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Public opinion changing patterns under the double-hazard scenario of natural disaster and public health event

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ABSTRACT

In the context of the COVID-19 epidemic, a "double-hazard scenario" consisting of a natural disaster and a public health event occurring simultaneously is likely to arise. Focusing on this double-hazard scenario, this study developed a new opinion dynamics model that verifies the effect of opinion dynamic in practical applications and extends the realistic meaning of the logic matrix. The new model can be used to quickly identify changing trends in public opinion about two co-occurring public safety events in China, helping the government to better anticipate and respond to these real double-hazard scenarios. The new model was tested with three real double-hazard scenarios involving natural disasters and public health events in China and the simulation results were analyzed. Using visualization and Pearson correlation coefficients to analyze more than a million items of network-wide public opinion data, the new model was found to show a good fit with reality. The study finally found that in China, public attention to both natural hazards and public health events was greater when these public safety events co-occurred (double-hazard scenario) than when they occurred separately (single-hazard scenarios). These results verify the coupling phenomenon of different disasters in a multi-hazard scenario at the information level for the first time, which is greatly meaningful for multi-hazard research.

1. Introduction

Public safety incidents are major issues inevitably faced by human society in its continuous development. The occurrence of any public safety event can cause substantial economic losses. Therefore, it is necessary to understand and study public safety incidents in depth. Recently, as the field of public safety has evolved, scholars have identified specific categories of public safety incidents. Specifically, they have distinguished four major categories of such events: natural disasters, accident disasters, public health events, and social security events (The Central People's Government of the People's Republic of China, 2006). Governments in various countries are paying increasing attention to public safety incidents, including understanding, prevention, and response. Members of the public are also becoming more and more concerned about public safety incidents (Barnett, 1999; Ma et al., 2014). In the past, people obtained information about public safety incidents from traditional media, such as newspapers and TV, which was a relatively inefficient way of obtaining relevant information. With the development of Internet technology and new media represented by social media, access to

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information is increasing and it is becoming more convenient to obtain information when a public safety event occurs. Hence, combining traditional with new media, especially social media, is now one of the most important ways to do public safety research (Imran et al., 2020; Kaufhold et al., 2020; Li et al., 2017). Some scholars have explored the roles and functions of social media in natural disasters (de Albuquerque et al., 2015; Middleton et al., 2014; Yates & Paquette, 2011), while others have investigated social media in the context of public health events (Finch et al., 2016; Fung et al., 2015; Muniz-Rodriguez et al., 2020). There is no doubt that social media will play a pivotal role in the public safety research field in the future.

Understanding all types of public safety events can help human society avoid many deaths, injuries, and other losses. Many recent studies have explored various types of single public safety events. For instance, scholars have researched different kinds of natural disasters, including earthquakes, landslides, and fires (Guzzetti et al., 1999; McCaffrey, 2015; Yates & Paquette, 2011). Others have focused on technological disasters (Yang et al., 2020). Given the high level of transmissibility of COVID-19, our society will coexist with the virus for a long time. Major public health events like the COVID-19 pandemic will recur many times, bringing people's attention to public health events to a new peak. Moreover, there is a growing probability that multiple types of public health events will occur simultaneously, representing the "multi-hazard scenario" emphasized by scholars of public safety (Cozzani et al., 2010; Krausmann et al., 2011). In fact, from the current state of multi-hazard research, the existing studies related to multi-hazard scenarios only focus on the physical level. To be more specific, the coupling effect among different disasters from physical level is mainly studied by these researches. For example, the study of the combined effect from a natural disaster and the industrial accidents caused by this natural disaster is a typical research scenario in multi-hazard field (Wang et al., 2020). However, the impact of disasters on the real world is not only at the physical level, but also at the information level. The public opinion on disasters in one of the most typical instances of the impact of disasters at the information level. In multi-hazard scenario, this kind of impact of disasters at the information level still exists, but there is no research exploring whether the coupling effect among different disasters in the multi-hazard scenario still exist at the information level as they do at the physical level. In other words, there is no existing previous method which can directly verify the existence of this kind of coupling effect at the information level and can describe the specific pattern of it if it does exist. This creates a gap in the field of multi-hazard research.

Given this situation and the current interest in social media applications in public safety research, how the patterns of public opinion on disasters change when different types of public safety events co-occur will be a very meaningful research question. It can fill the gap that there is lack of researches to study the coupling effects of different disasters at the information level in the field of multi-hazard research. It is important to explore public opinion in disaster scenarios because public opinion on disasters is often accompanied by strong emotions, which may be transmitted widely and affect the stability of society. In addition, bringing more public attention to disaster situations can often support government disaster relief. In the context that the number of double-hazard scenarios consisting of natural disasters and public health events will increase in the future due to the existence of COVID-19 and based on the considerations about the importance of exploring public opinion in multi-hazard scenarios, the study decides to focus on double-hazard scenarios where natural disasters and public health events occur simultaneously in China. The specific target of the study is to ask whether and how trends in public opinion on natural disasters and public health events differ when such events occur separately compared with when they co-occur in China. It sought to determine whether the coupling effect of natural disasters and public health events still exists at the information level when these two different kinds of public safety events occur simultaneously. On the other hand, the study also tried to find a new model which can describe the changing trend of public opinion on the two different kinds of public safety events under the ND-PHE double disaster scenario in Chinese society to help governments better face the public opinion situation in real double-hazard scenarios.

As scholars have usually studied changes in public opinion or sentiment regarding a disaster in single-hazard scenarios, no previous method can be generalized to describe changes in people's opinion on two different disasters in a double-hazard scenario. A new method is needed. Opinion dynamics can simulate changes in people's opinions in a social network. This suggests that an opinion dynamics model can also represent public opinion and attention in the real world. Thus, this study sought to adapt an opinion dynamics model to suit the research context. Chinese society and Chinese people were chosen as the research background and subjects. In the first step, a double-hazard scenario consisting of a natural disaster and a public health event was constructed. It was given a clear definition for our study, named the Natural Disaster–Public Health Event (ND-PHE) double-hazard scenario. In addition, four types of public opinion based on logical relationships between natural disasters and public health events were set up. Next, to explore the changing patterns of people's opinion on these two different kinds of public safety incidents, the study chose an opinion dynamics model, a theoretical approach to modeling changes in public opinion. The Fredkin–Johnson (F-J) model was selected as the specific basic model. We improve the FJ opinion dynamics model under logistic constraints to make it more applicable to the ND-PHE scenario, naming the new model the double-hazard (DH) F-J model. Simulation results were obtained using the improved FJ model and finally visualized. In addition, after the simulation, empirical testing in realistic ND-PHE scenarios was conducted. It was found that public attention to both natural hazards and public health events increased when they co-occurred in China.

Three cases were chosen: "rainstorm–COVID-19″ in Henan from July to August 2021, "typhoon–COVID-19″ in Jiangsu from July to August 2021, and "blizzard–COVID-19″ in Liaoning in November 2021. Related public opinion data on these three cases were collected from the Chinese network and processed, counted, and visualized. Comments and other text expressing extreme fears were screened to more accurately represent the opinions of the people simulated. The change trend of public opinion on every different disaster in three double-hazard cases above has been described by visualization. The phenomenon of increasing of public fear and panic about each specific disaster during the period when the disasters were not occurring or had already stopped has been highlighted in the empirical test. It reflects the conclusion that public opinion on natural disasters and public health events will both increase when they occur simultaneously in China. In addition, the Pearson correlation coefficient was also used to detect the goodness of fit of the model. The final validation results were generally consistent with the previous simulation results. The study also analyzed and sought to explain the possible causes of errors.

The novelty of this study for security science is that, unlike the traditional use of information science to study public safety issues in single-hazard scenarios only, this study applied information science approaches to study multi-hazard scenarios for the first time. The phenomenon of coupling among different disasters in multi-hazard scenarios is a crucial element of public safety research. Related studies have only studied this coupling phenomenon in multi-hazard scenarios from the physical perspective; they have not considered the coupling effect among different disasters at the information level. The contribution of this study is to break through only focusing on the coupling effects of physical level between different hazards in multi-hazard scenarios. It used opinion dynamics to verify the existence of coupling between different public safety events in multi-hazard scenarios at the information level for the first time, which is of great significance to multi-hazard scenario research. Regarding opinion dynamics, this study distinguishes itself from traditional opinion dynamics based on multiple topic models, which are limited to theoretical simulations of public opinion, by applying opinion dynamics to real scenarios. The study extends the practical meaning of the logic matrix proposed in opinion dynamics research, so that it is no longer limited to the logical relationships between topics but can be extended to reflect the interaction of different events in reality. It further verified the effectiveness of opinion dynamics in practical application, which is also important contribution to the research on opinion dynamics. Apart from this, the new model proposed in the study reflects the changing patterns and trends of people's opinions over time in real ND-PHE double-hazard scenarios. It can help the government identify public opinion situations more quickly in real double-hazard scenarios and develop more effective public opinion response strategies, which is greatly meaningful for the government in responding to the multi-hazard scenarios in the real world.

In the discussion section of the paper, the theoretical and practical implications of the study are explained. At the end of the paper, the conclusions and limitations are summarized and discussed. A theory of how public opinion on natural disasters and public health events changes in the ND-PHE scenario is initially proposed. Furthermore, the paper makes some hypotheses based on the conclusions of the study and presents relevant future directions for research.

2. Literature review

2.1. Information science and public safety

With the development of information technology and new media, especially social media, many scholars have started to try to combine information science and public safety science to solve problems related to public safety at the information level in recent decades. Rogstadius et al. (2013) presented an online system called CrisisTracker that can capture distributed situation awareness reports based on social media activity during large-scale events represented by natural disasters. Li et al. (2020) used a classic SIR epidemic model to analyze three groups in time and space through social network theory and analog simulation analysis and conducted empirical tests. Zahra et al. (2020) used sensory and emotional characteristics and labeled data to train several machine learning classifiers and contributed a successful example of combining crowdsourced and machine learning analysis, helping to identify valuable eyewitness reports during disasters. Kryvasheyeu and Chen (2016) proposed that massive online social networks can be used to rapidly assess the damage caused by a large-scale disaster and verified this conclusion. Shi et al. (2021) proposed a meteorological briefing formalization module composed of a text form judgment model, a formalization word detection model, and an event knowledge guided text formalization model that achieved better results than baseline models in terms of the BLEU score. Sorkhabi et al. (2020) combined the public health field, proposing a systematic pre-processing approach called PEPMED, which dramatically improved accuracy of the Electronic Health Records data.

However, many studies of public safety have considered only single-hazard scenarios. In reality, there are often situations in which multiple hazards occur at the same time. This kind of situations are called multi-hazard scenarios in public safety research. The United Nations Office for Disaster Risk Reduction (UNDRR) defined the multi-hazard scenario approach as "an approach that considers more than one hazard in a given place and the interrelations between these hazards, including their simultaneous or cumulative occurrence and their potential interactions" (UNDRR, 2015). Indeed, focusing on the interaction between hazards rather than considering them separately is more in line with reality (He & Weng, 2020). In recent years, scholars of public safety have paid increasing attention to multi-hazard scenarios. Wang et al. (2020) reviewed a series of risk analysis methods to examine the relationships between hazards in a multi-hazard scenario and presented possible challenges and solutions. He and Weng (2021) presented a Choquet integral multiple linear regression model to overcome the problem of nonlinear additivity in multi-hazard scenarios and concluded that the composite individual risk of multi-hazard coupling disasters is greater than that of the simple sum of the risk of each hazard. Many other scholars have conducted relevant studies for different multi-hazard scenarios (Chen et al., 2018; Gehl & D'Ayala, 2016). However, a literature review reveals that studies of multi-hazard scenarios have always focused on the physical level. Few such studies are related to the effects of different hazard interactions in multi-hazard scenarios at the information level. For the first time, this study combined information science methods with security science scenarios to explore whether there are also interrelations among different disasters in multi-hazard scenarios at the information level.

