International Journal of Disaster Risk Reduction 70 (2022) 102762

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: www.elsevier.com/locate/ijdrr

Spatial evolution patterns of public panic on Chinese social networks amidst the COVID-19 pandemic

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ARTICLE INFO

Keywords:
COVID-19 pandemic
Panic
Spatiotemporal distribution
Sentiment analysis
Social media
Latent dirichlet allocation (LDA) topic model

ABSTRACT

Novel coronavirus pneumonia has had a significant impact on people's lives and psychological health. We developed a stage model to analyse the spatial and temporal distribution of public panic during the two waves of the coronavirus disease 2019 (COVID-19) pandemic. We used tweets with geographic location data from the popular hashtag 'Lockdown Diary' recorded from 23 January to April 8, 2020, and 'Nanjing Outbreak' recorded from 21 July to 1 September 2021 on Weibo. Combining the lexicon-based sentiment analysis and the grounded theory approach, this panic model could explain people's panic and behavioural responses in different areas at different stages of the pandemic. Next, we used the latent Dirichlet allocation topic model to reconfirm the panic model. The results showed that public sentiments fluctuated strongly in the early stages; in this case, panic and prayers were the dominant sentiments. In terms of spatial distribution, public panic showed hierarchical and neighbourhood diffusion, with highly assertive expressions of sentiment at the outbreak sites, economically developed areas, and areas surrounding the outbreak. Most importantly, we considered that public panic was affected by the 17 specific topics extracted based on the perceived and actual distance of the pandemic, thus stimulating the process of panic from minimal, acute, and mild panic to perceived rationality. Consequently, the public's behavioural responses shifted from delayed, negative, and positive, to rational behavioural responses. This study presents a novel approach to explore public panic from both a time and space perspective and provides some suggestions in response to future pandemics.

1. Introduction

The coronavirus disease 2019 (COVID-19)[1] pandemic has become a persistent global crisis. Whenever the pandemic was encountered, the rapid exponential increase in the number of cases and multiple mutations of the coronavirus have become a source of panic, fear, and anxiety among people. Owing to uncertainty and unpredictability, people suffer from negative emotions, and several vulnerable groups (healthcare workers and people with mental illness) even have psychological infirmities [1]. Among them, a seriously negative emotion, i.e. panic, could threaten personal mental health [2] and amplify social problems, such as panic buying, communal disharmony, regional stigma, and racial discrimination [3].

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[1] COVID-19, coronavirus disease 2019; LDA, latent Dirichlet allocation.

https://doi.org/10.1016/j.ijdrr.2021.102762
Received 18 May 2021; Received in revised form 3 December 2021; Accepted 28 December 2021
Available online 3 January 2022

Panic is an extreme emotion that encompasses fear and anxiety when individuals face real or imagined threats [4]. Keating [5] believed that panic was a unique collective phenomenon when fear was the dominant psychological effect of a group. The state of panic might make human rationality disappear into a cloud of pressure, anxiety, fear, and panic, thus prompting irrational behaviours [6–8]. When constantly exposed to panic, individuals are likely to suffer from panic attacks, which include several symptoms such as palpitations, tremors, shortness of breath, chest pain, nausea, dizziness, and loss of control [9]. Because panic is an existential state, it is burdensome to manage public panic and avoid irrational behavioural responses caused by panic. However, few studies have explored public panic from the perspective of social science. Understanding panic and its response can help policymakers manage public mental health and take proper preventive measures against pandemic containment.

With the development of the Internet, people are increasingly engaged and connected [10]. During this global pandemic, people have turned towards social media to obtain information and express feelings [11]. Analysing social media data with users' geo-mapped opinions and sentiments can help obtain a holistic view of the country's general mood regarding a pandemic and understand the distribution and patterns affected by this crisis [12,13]. Previous studies on social media sentiment analysis during the COVID-19 pandemic have focused on the percentage and distribution of positive, negative, and neutral sentiments in large-scale tweets [14], and machine learning techniques for sentiment identification and text analysis of particular topics such as vaccines [15] and prevention attitudes [16]. However, mainstream machine learning methods are not sufficiently accurate for fine-grained sentiment analysis. Although some scholars have combined machine learning-based and lexicon-based sentiment analysis methods to explore people's fear, anger, and sadness during the pandemic [17], related research still needs to be developed. In addition, sentiment analysis is often used together with topic analysis to explore the influencing factors, but it cannot identify the intrinsic mechanism of emotions. Hence, we chose a lexicon-based approach to analyse the spatiotemporal distribution of panic as well as the grounded theory approach to construct the spatial evolution panic model and explain the perception-emotion-behaviour process of panic. Finally, the latent Dirichlet allocation (LDA) topic model was used to validate the panic model. Some management suggestions are provided for challenges that need to be dealt with in the escalating coronavirus pandemic.

2. Literature review

2.1. Public panic emotion during pandemics

Pandemics may not comprise the most lethal diseases, but they can cause long-term mental health problems in individuals. Panic was primarily considered to be equivalent to extreme and groundless fear; subsequently, people began to focus on whether panic would cause irrational behaviours [18]. Based on cognitive emotion theory, panic is a direct result of our cognitive assessment of the external environment [19]. Early empirical studies by sociologists focused on studying human and group behaviour in natural and technological disasters and found that panic was prone to be characterised as irrational [18]. Psychologists also cited the sociological sources of panic and regarded it as a negative psychological state. In their widely acclaimed work, the nature of panic was considered as a negative emotion provoked by external information [20]. And recently, Liu et al. [21] also defined it as 'a complex emotional experience that is a mixture of several generic negative emotions'. Reducing public panic is essential for governments to adopt preventive measures [22]. Hence, in this present study, we assume that panic is an extreme negative emotion which contains fear and anxiety, and that it may cause irrational behaviours.

The focus of panic has recently shifted to two themes: psychological disorders, such as the characterisation and treatment of panic attacks and panic disorders [23,24], and economic impacts, such as panic buying [25,26] and volatility of the stock market [27]. Several studies have considered the importance of panic during the COVID-19 pandemic. Liu et al. [28] and Wu et al. [22] discussed the relationship between information disclosure and panic, and concluded that pandemic information released by social media can reduce citizens' panic; Parry [29] explored the influence of abandoning pets owing to panic. These studies showed that high levels of panic and anxiety are related to a lack of information, uncertainty, and uncontrollability [30]. Nicomedes and Avila [3] explored panic in the Filipino population by building a panic framework that includes negative emotions (i.e. indifference, anxiety, sadness, and fear), positive reactions (i.e. compliance, protection, optimism, and awareness of health), and external influences (i.e. virus spread and government accusations). However, panic-related studies have mostly focused on sociological and economic aspects using questionnaire surveys [3], semi-structured interviews [31], and psychological experiments [32]. Few studies have explored the spread and distribution of panic from a geographical perspective, although panic behaviour is believed to be contagious. Armfield [33] considered that the danger levels of a disaster strongly impact the severity and distribution of panic. More precisely, panic was influenced by people's perception of risk [34], infection, rumors, and fake news that people receive from social media and friends [35]. In addition, Xu et al. [36] used a web-based data search using the Baidu Index to map health literacy and social panic in China during COVID-19. Chen et al. [37] found that the spatial distribution of risk perception was inconsistent with infection during the COVID-19 pandemic. Psychological interventions and release of accurate online information were also found to influence the speed and intensity of panic spread [38]. The extent of panic distribution has not yet been explored in depth. Therefore, the current study provides a novel perspective to explore the spatiotemporal distribution of panic and analyses the rational and irrational behaviour responses to panic.

2.2. Sentiment analysis with social sensing data during pandemics

Sentiment analysis of social media is crucial for crisis management. With the development of machine learning, information on geographic locations has been gradually utilised to study user-generated information [39]. Liu et al. [40] proposed the concept of 'social sensing' data, which obtains human behaviour trajectories, reflects group behaviours, and characterises social-economic phenomena on a large scale [41]. Regarding the COVID-19 pandemic, several studies have focused on sentiment distribution and public opinion using social sensing data through location-based social network services, such as Twitter [43], Facebook [44], and

Weibo [45]. Prentice et al. [46] found a close relationship between public panic buying and government interventions through sentiment analysis on Twitter. Although these studies have made considerable progress in relation to infectious diseases, most studies used machine learning methods to analyse sentiments based on social sensing data. Few studies have performed fine-grained sentiment analysis, primarily focusing on negative sentiments during pandemics. Therefore, research gaps exist in the analysis of sentiment analysis and the spatial distribution of panic emotions.

With the emergence of computer science and sentiment analysis, several sentiment classification technologies have been developed, such as the lexicon-based approach, machine learning-based approach, and hybrid-based approach [47]. Behl et al. [48] used supervised machine learning approaches and multi-class classification to analyse Twitter data on COVID-19 and found the performance of deep learning algorithms superior among the tested algorithms. Although mainstream research uses the machine learning-based method frequently, the method suffers from insufficient precision and unclear sentiments. When responding to pandemics, it is not enough to study polarity sentiments; changes and patterns of specific sentiments deserve increased attention. Plutchik [49] argued that there are eight basic and prototypical emotions: joy, anger, sadness, trust [27], fear, disgust, surprise, and anticipation. Shah et al. [17] improved the LDA topic model and lexicon-based approach sentiment analysis tool to analyse patients' comments on physician rating websites and found that negative emotions (fear, anger, and sadness) frequently appeared during the COVID-19 pandemic. In the current study, we also chose a hybrid-based approach to achieve fine-grained sentiment analysis using natural language processing techniques to perform data pre-processing and determine semantic relations.

2.3. Application of the grounded theory and LDA topic model in social media

The popularity of social media provides available data for crisis managers and responders to understand the popular events on the Internet and provide guidance opinions [47,50]. The LDA topic model, as a technique for extracting and summarising trending issues from documents, is widely used for long document analysis. With the development of large-scale text-processing techniques, it is gradually being applied to short texts, such as tweets. Studies employing the LDA topic model in social media have surged (e.g. sentiment analysis of pandemics [51] and product opinions [52]). However, it is mainly useful for topic classification and extraction, and it hardly explores inter-topic mechanisms. In contrast, grounded theory is beneficial when there are no or insufficient theories regarding a particular phenomenon [53]. Charmaz [54] defined grounded theory as a systematic, inductive, and comparative approach to conducting an enquiry to construct theory. Zhang et al. [55] used grounded theory to construct a theoretical model of crowdsourcing in tourism and explored its mechanisms through semi-structured interviews. Although it is important to construct theoretical models, grounded theory is not very applicable to online texts because of the limitation of massive data. Previous studies have used the grounded theory approach for topic analysis and construction of theoretical frameworks for review comments [56] and social media opinions [57]. Hence, in the current study, we combined the two approaches for panic mechanism analysis, first exploring the conceptual model of panic evolution using grounded theory, and then, validating the model using the LDA topic model.

