar or identical psychological security states are prone to clustering and differentiation, while differentiated group psychological security is more prone to polarization, leading to group psychological security risks and then posing a threat to social stability and national security. However, existing studies mostly use qualitative analysis methods to study group emotional risks. There are still limitations in the study of dynamics of group psychological security risks through mining real data of social media.

Purpose: The study aims to use intelligent analysis methods to understand how group psychological security risks dynamically change.

Methods: The study draws on text sentiment analysis, Markov chains and time series analysis to construct a framework for the evolution of group psychological security risks. Based on this framework, text data was crawled on Sina Weibo platform, mainly consisting of posts during public health emergencies (March 1st to June 30th, 2022) in Shanghai, and a psychological security lexicon in the field of public health emergencies was constructed. This laid the foundation for identifying the tendencies, intensity, and transitions of individual text psychological security, and then exploring the evolution trend of group psychological security risks.

Results: Compared with the generation and reduction periods, group psychological security risks are more likely to occur during the outbreak and recovery periods, and the intensity level is also higher. The overall intensity of group psychological security risks shows an evolution trend of first increasing, then decreasing, and then increasing again.

Conclusion: The paper provides an opportunity to explore the dynamics of psychological security in the digital space. Meanwhile, we call on the government and relevant management departments to pay more attention to the group psychological security risks formed during the outbreak and recovery periods of public health emergencies, and take corresponding measures in a timely manner to guide the public to transform the extreme psychological security state into the normal psychological security state, in order to prevent and resolve group psychological security risks, promote social stability and national security.

Keywords: group psychological security risks, psychological security lexicon, machine learning, evolution trend

Introduction

Psychological security (also known as mixed psychological security) refers to public subjective response to internal and external environmental stimuli, or can be seen as a kind of emotional experience,[1] which conforms to the bivariate model and includes both security and insecurity.[2] Group psychological security includes both group security and group insecurity, which are obtained by aggregating individual level psychological security to the group level. With the development and expansion of online social media platforms, social media has become an indispensable part of public daily life, and has also provided channels for the rapid dissemination of information related to public health emergencies and the emergence and evolution of public diversified emotions.[3–5] For example, in the outbreak of the new coronavirus epidemic in 2020, social media platforms

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have become the main battlefield for hundreds of millions of Weibo users to obtain epidemic information, and also the gathering place for hundreds of millions of Weibo users to express their psychological security. However, after public with similar or identical psychological security states gather, it is easy to trigger group psychological security differentiation, and the differentiated group psychological security is more prone to polarization (that is, excessive group security or excessive group insecurity),[6,7] inducing group psychological security risks. For example, excessive group security can easily lead to group slackness, numbness, and apathy, and even inability to respond rationally in crisis situations, further hiding risks. Excessive group insecurity can easily lead to group panic, group contradictions and conflicts, and even outbreaks of group incidents, disrupting existing social order and hindering social harmony and stability.[8,9] Therefore, in the context of public health emergencies, it is crucial to trace, identify, and analyze the evolution of group psychological security risks by mining massive data on social media.

Looking at previous literature, we found that (1) most studies focus on group emotions, while few studies on group psychological security. In the study of group emotions, Veltmeijer et al[10] reviewed the research on automatic group emotion recognition. Wang et al[11] proposed a framework consisting of three networks: FacesNet, SceneNet, and ObjectsNet, and utilized the information of faces, scene, and objects in images to identify group emotions. Yao et al[12] divided the development of public opinion into different stages based on the life cycle theory, revealing the evolution laws of group emotions in the phenomenon of topic resonance at different stages. Sharma et al[13] proposed an audio-visual approach to identify group-level affect. In the study of group psychological security, Liu[14] revealed the process and rules of the propagation of group security and group insecurity based on the theory of emotional contagion. Zhang[15] used the 2012 and 2014 China Family Tracking Survey to construct two balanced panel data, and used the PSM-DID estimation method to explore the impact of the subsistence allowance system on the subjective well-being, acquisition, and security of the poor groups. (2) Although there are studies on group emotional risks, qualitative research methods such as case analysis are also used to analyze how group emotional risks forms and evolve, with less involvement in group psychological security risks. For example, based on online case data and practical experience, Wu[9] drew on theory of rheology-mutation to propose the evolution mechanism of social psychological risks in megacities, which includes two aspects: first, the diffusion from individual psychological risk to group psychological risk, and then from group psychological risk to social psychological risk; second, the evolution from social psychological risk to social psychological crisis, and then from social psychological crisis to social crisis. (3) In recent years, social media platforms have provided channels for the generation and evolution of multiple emotions among the public.[16] Research on the evolution of group emotions has gradually begun to adopt machine learning methods. However, at present, few scholars have conducted intelligent analysis on the evolution of group psychological security risks. For example, Zhu et al[17] calculated the emotional intensity values in text topics under different time dimensions, and conducted dynamic evolution analysis on emotions. Feng et al[18] used the Boson emotional dictionary and time series analysis method to study the evolution of Zhihu topics, revealing the evolution trend of daily average emotions in public Zhihu topics. Adikari et al[19] integrated natural language processing techniques, word embedding, Markov chains, and growing self-organizing maps to construct a self-structuring artificial intelligence framework that identifies individual emotional intensity, transitions, and group emotional intensity in social media data.

Based on this, we will adopt machine learning methods, draw on text sentiment analysis, Markov chains, and time series analysis to construct a framework for the evolution of group psychological security risks, and then analyze the evolution trend of group psychological security risks based on this framework. The contributions of this paper are mainly reflected in three aspects: firstly, this paper conducts research on the evolution trend of group psychological security risks for the first time. This helps to timely grasp the development trajectory of group psychological security risks under public health emergencies, and thus helps the government and relevant management departments to take measures to prevent and resolve group psychological security risks, which is of great significance to social stability and national security. Secondly, this paper constructs a psychological security lexicon in the field of public health emergencies for the first time. This helps to conduct real-time analysis of individual text psychological security tendencies and intensity levels after the occurrence of public health emergencies, avoiding the lag of questionnaire responses, and controlling the social desirability effect of participants. Thirdly, this paper uses machine learning algorithms for the first time to conduct intelligent analysis of group psychological security risks. The hidden rules of data are mined from real text data, which overcomes the limitations of linear and static methods in previous research on group psychological security, and expands the models and methods of group psychological security research.

Methods

The evolution framework of group psychological security risks proposed in this paper includes the following six aspects, as shown in Figure 1.

Data Collection

Data was collected on China's most influential Sina Weibo platform. In the "advanced search" function of Sina Weibo, the keywords were set as four combinations of "Shanghai" and "Virus", "Novel Coronavirus", "New Cases", and "Quarantine". The type was set to "Original". The time was set to "March 1st to June 30th, 2022", that is, starting from the first domestically transmitted case in Shanghai (March 1st) and ending one month after the fully restore normal work and life across the city (June 30th). Octoparse was used, which mainly collects fields such as user ID, text time, and text contents. Finally, a total of 92,692 text data related to public health emergencies in Shanghai were obtained. According to the life-cycle theory,[20,21] the development of external environmental stimuli and events can be summarized as going through four evolution stages: generation, outbreak, reduction, and recovery. Hence, based on publicly available coronavirus cases (see Figure 2) and policy information at the time of public health emergencies in Shanghai, the data during this period can be divided into four stages: generation period (3.1–3.31), outbreak period (4.1–4.31, city-wide lockdown), reduction period (5.1–5.31, further diminish lockdown and control zones across the city), and recovery period (6.1–6.30, fully restore normal work and life across the city). Among them, a total of 17,981 text data in March, 23,021 text data in April, 18,909 text data in May, and 32,781 text data in June.