2.2. Public health events

Public health events can not only incur huge economic losses for society but also cause widespread damage to people's health and even loss of life. The WHO proposed the designation "Public Health Emergency of International Concern" (PHEIC) after the SARS outbreak. If public health events pose a significant risk to the global community, they are classified as PHEICs (Mullen et al., 2020). Public health events that have been classified as PHEICs by the WHO include the influenza A (H1N1) outbreak in 2009, the polio outbreak in 2014, the Ebola outbreak in West Africa in 2014, the Zika outbreak from 2015 to 2016, and the Ebola outbreak in the Congo in 2018. The COVID-19 pandemic has also been named a PHEIC.

It is necessary to explore the causes, preventive measures, and other intrinsic characteristics of public health events. This can reduce the losses of public health events to human society. Many scholars have explored public health events, such as the diseases that cause such events. Fraser et al. conducted an early assessment of the transmissibility and severity of H1N1 by analyzing early data collected from the outbreak of H1N1 in Mexico. They found that the transmissibility of H1N1 was substantially higher than that of seasonal flu (Fraser et al., 2009). Mehndiratta et al. (2014) presented the history of and current challenges to the eradication of poliomyelitis, emphasizing the need for the whole world to fight against poliomyelitis . Yakovenko et al. reviewed the outbreak of poliomyelitis in 2010 in Tajikistan and Alexander et al. reviewed the history and progress of poliomyelitis eradication efforts in Pakistan, which contributed to further research on the eradication of poliomyelitis (Alexander et al., 2014; Yakovenko et al., 2014). Kalenga et al. (2019) reviewed the development of the Ebola epidemic in Congo from 2018 to 2019 and analyzed future challenges in facing the epidemic. Buseh et al. (2015) examined the sociopolitical and economic conditions that created the environment for the Ebola epidemic to occur and discussed policy recommendations for facing the Ebola epidemic. They all focused on the outbreak of the Ebola epidemic in different periods in different areas and tried to get a better understanding of Ebola to help eradicate or prevent it. The Zika virus has also been examined by many scholars, especially since the outbreak of Zika from 2015 to 2016. Wang et al. reviewed the virological, epidemiological, and clinical characteristics of ZIKV infection in around 2016 (Wang et al., 2016). de Laval et al. (2016) also summarized current knowledge of ZIKV infection, such as its transmission, epidemiology, and clinical characteristics. After the outbreak of COVID-19 epidemic, many researches about COVID-19 have been done. For instance, Pian et al. (2021) have made a systematic review which synthesizes the existing literature on the causes and impacts of COVID-19 infodemic and summarize the proposed strategies to fight with COVID-19 infodemic, suggesting the future research directions. Yao et al. (2021) have investigated the effects of online social support on the public's beliefs in overcoming COVID-19 by embracing their cognition and emotion during the epidemic. Piri et al. (2022) have used COVID-19 samples as cases to validate a novel discrete artificial gorilla troop optimization (DAGTO) technique which can handle FS tasks in the healthcare sector they proposed.

Many scientific questions remain to be studied in the field of public health. This study explored the patterns of changing public opinion on different public safety events in double-hazard scenarios involving natural disasters and public health events.

2.3. Opinion dynamic

The opinion dynamics approach is based on social network theory and graph theory, and it is used to study the changes in opinion of individuals in a social network (Anderson & Ye, 2019). A social network is a network constructed by many different individuals who can affect each other (Krinsky & Crossley, 2014; Newman, 2003). Graph theory offers an excellent way to describe a social network (Godsil, 2001; Harary, 1969).

French Jr proposed opinion dynamics theory in 1956 and Degroot proposed the first important and widely received opinion dynamics model in 1974 (Degroot, 1974; French, 1956). As scholars continued to study opinion dynamics, more and more different opinion dynamics models were proposed, such as the FJ model, Ising model, and Hegselmann-Krause model (Castellano, Fortunato, & Loreto, 2009; Friedkin, 2001; Hegselmann & Krause, 2002). This study adapted the F-J model to form a new model with logical constraints that could be better applied to double-hazard scenarios. F-J model was proposed by Friedkin (2001) and it is a widespread accepted opinion dynamic model nowadays. Some scholars have also conducted more in-depth studies for the F-J model. For instance, Yao et al. (2022) have studied the cluster consensus of Friedkin-Johnsen (F-J) model with one or more stubborn nodes and establish some consensus criterion. Wang et al. (2021) have proposed a concatenated Friedkin-Johnsen (FJ) model which is a two time-scale opinion dynamics model and obtained sufficient conditions under which the opinions of the agents converge to consensus. Pironti (2019) deeply study the F-J model, finding that the F-J model converges to a quasi-consensus condition among the agents when the coefficients weighting the agent susceptibilities to interpersonal influence approach 1 and the consensus value will be different from the one obtained by the corresponding DeGroot model.

Most studies of opinion dynamics have focused on changes in people's opinion on a specific topic, such as the traditional F-J model and Degroot model. However, in the real world, people in a social network may discuss two or more topics in a given period. There is likely to be a logical relationship between the topics discussed by people in a social network. Scholars have presented such relationships in the form of a logical matrix. Anderson and Ye (2019) demonstrated the logical correlation between the topics "mental challenges are as exhausting as physical challenges" and "Go and chess should be Olympic sports", using a logical matrix to clearly represent the changes in individuals' perceptions of these two opinions. Based on this background, some scholars have proposed opinion dynamics models with logistic constraints on multiple topics. Noipitak and Allen (2021) have proposed a new model which can allows agents to revise their opinions on multiple interdependent topics based on Degroot model and this new model can describe the dynamics of the opinions of individuals in a group on one topic by pooling their neighbors' opinions and the influences of their own opinions on multiple topics. Ahn et al. (2020) have proposed a new model for opinion dynamics on cross-coupling topics under a state-dependent matrix weighted consensus setup and they have analyzed complete opinion consensus and partial opinion consensus is presented for both the cases when the coupling matrices are positive semidefinite and indefinite. One of the most widely accepted new opinion model with logistic constraints was still proposed by Friedkin et al. (2016) who have further investigated how the existence of logical constraints influences a group to converge on a common opinion in a belief system and proposed a new F-J model with logistic matrix. Based on their results, other scholars have continuous studied it deeply. Parsegov et al. (2017) reformulated the Degroot model and F-J model under logistic constraints by combining both models with the concept of a logical matrix. Ye et al. (2018) have cancelled the stubborn individuals and continuous studied the opinion dynamics model which considers a network of individuals simultaneously discussing a set of logically interdependent topics, explaining the phenomenon of strong diversity of opinions often observed in a strongly connected network. He et al. (2022) have also proposed a model which antagonistic and cooperative relationships are considered simultaneously based on the F-J model with logical constraints, showing that network topology, stubborn coefficient and the logic matrix will jointly affect the evolution of opinions. These researches have contributed to the development of opinion dynamics on multiple topics.

As the goal of the current study was to identify patterns in changing public opinion on different public safety events in double-hazard scenarios and previous information technology methods of addressing public safety questions have focused on single-hazard scenarios, it was necessary to find a new method to suit double-hazard scenarios. An opinion dynamics model with logical constraints was a good choice to help achieve the research goal. However, traditional opinion dynamics models, such as the Degroot model and F-J model, are not appropriate for double-hazard scenarios, because these models cannot describe the logistic relation among multiple events. On the other hand, the existing opinion dynamics models with logistic matrix on multiple topics are not applicable to the double-hazard scenario either, because they are basically studied from theoretical aspects, such as studying the convergence of the model or the conditions for reaching consensus of opinions. These existing models cannot correlate well with real scenarios, lacking the parameters or dimensions that can describe the specific impact of the real scenarios itself on the individual, and nearly none of them can describe the real specific change patterns of opinions over time. These models have a limited ability to represent the impact of disasters on people amid the complexities of double-hazard scenarios. Therefore, the study adapted the F-J model to form a new model with logical constraints that could be better applied to double-hazard scenarios. The new model combined with real double-hazard scenarios and proposed new parameters which can show the human impact of real disasters, such as people's sensitivity to disasters, which allows the new model with logistic matrix to be better applied to the double-hazard scenarios. The advantages and limitations of the new model are briefly presented by Table 1.

More specific details of the advantages and limitations of the new model will be explained in later chapters. This study is the first to apply opinion dynamics to a multi-hazard public safety scenario to study problems related to the field of security science.

3. Method

3.1. Construction of the ND-PHE double-hazard scenario

In real life, two public safety events rarely occur precisely simultaneously; "co-occurrence" is thus taken here as sequential occurrence over a very short period. This study constructed a viable and reasonable double-hazard scenario consisting of a natural disaster and a public health event, named the ND-PHE double-hazard scenario. The ND-PHE double-hazard scenario was required to satisfy the following conditions. **(1)** Must consist of the natural disaster and the public health event. **(2)** Must consist of one type of natural disaster and one type of public health event. **(3)** Both public safety events must occur at or within the same province-level location. **(4)** The interval between the start date of the first public safety event and the start date of the second public safety event should be less than 20 days. **(5)** Either of the two types of public safety events can occur first.

3.2. DH F-J model

The F-J model is shown as below:

$$\boldsymbol{X}(\boldsymbol{k}+1) = \boldsymbol{AWX}(\boldsymbol{k}) + (\boldsymbol{I}-\boldsymbol{A})\boldsymbol{X}(0) \tag{1}$$

where $\boldsymbol{k} = 0, 1, 2, \ldots\ldots$ $\boldsymbol{I}$ is an identity matrix. $\boldsymbol{X}$ is a matrix consisting xij with $\boldsymbol{n}$ individuals and $\boldsymbol{m}$ opinions. $xij(k) \in [0,1]$ represents individual i's trust in opinion j. If individual i has the maximum possible trust in opinion j, its value will be 1; if individual i has the minimum possible trust in opinion j, its value will be 0. The extent of an individual's trust in an opinion reflects their level of support for the opinion. In other words, cell value 1 indicates complete support for the opinion while cell value 0 indicates no support at all for the opinion. $\boldsymbol{W}$ is an **n** x **n** matrix of weights, which satisfies $0 \le wij \le 1,\ \forall ij,\ \sum_{j=1}^{n} wij = 1\ \forall i$. It represents the allocations of weights to **n** individuals' influence from other individuals. wij represents individual i's sensitivity to individual j' s opinion. A sum of each row equal to 1 means that the sum of sensitivity weights for each individual is unified as 1. $\boldsymbol{A}$ is a **n** x **n** diagonal matrix that satisfies $0 \le aii \le 1,\ aii = 1 - wii\ \forall i$, where aii corresponds to the degree of openness of individual i.