3. Data and methods

3.1. Data source and pre-processing

As the first country to report the COVID-19 pandemic, China experienced a large-scale first-round outbreak in January 2020, which caused a state of panic among its people. Owing to effective prevention measures, China was the first to return to normality. However, as the coronavirus mutation escalated, a second global outbreak occurred. Despite stringent prevention measures and widespread vaccination, there have also been small localised outbreaks in China. Furthermore, the Nanjing outbreak in July 2021, which was affected by the Delta Coronavirus, was the largest number of confirmed cases to date. During the outbreaks, significant changes have taken place in people's lives and have affected their emotions. We chose these two outbreaks as cases to explore the evolution of panic.

Weibo is a popular social media platform in China, like the Chinese version of Twitter. In the first round of the outbreak, we searched for tweets posted between January 23, 2020 and April 8, 2020 using the popular hashtag 'Lockdown Diary'. We used Python 3.7.0 software combined with a crawler toolkit to obtain 33,611 original tweets and recorded content, posting time, username, location, and other relevant information. In the second round of the outbreak, we searched the hashtag 'Nanjing Outbreak' between July 21, 2021 and September 1, 2021. In total, 68,095 original tweets were obtained. Compared with the pandemic-related tweets, tweets from these popular hashtags were highly relevant in expressing emotions and recording their lives. In addition, the tweets contained time-series data, which facilitated the assessment of emotional changes at different stages of the pandemic. Furthermore, only tweets posted by individual users (not institutions or news agencies) were included in this study.

Natural language processing technology was used to pre-process the data: (1) Only tweets containing positioning information (or hometown location instead when lack of positioning information) were retained. (2) Word2vec and regular expression operations ("re" module) were used to remove interfering information. For example, invalid content, such as #, [], @, and other meaningless symbols, digital URL links, hashtags, and emoticons, were deleted. Finally, we obtained 31,187 and 62,357 valid tweets. (3) The Jieba toolkit was used to split the words and sentences. Some stop words were removed from the lists of words, and the processed words were retained to conduct the sentiment analysis.

3.2. Methods

3.2.1. Sentiment analysis

Because the sentiments in microblogs are multiple, the lexicon-based method satisfies our requirements to identify fine-grained sentiment [58]. Therefore, we used the authoritative simplified database 'Chinese *Sentiment Lexicon Ontology Database*' published by the Dalian University of Technology to classify the pre-processed words into sentiment categories and label them with sentiment intensity [59]. The lexicon contains 27,466 inspirational words, including seven emotion categories of 'Happiness, Good, Anger, Sadness, Fear, Evil, and Surprise' and 21 subcategories. We selected four features from this lexicon database: words, speech tags, sentiment categories, and sentiment intensity. Sentiment intensity included five levels of 1, 3, 5, 7, and 9 on an increasing scale with 1 being the lowest and 9 being the highest. In this corpus of 'Lockdown Diary', we deleted the surprise category, as Weibo users seldom mentioned such terms and classified anxiety in the panic category. Furthermore, 67 new emotional words extracted by manual coding were added to the subsequent analysis. An example of the special sentiment lexicon of the COVID-19 pandemic and its structure is presented in Table 1.

3.2.2. Kernel density estimation

Kernel density estimation is generally used to detect the intensity of events by generating a smooth surface using a quadratic kernel function [60]. To identify the hotspots of public panic reflected in Weibo tweets, we used kernel density estimation to perform the distribution and clustering analyses using ArcGIS 10.2 software.

3.2.3. Grounded theory approaches

Grounded theory is an 'inductive method of theoretical development' proposed by Glaser and Strauss [61], which contributes to substantive or formal theory through an abstract heuristic process. In the present study, it was used to analyse changes in panic during the pandemic. We randomly selected 4000 tweets as the original data, selected 3000 of these for coding analysis, and retained 1000 for coding verification analysis through the classic saturation test method proposed by Pandit NR [62]. The core aspects of the method include three main steps: open coding, spindle coding, and core coding. We used Nvivo 11.0 software to perform auxiliary coding. We obtained 17 categories and 64 concepts. Examples of the open coding process are shown in Table 2, and the results of the categories and concepts are listed in Table 3.

Regarding core coding, we finally determined the four core categories of influencing factors, regulatory behaviour (information search), emotions, and action results based on the relationship structure of the categories. The main category relationship structure is shown in Fig. 1.

Fig. 1 shows that the personal subjective factors that influence panic are mainly derived from external stimuli and internal perceptions. The irrational responses include passive prevention, physiological response, moral kidnapping, and rumour spreading during the incubation period and the outbreak period. The rational responses include proactive prevention, home quarantine, and assistance.

3.2.4. LDA topic model

The LDA topic model is the dominant method used for collaborative filtering, text classification, and document modelling. This is a three-level hierarchical Bayesian model. Each item of a collection is modelled as 'a finite mixture over an underlying set of topics' and each topic is also modelled as 'an infinite mixture over an underlying set of topic probabilities' [63]. To estimate the topics related to panic during the COVID-19 pandemic, we implemented the sk-learn module and used the LDA topic model with Python 3.6. Considering that the grounded theory included 17 concepts, we set 20 topics for analysis.

3.3. Proposed methodology

In this study, we used a mixed-approach method to evaluate panic and its impact on the Chinese population during the COVID-19 pandemic. Fig. 2 shows the convergent mixed-method design, where both qualitative and quantitative methods were used in parallel, analysed separately, and then merged.

The first phase involved gathering Weibo tweets with location information through Python crawlers and pre-processing the data for subsequent analysis. In the second phase, we analysed the tweets from the first round of the nationwide outbreak in January 2020. A dictionary-based sentiment analysis method was used to perform a fine-grained sentiment analysis that contained both time and space analyses. In addition, the grounded theory approach was used to randomly select 4000 texts for coding and explore the influencing factors and behavioural responses to panic. In the third phase, by combining qualitative and quantitative methods, a conceptual spatial evolution model of public panic was summarised and used to explore the role of panic at different stages and in different regions of the pandemic. Finally, we analysed tweets from the second round of the Nanjing outbreak in July 2021. The LDA topic model method was used to obtain the topics for each stage and to verify the rationality of the panic model. In the following sections, we present the results of the analyses performed using this methodology.

Table 1
Sentiment classification and structure examples of the COVID-19 pandemic's special sentiment lexicon.

Category of sentiment	Type of sentiment	Emotional words	Speech tagging	Sentiment classification	Intensity
Happiness	Happiness (PA); Relax (PE)	Optimism	adjectives	Happiness PA	3
Anger	Anger (NA); Hatred (ND)	Displeasure	adjectives	Anger NA	5
Sadness	Sadness (NB); Guilty (NH) Disappointment (NJ)	Heartbreak	adjectives	Sadness NE	9
Panic	Panic (NI); Fear (NC) Anxiety (NE)	Bewilderment	adjectives	Panic NI	3
Good	Respect (PD); Trust (PG) Praise (PH); Pray (PK) Preference (PB)	Blessing	verbs	Good PK	5

Table 2
Examples of the open coding process.

Microblog content	Concept	Category
As a homebody, it's really nothing to stay home, but what tortures me is the fear of the uncertainty and the constant anxiety …	Fear & Anxiety	Emotion
On the fifth day of Wuhan's lockdown, it is a rare sunny day. Accompanied by the song "My Motherland and Me" on the community radio, I felt a lot better and cheered up.	Hopefulness	
Today, Wuhan was clearing up, and I went to Zhongbai Supermarket to purchase daily necessities and vegetable supplies! There are obviously more people in the supermarket today, and I have waited almost half an hour for the food.	Purchasing daily necessities	Proactive protection
As soon as he came back home, he took off his mask and threw it away, took off his coat and washed it off, then washed his hands and face carefully, and put on clean clothes at home (he will not go out in the next several days).	Prevention behaviour	

Table 3
Categories and concepts of the open coding process.

NO.	Category	Concept
1	Proactive Prevention	Asking for help, Self-prevention, Convincing relatives and friends, Preventive measures, Purchasing supplies, Physical fitness
2	Passive Prevention	Going out as usual, Not wearing masks
3	Event Concern	Continuous attention to event development, Ignoring event development
4	Physiological Response	Headache, Cough, Loss of appetite, Obsessive-compulsive disorder, Trembling, Tearing, Insomnia, Hypochondria
5	Rumour Spreading	Supplies shortage, Special medicine, Anti-social disinformation
6	Emotions	Regret, Trust, Helplessness, Blessing, Optimism, Boredom, Self-regulation, Gratitude, Anger, Anxiety, Depression, Fear, Sympathy and distress
7	Pandemic Characteristics	Severity, Speed, Scope
8	Pandemic Uncertainty	Duration, Personal contact, Social influence, Overseas influence
9	Danger Nearby	Neighbourhood influence, Relatives and friends confirmed, Acquaintances informed
10	Supply Demand	Health system crashes, Shortage of medicines, Insufficient supply of necessities
11	Public Opinions	Media reports, Contacting with each other, Official releases, Social information
12	Assistance	Voluntary, Official support, Supply guarantee, Network encouragement, Donations
13	Moral Kidnapping	Regional discrimination, Sarcasm
14	Dereliction of Duty	Inaction, Wrong command, Weak response
15	Pray Online	Pray for Wuhan, Encouraging each other
16	Home Quarantine	Working from home, Family entertainment
17	Reopening Life	Reopened shops, Returning to work and production, Resuming transportation

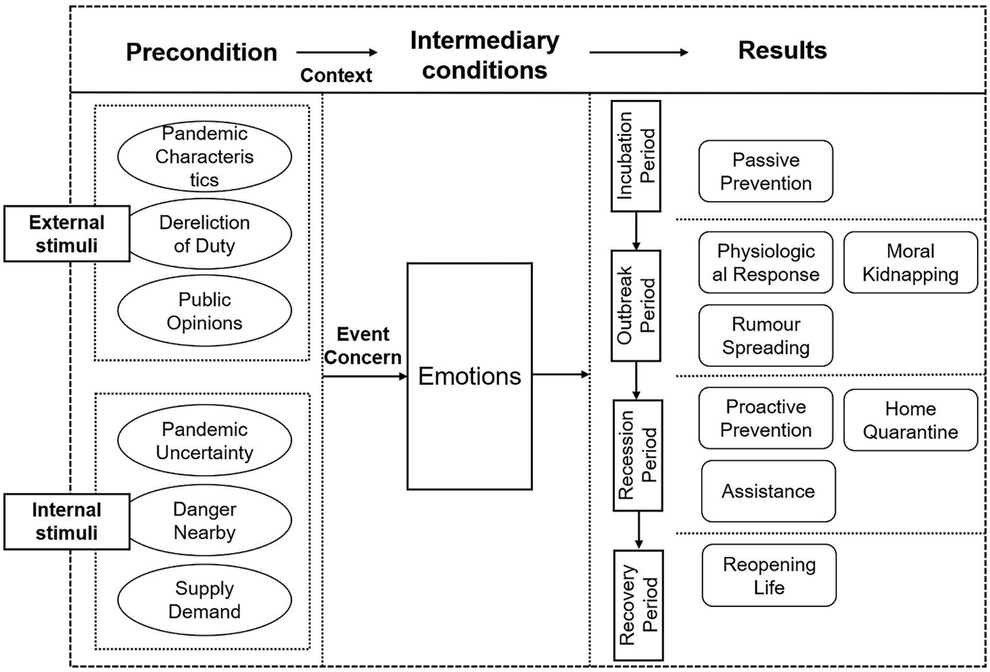


Fig. 1. Typical category relationship structure of core coding using the 3000 tweets selected randomly.