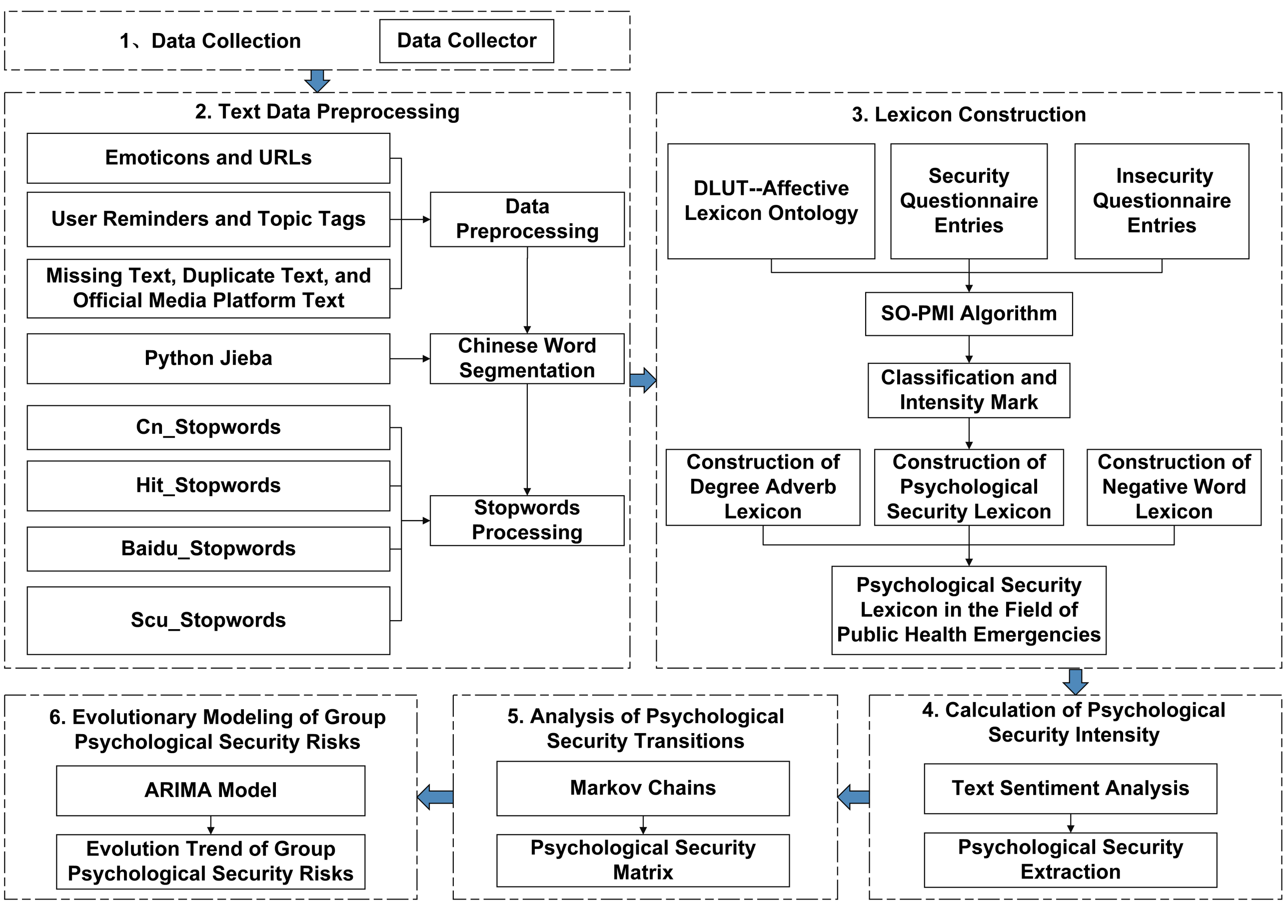

Figure 1 Evolutionary framework of group psychological security risks.

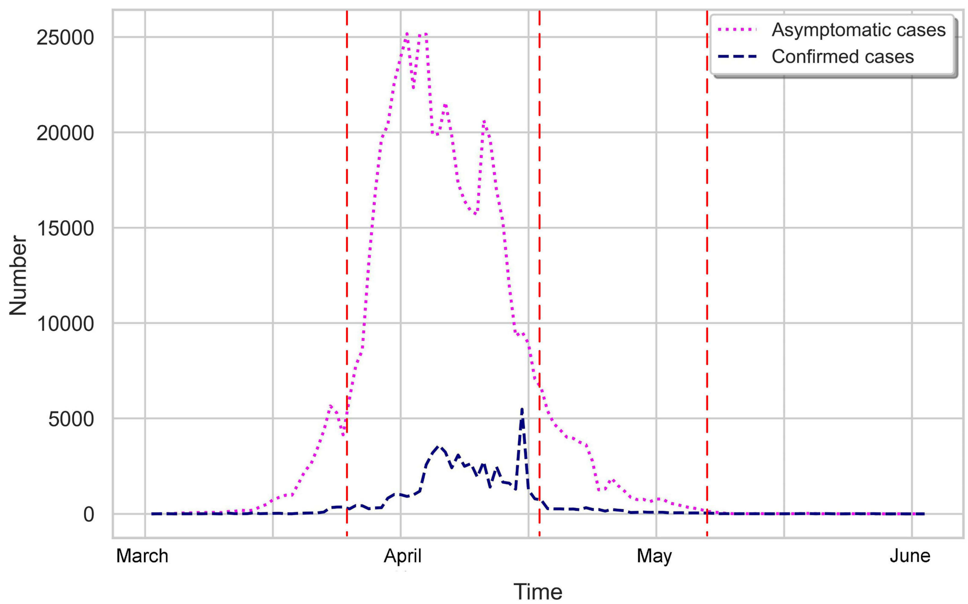

Figure 2 Publicly available coronavirus cases during public health emergencies in Shanghai.

Data Preprocessing

Combined with Python regular expression matching and manual operation, emoticons, user reminders, URLs, topic tags, missing texts, duplicate texts, and official media platform texts were removed, and 38,717 text data were obtained. Among them, a total of 9275 text data in March, 10,146 text data in April, 8220 text data in May, and 11,076 text data in June. Next, 38,717 text data were segmented using the Jieba algorithm for Chinese segmentation in Python. Meanwhile, by integrating the cn_stopwords, hit_stopwords, baidu_stopwords, and scu_stopwords, a more comprehensive stop-words_list was constructed, 2270 stopwords were obtained, and the text data were processed. Finally, missing values were removed and a total of 38,629 text data were obtained for the subsequent construction of psychological security lexicon. Wherein, 9257 text data in March, 10,123 text data in April, 8215 text data in May, and 11,034 text data in June.