Based on the F-J model and the concept of logical constraints (Anderson & Ye, 2019; Friedkin, 2001; Parsegov et al., 2017, 2016), the study proposed an improved F-J model under logical constraints to describe changes in public opinion on two different types of public safety events in the ND-PHE double-hazard scenario proposed in the previous part. The resulting model was named the double-hazard (DH) F-J model. Consider that there are $\boldsymbol{n}$ individuals in a network of influence in the ND-PHE scenario. As public safety

Table 1
The advantages and limitation of the new model.

Advantages	Limitations
1.Can be applied to real double-hazard scenarios 2.Can describe the change of public opinion to different disasters in double-hazard scenarios 3.Expand the practical implication of the logic matrix	1.Currently only applicable to the safety science field 2.Currently not validated for all multi-hazard scenarios

events affect individuals in different ways, $\boldsymbol{q}$ individuals are considered to be those in the local area where a public safety event occurs, while $\boldsymbol{n}$-$\boldsymbol{q}$ individuals are considered to be those who are not in the local area where a public safety event occurs. The crowd of $\boldsymbol{q}$ individuals is part of the $\boldsymbol{n}$ individuals in our influence network. In this influence network, all individuals hold a total of $\boldsymbol{m}$ opinions. The tensor matrix equation defines the dynamics of this $\boldsymbol{n}$-individual influence network on $\boldsymbol{m}$ opinions as follows:

$$\boldsymbol{X}(\boldsymbol{k}+1) = \boldsymbol{AWX}(\boldsymbol{k})\boldsymbol{C} + (\boldsymbol{I}-\boldsymbol{A})\boldsymbol{X}(0) + \boldsymbol{BD}(\boldsymbol{k}) \tag{2}$$

where $\boldsymbol{k} = 0, 1, 2, \ldots\ldots$ $\boldsymbol{I}$ is an identity matrix. The definitions of matrices $\boldsymbol{X}$, $\boldsymbol{W}$ and $\boldsymbol{A}$ are the same as in the F-J model. In the new model, $\boldsymbol{X}(0)$ satisfies:

$$\boldsymbol{X}(0) = \boldsymbol{BD}(0) \tag{3}$$

$\boldsymbol{B}$ is a **n** x **n** diagonal matrix where bii represents individual i's sensitivity to disasters, which satisfies $0 \le bii \le 1$. However, the sensitivity weight value range differs for local residents in areas where public safety events occur and non-local residents. $\boldsymbol{D}$ is a **n** x **m** matrix consisting of $\boldsymbol{n}$ rows of vector $\boldsymbol{d}$. Row vector $\boldsymbol{d}$ has $\boldsymbol{m}$ elements, which satisfies $0 \le di \le 1, \ \forall i$, corresponding to the severity of the actual public safety events, which depends on evaluation metrics chosen in the actual specific public safety events. $\boldsymbol{C}$ is a **m** x **m** matrix called a logistic matrix and contains the interdependencies among **m** opinions, which satisfies $0 \le cij \le 1, \ \forall ij, \ \sum_{j=1}^{m} cij = 1 \ \forall i$.

3.3. Research framework

The full method to achieve the goal of the study is to use the DH F-J model to simulate the public opinion in the single-hazard

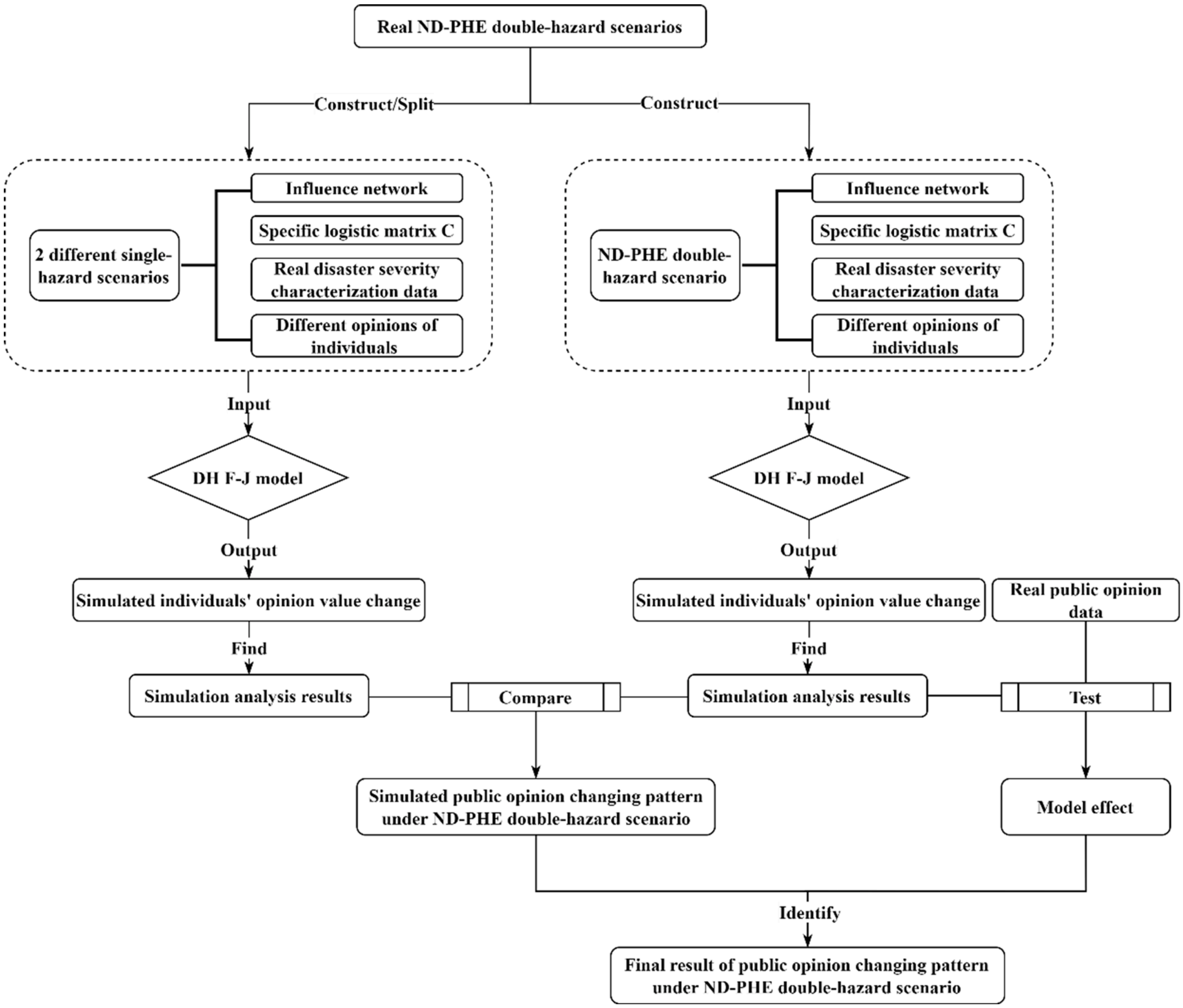


Fig. 1. The details of the research framework.

scenarios and the ND-PHE double-hazard scenarios separately, comparing the simulation results to find the change pattern of people's opinion to different public safety events in these 2 different kinds of hazard scenarios. After getting the final simulation results, the empirical test is used to verify the simulation results. The specific steps are shown in Fig. 1.

3.4. Data collection & processing

To verify the conclusions of the simulation analysis, three cases in the real world were chosen: a Henan ND-PHE double-hazard scenario, consisting of a rainstorm and the COVID-19 epidemic from July to August 2021; a Jiangsu ND-PHE double-hazard scenario, consisting of a typhoon and the COVID-19 epidemic from July to August 2021; and a Liaoning ND-PHE double-hazard scenario, consisting of a blizzard and the COVID-19 epidemic in November 2021. By analyzing the discussion of these cases by Internet users on social media, the study explored the changes in public opinion on each public safety event in these real ND-PHE double-hazard scenarios.

The data used for validation came from two of the largest social media platforms in China: Sina Weibo and the WeChat public platform. According to Weibo's and Tencent's third-quarter 2021 earnings reports, Sina Weibo and WeChat have, respectively, 573 million and 1.26 billion monthly active users, which means that both are essential platforms for expressing public opinions on public events in China. To be more specific, Sina Weibo platform where users can publish their views and comments through Weibo publicly, usually in the form of short texts with dozens of words, and by the ways of forwarding, commenting and liking to interact. On the other hand, WeChat is a new media tool which provides the instant messaging services and it is the largest instant messenger in China. However, in addition to interpersonal communication, WeChat also provides the function of WeChat media platform. Traditional media and we-media can publish articles through WeChat official account, and ordinary users can forward, comment and like on these articles. It should be noted that not all user comments are visible on the article page, and only some "selected comments" approved by the article author can be displayed below the article. The data were collected in these 2 platforms by using keyword hits, extracting original microblog posts related to the six cases of the Henan rainstorm, Henan epidemic, Jiangsu typhoon, Jiangsu epidemic, Liaoning blizzard, and Liaoning epidemic, as well as selected comments on WeChat public platforms in a specific time range. To be more specific, for Weibo platform, the original posts have been selected as the research data. For the WeChat public platform, the articles related to topics were collected by keyword hitting the title, and selected comments related to these articles were further collected. Selected comments are considered as the research data and to represent the attitudes and views of public netizens on topics, and their text content and release time are used for subsequent analysis. The specific key words are displayed in the supplementary materials. Next, the collected data were cleaned and duplicate text was removed. The study collected public opinion data focusing on local epidemic outbreaks in the selected cases based on the geographic constraints of the ND-PHE double-hazard scenario presented in this study and the multi-hazard study scenario requirement. The final sample statistics are shown in the following Table 2:

It is worth emphasizing that the form of data collected from both platforms is textual data. In other words, these texts constructed by sentences and words are the object analyzed in the data analytics part for the study. After obtaining relevant netizen discussion text for each case, the study performed sentiment analysis of the text content and judged the netizens' opinions on and attitudes toward the public safety events based on the type of sentiment identified. The lexical method was adopted as the text emotion classification model. The emotion analysis model used in this study is based on lexicon. The lexicon is formed by the combination of the lexicon of 21 general emotions provided by Dalian Institute of technology and the lexicon of 8 general emotions provided by the National Research Council of Canada (NRC), in which the former emotional annotations are marked manually by experts and the latter by crowdsourcing based on Turkish robots (Mohammad & Turney, 2013; Xu et al., 2008). Combining the lexicon of the two, we finally get an emotion lexicon including 22 emotion categories (happiness, peace of mind, respect, praise, trust, love, blessing, anger, sadness, disappointment, guilt, missing, panic, fear, shame, irritability, disgust, derogation, jealousy, doubt, surprise, anxiety). There are specific keywords under each emotion category, and each keyword has its corresponding emotional weight. By accumulating the emotional weight of each word in the text, the values of various emotions in the text are obtained. The emotion is further integrated according to whether the text before and after the keyword contains degree adverbs and negative words. Finally, the emotion category with the highest score is classified as the emotion of the text. If there are no emotion words of the lexicon included in the test, the text does not contain any emotion. The specific data processing method is shown in the Fig. 2.

After classifying the emotions of all of the netizen discussion samples from social media, fear, panic, anxiety, disgust, and irritability were selected from 22 emotions that characterized the degree of importance of public safety events and epidemics. The final data obtained to express these negative emotions is still textual data consisting of words. The study used this emotion change to verify the changes in public opinion.

Table 2
Details of collected data.