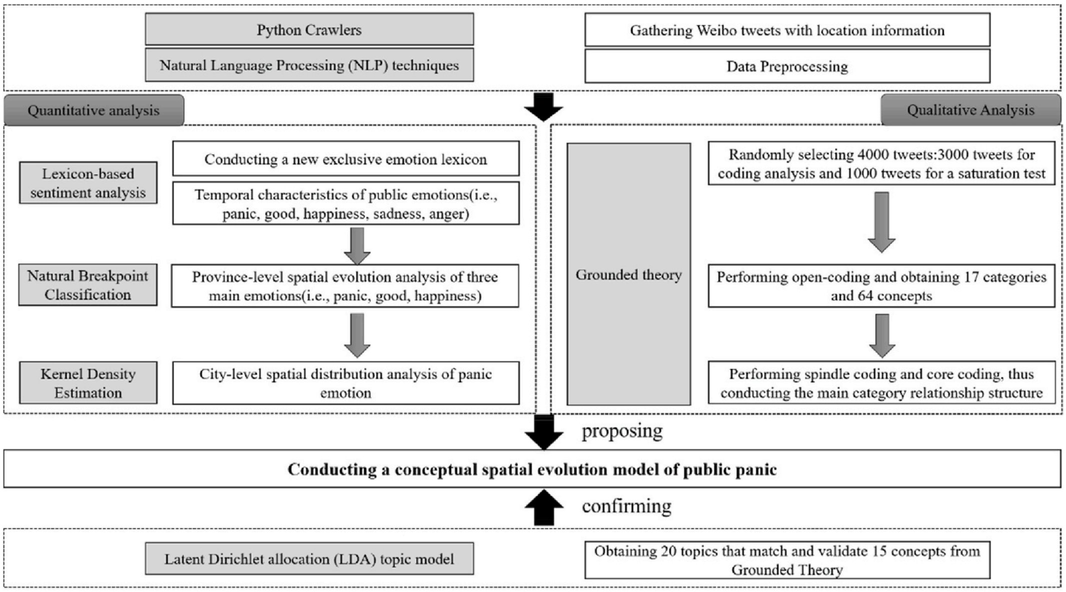


Fig. 2. Combination of qualitative and quantitative methods applied in this research.

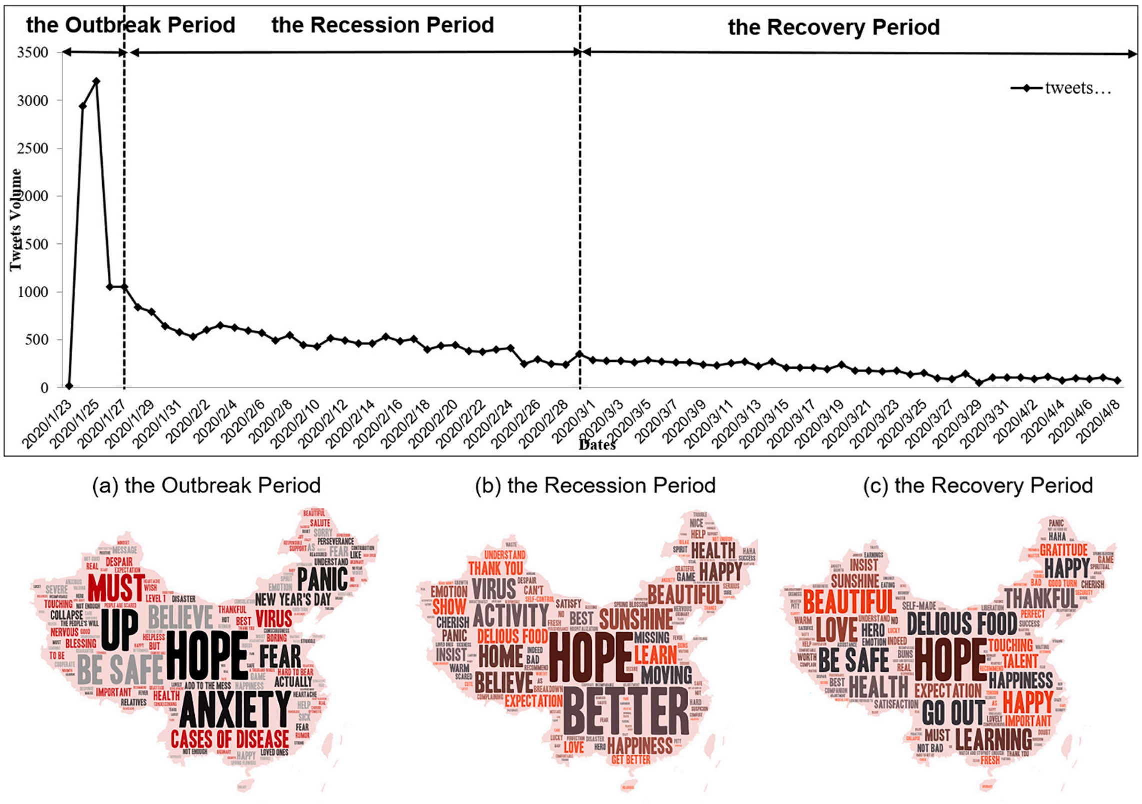


Fig. 3. Fluctuation in the volumes of Weibo tweets at different stages of the pandemic and high-frequency word clouds during the first-round nationwide outbreak in January 2020.

4. Results

4.1. Study 1: first-round of the nationwide outbreak in January 2020

4.1.1. Temporal differentiation characteristics of public emotions

4.1.1.1. Stage division of the nationwide outbreak. Combining disaster evolution theories [64], this pandemic event as seen on Weibo was divided into four stages: 'Incubation Period', 'Outbreak Period', 'Recession Period', and 'Recovery Period'. Before the Weibo hashtag of 'Lockdown Diary' was created, mention of the coronavirus appeared with only a few concerns; therefore, this stage was considered the incubation period. The other three stages were divided by a cluster analysis of tweet volumes and confirmed cases. The tweet volume, stage division, and high-frequency word clouds are shown in Fig. 3.

During the incubation period (before January 23, 2020), few netizens posted tweets mentioning 'Wuhan' and 'pneumonia' together. Most of the tweets were from organisations, and people lived their lives as usual. During the outbreak period (23–January 26, 2020), there was a sharp increase in microblog posts, and people had just experienced a lockdown in Wuhan. The words 'be safe' and 'hope' were mentioned most frequently on Weibo. In addition, some negative emotional words such as anxiety, panic, fear, and despair appeared frequently. During the recession period (27 January to March 1, 2020), the number of tweets gradually stabilised after a precipitous decline. At this time, people paid less attention to the pandemic as they adapted to the new environment. Emotional words such as boredom and autism increased, and references to home lifestyles such as 'learning', 'show', and 'activity' increased. Expressions of gratitude such as 'better', 'moving', 'love', and 'happy' appeared. During the recovery period (2 March to April 8, 2020), the number of tweets decreased over time, and the impact of the pandemic on people gradually decreased. The society affected by the pandemic was normalised, and Internet users returned to their lives.

4.1.1.2. Temporal-level analysis of public emotions. Taking a day as a unit, we calculated the intensity of the average sentiment (good, happiness, sadness, anger, and panic) of each sentence and tweet. The temporal characteristics of public emotions during the COVID-19 pandemic are shown in Fig. 4.

Good and panic were the dominant sentiments of the public during the pandemic. It showed a high sentiment intensity trend in the early stage, peaking after experiencing dramatic fluctuations and slowly decreasing later [65]. The result was influenced by the developmental stage of the pandemic and the occurrence of popular events. Specifically, the average intensity of the good sentiment was the highest (value = 6.22). It reflected people's wishes and prayers for the future, with 'God bless' and 'hold on to Wuhan' being frequently mentioned. Panic ranked second in the average intensity of sentiment intensity (value = 4.18) and exceeded 5 in the first three days. During the outbreak period, there were some popular events such as 'panic buying of medicine' and 'the negligence of the Red Cross'. People felt uncertain about the future with severe panic and anxiety, and some netizens even experienced physiological reactions such as insomnia, loss of appetite, and crying. For the other three emotions, the average intensity of 'happiness' was significantly affected (value = 3.31), whereas the average intensity of 'sadness' and 'anger' was below 2. This showed that sadness and anger were not primary emotions. As for happiness, people realised that they had problems with their mental health and started to adjust their mental state. Several terms such as 'self-adjustment', 'stay optimistic', and 'stay positive' were often recorded in tweets.