Lexicon Construction

To analyze the psychological security of texts under public health emergencies, it is necessary to construct a psychological security lexicon. Therefore, firstly, in the previous universal emotional lexicon, the Dalian University of Technology-affective lexicon ontology was chosen as seed words for security and insecurity.[22] Because it has richer information, such as sentiment vocabulary, part-of-speech tagging, sentiment classification, polarity value. At the same time, combined with the security and insecurity questionnaire items prepared by Gao and Liu[23] and Zou[24] as seed words. Semantic orientation pointwise mutual information (SO-PMI) algorithm was applied to obtain the psychological security tendencies, SO-PMI values, word length, and part-of-speech of candidate words in text data.[25,26] Next, candidate words were manually screened. Specifically manifested in: (1) SO-PMI values of candidate words were screened, that is, candidate words with "SO-PMI=0" were selected as neutral words, candidate words with "SO-PMI>0" were used as security words, candidate words with "SO-PMI<0" were used as insecurity words. (2) Excel was used to further screen candidate words, retaining psychological security words with part-of-speech of adjective, adverb, adnoun, idiom, noun, verb, gerund, and so on. (3) According to the Dalian University of Technology-affective lexicon ontology, words of length 1 were removed and words of length 2 or more were retained. (4) Candidate words for security and insecurity that were missed and not included in the vocabulary were removed. (5) All screened candidate words were merged and deduplicated with the Dalian University of Technology-affective lexicon ontology, and questionnaire items of security and insecurity, then a psychological security lexicon in the field of public health emergencies was constructed with the above seed words as an extension (a total of 27,828 words). The constructed psychological security lexicon follows the

Dalian University of Technology-affective lexicon ontology and Ekman's emotional classification method, which is divided into two categories: security and insecurity. The security lexicon is divided into three major types (joy, good, and surprise) and eight subtypes. The insecurity lexicon is divided into four major types (anger, sad, fear, and disgust) and thirteen subtypes. We invited four scholars to refers to the construction standards of the Dalian University of Technology-affective lexicon ontology, conduct multiple rounds of negotiation, analysis, and discussion on the newly added psychological security words, and classify them into fine-grained categories. Using a 5-level scoring system, with a score of 1–5 for security and −1 to −5 for insecurity.

In the process of analyzing the emotional intensity of text, scholars often add degree adverbs to further strengthen or weaken the emotional intensity, and thus obtain a new emotional intensity value,[27] such as "too anxious", "pretty happy". Therefore, this paper integrated the degree adverb lexicon constructed by Han et al[28] and Guo et al[27] to construct a new and more comprehensive degree adverb lexicon. The final degree adverb lexicon contains a total of 143 words, and the score intensity increases successively according to 6 levels, which are 0.5, 0.8, 1.2, 1.5, 1.8, and 2, respectively.

In the process of analyzing the emotional intensity of text, scholars often add negative words to correctly identify the emotional polarity of the text and obtain a new emotional intensity value. Therefore, this paper integrated the negative words constructed by Hownet[29] and Guo et al[27] to construct a new and more comprehensive negative word lexicon. The final negative word lexicon contains a total of 76 words.

Calculation of Psychological Security Intensity

Based on the above psychological security lexicon, degree adverb lexicon, and negative word lexicon, the intensity of security and insecurity were calculated.

The formula for calculating the psychological security intensity of a text with only psychological security words (such as "happy") is as follows:

$$\mathrm{Word}_{i\in\ \mathrm{joy,good,surprise,anger,sad,fear,disgust}}=\alpha*\beta \tag{1.1}$$

Where, Word_i represents the psychological security intensity of text with only psychological security words. i ∈ joy, good, surprise, anger, sad, fear, disgust, α indicates the intensity values of this psychological security word, which are 1, 2, 3, 4, and 5, respectively. β shows the polarity values of this psychological security word, which are −1, 0, and 1, respectively.

The formula for calculating the psychological security intensity of a text with only psychological security words and degree adverbs (such as "too happy") is as follows:

$$\mathrm{Word}_j = \gamma^* \mathrm{Word}_i \tag{1.2}$$

Where, Word_j represents the psychological security intensity of text with only psychological security words and degree adverbs. γ indicates the intensity values of this degree adverb, which are 0.5, 0.8, 1.2, 1.5, 1.8, and 2, respectively.

The formula for calculating the psychological security intensity of a text with only psychological security words and negative words (such as "not happy") is as follows:

$$\mathrm{Word}_z = (-1)^{m*} \mathrm{Word}_i \tag{1.3}$$

Where, Word_z represents the psychological security intensity of text with only psychological security words and negative words. (−1) indicates the intensity values of this negative word. m shows the number of negative words, that is, the psychological security intensity of words is opposite when m is odd, the psychological security intensity of words remains unchanged when m is even.

In addition, psychological security words, degree adverbs, and negative words often appear simultaneously in the text content, while the order of presentation of degree adverbs and negative words has different effects on the calculation of psychological security intensity of the text. If presented in the order of degree adverbs, negative words, and psychological security words, the formula for calculating the psychological security intensity of a text is as follows:

$$\mathrm{Word}_k = (-1)^{m*} \mathrm{Word}_j \tag{1.4}$$

Where, $Word_k$ represents the psychological security intensity of text in the order of degree adverbs, negative words, and psychological security words.

If presented in the order of negative words, degree adverbs, and psychological security words, such as "not too happy", the formula for calculating the psychological security intensity of a text is as follows:

$$Word_l = (-1)^{m*} Word_j{}^{*} 0.5 \tag{1.5}$$

Where, $Word_l$ represents the psychological security intensity of text in the order of negative words, degree adverbs, and psychological security words.

In addition, due to the fact that each Weibo text data may have a separate security or insecurity, or both, or may even no security or insecurity, that is, neutral text, the calculation method for the psychological security intensity of the text is also different. If security or insecurity exists alone in Weibo text data, the formula for calculating the psychological security intensity of a text for this word is as follows:

$$Word_s = Word_{joy \in PA,PE} + Word_{good \in PD,PH,PG,PB,PK} + Word_{surprise \in PC} \tag{1.6}$$

$$Word_{is} = Word_{anger \in NA} + Word_{sad \in NB,NJ,NH,PF} + Word_{fear \in NI,NC,NG} + Word_{disgust \in NE,ND,NN,NK,NL} \tag{1.7}$$

Where, $Word_s$ denotes the psychological security intensity of the text where the security word exists alone. $Word_{is}$ shows the psychological security intensity of the text where the insecurity word exists alone. $Word_{joy}$ denotes the intensity of joy words. $Word_{good}$ denotes the intensity of good words. $Word_{surprise}$ denotes the intensity of surprise words. $Word_{anger}$ denotes the intensity of anger words. $Word_{sad}$ denotes the intensity of sad words. $Word_{fear}$ denotes the intensity of fear words. $Word_{disgust}$ denotes the intensity of disgust words.