Case	Period	Sample Size	Weibo	Wechat
Rainstorm in Henan	2021.7.18~2021.8.31	975,874	791,265	184,609
Epidemic in Henan	2021.7.18~2021.8.31	34,071	22,994	11,077
Typhoon in Jiangsu	2021.7.10~2021.8.31	27,280	22,059	5221
Epidemic in Jiangsu	2021.7.10~2021.8.31	113,933	73,479	40,454
Blizzard in Liaoning	2021.11.1~2021.12.10	12,677	10,968	1709
Epidemic in Liaoning	2021.11.1~2021.12.10	46,263	38,632	7631
Sum		1210,098	959,397	250,701

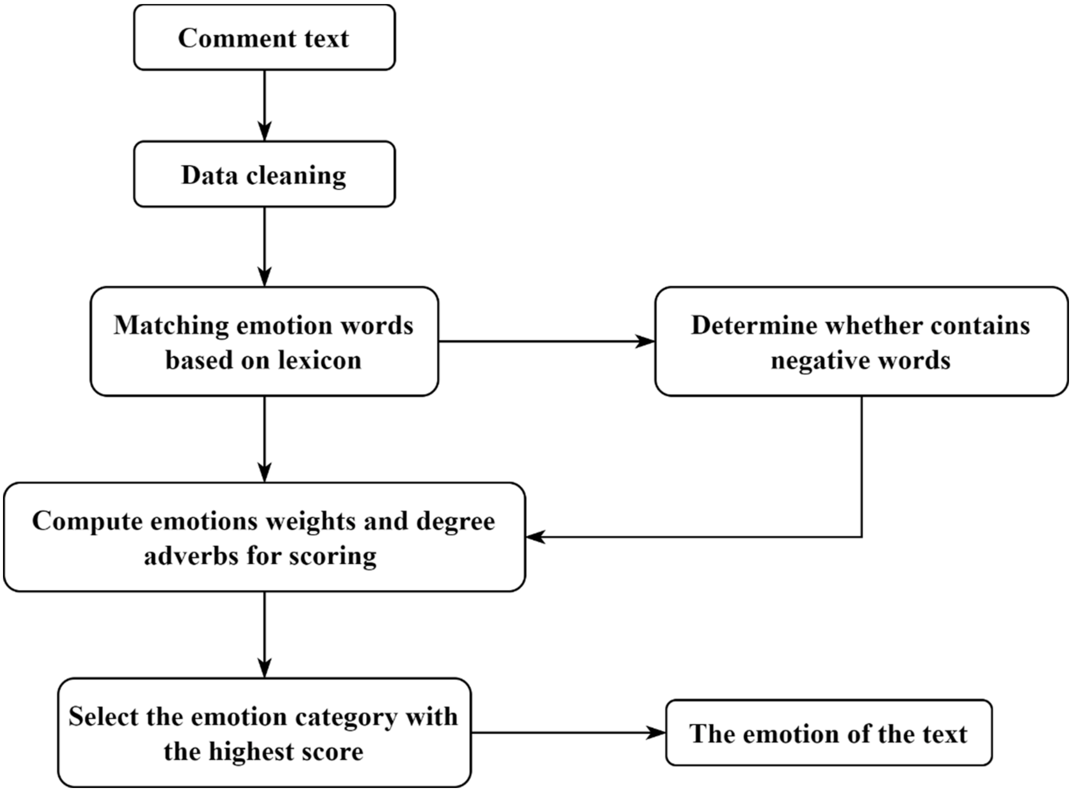


Fig. 2. The process of data collection.

4. Simulation results and case verification

4.1. Scenario construction

A simulated ND-PHE double-hazard scenario and a simulated small social influence network were constructed. In this influence network, $\boldsymbol{k}$ represents time in days, i.e. $\boldsymbol{k} = 0$ represents the first day of hazard duration. There were $\boldsymbol{n}$ individuals in the influence network and $\boldsymbol{q}$ individuals in the local area in which a disaster occurs. The value of $\boldsymbol{t}$ ranged from 30 to 50 days, depending on the simulation requirements. For $\boldsymbol{W}$ matrix, as for the other indexes related to individual characteristics, the cell values were randomized based on the definitions and conditions in Section 3.2 to simulate the influence weights of individuals' relationships for this matrix. Clearly, people who are in the area in which a public safety event occurs are more sensitive to the disaster. Therefore, for $\boldsymbol{B}$ matrix, $0.7 \leq bii \leq 1$ for individuals who are in the local area where public safety events occur while $0 \leq bii \leq 0.7$ for the other individuals in the influence network. These settings reflected the reality of human sensitivity to disasters. The specific values input into matrix $\boldsymbol{D}$ were normalized using the algorithm below:

$$\boldsymbol{D}_{\boldsymbol{norm}} = (\boldsymbol{D} - D_{min})/(\boldsymbol{D} - D_{max}) \tag{4}$$

where $\boldsymbol{D}$ satisfies the condition in Section 3.2 above: $0 \leq di \leq 1, \ \forall \boldsymbol{i}$.

Analysis of all of the data collected revealed that people's opinions were of two main types: perceptions of the objective extent of the disaster and subjective opinions on the disaster. To facilitate analysis, these two general kinds of opinions were represented by two specific appropriate opinions which under logical constraints existing in public for each public safety event in ND-PHE double-hazard scenarios constructed in the study. Specifically, for the natural disaster, here are the 2 opinions:

Opinion 1: The natural disaster is severe.
Opinion 2: Public opinion attention to the natural disaster should be raised.

For the public health events, here are the 2 opinions:

Opinion 3: The public health event is severe.
Opinion4: Public opinion attention to the public health event should be raised.

Additionally, the "natural disaster" and "public health event" can be replaced by the real specific case in the real specific disaster scenarios.

In the ND-PHE double-hazard scenario constructed for the research, people's opinions about these two different public safety events were considered, as there is a logical relationship between them, described by logical matrix $\boldsymbol{C}$. Additionally, as opinion 1 and opinion 3 were more likely to change based on the realistic hazard level of each public safety event, the logical relation linking opinion 2 with other opinions and opinion 4 with different opinions were the focus of the study. It was speculated that the change in opinion 2 and opinion 4 were more likely to represent public opinion on each disaster in the ND-PHE double-hazard scenario in the real world. In addition, before studying the ND-PHE double-hazard scenario, the change of each opinion in a single-hazard scenario that contained only two opinions, including the natural disaster and the public health event, was simulated as a control group. In this context and due to the countless possibilities of the values of $\boldsymbol{C}$, it was necessary to set a probable $\boldsymbol{C}$ for each scenario separately to perform the simulation for the convenience of the research. Therefore, a suitable $\boldsymbol{C}$ was set, respectively, for single-hazard scenarios and the ND-PHE double-hazard scenarios. The next section shows the simulation results for the trend of change of each opinion in the real ND-PHE double-hazard scenarios and the results of empirical tests of our simulation results.

4.2. *Single-hazard scenario*

The study focused on ND-PHE double-hazard scenarios in Chinese society. It was necessary to select realistic ND-PHE double scenarios that satisfy the conditions of the ND-PHE double scenario proposed above as the focus of the research. It is important to note here that there is no official definition of the beginning or the end of the COVID-19 pandemic. The following standard definitions were used in this study. The first day of the COVID-19 epidemic outbreak was required to satisfy the following criteria. (1) There are confirmed cases. (2) No confirmed cases for three consecutive days before the first day. (3) The average number of confirmed cases in the week before the beginning day is less than 1. (4) From the first day, there are confirmed cases for three consecutive days. The end day of the COVID-19 epidemic outbreak was required to satisfy the following criteria: (1) No confirmed cases for three consecutive days. (2) The average number of confirmed cases in a week from the end day is less than 1.

At the time of the rainstorm in Henan in July 2021, the typhoon in Jiangsu in July 2021 and the blizzard in Liaoning in November 2021, the local COVID-19 epidemic was ongoing simultaneously in these provinces. In addition, these three natural disasters are very representative and have attracted a lot of attention from Chinese society. Therefore, the study selected three ND-PHE double-hazard scenarios: rainstorm–COVID-19 scenario in Henan in July 2021, typhoon–COVID-19 scenario in Jiangsu in July 2021, and blizzard–COVID-19 scenario in Liaoning in November 2021. There are some differences between the three ND-PHE double-hazard scenarios. In the Henan ND-PHE double-hazard scenario, the rainstorm occurred before the COVID-19 epidemic. The interval between the two different public safety events was extremely short, but they did not completely overlap during this period. In the Jiangsu ND-PHE double-hazard scenario, the typhoon occurred before the COVID-19 epidemic. There was a period of time for which the typhoon and the COVID-19 epidemic completely overlapped. In the Liaoning ND-PHE double-hazard scenario, the COVID-19 epidemic occurred before the blizzard. There was a period of time in which the blizzard and the COVID-19 epidemic completely overlapped. In summary, the three ND-PHE double-hazard scenarios were representative ND-PHE scenarios with different characteristics.

As the first step, the improved F-J model proposed above was used in single-hazard scenarios instead of in ND-PHE double-hazard scenarios. This enabled exploration of the relationship between the trend of change in the focal opinions occurring in the different single-hazard scenarios and the severity of each public safety event in a single-hazard scenario.

Different single-hazard scenarios based on the three real-life cases mentioned above were constructed first. In the single-hazard scenarios of natural disasters, daily precipitation was chosen to represent the hazard level of the rainstorm occurring in Henan; daily average wind speed was considered to illustrate the hazard level of the typhoon occurring in Jiangsu; and daily snowfall was selected to show the hazard level of the blizzard occurring in Liaoning. The daily number of confirmed COVID-19 epidemic cases was selected to represent the hazard level of the COVID-19 epidemic in the three target provinces. The specific values input into matrix $\boldsymbol{D}$ needed to be normalized. It is essential to emphasize that the values of the evaluation metrics of hazard level outside the disaster period were 0. All of the data used to describe the hazard level were selected from the meteorological stations of the three provinces. As there

Table 3
Opinions held by individuals in single-hazard Scenarios.

Single-hazard Case	Opinion
Rainstorm in Henan	1. The rainstorm is severe. 2. Public opinion attention to the rainstorm should be raised.
Epidemic in Henan	3. The COVID-19 epidemic is severe 4. Public opinion attention to the COVID-19 epidemic should be raised
Typhoon in Jiangsu	1. The typhoon is severe. 2. Public opinion attention to the typhoon should be raised.
Epidemic in Jiangsu	3. The COVID-19 epidemic is severe 4. Public opinion attention to the COVID-19 epidemic should be raised
Blizzard in Liaoning	1. The blizzard is severe. 2. Public opinion attention to the blizzard should be raised.
Epidemic in Liaoning	3. The COVID-19 epidemic is severe 4. Public opinion attention to the COVID-19 epidemic should be raised

is more than one meteorological station in one province, the study counted data from all meteorological stations within each province and calculated the average value to characterize the hazard level. The study sets specific $\boldsymbol{n}$ and $\boldsymbol{q}$ values for each single-hazard scenario. Since the number of individuals in the real province is too large for simulation, the initial number of individuals in the simulation is considered as less than a thousand so that the simulation is feasible. In addition, in the real world, the proportion of a province's population to the total population is less than 10 percents in China and the real number of people affected by disasters in each province will be smaller. Therefore, an appropriate set of n and c has been chosen to satisfy the reasonable and feasible of the simulation for the research. It finally sets $\boldsymbol{n} = 300$, $\boldsymbol{q} = 3$. Besides, the specific value of matrix C is also been set in each single-hazard scenario. The first opinion in the single-hazard scenario reflects the impact the of disaster from objective aspects, meaning it is not influenced by factors other than objective disaster severity. In other words, it won't be influenced by other opinions. The second opinion which is focused on in the study reflects the individuals' subjective perceptions of disaster severity, meaning it will be influenced by other opinions.