4.1.2. Spatial differentiation characteristics of public emotions

4.1.2.1. Spatial-level analysis of public emotions. Although the pandemic swept through all provinces and cities in China, Weibo users' tweets on the pandemic showed some heterogeneity in the spatial distribution owing to differences in social conditions and the severity of the pandemic. The three main sentiments of 'panic', 'good', and 'happiness' were selected as representatives to explore public

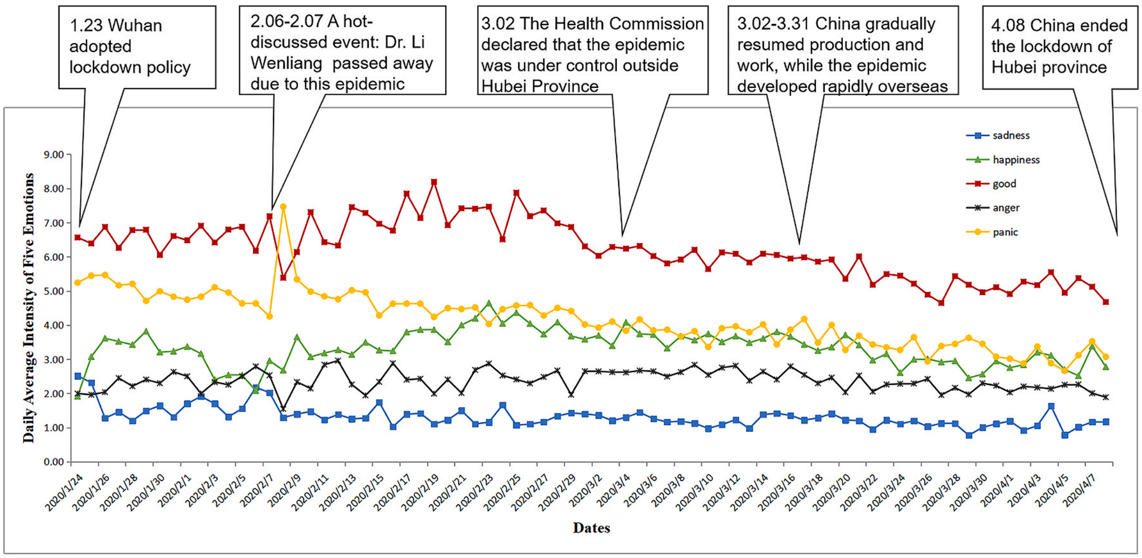


Fig. 4. Daily average intensity of public sentiments and the popular events occurring during the first-round nationwide outbreak in January 2020.

sentiments in different provinces at different stages of the COVID-19 pandemic, and the results are shown in Fig. 5. For panic, we also counted the frequency of panic words mentioned on a provincial scale in the three phases, as shown in Fig. 6.

The high panic intensity values were mainly concentrated in the outbreak sites (Hubei), the economic development areas (Guangdong, Beijing, Shanghai, Jiangsu, and Zhejiang), and areas surrounding the outbreak (Henan, Sichuan, Hunan, Shandong, and Shanxi). The number of panic words in Hubei, where the pandemic occurred (i.e. the core area), was much higher than in other regions, with figures for 11,061, 24,388, and 6704 in the outbreak, recession, and recovery periods, respectively. The intensity of panic and the frequency of panic-related words in economically developed regions were the second highest category in all three periods. The values of peripheral areas were higher than those of distant areas in the outbreak and recession periods, and they were at the lowest in the recovery period, with values similar to those of distant areas. From the outbreak period to the recession period, the panic was highly concentrated in the core area and spread to the surrounding areas, decreasing in intensity and expanding in scope. This indicated that more people perceived the existence of the pandemic, in addition to the outbreak sites, the economic development areas, and the areas surrounding the outbreak. From the recession period to the recovery period, people perceived the pandemic as being far away from them, as the number of new confirmed cases in most parts of the country reached zero and the cure rate increased significantly. The public's panic re-clustered in the outbreak sites, economic development areas, and areas surrounding the outbreak, showing spatial contraction.

Combined with Figs. 4 and 5, it can be noted that the spatial distribution of panic showed neighbourhood diffusion and hierarchical diffusion. For neighbourhood diffusion, panic spread from the outbreak area (i.e. the core area) to the areas surrounding the outbreak (i.e. the radiation area) and then to other parts of the country (i.e. the distant area). The rapid and significant perception of panic followed the first law of geography and was owing to the physical proximity of these radiation areas to Wuhan. As an important transportation hub and megacity in China, Wuhan has a high population and traffic flow with neighbouring provinces. As for hierarchical diffusion, the panic spread from the outbreak area to the economically developed areas (i.e. the diffusion sub-centre) to the central areas surrounding the outbreak (i.e. the radiation area), and then to the other areas (i.e. the distant area). Although the diffusion centres were far away from the outbreak area, they were represented by large urban clusters, such as the Yangtze River Delta and the Pearl River Delta, the large population size and the development of fast transportation (e.g. high-speed rail and airplane) accelerated population mobility and achieved a hierarchical spread of panic. Moreover, people in economically developed areas paid

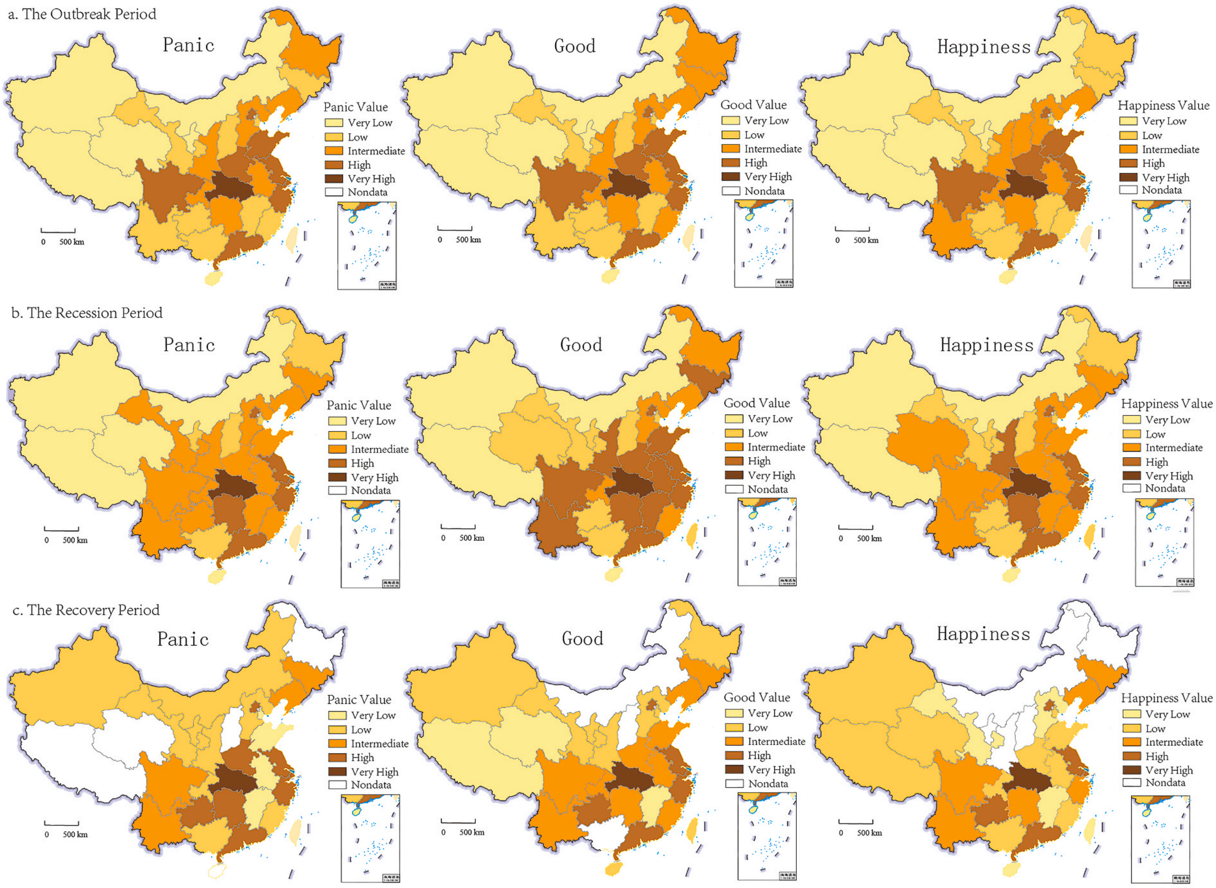


Fig. 5. Distribution of panic, good, and happiness sentiments during different stages of the first-round nationwide outbreak in January 2020 (a. Outbreak Period, b. Recession Period, c. Recovery Period).

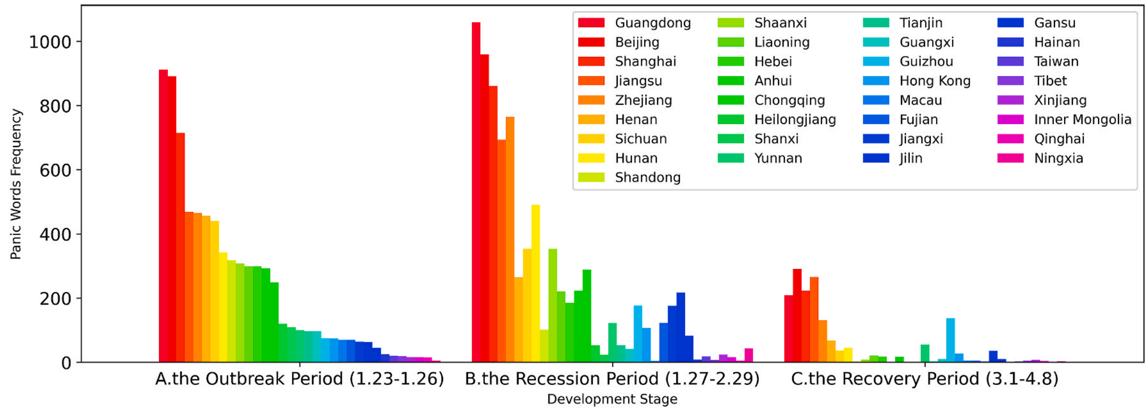


Fig. 6. Frequency of panic words according to provinces during the different stages of the first-round nationwide outbreak in January 2020 (except Hubei).

increased attention to online information and were easily influenced by public opinion dissemination. The distant areas were concentrated in the western and northeast regions, and there were few contacts with Wuhan and few confirmed cases.

Another finding was that panic with good and happiness emotions was similarly distributed during the outbreak period. People in areas with high panic intensity had a relatively high intensity of good and happiness. People in these areas were more concerned about the pandemic, had more information resources, and expressed more feelings to actively adjust their psychological state.

4.1.2.2. Spatial characteristics of public panic. Excessive panic regarding a pandemic threatens people's physical and mental health. Therefore, it is necessary to explore the spatial distribution of panic. We analysed the daily average value of widespread panic in cities at the prefecture level (identified 209/385 cities nationwide) from 23 January to April 8, 2020. Fig. 7 shows a graphical kernel density estimate of the panic sentiment of tweets.