If both security and insecurity exist in Weibo text data, the formula for calculating the psychological security intensity of a text is as follows:

$$Word_{ps} = Word_s + Word_{is} \tag{1.8}$$

Where, $Word_{ps}$ represents the psychological security intensity of the text where both security words and insecurity words coexist. If $Word_{ps} = 0$, the psychological security of the text tends to be neutral. If $Word_{ps} > 0$, the psychological security of the text tends to be security-dominated. Among them, $0 < Word_{ps} < 3.92$ represents normal security, $Word_{ps} \geq 3.92$ represents extreme security. If $Word_{ps} < 0$, the psychological security of the text tends to be insecurity-dominated. Among them, $-3.92 < Word_{ps} < 0$ represents normal insecurity, $Word_{ps} \leq -3.92$ represents extreme insecurity.

If there are no words with security or insecurity in the Weibo text data, the Weibo text will be classified as neutral.

Analysis of Psychological Security Transitions

Individual psychological security will change dynamically with the passage of time. Therefore, the transitions of individual psychological security in this paper will be carried out on the basis of identifying the tendencies and intensity of psychological security. The specific method refers to the Markov chains based emotional transitions method proposed in previous studies.[19,30] The specific process is as follows:

Firstly, in order to generate psychological security transitions, it is necessary to define a psychological security space, as shown in formula 1.9:

$$Word_{ps} = \{q_i | i \in [1, n]\} \tag{1.9}$$

Where n denotes the number of psychological security states.

Secondly, in text analysis, the changes between different psychological security states denotes transitions, and the probability that an individual changes from one psychological security state to another refers to transition probability. Therefore, based on time psychological security sequences extracted from different types of psychological security, the interaction between psychological security states was formed, and modeled using the psychological security transitions matrix (A_{ij}) as shown in formula 1.10:

$$A_{ij}=\begin{bmatrix} a_{11}, & a_{12}, & \cdots & a_{1n} \\ \ldots & \ddots & \ddots & \ldots \\ a_{n1}, & a_{n2}, & \cdots & a_{nn} \end{bmatrix} \tag{1.10}$$

Where n denotes the number of psychological security states. a_{ij} denotes psychological security transitions from Q_i to Q_j.

$$a_{ij} \in [0,1], i,j \in [1,n] \tag{1.11}$$

$$\sum_{k=1}^{n} a_{jk} = 1 \tag{1.12}$$

Evolutionary Modeling of Group Psychological Security Risks

Autoregressive integrated moving average (ARIMA) model is currently a popular time-series prediction and analysis model. Based on autoregressive (AR) model, moving average (MA) model, and autoregressive moving average (ARMA) model, the difference method is introduced to transform any non-stationary time series into stationary time series for research. It has higher mathematical accuracy and reliability.[18,31]

In this paper, ARIMA model was used to construct time-series analysis equation for group psychological security risks, and predict and analyze the evolution trend of group psychological security risks. Specifically, according to the affective convergence mechanism,[8] similar psychological security states after psychological security transitions were aggregated in units of a time-step (/day). The group psychological security risks refer to the psychometric standard, which takes a score of upper and lower 27% from the 5-level score.[32] Security value greater than or equal to 3.92 is considered extreme security, and the same or similar extreme security will converge to form a security risk group. Insecurity value less than or equal to −3.92 is considered extreme insecurity, and the same or similar extreme insecurity will converge to form an insecurity risk group. On this basis, time-series data of security risk group and insecurity risk group were extracted. Then, Augmented Dickey-Fuller was used to conduct unit root test on the time-series data. $P < 0.05$ proves that the data is stationary and ARMA (p, q) is directly used for prediction and analysis. $P > 0.05$ proves that the data is non-stationary data, the sequence is operated via difference method (d represents the order of difference for non-stationary data, generally 0,1,2) and logarithm is taken to convert non-stationary data into stationary data. Next, Ljung-Box was used to conduct white noise testing on the data. $P < 0.05$ proves that the data is a non-white noise sequence, and subsequent analysis and prediction can be carried out. Once again, MA (q) and AR (p) of the data were determined using the autocorrelation function and partial autocorrelation function, and Akaike information criterion, respectively, and then ARIMA (p, d, q) was used for prediction and analysis. Finally, the difference between real and predicted values was calculated to obtain the residual sequence, and Ljung-Box was used again to test whether the residual sequence is a white noise sequence. $P > 0.05$ proves that the data is a white noise sequence, and the model performance is well, thus obtaining a stable evolution trend of group psychological security risks.[18,31]

Results

On the basis of the above framework for the evolution of group psychological security risks, the intensity and tendencies of 38,629 text data were identified one by one. Based on the life-cycle theory, public health emergencies in Shanghai can be divided into four periods: generation period (3.1–3.31), outbreak period (4.1–4.31), reduction period (5.1–5.31), and recovery period (6.1–6.30). Hence, this article only selects representative individual (that is, more Weibo posts and longer participation time) in each stage to analyze and display their psychological security intensity, tendencies, and dynamic transitions. The specific results are as follows:

Identification of Individual Psychological Security Intensity and Tendencies

During the generation period (3.1–3.31), representative individual A was selected and a total of 6 texts were published. Among them, two of the texts were security-dominated, one was neutral, and three were insecurity-dominated. The identification of text psychological security intensity and tendencies are shown in (Figure 3a). On March 13th, the individual released neutral text (intensity = 0). On March 14th, the individual posted both extreme insecurity text

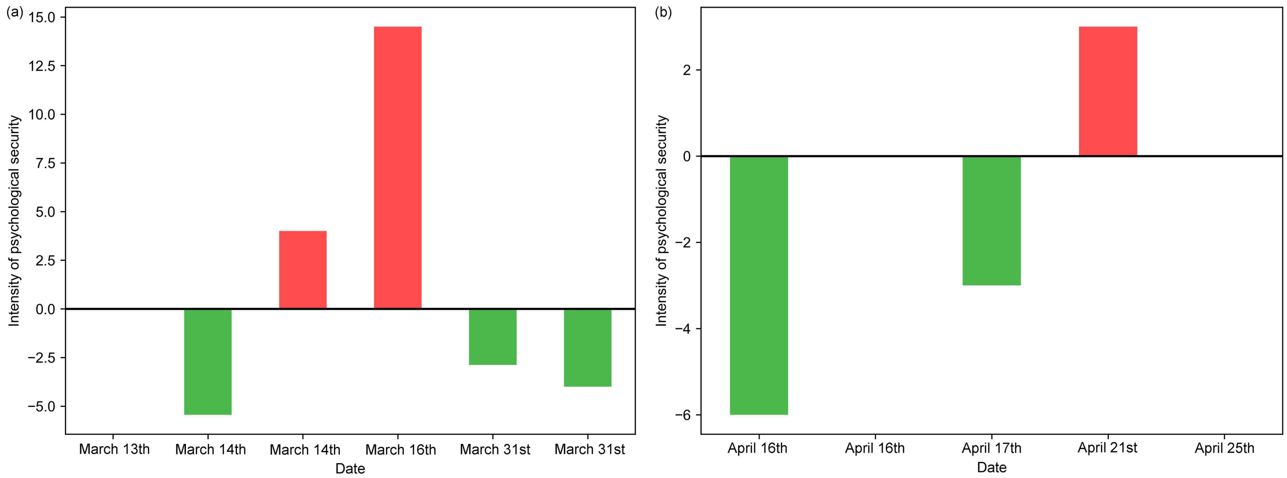

Figure 3 Individual psychological security intensity and tendencies during the generation and outbreak periods.
Notes: (**a**) the generation period; (**b**) the outbreak period.