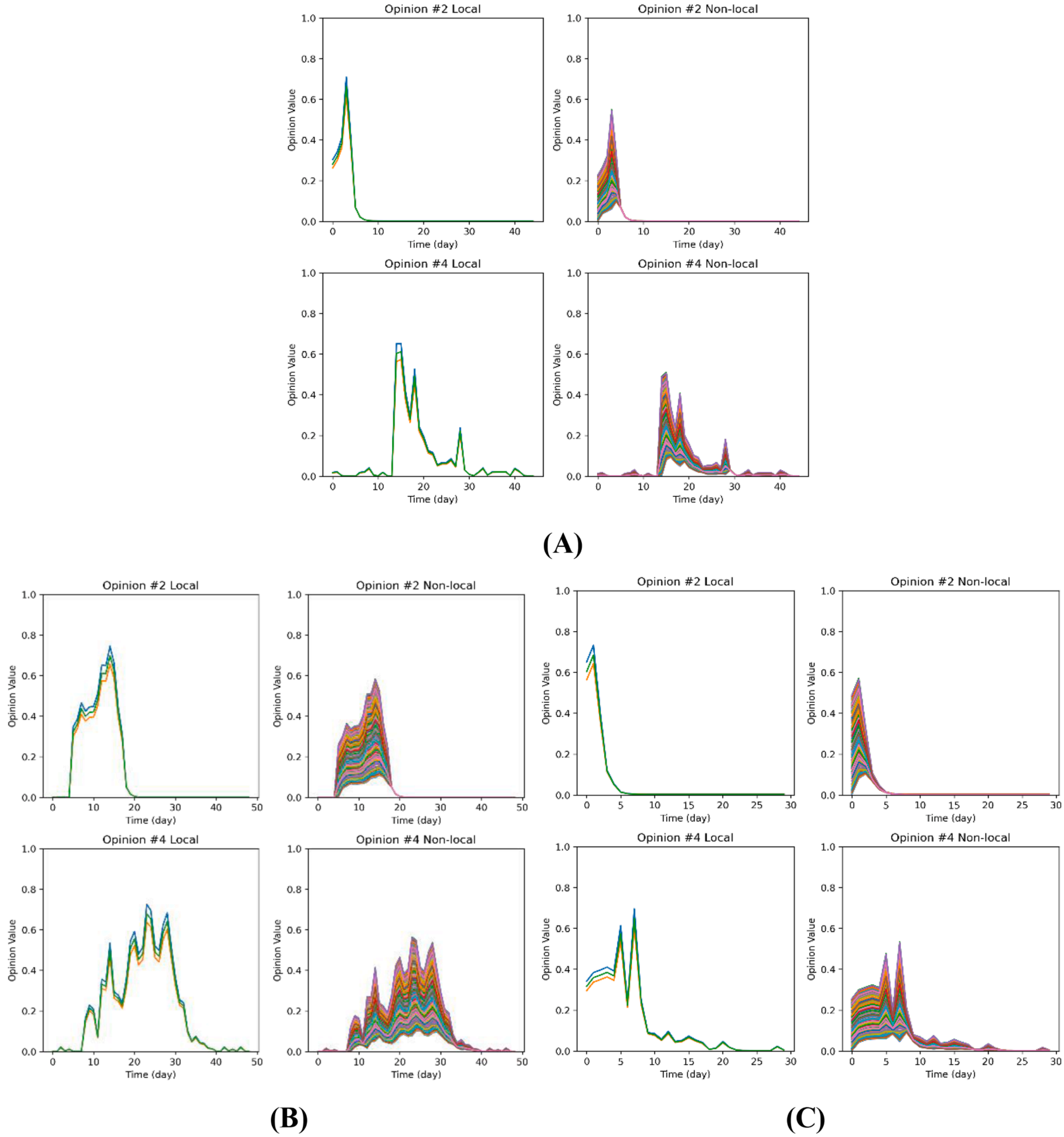


Fig. 3. The change of opinion 2 and opinion 4 for each single-hazard case: (A) Henan; (B) Jiangsu; (C) Liaoning.

However, in the disaster scenario, the biggest impact of disasters to individuals is mainly from the objective exist disaster. Therefore, the second opinion is also considered that to be more influenced by objective disaster severity. Based on the consideration above, the specific $\boldsymbol{C} = \begin{pmatrix} 1 & 0 \\ 0.7 & 0.3 \end{pmatrix}$ is finally set for the single-hazard scenario simulation. Moreover, the specific opinions set are shown in the Table 3.

Python is used to run the model proposed in the study throughout the simulation work. Some key packages are adopted to achieve the construction of the model. Firstly, package "*numpy*" is used to handle all matrix-related operations and calculations. Next, package "*matplotlib*" is used to plot all visualizations. Additionally, package "*sklearn.preprocessing*" is used for normalizations. The DH F-J model is input into the Python and the simulation program traverses through time series of the double-hazard scenario case period between case date range [1, T] (day 1 to day T). Opinion value of each individual in each day will be calculated during time traversal according to our DH F-J model. The simulation results for the single-hazard scenarios are shown in Fig. 3.

Every line of different color represents every different individual in the simulation. From the simulation results, Fig. 3 shows that the change trend of opinion of local residents in areas where public safety events occur is basically the same as the change trend of opinion of non-local residents. However, the opinion value of local residents in areas where public safety events occur is obviously larger than the opinion value of non-local residents. Taking Fig. 3(A) as an example. The change trend of opinion2 of local residents is basically the same as that of non-local residents while the opinon2 value is larger than the opinion2 value of non-local residents. Fig. 3 (B), (C) has also shown the same results. On the other hand, Fig. 3 also shows that the trend of every opinion followed the trend of the severity of the disaster when there was only one type of public safety event. In addition, Fig. 3 shows that people's opinions converged to 0 when there was no public safety event or after a public safety event had ended. Also taking Fig. 3(A) as an example, for the rainstorm single-hazard scenario, the individual's opinion value varies with the precipitation and it converges to 0 when the rain stops. The same results can be got from Fig. 3(B), (C) for other different single-hazard scenarios. Therefore, it can be inferred that the trend of public opinion change follows the trend of the severity of the disaster if there is only one type of public safety event.

4.3. *Three real nd-phe double-hazard scenarios test*

The study sets specific values of $\boldsymbol{n}$ and $\boldsymbol{q}$ based on the same reason mentioned previously for the three real double-hazard scenarios, namely the Henan, Jiangsu and Liaoning ND-PHE double-hazard scenarios. However, to alleviate the influence of the initial size of the influence network and the local area where a disaster occurs, the specific values of $\boldsymbol{n}$ and $\boldsymbol{q}$ in three different simulation ND-PHE double-hazard scenarios were set to different values. The specific values of $\boldsymbol{n}$ and $\boldsymbol{q}$ are shown in the Table 4.

The new matrix C for the ND-PHE double-hazard scenarios is also set based on the same process mentioned in previous section. One note to add is that the opinion 2 (reflecting the natural disaster) in the ND-PHE double-hazard scenario is considered that it is more influenced by itself than by opinion 4, which fits the reality. The opinion 4 (reflecting the public health event) is the same. Therefore, an appropriate specific $\boldsymbol{C} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0.5 & 0.3 & 0 & 0.2 \\ 0 & 0 & 1 & 0 \\ 0 & 0.2 & 0.5 & 0.3 \end{pmatrix}$ is set for the ND-PHE double-hazard scenarios. The study also lists all possible public opinions on each public safety event in different ND-PHE double-hazard scenarios. The specific opinions are shown in the Table 5.

4.3.1. *Simulation*

Representative characteristics were used to represent the hazard level of each natural disaster. Daily precipitation, daily average wind speed, and daily snowfall represented the hazard level of the rainstorm in Henan, typhoon in Jiangsu and blizzard in Liaoning, respectively. The daily number of actual confirmed COVID-19 epidemic cases (actual number of confirmed cases = number of confirmed cases + number of asymptomatic infected persons – number of confirmed cases among asymptomatic infected persons) represented the hazard level of the COVID-19 epidemic (public health event). The specific values input into matrix $\boldsymbol{D}$ in each case had already been normalized and the values of the representative characteristics of the disasters outside the disaster period were considered 0. The period of the simulation of the three cases is shown in the Table 6.

Using the proposed DH F-J model, an improvement on the F-J model, the process of change of each kind of public opinion over time in the three realistic ND-PHE double-hazard scenarios were simulated. The specific simulation process in Python is the same as the process mentioned previously and the specific simulation results are shown in Figs. 4-6.

In each figure, every line of different color represents every different individual in the simulation. Regarding the simulation results

Table 4
The values of n and q in different cases.

ND-PHE double-hazard Case		n	q
Henan ND-PHE double-hazard Case	Rainstorm in Henan Epidemic in Henan	300	3
Jiangsu ND-PHE double-hazard Case	Typhoon in Jiangsu Epidemic in Jiangsu	300	20
Liaoning ND-PHE double-hazard Case	Blizzard in Liaoning Epidemic in Liaoning	600	40

Table 5
Opinions held by individuals in ND-PHE double-hazard Scenario.

ND-PHE double-hazard Case		Opinion
Henan ND-PHE double-hazard Case	Rainstorm in Henan	1. The rainstorm is severe. 2. Public opinion attention to the rainstorm should be raised.
	Epidemic in Henan	3. The COVID-19 epidemic is severe 4. Public opinion attention to the COVID-19 epidemic should be raised
Jiangsu ND-PHE double-hazard Case	Typhoon in Jiangsu	1. The typhoon is severe. 2. Public opinion attention to the typhoon should be raised.
	Epidemic in Jiangsu	3. The COVID-19 epidemic is severe 4. Public opinion attention to the COVID-19 epidemic should be raised
Liaoning ND-PHE double-hazard Case	Blizzard in Liaoning	1. The blizzard is severe. 2. Public opinion attention to the blizzard should be raised.
	Epidemic in Liaoning	3. The COVID-19 epidemic is severe 4. Public opinion attention to the COVID-19 epidemic should be raised

Table 6
The period of different cases.

ND-PHE double-hazard Case		Period
Henan ND-PHE double-hazard Case	Rainstorm in Henan Epidemic in Henan	2021.7.18~2021.8.31
Jiangsu ND-PHE double-hazard Case	Typhoon in Jiangsu Epidemic in Jiangsu	2021.7.14~2021.8.31
Liaoning ND-PHE double-hazard Case	Blizzard in Liaoning Epidemic in Liaoning	2021.11.7~2021.12.6

for the Henan case, Fig. 4 shows that people's opinions also converged after the rainfall ended. However, in contrast with the single-hazard scenario, the value of people's opinions did not converge to 0. To be more specific, Fig. 4(A) shows that the value of opinion 2, "public attention to the rainstorm (natural disaster) should be raised," rose again from 0 several days after the rainstorm (natural disaster) has already stopped. It is worth noting that the COVID-19 epidemic broke out at the same time at which the value of opinion 2 began to rise. Therefore, it can be inferred that public opinion on the rainstorm (natural disaster) in the ND-PHE double-hazard scenario increased even after the rainstorm had already stopped. On the other hand, Fig. 4(B) shows that even though the COVID-19 epidemic did not break out during the rainstorm (natural disaster), the converged value for opinion 4 rose while the rainstorm was happening. This may suggest that public attention to the COVID-19 epidemic (public health event) in the ND-PHE double-hazard scenario will increase even though the COVID-19 epidemic has not happened yet. Thus, the simulation results above illustrate that people's attention to both the rainstorm (natural disaster) and the COVID-19 epidemic (public health event) increased. In other words, both types of public safety events gained more public attention in the ND-PHE double-hazard scenario in Henan.