As seen in Fig. 7, the spatial distribution of panic in prefecture-level cities also showed the existence of neighbourhood diffusion and hierarchical diffusion and formed several clusters. Wuhan was the centre of the largest cluster of panic, and the panic intensity of cities around Wuhan was also higher than that of the relatively far radiation area. Therefore, we further divided 'the radiation area' into the neighbouring areas (the cities in Hubei except Wuhan) and the radiation area (the cities in areas surrounding Hubei).

The results showed that the spatial distribution of panic was correlated with the infection but was significantly different. A clear finding was that the coronavirus spread from Wuhan to the entire country through confirmed cases, and the perception of public panic about the pandemic spread along the same path. When a city had a confirmed case, people perceived that the virus was close and the risk was increasing, which could quickly trigger high panic. However, the intensity and frequency of panic in the diffusion sub-centres were higher than in the radiation area where there were more confirmed cases. Considering the coding analysis of grounded theory, there are two reasons for this. First, the huge mobile population and traffic-carrying capacity of the diffusion sub-centre provided opportunities for the large-scale spread of the virus, which would reduce the actual distance from the infectious disease. '*The flow of people from around Wuhan to Beijing is still flowing by rail and air, and the number of new cases of coronary pneumonia is actually increasing because Wuhan is out of control*' (recorded on 24 January Beijing). Another reason was that the economically developed areas were also Internet hubs in China, and people were sensitive to Internet information and easily received information from outbreak sites. This brought people closer to the perception of pandemics and inspired panic. *'I don't know if anyone like me watches Weibo and even feels pneumonia symptoms, chest tightness, and shortness of breath … Go Wuhan, we can win!'* (recorded on 25 January Shanghai).

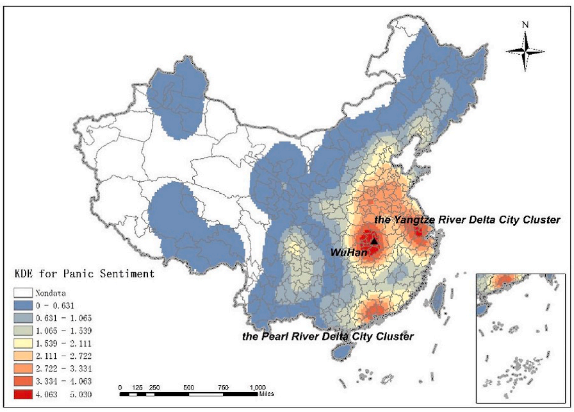


Fig. 7. Kernel density estimate (KDE) for public panic sentiment of geo-tagged tweets in prefecture-level cities during the first-round nationwide outbreak in January 2020.

4.2. Public panic spatial evolution model in the COVID-19 pandemic

4.2.1. 'Cognition-emotion-behaviour' theory

Based on the 'cognition-emotion-behaviour' theory of psychology, panic was found to affect psychological cognition of the pandemic and behavioural response to the pandemic. Public panic was affected by psychological perception of distance and the actual distance of the pandemic, making people adopt different behavioural responses. From the perspective of 'cognition', public perception of distance of the pandemic was affected by the development stage and the pandemic's spatial distance. Furthermore, people considered the pandemic with individual subjective focus factors such as characteristics of the pandemic, uncertainty, public opinions, daily necessities, and threats around, generating panic emotion as a response. Individual emotions endowed the space with positive and negative attributes so that the space had the subjective meaning of the core area, diffusion sub-centre, radiation area, and distant area [66]. From the perspective of 'behaviour', people adopted the typical behavioural response to the pandemic based on the panic reaction. The conceptual framework is illustrated in Fig. 8.

4.2.2. Spatial evolution model of public panic during the COVID-19 pandemic

According to the qualitative and quantitative mixed methods (i.e. sentiment analysis and the grounded theory approach), a spatial evolution model of public panic was established, as shown in Fig. 9.

Overall, the spatial evolution model consisted of three components: spatiotemporal perception of the pandemic, emotional perception of panic, and behavioural response. During the incubation period, people in the core area, neighbouring area, and the radiation area started to care about the pandemic owing to the proximity of confirmed cases. In hierarchical diffusion, people in the diffusion sub-centres and radiation area centres were slightly concerned because of information dissemination. In the latter two stages, the panic value in the hierarchical diffusion areas was higher than that in the neighbourhood diffusion areas. The hierarchy diffusion was mainly owing to the large population size of the cities and the high attention paid to disaster information on the Internet. The neighbourhood diffusion was mainly owing to physical distance, frequent traffic, and population flow. During the recovery period, panic persisted in the core area because the cure rate was not improved, and in the diffusion centres owing to the high mobility of the population and exposure to the information released. In contrast, panic in the radiation and remote areas disappeared. In addition, panic in response to the pandemic perception was experienced in four stages: rare panic, dramatic panic, regulating panic, and rational response. Their behavioural responses corresponded to the concepts obtained through coding analysis based on the grounded theory approach.

4.3. Study 2: second-round of outbreak in Nanjing in July 2021

4.3.1. LDA topic extraction

According to the stage division method, this outbreak also experienced four stages: the Incubation Period (before July 21, 2021), the Outbreak Period (21.7–29.7.2021), the Recession Period (30.7–4.8.2021), and the Recovery Period (4.8–1.9.2021).

Combined with the concepts obtained from the grounded theory above, we set the number of topics of the LDA topic model to 20, and finally matched 20 topics with 15 concepts effectively, as shown in Table 4.

All topics corresponded to the panic concepts analysed above, whereas the concepts of 'danger nearby' and 'supply demand' were found not to be extracted. Because the LDA topic model selects the top 200 high-frequency words in these topics to correspond to the related concepts, these two may have been less mentioned. Otherwise, topic 19 belongs to both the concepts of 'emotions' and 'reopening life'.

4.3.2. Validation of the public panic spatial evolution model

4.3.2.1. Temporal-level analysis of topics. The sentence frequency for LDA topics which matched the panic concepts at each stage was counted and is shown in Fig. 10. It reveals a basic correlation relationship between the topics and the behavioural responses proposed by the panic model at each stage. During the outbreak period, there were far more tweets than I n the latter two periods. The percentage of 'passive prevention' at each stage was first 4.57% and then decreased to 3.86% and 2.81%, respectively, showing a decreasing trend. The concepts of 'proactive prevention', 'home quarantine', and 'reopening life' remained high in the latter two

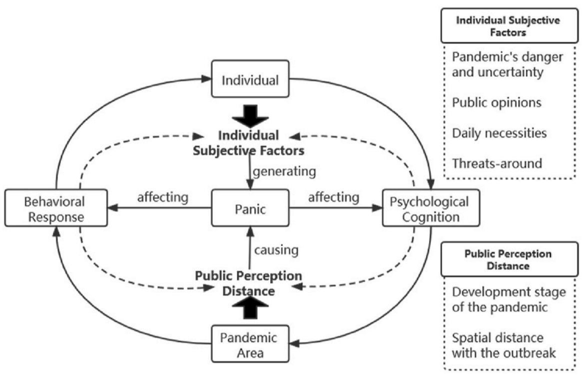
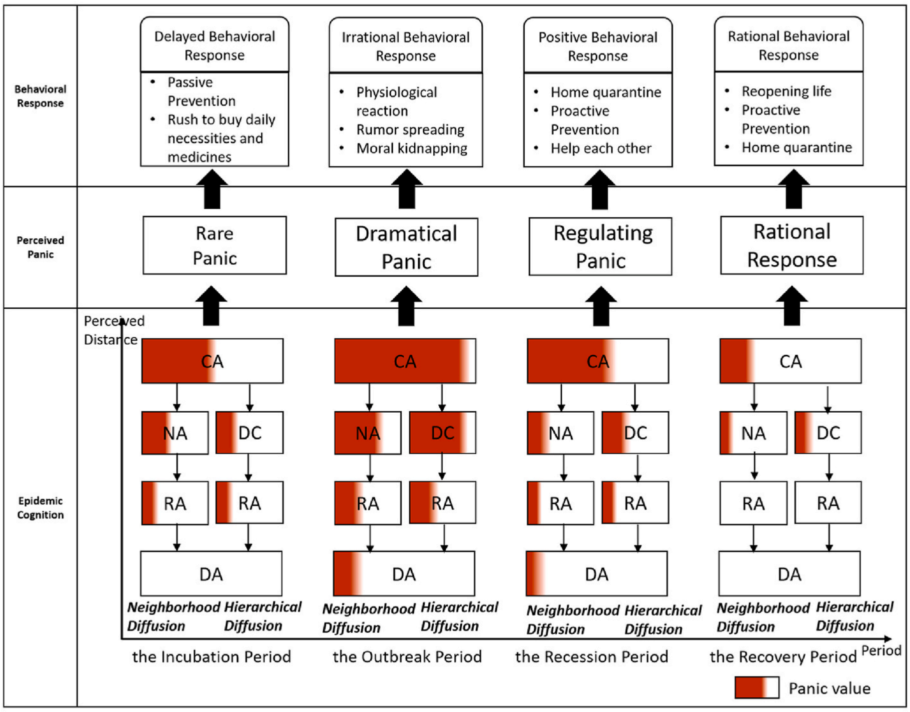


Fig. 8. Conceptual framework of the panic emotion effects in the relationship between humans and space during the COVID-19 pandemic.



Notes. *CA*, core area; *NA*, neighbouring areas; *RA*, radiation area; *DA*, distant areas; *DC*, diffusion sub-centre.

Fig. 9. Spatial evolution pattern of public panic in China during the COVID-19 pandemic.

Table 4
Latent Dirichlet allocation (LDA) topics matched with the concepts of open coding in the three stages during the Nanjing outbreak.