(intensity=−5.44) and extreme security text (intensity = 4). On March 16th, the individual published extreme security text (intensity = 14.5). On March 31st, the individual posted both normal insecurity text and extreme insecurity text (intensity=−2.88, intensity=−4).

During the outbreak period (4.1–4.31), representative individual B was selected and a total of 5 texts were published. Among them, one text was security-dominated, two were neutral, and two were insecurity-dominated. The identification of text psychological security intensity and tendencies are shown in (Figure 3b). On April 16th, the individual released both extreme insecurity text (intensity=−6) and neutral text (intensity = 0). On April 17th, the individual posted normal insecurity text (intensity=−3). On April 21st, the individual published normal security text (intensity = 3). On April 25th, the individual posted neutral text (intensity = 0).

During the reduction period (5.1–5.31), representative individual C was selected and a total of 10 texts were published. Among them, two of the texts were security-dominated, four were neutral, and four were insecurity-dominated. The identification of text psychological security intensity and tendencies are shown in (Figure 4a). On May 6th, the individual posted both normal insecurity text (intensity=−2) and neutral text (intensity = 0). On May 7th and 16th, the individual released both normal security text (intensity = 2.7, intensity = 3) and neutral text (intensity = 0). On May 11th, the individual posted normal and extreme insecurity text (intensity=−3.1, intensity=−6). On May 17th, the individual published normal insecurity text (intensity=−0.6). On May 19th, the individual posted neutral text (intensity = 0).

During the recovery period (6.1–6.30), representative individual D was selected and a total of 20 texts were published. Among them, eight of the texts were security-dominated, ten were neutral, and two were insecurity-dominated. The identification of text psychological security intensity and tendencies are shown in (Figure 4b). On June 13th and 17th, the individual both posted 2 neutral texts (intensity = 0). On June 16th and 28th, the individual published normal security text (intensity = 3, intensity = 1). On June 18th and 20th, the individual both posted normal security texts (intensity = 3.6) and neutral texts (intensity = 0). On June 19th, the individual released both extreme security text (intensity = 4.8) and neutral text (intensity = 0). On June 21st, the individual posted both extreme security text (intensity = 7) and normal insecurity text (intensity=−2). On June 22nd, the individual posted both normal insecurity text (intensity=−3) and neutral text (intensity = 0). On June 24th and 29th, the individual published neutral text (intensity = 0). On June 25th, the individual posted 2 extreme security texts (intensity = 5.4, intensity = 4.5).

Through the analysis of the intensity and tendencies of text psychological security in the above four stages, it lays a foundation for the following analysis of individual psychological security transitions.

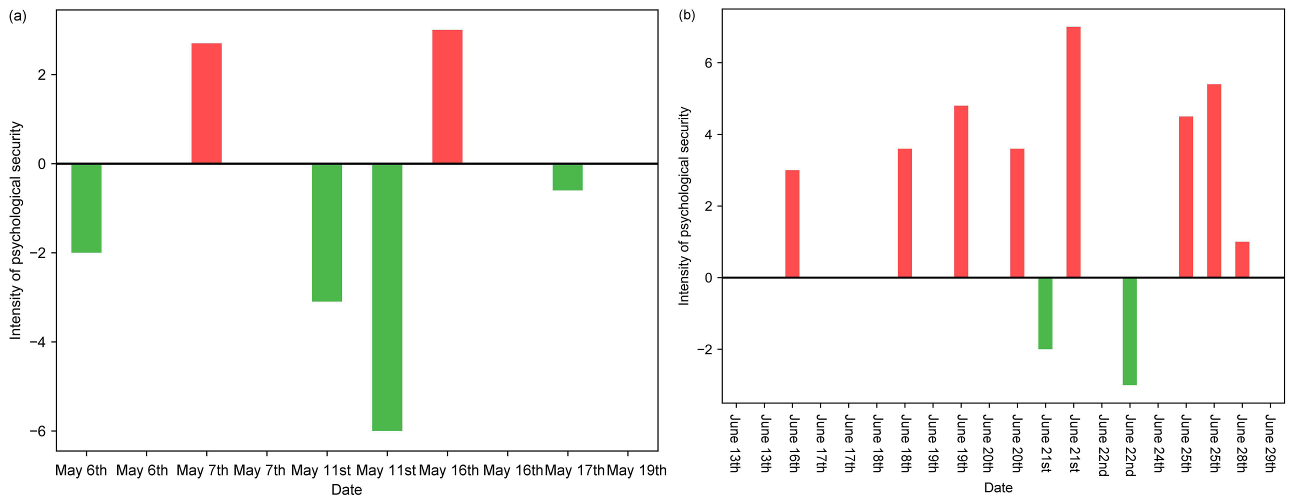

Figure 4 Individual psychological security intensity and tendencies during the reduction and recovery periods.
Notes: (**a**) the reduction period; (**b**) the recovery period.

Identification of Individual Psychological Security Transitions

Based on the generated time psychological security sequences from March to June, input the sequences into the psychological security transitions model, the psychological security state transitions graphs were obtained. Over time, the psychological security transitions of individual A are shown in (Figure 5a). At t1, the individual is in a neutral state. At t2, the individual's neutral state transitions to extreme insecurity. At t3, the individual's extreme insecurity transitions to extreme security. At t4, the individual's extreme security does not transition. At t5, the individual's extreme security transitions to normal insecurity. At t6, the individual's normal insecurity does not transition. Over time, the psychological security transitions of individual B are shown in (Figure 5b). At t1, the individual is in an extreme insecurity state. At t2, the individual's extreme insecurity transitions to neutral state. At t3, the individual's neutral state transitions to normal insecurity. At t4, the individual's normal insecurity transitions to normal security. At t5, the individual's normal security transitions back to neutral state.