Regarding the simulation results for the Jiangsu case, in Fig. 5, the changing trend of each opinion was also different compared with the single-hazard scenario. Fig. 5(A) shows that the value of opinion 2 on the typhoon (natural disaster) did not converge to 0 when the typhoon (natural disaster) had ended while the COVID-19 epidemic (public health event) continued, which indicates that the occurrence of a public health event increased public attention to the co-occurring natural disaster. Meanwhile, it can be found that after the period when typhoon was over, the change trend of opinion 2 on the typhoon is basically approximates to the change trend of opinion 4 on the COVID-19 epidemic. Furthermore, when the COVID-19 epidemic is over as well, the value of opinion 2 on the typhoon converges to 0 and no longer fluctuates, which further verifies that the occurrence of public health events will influence people's attention to natural disasters. On the other hand, compared with the result for the Jiangsu single-hazard scenario shown in Fig. 3(B) over the same period, both the peak value and the upward trend of opinion 2 and opinion 4 increased during the period when the typhoon (natural disaster) and COVID-19 (public health event) occurred simultaneously in the ND-PHE double-hazard scenario in Jiangsu. Specifically, observing the peaks of values of opinion 2 and opinion 4 in the period when the typhoon and the COVID-19 epidemic are overlapping as examples in Fig. 5(A),(B). Comparing these points to the points in the same time in Fig. 3(B), it can be observed that values of opinions has been increased for both local and non- local residents. These results demonstrates that public opinion on natural disasters and public opinion on public health events can positively influence each other. Therefore, it is reasonable to speculate that both the natural disaster and the public health event gain more public attention in the ND-PHE double-hazard scenario.

Regarding the simulation results for the Liaoning case, Fig. 6(A) shows that the value of opinion 2 converges when the blizzard stops and increases again instead of going back to 0 when the COVID-19 epidemic is still occurring. Until the COVID-19 epidemic has stopped, the value of opinion 2 converge to 0. In addition, compared with Figs. 3(C), 6(A) shows that the peak value of opinion 2 in the period when the blizzard and the epidemic coexist in the Liaoning ND-PHE double-hazard scenario is higher than the peak value in the Liaoning single-blizzard scenario. Both simulation results for the change of opinion 2 indicate that public attention to the blizzard (natural disaster) was positively affected by the COVID-19 epidemic (public health event). On the other hand, compared with Figs. 3 (C), 6(B) shows that the first two peak values for opinion 4 located during the period when the blizzard and the epidemic co-occurred in the Liaoning ND-PHE double-hazard scenario were also higher than the two peaks located during the same period in the Liaoning

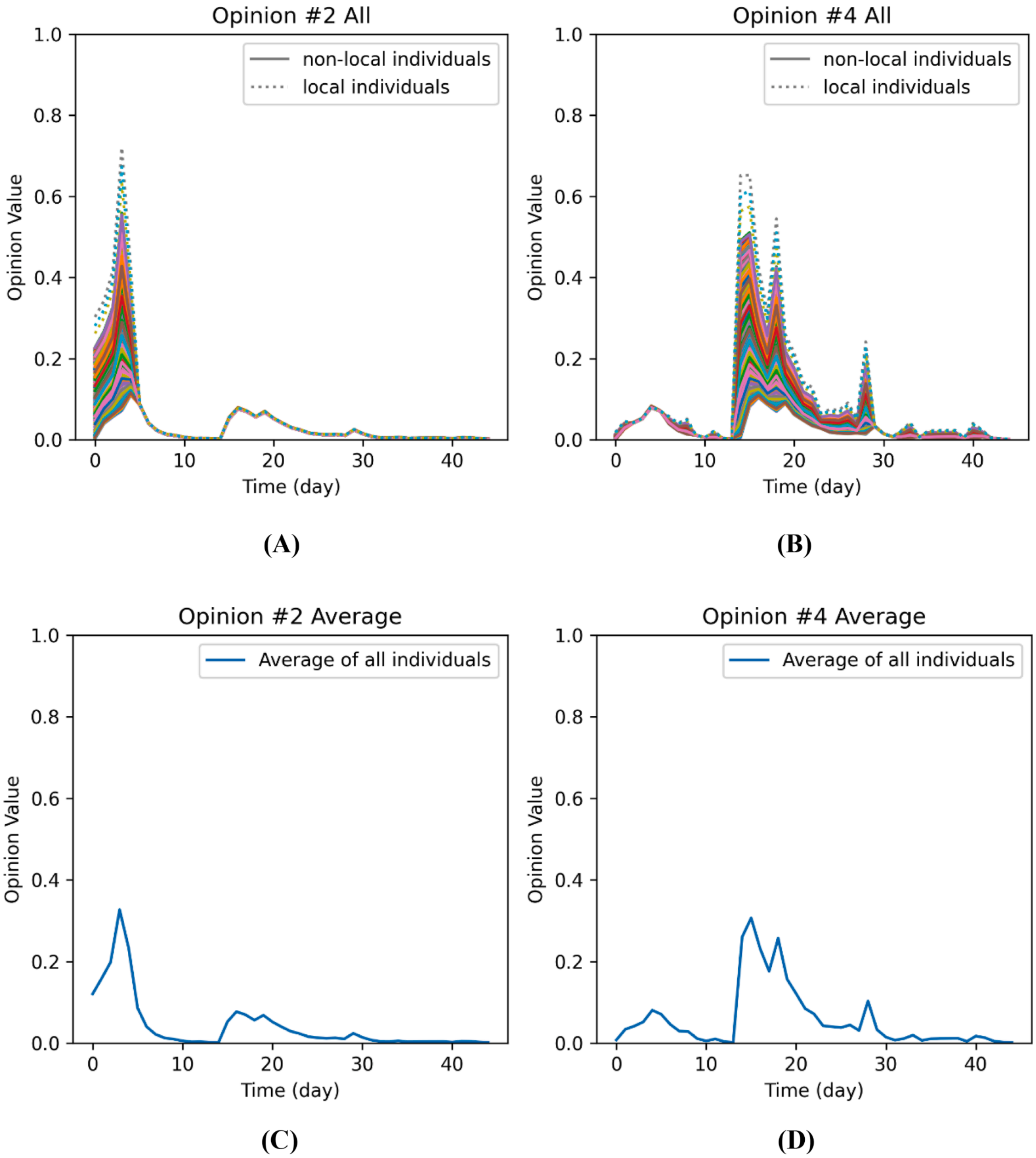


Fig. 4. Change of value of opinion 2 and opinion 4 in Henan ND-PHE double-hazard scenario consisting of rainstorm and COVID-19 epidemic. (A) Opinion 2. (B). Opinion 4. (C) Average of Opinion 2. (D) Average of Opinion 4.

single-COVID-19 scenario, which illustrates that public attention to the COVID-19 epidemic was increased by the blizzard as well. Thus, in the Liaoning ND-PHE double-hazard scenario, both the natural disaster and the COVID-19 epidemic positively influenced each other to receive more public attention.

4.3.2. Empirical test

The study collected 975,874 items of data on the Henan rainstorm, 34,071 items of data on the Henan COVID-19 epidemic, 27,280 items of data on the Jiangsu typhoon, 113,933 items of data on the Jiangsu COVID-19 epidemic, 12,677 items of data on the Liaoning blizzard and 46,263 items of data on the Liaoning COVID-19 epidemic from the Weibo and WeChat public platform. After cleaning and processing the data as described above, trends in the spread of negative emotions regarding the natural disasters and COVID-19 epidemic in the three cases were identified, as shown in the Figs. 7-9.

4.3.2.1. Analysis of spread of negative emotions of three real cases. For the Henan case, as the rainstorm period was from July 18th to

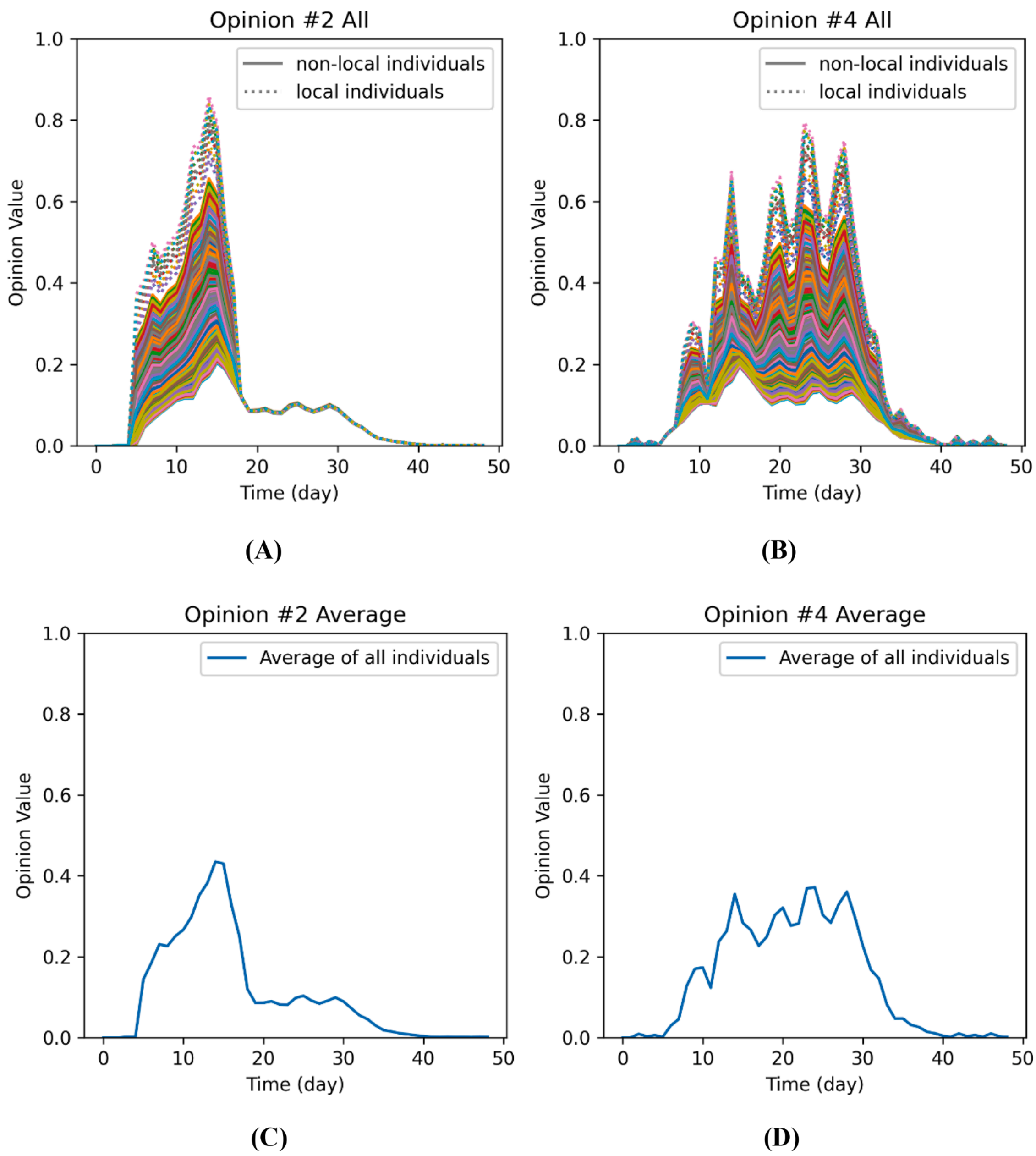


Fig. 5. Change of value of opinion 2 and opinion 4 in Jiangsu ND-PHE double-hazard scenario consisting of typhoon and COVID-19 epidemic. (A) Opinion 2. (B) Opinion 4. (C) Average of Opinion 2. (D) Average of Opinion 4.