NO.	Category	Topic No.	The Outbreak Period		The Recession Period		The Recovery Period	
			Fre	Per	Fre	Per	Fre	Per
1	Proactive Prevention	1、3	14,948	14.86%	2553	8.92%	906	9.75%
2	Passive Prevention	14	4598	4.57%	1105	3.86%	261	2.81%
3	Event Concern	4、13	9132	9.08%	3304	11.55%	1147	12.34%
4	Physiological Response	0	6191	6.15%	2196	7.67%	629	6.77%
5	Rumors Spreading	8	1923	1.91%	698	2.44%	339	3.65%
6	Emotions	19	6268	6.23%	1590	5.56%	553	5.95%
7	Pandemic Characteristics	2	3854	3.83%	1649	5.76%	383	4.12%
8	Pandemic Uncertainty	17	3922	3.90%	1107	3.87%	440	4.74%
9	Danger Nearby	/						
10	Supply Demanding	/						
11	Public Opinions	7	3453	3.43%	781	2.73%	344	3.70%
12	Assistance	11	3123	3.10%	784	2.74%	223	2.40%
13	Moral Kidnapping	16	3643	3.62%	1678	5.86%	509	5.48%
14	Dereliction of Duty	10、12	13,406	13.32%	4327	15.12%	1071	11.53%
15	Pray Online	6、9	14,753	14.66%	3591	12.55%	1366	14.70%
16	Home Quarantine	5、15、18	11,394	11.33%	3252	11.36%	1121	12.06%
17	Reopening Life	19	6268	6.23%	1590	5.56%	553	5.95%

Notes. *Fre*, frequency count of the sentences; *Per*, percentage of the total tweets at each stage.

stages.

However, a difference was found that ‘proactive prevention’, ‘dereliction of duty’, and ‘home quarantine’ became the most important and persistent topics of public interest. Along with the coronavirus, people have adapted to the pandemic and have generally taken proactive measures to cope with the outbreak, such as getting nucleic acid testing, vaccinations, and staying at home.

Compared to the first-round nationwide outbreak, the duration of these two outbreaks stabilised at approximately 45 days (decreased from 47 days to 45 days). While it is known that the intensity of panic in the first-round national outbreak was higher, the duration of the outbreak period increased from 5 days to 9 days. This may be influenced by the stage division method we used. In this case, the concept of ‘dereliction of duty’ was expressed more often than before, and the figure increased from 13.32% to 15.12%, then

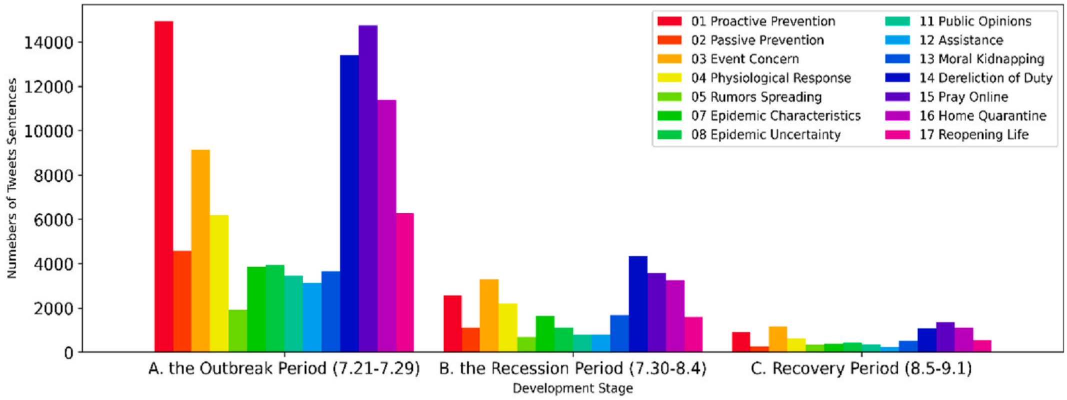


Fig. 10. Sentence frequency of latent Dirichlet allocation (LDA) topics during different stages in the Nanjing outbreak.

decreased to 11.53% during the three stages. In addition, 'rumour spreading' and 'moral kidnapping' were also frequently mentioned during this outbreak. Another possible explanation is that the upgradation of the Delta virus has increased panic, and negligent behaviour of government departments has hurt citizens' preventive motivation, compared to successful responsive experiences such as Wuhan and Guangzhou.

4.3.2.2. Spatial-level analysis of public panic. Using the same sentiment analysis and kernel density analysis, we analysed the distribution of panic in the Nanjing outbreak, and the results are shown in Fig. 11.

As shown in Fig. 11, the centre of public panic was also concentrated at the outbreak site. The Yangtze River Delta and Pearl River Delta regions, as regions with developed transportation and high Internet usage, still had a high level of panic. Other adjacent cities in Jiangsu Province are areas neighbouring the spread centre, and the level of panic was relatively high. What was noticeable here was that the intensity of panic in Hunan Province was high and formed a centre among the surrounding cities. The Nanjing outbreak rapidly infected tourists travelling to Zhangjiajie (a tourism attraction belonging to Hunan Province) and formed a chain of pandemic transmission that exacerbated the public panic in Hunan Province. In general, the characteristics of hierarchical spread and the neighbourhood spread of panic were reconfirmed. The actual distance from the pandemic, transportation, and social media play an

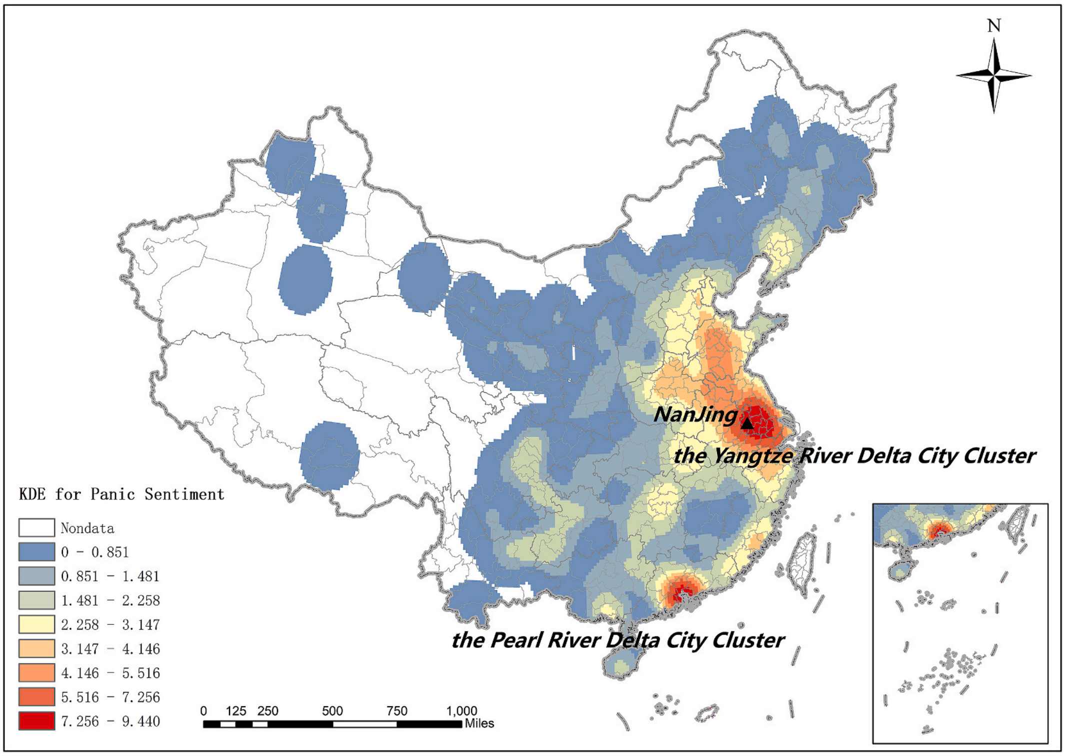


Fig. 11. Spatial evolution pattern of public panic in China during the Nanjing outbreak.

essential role in the spread of panic.

5. Discussion and conclusion

5.1. Discussion

In the current study, we collected two large corpora of 31,187 and 62,357 popular hashtag tweets from Weibo during the two waves of the COVID-19 pandemic. Based on a combination of sentiment analysis, kernel density estimation, the grounded theory approach, and the LDA topic model methods we conducted a spatiotemporal public panic evolution model of the COVID-19 pandemic. We then assumed and explained the perception-emotion-behaviour process of panic when people face challenges owing to the pandemic. Some highlighted findings and implications are as follows.

Regarding the temporal analysis, public sentiments fluctuated intensely, and panic sentiment peaked in the early stage of the pandemic, especially during the outbreak period. In the early stage, people were highly concerned about the pandemic and actively expressed their feelings, with a surge in social media posts. The panic sentiment accompanied by 'good' sentiment was dominant. The results showed that the main topics mentioned in the early period were pandemic characteristics, dangers, and related event concerns, whereas in the later period, topics focused on life recovery and home isolation. In addition, it was found that people were highly concerned regarding the popular events, the government's ability to manage the pandemic, and the supply of necessities in the early stage. Hence, policymakers need to focus on people's mental health issues, pay attention to topics of public concern, and release official information as soon as possible [21]. It is beneficial for alleviating panic and avoiding negative behaviours such as rumour spreading, moral kidnapping, and proactive prevention.

The results of the geographic analysis indicated that public sentiment was influenced by both the perceived distance and the actual distance of the outbreak. Panic was consistent with the theory of distance decay during the development stages of the pandemic, and there were two types of spatial diffusion of public panic: hierarchical diffusion and neighbourhood diffusion. Regarding hierarchical diffusion, the highest public panic was in the outbreak sites, and the second highest intensity of panic was in the densely populated and economically developed urban clusters such as the Yangtze River Delta and Pearl River Delta. The reason may be the great mobility of the population in economically developed areas, coupled with an enormous traffic-carrying capacity and the abundant access to the Internet [67]. Regarding neighbourhood diffusion, the neighbouring areas and the radiation areas had high panic owing to their close proximity to the outbreak sites. The small waves of outbreaks were unique in that the diffusion sub-centres along the transmission chain also generated a high intensity of panic, despite their considerable distance from the outbreak site. Overall, this indicates that managers need to pay attention to the impact of social media on the spread of panic; sometimes, social media information may increase public panic. In addition, it is important to focus on people's mental health in economically developed areas, the outbreak periphery areas, and the sub-centres of the outbreak transmission chain.

In both the evaluated outbreak cases, the evolution of the public panic model showed four stages: incubation period, outbreak period, recession period, and recovery period. In this process, behavioural responses to public panic changed from delayed, negative to positive, and rational behavioural responses [3]. A notable observation was that people experienced a longer high-intensity panic period in the small wave than in the nationwide outbreak. This result might be influenced by the stage division methodology, but also because the escalation of the virus increased public panic and the poor performance of local authorities undermined citizens' confidence. Shortening the time people stay in a high panic state during the outbreak period can help them adjust their emotions and behave rationally as early as possible. Furthermore, panic occurred along with prayers and positive emotions during these two outbreaks, which can enhance national identity and promote cooperation in pandemic prevention [68], and promoting 'post-traumatic growth' to adopt self-adjustment behaviours [69]. Hence, policymakers should encourage people to maintain positive emotions, cooperate with prevention measures effectively, and actively seek mutual assistance.