Over time, the psychological security transitions of individual C are shown in (Figure 6a). At t1, the individual is in a normal insecurity state. At t2, the individual's normal insecurity transitions to neutral state. At t3, the individual's neutral state transitions to normal security. At t4, the individual's normal security transitions to neutral state. At t5, the individual's neutral state transitions to normal insecurity. At t6, the individual's normal insecurity transitions to extreme insecurity. At t7, the individual's extreme insecurity transitions to normal security. At t8, the individual's normal security

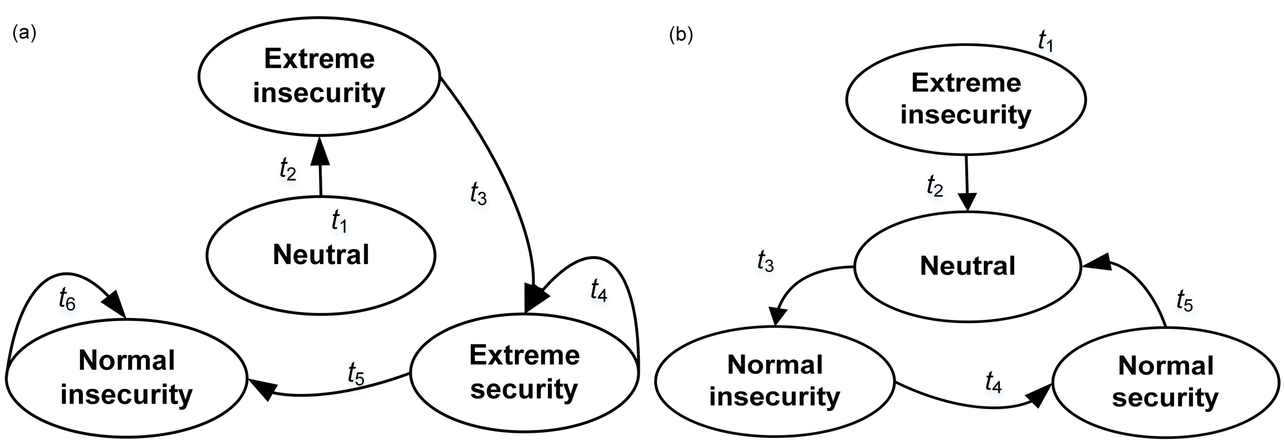

Figure 5 Individual psychological security transitions during the generation and outbreak periods.
Notes: (**a**) the generation period; (**b**) the outbreak period.

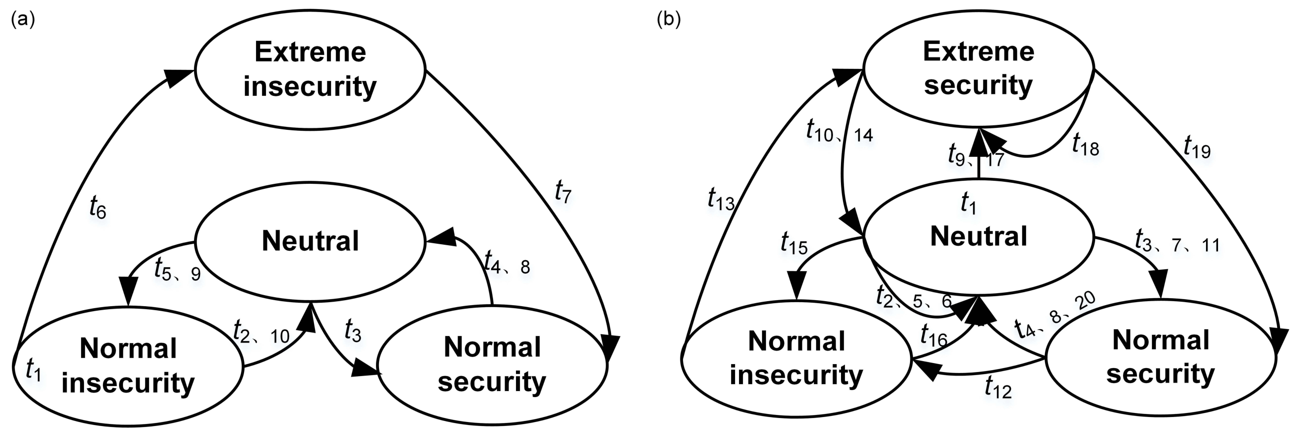

Figure 6 Individual psychological security transitions during the reduction and recovery periods.
Notes: (**a**) the reduction period; (**b**) the recovery period.

transitions to neutral state. At t9, the neutral state of the individual transitions to normal insecurity. At t10, the individual's normal insecurity transitions back to neutral state. Over time, the psychological security transitions of individual D are shown in (Figure 6b). At t1, the individual is in a neutral state. At t2, the individual's neutral state does not transition. At t3, the individual's neutral state transitions to normal security. At t4, the individual's normal security transitions back to neutral state. At t5 and t6, the individual's neutral state does not transition. At t7 and t11, the individual's psychological security transitions state is the same as at t3. At t8, the individual's psychological security transitions state is the same as at t4. At t9, the individual's neutral state transitions to extreme security. At t10, the individual's extreme security transitions back to neutral state. At t12, the individual's normal security transitions to normal insecurity. At t13, the individual's normal insecurity transitions to extreme security. At t14, the individual's psychological security transitions state is the same as at t10. At t15, the individual's neutral state transitions to normal insecurity. At t16, the individual's normal insecurity transitions to neutral state. At t17, the individual's psychological security transitions state is the same as at t9. At t18, the individual's extreme security does not transition. At t19, the individual's extreme security transitions to normal security. At t20, the individual's normal security transitions back to neutral state.

Evolution Trend of Group Psychological Security Risks

Through the integration of the number and intensity of different types of extreme psychological security tendencies formed in four stages (absolute value processing of extreme insecurity values here, the same below), the evolution trend of the number and intensity of security risk group and insecurity risk group were further obtained over time. The specific results are shown in (Figure 7a and b) (each stage) and (Figure 8a and b) (overall). In the texts published from the generation period to the recovery period, the number of security risk group is the highest, followed by the insecurity risk group. Among the intensity level from the generation period to the recovery period, the intensity level of the security risk group is also the highest, followed by the intensity level of the insecurity risk group. From the generation period to the recovery period, both the security risk group and the insecurity risk group showed a trend of first increasing, then decreasing, and then increasing, with a larger range of changes. Compared with the generation and reduction periods, the number of security risk group and insecurity risk group during the outbreak and recovery periods was higher. From the generation period to the recovery period, the intensity level of security risk group also showed a trend of first increasing, then decreasing, and then slightly increasing, while the intensity level of insecurity risk group showed a trend of first increasing, then decreasing, and then increasing again. It can be seen that during the outbreak and recovery periods, it is easier to form security risk group and insecurity risk group, and the intensity level is also higher.

As the number and intensity trends of security risk group and insecurity risk group are roughly the same, we only used the intensity time-series data of the security risk group and insecurity risk group to model and analyze them using

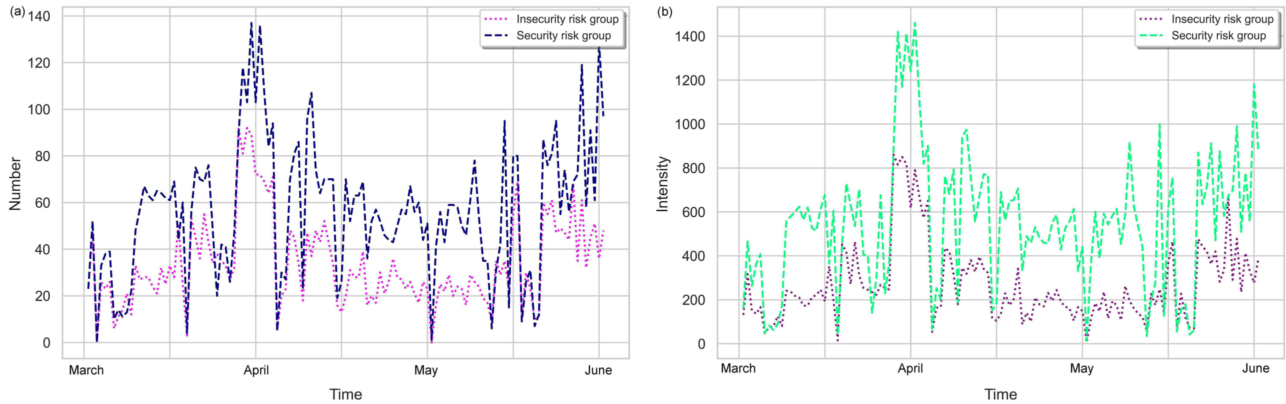

Figure 7 Evolution trend of the number and intensity of different types of extreme psychological security tendencies (each stage).
Notes: (**a**) the number; (**b**) the intensity.