July 21st, while the COVID-19 epidemic started on July 23rd, the two different public safety events did not entirely overlap. Comparing Fig. 7(A) and Fig. 7(B) with Fig. 4(A) and Fig. 4(B), the trend in negative public sentiment in the Henan ND-PHE double-hazard scenario real case was closer to the trend in the change of values for opinion 2 and opinion 4 obtained by simulation. Specifically, Fig. 7(A) shows that negative public sentiment about the rainstorm grew rapidly and reached a peak around July 21st. However, Fig. 7(B) illustrates that negative public sentiment about COVID-19 grew up around July 21st without the occurrence of the COVID-19 epidemic. This phenomenon shows an increase in public attention to the COVID-19 epidemic due to the heavy rain, which fits the simulation results in Fig. 4(B). By August 2nd, the COVID-19 epidemic had just broken out and the rainstorm had already stopped. However, Fig. 7(A) shows that negative public emotion about the rainstorm increased again at around this time. The public's negative emotion about the rainstorm continuously decreased before August 2nd because the rainstorm had stopped by July 23rd. This result indicates that public attention to the rainstorm increased again due to the COVID-19 epidemic, which fits the simulation results in Fig. 4(A).

In the case of Jiangsu, the typhoon occurred from July 18th to July 30th, while the COVID-19 epidemic ran from July 21st to August

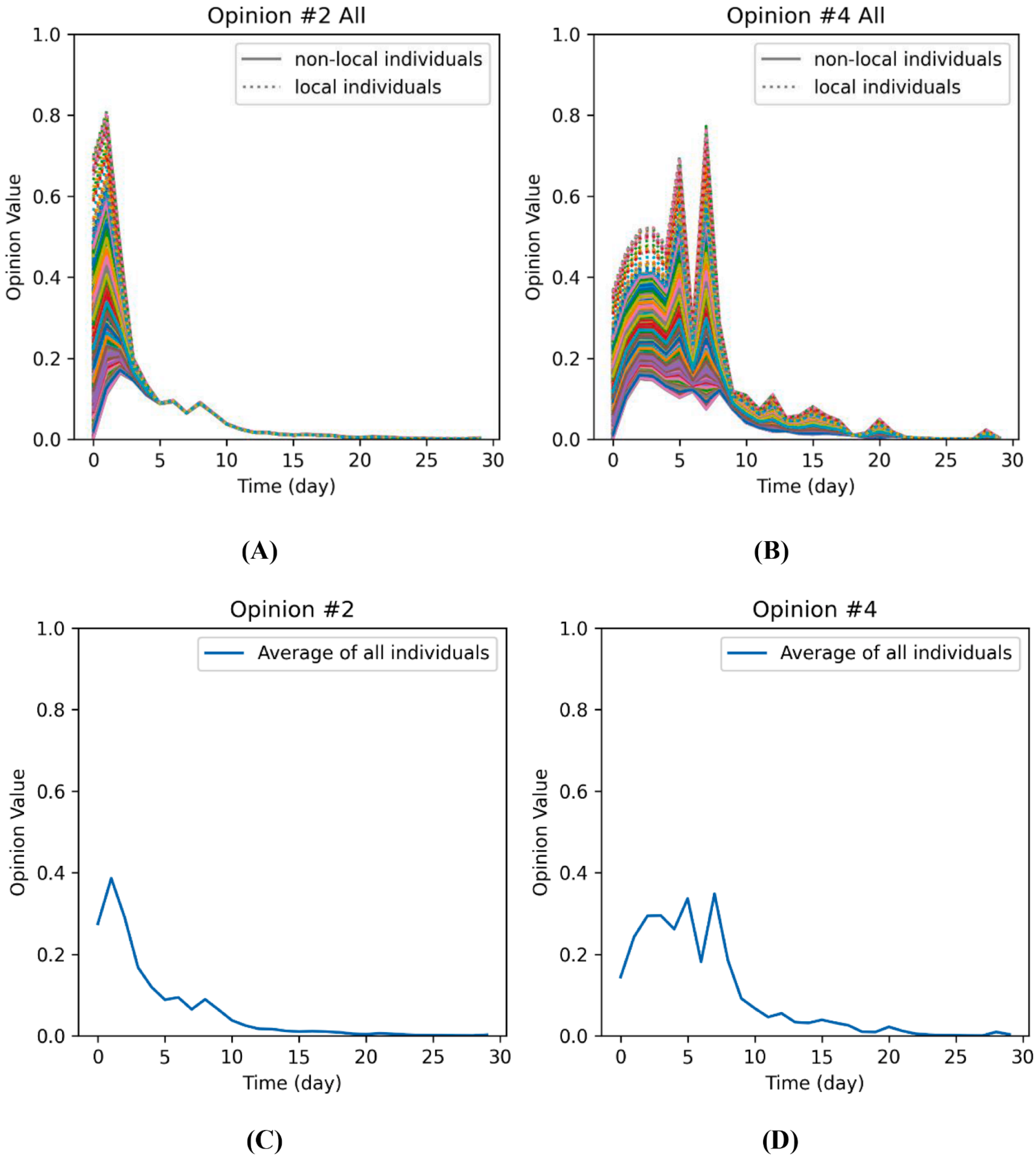
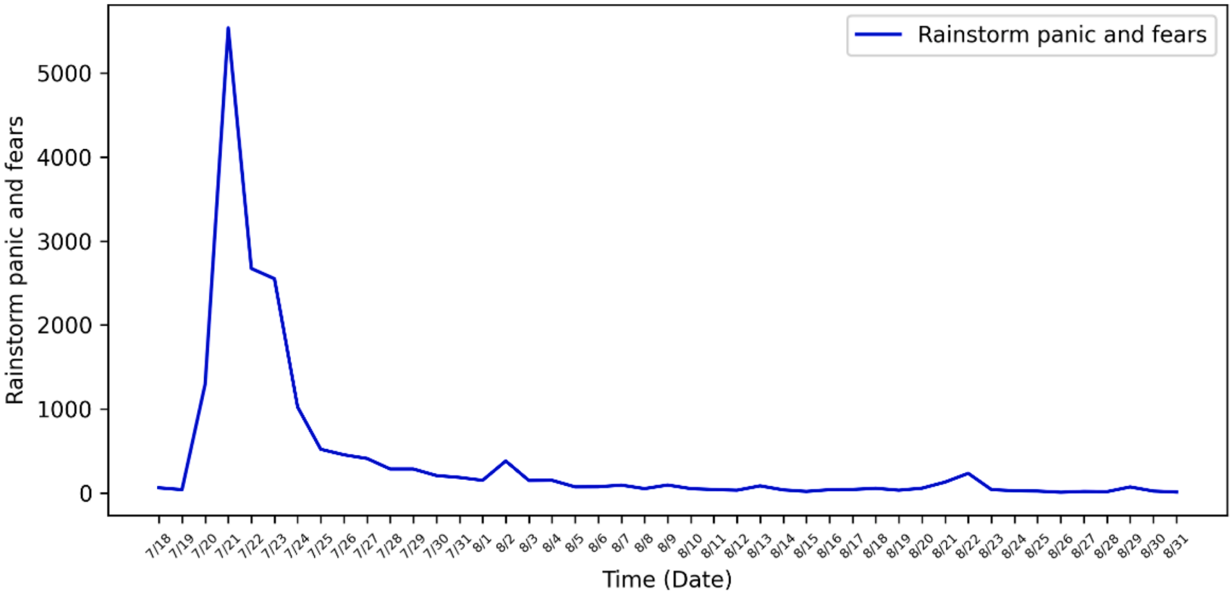


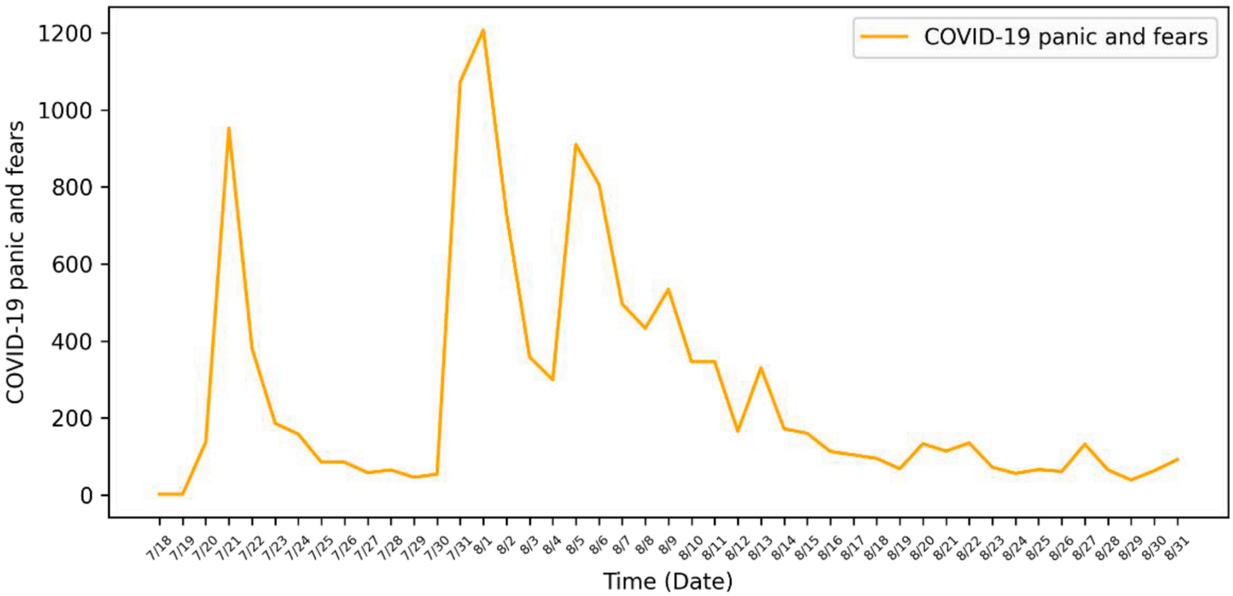
Fig. 6. Change of opinion 2 and opinion 4 in Liaoning ND-PHE double-hazard scenario consisting of blizzard and COVID-19 epidemic. (A) Opinion 2. (B) Opinion 4. (C) Average of Opinion 2. (D) Average of Opinion 4.