5.2. Conclusion

This study explores the spatial and temporal distribution of panic, which has similarities to and significant differences from the spread of a pandemic and virus [70]. In studies on infectious disease, proximity and hierarchical diffusion of infections is observed with the development of an epidemic or pandemic [71]. However, panic is generated concurrently to receiving information, although the intensity of panic varies in different regions at different stages. Therefore, panic also shows the characteristics of proximity and hierarchical diffusion with the development of the pandemic stage. This study provides new insights into the spread and distribution of panic emotions during a pandemic.

In addition, previous studies have primarily used questionnaires and interviews to explore the impact of negative emotions, although cross-sectional data cannot reflect the dynamic nature of psychological states and preventive behaviours of citizens during the pandemic and might not reflect the causal relationship between variables [22,72]. The significance of our work lies in developing a systematic framework of panic diffusion from both a temporal and spatial perspective. This panic evolution model explains the developmental changes, influencing factors, and behavioural responses of public panic in different areas during a pandemic. This panic framework is also conceptualised with the following 17 themes arranged from negative to rational behaviours: proactive prevention, passive prevention, event concern, physiological response, rumour spreading, emotions, pandemic characteristics, pandemic uncertainty, danger nearby, supply demand, public opinion, assistance, moral kidnapping, dereliction of duty, prayer online, home quarantine, and reopening life. It is valuable for managers to understand the various stages of public panic and to take targeted prevention measures in response to the normalised situation of the COVID-19 pandemic and future pandemics.

This study had some limitations. The selection of tweets from a popular hashtag as the research object, which has the limitation of a lack of geographic information and limited numbers of unbalanced sample ages (microblog users are primarily young), may lead to biased results. The dictionary-based sentiment analysis method is inferior to the machine learning method in terms of accuracy and efficiency; however, analysis and identification of fine-grained sentiment with the machine learning method is challenging. As an extension of this work, combining machine learning methods to analyse fine-grained sentiment can be considered to further explore the sentiment of large-scale populations. Studies related to the spatiotemporal distribution and spread of panic during the pandemic are still scarce; hence, panic spread and its mechanism should be further studied in the future.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] N. Das, S. Narnoli, A. Kaur, S. Sarkar, Pandemic, panic, and psychiatrists - what should be done before, during, and after COVID-19? Asian J Psychiatr 53 (2020) 102206, https://doi.org/10.1016/j.ajp.2020.102206.
[2] B. Person, F. Sy, K. Holton, B. Govert, A. Liang, N.S.C.O. Team, Fear and stigma: the epidemic within the SARS outbreak, Emerg. Infect. Dis. 10 (2) (2004) 358–363, https://doi.org/10.3201/eid1002.030750.
[3] C.J.C. Nicomedes, R.M.A. Avila, An analysis on the panic during COVID-19 pandemic through an online form, J. Affect. Disord. 276 (2020) 14–22, https://doi.org/10.1016/j.jad.2020.06.046.
[4] E. Gullone, The development of normal fear: a century of research, Clin. Psychol. Rev. 20 (4) (2000) 429–451, https://doi.org/10.1016/S0272-7358(99)00034-3.
[5] J.P. Keating, The myth of panic, Fire J. 76 (3) (1982) 57–61.
[6] N.J. King, D.I. Hamilton, T.H. Ollendick, Children's Phobias: A Behavioural Perspective, 1988.
[7] T. Miyoshi, H. Nakayasu, Y. Ueno, P. Patterson, An emergency aircraft evacuation simulation considering passenger emotions, Comput. Ind. Eng. 62 (3) (2012) 746–754, https://doi.org/10.1016/j.cie.2011.11.012.
[8] L. Yu, L. Li, L. Tang, What can mass media do to control public panic in accidents of hazardous chemical leakage into rivers? A multi-agent-based online opinion dissemination model, J. Clean. Prod. 143 (2017) 1203–1214, https://doi.org/10.1016/j.jclepro.2016.11.184.
[9] Craske, M.G., D.H. Ba Rlow, and M.G. Graske, Mastery of Your Anxiety and Panic : Therapist's Guide for Mastery of Your Anxiety, Panic, and Agoraphobia. 2000: Mastery of your anxiety and panic : therapist's guide for Mastery of your anxiety, panic, and agoraphobia.
[10] U. Aslam, F. Muqadas, M.K. Imran, U.-U. Rahman, Exploring the sources and role of knowledge sharing to overcome the challenges of organizational change implementation, Int. J. Organ. Anal. 26 (3) (2018) 567–581, https://doi.org/10.1108/IJOA-07-2017-1189.
[11] P. Singh, S. Singh, M. Sohal, Y.K. Dwivedi, K.S. Kahlon, R.S. Sawhney, Psychological fear and anxiety caused by COVID-19: insights from Twitter analytics, Asian J Psychiatr 54 (2020) 102280, https://doi.org/10.1016/j.ajp.2020.102280.
[12] V.K. Neppalli, C. Caragea, A. Squicciarini, A. Tapia, S. Stehle, Sentiment analysis during Hurricane Sandy in emergency response, Int. J. Disaster Risk Reduc. 21 (2017) 213–222, https://doi.org/10.1016/j.ijdrr.2016.12.011.
[13] X. Pan, D.M. Ojcius, T. Gao, Z. Li, C. Pan, C. Pan, Lessons learned from the 2019-nCoV epidemic on prevention of future infectious diseases, Microb. Infect. 22 (2) (2020) 86–91, https://doi.org/10.1016/j.micinf.2020.02.004.
[14] Z. Yao, J. Yang, J. Liu, M. Keith, C. Guan, Comparing tweet sentiments in megacities using machine learning techniques: in the midst of COVID-19, Cities 116 (2021) 103273, https://doi.org/10.1016/j.cities.2021.103273.
[15] C.A. Melton, O.A. Olusanya, N. Ammar, A. Shaban-Nejad, Public sentiment analysis and topic modeling regarding COVID-19 vaccines on the Reddit social media platform: a call to action for strengthening vaccine confidence, J. Infect. Publ. Health (2021), https://doi.org/10.1016/j.jiph.2021.08.010.
[16] M.S. Satu, M.I. Khan, M. Mahmud, S. Uddin, M.A. Summers, J.M.W. Quinn, M.A. Moni, TClustVID: a novel machine learning classification model to investigate topics and sentiment in COVID-19 tweets, Knowl. Base Syst. 226 (2021) 107126, https://doi.org/10.1016/j.knosys.2021.107126.
[17] A.M. Shah, X. Yan, A. Qayyum, R.A. Naqvi, S.J. Shah, Mining topic and sentiment dynamics in physician rating websites during the early wave of the COVID-19 pandemic: machine learning approach, Int. J. Med. Inf. 149 (2021) 104434, https://doi.org/10.1016/j.ijmedinf.2021.104434.
[18] E. Quarantelli, Sociology of Panic, International Encyclopedia of the Social & Behavioral Sciences, 2001, pp. 11020–11023. http://dspace.udel.edu/handle/19716/308.
[19] S. Schachter, J.E. Singer, COGNITIVE, social, and physiological determinants OF emotional state, Psychol. Rev. 69 (5) (1962) 379–399, https://doi.org/10.1037/h0046234.
[20] L. Clarke, panic: myth or reality? Contexts 1 (3) (2002) 21–26.
[21] B. Liu, S. Lin, Q. Wang, Y. Chen, J. Zhang, Can local governments' disclosure of pandemic information decrease residents' panic when facing COVID-19 in China? Int. Publ. Manag. J. 24 (2) (2021) 203–221, https://doi.org/10.1080/10967494.2020.1840463.
[22] G. Wu, X. Deng, B. Liu, Managing urban citizens' panic levels and preventive behaviours during COVID-19 with pandemic information released by social media, Cities (2021) 103490, https://doi.org/10.1016/j.cities.2021.103490.
[23] A. Kumar, C. Cohen, Post-COVID-19 panic disorder in older adults: two case reports, Am. J. Geriatr. Psychiatr. 29 (4) (2021) S58–S59, https://doi.org/10.1016/j.jagp.2021.01.050.
[24] M.S. Islam, M.Z. Ferdous, M.N. Potenza, Panic and generalized anxiety during the COVID-19 pandemic among Bangladeshi people: an online pilot survey early in the outbreak, J. Affect. Disord. 276 (2020) 30–37, https://doi.org/10.1016/j.jad.2020.06.049.
[25] M. Naeem, Do social media platforms develop consumer panic buying during the fear of Covid-19 pandemic, J. Retailing Consum. Serv. 58 (2021), https://doi.org/10.1016/j.jretconser.2020.102226.
[26] T. Islam, A.H. Pitafi, V. Arya, Y. Wang, N. Akhtar, S. Mubarik, L. Xiaobei, Panic buying in the COVID-19 pandemic: a multi-country examination, J. Retailing Consum. Serv. 59 (2021), https://doi.org/10.1016/j.jretconser.2020.102357.
[27] S. Aggarwal, S. Nawn, A. Dugar, What caused global stock market meltdown during the COVID pandemic–Lockdown stringency or investor panic? Finance Res. Lett. 38 (2021) https://doi.org/10.1016/j.frl.2020.101827.
[28] B.S. Liu, S. Lin, Q. Wang, Y. Chen, J.F. Zhang, Can local governments' disclosure of pandemic information decrease residents' panic when facing COVID-19 in China? Int. Publ. Manag. J. 24 (2) (2020) 203–221, https://doi.org/10.1080/10967494.2020.1840463.
[29] N.M.A. Parry, COVID-19 and pets: when pandemic meets panic, Forensic Sci. Int.: Rep. 2 (2020) 100090, https://doi.org/10.1016/j.fsir.2020.100090.
[30] W. Van Damme, W. Van Lerberghe, Editorial: epidemics and fear, Trop. Med. Int. Health 5 (8) (2000) 511–514, https://doi.org/10.1046/j.1365-3156.2000.00599.x.
[31] L. Eichelberger, SARS and New York's Chinatown: the politics of risk and blame during an epidemic of fear, Soc. Sci. Med. 65 (6) (2007) 1284–1295, https://doi.org/10.1016/j.socscimed.2007.04.022.
[32] S.L.D. Restubog, A.C.G. Ocampo, L. Wang, Taking control amidst the chaos: emotion regulation during the COVID-19 pandemic, J. Vocat. Behav. 119 (2020) 103440, https://doi.org/10.1016/j.jvb.2020.103440.
[33] J.M. Armfield, Cognitive vulnerability: a model of the etiology of fear, Clin. Psychol. Rev. 26 (6) (2006) 746–768, https://doi.org/10.1016/j.cpr.2006.03.007.
[34] H. Javelot, L. Weiner, Panic and pandemic: narrative review of the literature on the links and risks of panic disorder as a consequence of the SARS-CoV-2 pandemic, L'Encéphale. 47 (1) (2021) 38–42, https://doi.org/10.1016/j.encep.2020.08.001.