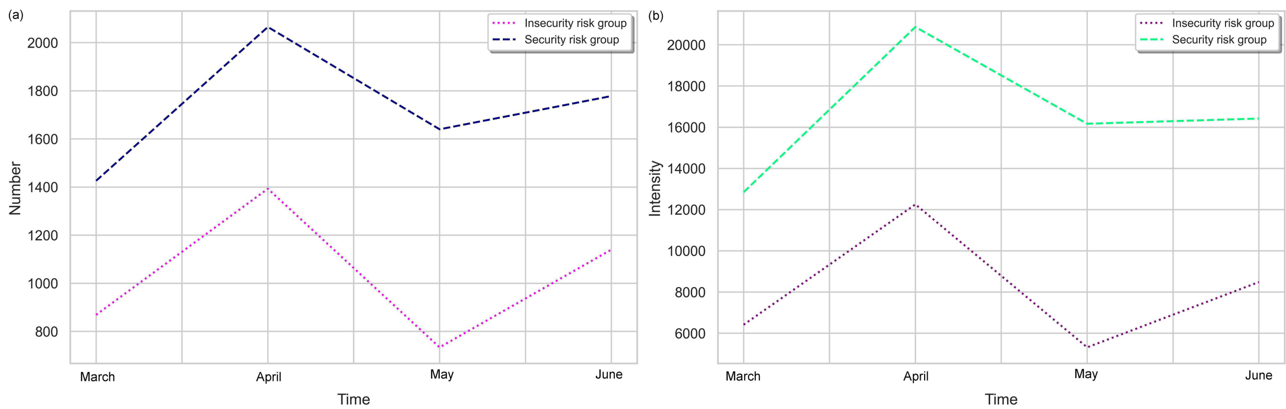

Figure 8 Evolution trend of the number and intensity of different types of extreme psychological security tendencies (overall).
Notes: (**a**) the number; (**b**) the intensity.

Python software. Firstly, after conducting the Augmented Dickey–Fuller unit root test, it was found that the time series of the two extreme psychological security groups, the intensity of group security risks ($p = 0.0006$) and group insecurity risks ($p = 0.009$), were stationary ($p < 0.05$), that is, $d = 0$. No differential data processing is required, and the ARMA model can be used for analysis. Secondly, after conducting white noise testing with Ljung-Box, it was found that the time series of group security risks intensity (p=1.639e-08) and group insecurity risks intensity (p=3.775e-13) were both non-white noise sequences ($p < 0.05$). Once again, the partial autocorrelation function, autocorrelation function, and smaller Akaike information criterion were used to determine the intensity of group security risks (p, d, q) as (0,0,4) and the intensity of group insecurity risks (p, d, q) as (2,0,0). Finally, a residual white noise test ($p > 0.05$) was performed on the model constructed with group security risks intensity ($p = 0.102$) and group insecurity risks intensity ($p = 0.296$), indicating that the model settings were reasonable. The comparison trend between the predicted results and the original results is shown in (Figure 9a and b). The intensity of group security risks and group insecurity risks both showed a trend of first increasing, then decreasing, and then slightly increasing. The predicted results were relatively close to the actual results, and the prediction model fits well. Meanwhile, based on the established time-series model (March-June), this paper predicted the trends of group security risks intensity and group insecurity risks intensity in the following month (July), as shown in (Figure 10a and b). The intensity of group security risks and group insecurity risks will both decrease slightly in the future period of time, and the overall also presents a trend of first increasing and then decreasing, increasing again and slightly decreasing again.

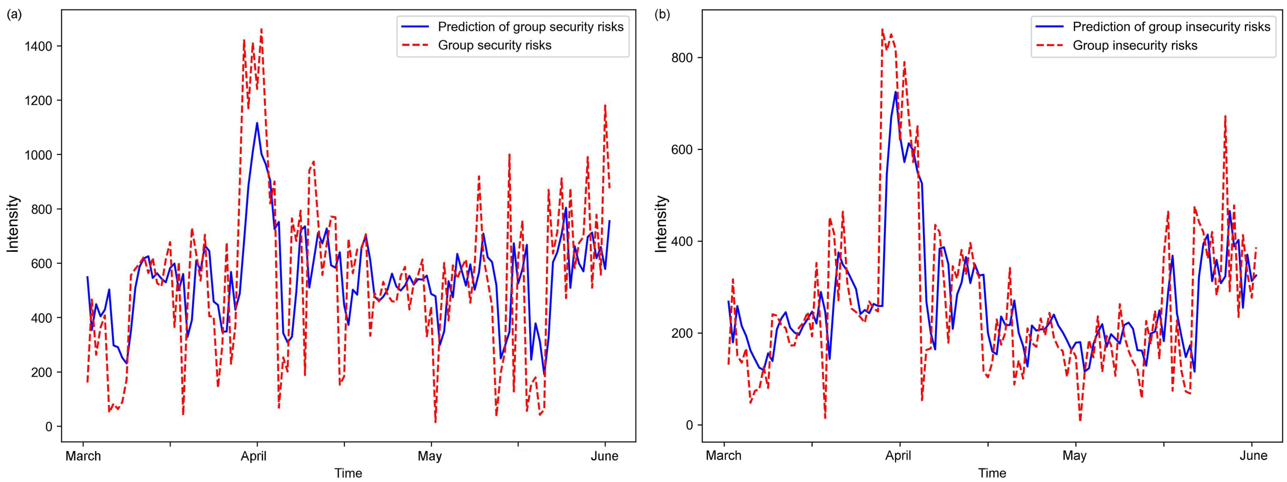

Figure 9 Comparison of evolution trend of group psychological security risks.
Notes: (**a**) group security risks; (**b**) group insecurity risks.

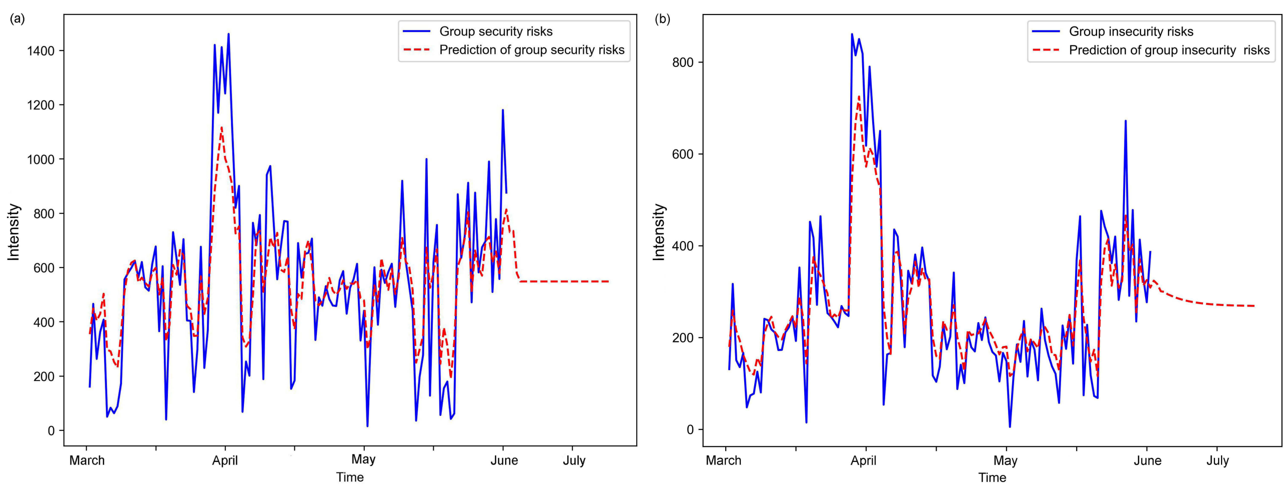

Figure 10 Prediction of evolution trend of group psychological security risks.
Notes: (**a**) group security risks; (**b**) group insecurity risks.

Discussion

This paper used machine learning methods, drawing on text sentiment analysis, Markov chains, and time-series analysis to model the evolution of group psychological security risks. On this basis, Weibo text data during public health emergencies was crawled, a psychological security lexicon in the field of public health emergencies was constructed, individuals' psychological security tendencies, intensity, and transitions were identified. At the same time, based on psychometric standards, time-series data on extreme psychological security was extracted using a time-step as a unit to explore the evolution trend of group psychological security risks under public health emergencies. The results of this paper found that compared with the generation and reduction periods, group psychological security risks are more likely to occur during the outbreak and recovery periods, and the intensity level is also higher. We believe that this may be due to the fact that most people do not perceive the hidden risks of the external environment and infectious disease events during the generation period, so the group psychological security risks formed should be relatively low. The outbreak period is the period of city-wide lockdown. At this time, the virus is rampant. Although the measures such as home isolation and enterprise shutdown taken by the government may reduce the infection rate to a certain extent, they have an impact on public normal production and life order, which will inevitably significantly enhance public insecurity and thus induce group insecurity risks. During the outbreak period, medical personnel from various regions rushed to Shanghai, and volunteers spontaneously formed teams to help Shanghai citizens solve various difficulties. However, excessive protection may also put public in an illusion of ease and calm, and lose their perception of external risks and uncertainties, and thus induce group security risks. Therefore, the intensity level of group security risks and group insecurity risks both show an upward trend during the outbreak period. The reduction period is the period of further diminish lockdown and control zones across the city. The efforts of the government, medical personnel, volunteers, and the public have achieved initial results. The development of epidemic situation of infectious diseases has gradually subsided, the infected cases have gradually decreased, and peoples' extreme psychological security has gradually calmed down. Hence, the group psychological security risks formed are gradually decreasing. The recovery period is the period of fully restore normal work and life across the city. The epidemic prevention and control in the recovery period has achieved a staged victory, and public security has been significantly enhanced, which can easily induce a small range of group security risks. However, there are still uncertainties about sporadic cases in some areas, and due to the impact of home isolation in the early stage, many enterprises have been forced to suspend production, and some have declared bankruptcy, employees have been forced to lose their jobs, and income cannot be guaranteed. Inevitably, it will significantly enhance public insecurity, and then induce group insecurity risks. Therefore, during the recovery period, the intensity of group security risks showed a slight upward trend, while the intensity of group insecurity risks showed a significant upward trend.

This paper suggests that local government administrators should take multiple measures to ensure the order of residents' lives. For example, after the occurrence of public health emergencies, it is necessary to coordinate the storage of residents' daily necessities, ensure the supply of residents' daily necessities, stabilize prices, and maintain good market order. It is possible to provide living allowances to public living on subsistence allowances, provide comfort and assistance, and maintain good work and life order. It is also necessary to improve the mental health service system, broaden the channels of social appeals, open-free psychological hotlines, strengthen the guidance of mental health services for the public, cultivate the public good emotional adjustment ability, and help them get rid of the sub-health state, so as to prevent and resolve group insecurity risks. In addition, official media platforms need to ensure that information is open and transparent, and at the same time, call on the public to always be the first responsible person for their own health, enhance their psychological resilience and risk perception, and help them properly avoid external risks. It is necessary to encourage the public to make more use of their leisure time to master new skills without affecting their own work, adapt to the requirements of the development of the times, learn more knowledge, continuously improve their professional level, avoid being too comfortable, content with the status quo, and not enterprising, so as to help prevent and resolve group security risks.

This paper used machine learning methods for the first time to explore the evolution trend of group psychological security risks under public health emergencies by mining massive data from social media. However, there are still some areas that need further expansion in this paper. Firstly, this paper only uses Sina Weibo texts as the data source. Due to the fact that Sina Weibo users cannot represent the entire Chinese group, we believe there are limitations in simulating group psychological security risks. However, given that Sina Weibo is the most influential social media platform in China, we believe it can capture most of the group's information. We suggest that future research can use multiple data sources to expand the research on group psychological security risks, such as Twitter, Tiktok, and Baidu Tieba to provide different insights for group psychological security risks research. Secondly, this paper only selects text data during the epidemic of infectious diseases in Shanghai, which pioneers the evolution trend of group psychological security risks. However, whether this data has strong external validity and is applicable to different countries and different types of public health emergencies still needs to be further verified. We suggest that future research can select public health emergencies of different countries, provinces, and cities, with different natures and harm degrees, to further verify the results of the evolution trend of group psychological security risks in this paper. Thirdly, this paper only analyzes the reasons for the evolution of group psychological security risks based on publicly available coronavirus cases and relevant policy information during the occurrence of public health emergencies in Shanghai. We call for future research to use text topic modeling methods, such as naive Bayes model, latent Dirichlet allocation, long short-term memory networks, to further explore potential topic factors in texts, more accurately and efficiently analyze the reasons for user posts and the evolution of group psychological security risks, and provide support for government decision-making.

Conclusion

This paper proposes a framework for the evolution of group psychological security risks and constructs a psychological security lexicon in the field of public health emergencies. It provides a method for identifying and quantifying the tendencies, intensity and transitions of individual psychological security on social media platforms, and the dynamic evolution of group psychological security risks. It provides an opportunity to explore the dynamics of psychological security in digital space. It also provides a new perspective for promoting social stability and national security.

Data Sharing Statement

These data were derived from the resources available in the public domain on Sina Weibo. Data are available from the corresponding author upon reasonable request.

Ethical Approval

Ethical approval was not required as publicly available data were used in this study.

Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising, or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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Disclosure

The authors report no conflicts of interest in this work.

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