[35] E. Radwan, A. Radwan, W. Radwan, The role of social media in spreading panic among primary and secondary school students during the COVID-19 pandemic: an online questionnaire study from the Gaza Strip, Palestine, Heliyon 6 (12) (2020), e05807, https://doi.org/10.1016/j.heliyon.2020.e05807.
[36] C.J. Xu, X.Y. Zhang, Y.G. Wang, Mapping of health literacy and social panic via web search data during the COVID-19 public health emergency: infodemiological study, J. Med. Internet Res. 22 (7) (2020), https://doi.org/10.2196/18831.
[37] Y. Chen, J. Feng, A. Chen, J.E. Lee, L. An, Risk perception of COVID-19: a comparative analysis of China and South Korea, Int. J. Disaster Risk Reduc. 61 (2021) 102373, https://doi.org/10.1016/j.ijdrr.2021.102373.
[38] Z.-H. Hu, J.-B. Sheu, L. Xiao, Post-disaster evacuation and temporary resettlement considering panic and panic spread, Transp. Res. Part B Methodol. 69 (2014) 112–132, https://doi.org/10.1016/j.trb.2014.08.004.
[39] F. Yuan, M. Li, R. Liu, Understanding the evolutions of public responses using social media: hurricane Matthew case study, Int. J. Disaster Risk Reduc. 51 (2020) 101798, https://doi.org/10.1016/j.ijdrr.2020.101798.
[40] Y. Liu, X. Liu, S. Gao, L. Gong, C. Kang, Y. Zhi, G. Chi, L. Shi, Social sensing: a new approach to understanding our socioeconomic environments, Ann. Assoc. Am. Geogr. 105 (2015) 512–530, https://doi.org/10.1080/00045608.2015.1018773.
[41] P. Liu, H. Zhang, J. Zhang, Y. Sun, M. Qiu, Spatial-temporal response patterns of tourist flow under impulse pre-trip information search: from online to arrival, Tourism Manag. 73 (2019) 105–114, https://doi.org/10.1016/j.tourman.2019.01.021.
[43] A. Mollalo, B. Vahedi, K.M. Rivera, GIS-based spatial modeling of COVID-19 incidence rate in the continental United States, Sci. Total Environ. 728 (2020), https://doi.org/10.1016/j.scitotenv.2020.138884.
[44] S. Guarino, F. Pierri, M. Di Giovanni, A. Celestini, Information disorders during the COVID-19 infodemic: the case of Italian Facebook, Online Soc. Netw. Media 22 (2021) 100124, https://doi.org/10.1016/j.osnem.2021.100124.
[45] K. Hou, T. Hou, L. Cai, Public attention about COVID-19 on social media: an investigation based on data mining and text analysis, Pers. Indiv. Differ. 175 (2021) 110701, https://doi.org/10.1016/j.paid.2021.110701.
[46] C. Prentice, J. Chen, B. Stantic, Timed intervention in COVID-19 and panic buying, J. Retailing Consum. Serv. 57 (2020) 102203, https://doi.org/10.1016/j.jretconser.2020.102203.
[47] A.H. Alamoodi, B.B. Zaidan, A.A. Zaidan, O.S. Albahri, K.I. Mohammed, R.Q. Malik, E.M. Almahdi, M.A. Chyad, Z. Tareq, A.S. Albahri, H. Hameed, M. Alaa, Sentiment analysis and its applications in fighting COVID-19 and infectious diseases: a systematic review, Expert Syst. Appl. (2020) 114155, https://doi.org/10.1016/j.eswa.2020.114155.
[48] S. Behl, A. Rao, S. Aggarwal, S. Chadha, H.S. Pannu, Twitter for disaster relief through sentiment analysis for COVID-19 and natural hazard crises, Int. J. Disaster Risk Reduc. 55 (2021) 102101, https://doi.org/10.1016/j.ijdrr.2021.102101.
[49] R. Plutchik, Chapter 1 - a general PSYCHOEVOLUTIONARY theory OF emotion, in: R. Plutchik, H. Kellerman (Eds.), Theories of Emotion, Academic Press, 1980, pp. 3–33.
[50] S. Choi, J. Lee, M.-G. Kang, H. Min, Y.-S. Chang, S. Yoon, Large-scale machine learning of media outlets for understanding public reactions to nation-wide viral infection outbreaks, Methods 129 (2017) 50–59, https://doi.org/10.1016/j.ymeth.2017.07.027.
[51] G.P. Cuaton, L.J.B. Caluza, J.F.V. Neo, A topic modeling analysis on the early phase of COVID-19 response in the Philippines, Int. J. Disaster Risk Reduc. 61 (2021) 102367, https://doi.org/10.1016/j.ijdrr.2021.102367.
[52] B. Ozyurt, M.A. Akcayol, A new topic modeling based approach for aspect extraction in aspect based sentiment analysis: SS-LDA, Expert Syst. Appl. 168 (2021) 114231, https://doi.org/10.1016/j.eswa.2020.114231.
[53] J.W. Creswell, T.C. Guetterman, Educational research: planning, conducting, and evaluating quantitative and qualitative research, in: Educational Research: Planning, Conducting, and Evaluating Quantitative and Qualitative Research, sixth ed. sixth ed., 2018.
[54] K. Charmaz, Grounded Theory in the 21st Century: Applications for Advancing Social Justice Studies, The Sage handbook of qualitative research, 3rd ed. Sage Publications Ltd: Thousand Oaks (2005) 507–535.
[55] H. Zhang, X.Y. Leung, B. Bai, Y. Li, Uncovering crowdsourcing in tourism apps: a grounded theory study, Tourism Manag. 87 (2021) 104389, https://doi.org/10.1016/j.tourman.2021.104389.
[56] C.I. Ossai, N. Wickramasinghe, Text mining and grounded theory for appraising the self-management indicators of diabetes mobile apps, Endocrine Metabol. Sci. 4 (2021) 100101, https://doi.org/10.1016/j.endmts.2021.100101.
[57] C. Doidge, E. Ferguson, F. Lovatt, J. Kaler, Understanding farmers' naturalistic decision making around prophylactic antibiotic use in lambs using a grounded theory and natural language processing approach, Prev. Vet. Med. 186 (2021) 105226, https://doi.org/10.1016/j.prevetmed.2020.105226.
[58] Y. Lyu, J.C.-C. Chow, J.-J. Hwang, Exploring public attitudes of child abuse in mainland China: a sentiment analysis of China's social media Weibo, Child. Youth Serv. Rev. 116 (2020) 105250, https://doi.org/10.1016/j.childyouth.2020.105250.
[59] L. Xu, H. Lin, Y. Pan, H. Ren, J. Chen, Constructing the affective lexicon ontology, J. China Soc. Sci. Tech. Info. 27 (2) (2008) 180–185.
[60] B.W. Silverman, Density Estimation for Statistics and Data Analysis, vol. 26, CRC press, 1986.
[61] B. Glaser, A.L. Strauss, The discovery of grounded theory: strategy for qualitative research, Nurs. Res. 17 (4) (1968) 377–380.
[62] J. Corbin, A. Strauss, Grounded theory research - procedures, canons and evaluative criteria, Zeitschrift Soziol. 19 (6) (1990) 418–427, https://doi.org/10.1007/bf00988593.
[63] D.M. Blei, A.Y. Ng, M.I. Jordan, Latent dirichlet allocation, J. Mach. Learn. Res. 3 (null) (2003) 993–1022.
[64] B. Toole, Evolution of complex disasters, Lancet 346 (8981) (1995) 1012–1015, https://doi.org/10.1016/s0140-6736(95)91694-6.
[65] K. Mohamed Ridhwan, C.A. Hargreaves, Leveraging Twitter data to understand public sentiment for the COVID-19 outbreak in Singapore, Int. J. Info. Manag. Data Insights 1 (2) (2021) 100021, https://doi.org/10.1016/j.jjimei.2021.100021.
[66] D. Zi-han, Z. Min, Mechanism and influence of emotions arising in daily consuming spaces: a case study of nanjing, Hum. Geogr. 35 (1) (2020) 46–54, https://doi.org/10.13959/j.issn.1003-2398.2020.01.006.
[67] F. Zhen, B. Wang, Y. Chen, Chinas city network characteristics based on social network space: an empirical analysis of sina micro-blog, Acta Geograph. Sin. 67 (8) (2012) 1031–1043.
[68] G. Barkur, Vibha, G.B. Kamath, Sentiment analysis of nationwide lockdown due to COVID 19 outbreak: evidence from India, Asian J. Psychiatr. 51 (2020) 102089, https://doi.org/10.1016/j.ajp.2020.102089.
[69] E.G. Carbone, E.T. Echols, Effects of optimism on recovery and mental health after a tornado outbreak, Psychol. Health 32 (5) (2017) 530–548, https://doi.org/10.1080/08870446.2017.1283039.
[70] M.U.G. Kraemer, C.H. Yang, B. Gutierrez, C.H. Wu, B. Klein, D.M. Pigott, L. du Plessis, N.R. Faria, R.R. Li, W.P. Hanage, J.S. Brownstein, M. Layan, A. Vespignani, H.Y. Tian, C. Dye, O.G. Pybus, S.V. Scarpino, C.-D.W.G. Open, The effect of human mobility and control measures on the COVID-19 epidemic in China, Science 368 (6490) (2020), https://doi.org/10.1126/science.abb4218, 493-+.
[71] J. Wang, D. Du, Y. Wei, H. Yang, The development of COVID-19 in China: spatial diffusion and geographical pattern, Geogr. Res. 39 (7) (2020) 1450–1462.
[72] M. Seo, Amplifying panic and facilitating prevention: multifaceted effects of traditional and social media use during the 2015 MERS crisis in South Korea, J. Mass Commun. Q. 98 (1) (2021) 221–240, https://doi.org/10.1177/1077699019857693.

Further reading

[42] J. Song, T. Song, D.-C. Seo, D.-L. Jin, J. Kim, Social big data analysis of information spread and perceived infection risk during the 2015 Middle East respiratory syndrome outbreak in South Korea, Cyberpsychol., Behav. Soc. Netw. 20 (2017), https://doi.org/10.1089/cyber.2016.0126.