28th. The typhoon and the COVID-19 epidemic co-occurred from July 21st to July 30th. The empirically observed change in the trend of negative public emotion for each public safety event basically fitted the simulation results in Fig. 5(A) and Fig. 5(B). Notably, Fig. 8 (A) shows that even though negative public emotion declined after July 25th, it increased again from July 27th to July 28th, suggesting that the typhoon gained more public attention when the typhoon and the COVID-19 epidemic were co-occurring. Also, negative public emotion about the typhoon did not decrease to 0 after the typhoon had ended and even increased once again from August 3rd to 5th, when negative public emotion about the COVID-19 epidemic had reached a peak, which also illustrates that public attention to the typhoon was positively affected by public attention to the COVID-19 epidemic.

In Liaoning, the blizzard happened from November 7th to November 10th, 2021, while the COVID-19 epidemic ran from November 4th to the beginning of December 2021. The blizzard and the COVID-19 epidemic co-occurred from November 7th to November 10th, 2021. The changing trend of negative public emotions in the empirical results shown in Fig. 9 basically fitted the simulation results shown in Fig. 6. Fig. 9(A) shows that negative public emotion increased slightly from November 13th to November 14th, when the blizzard had stopped while the COVID-19 epidemic continued. Besides, as shown in Fig. 9(A), the rate of decreasing negative public emotion of the blizzard was much slower from November 10th to November 12th, when the COVID-19 epidemic had broken out. The



(A)



(B)

Fig. 7. The spread of negative emotions such as fear and panic about the rainstorm and COVID-19 epidemic in the Henan case. (A) The change in negative public emotions about the rainstorm. (B) The change in negative public emotions about the COVID-19 epidemic.

empirical results illustrate that public opinion on the blizzard was positively affected by the COVID-19 epidemic.

4.3.2.2. Pearson correlation coefficient test. Pearson correlation coefficient has the function that can calculate the linear correlation between the two sets of data (simulating data and real data) for every ND-PHE double-hazard case in our research. It can help this study judge the degree of fit between simulated data and real data by calculating the ratio between the covariance of the individuals' opinion value in simulation and the real public negative emotion data and the product of their standard deviations. Therefore, Pearson correlation coefficients were finally chosen to use to detect the model fitting effect for our research. Because the simulation results

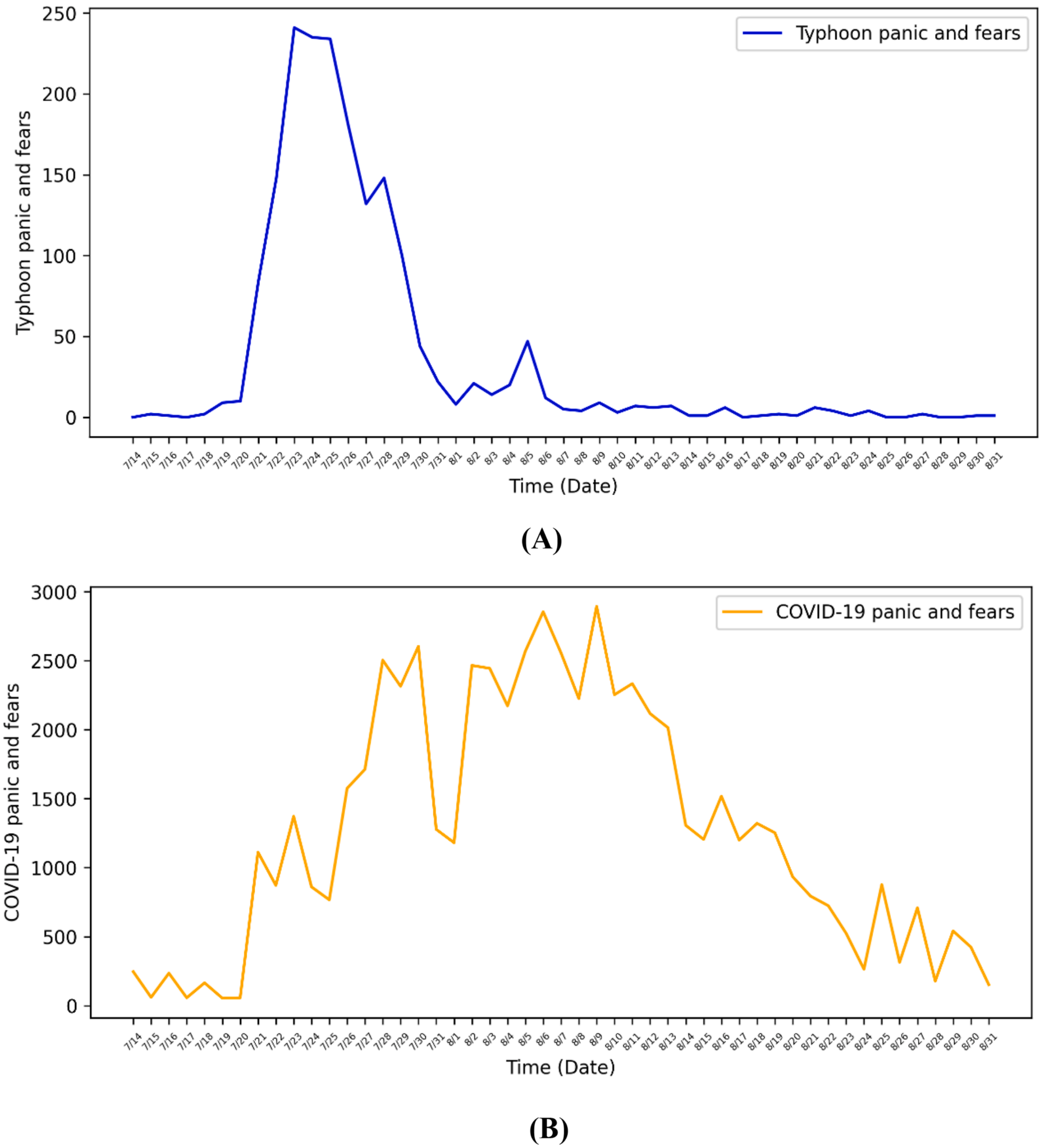
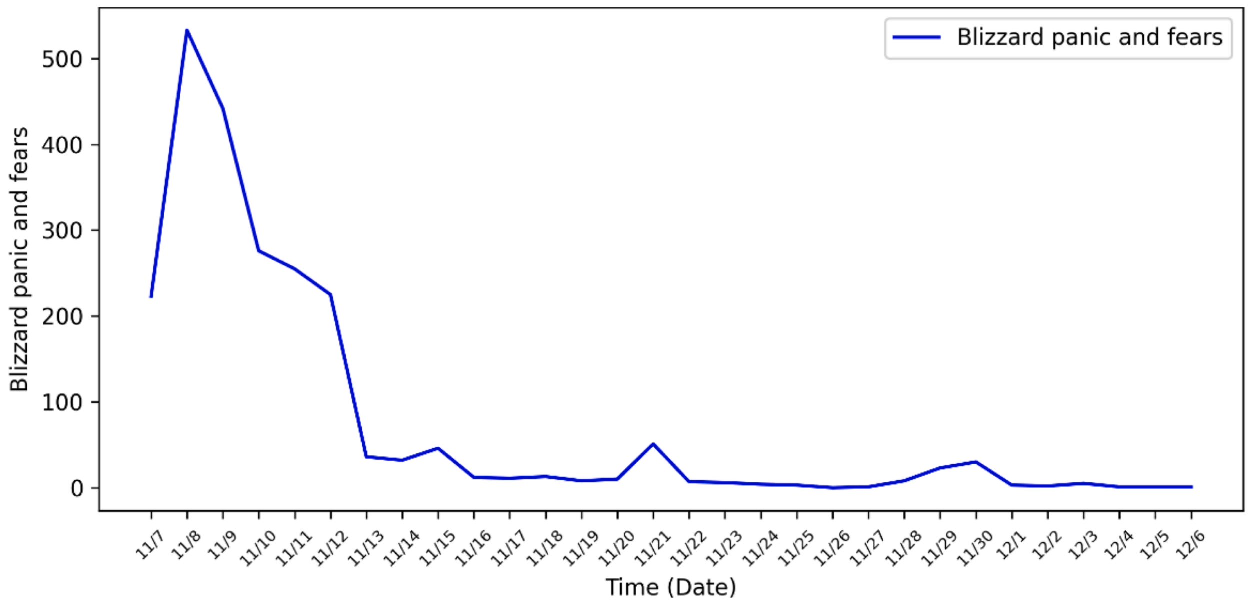


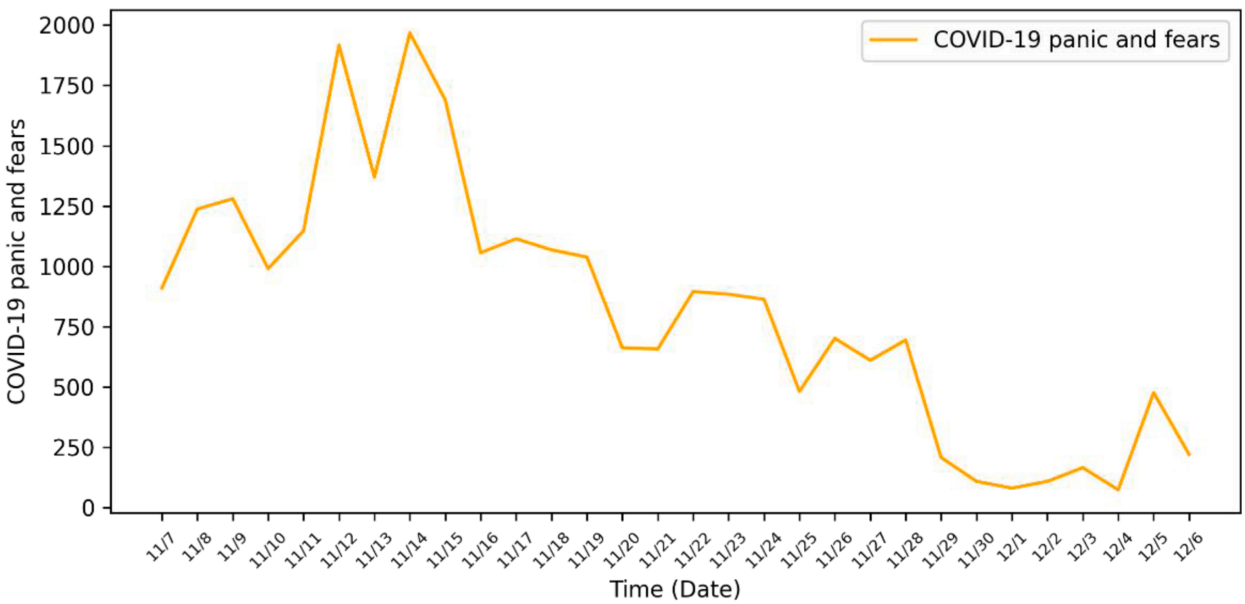
Fig. 8. The spread of negative emotions about the typhoon and COVID-19 epidemic in the Jiangsu case. (A) The change in public negative emotions about the typhoon. (B) The change in public negative emotions about the COVID-19 epidemic.

reflected the value of opinion change of **n** individuals, the study decided to take the average of the value of the opinions of these **n** individuals to compare with reality. Python is also used to implement the calculation of Pearson correlation coefficient for our study. Specifically, package "*scipy.stats*" and the function "*pearsonr*" which is sub-method of package "*scipy.stats*" are used to implement specific calculations. The original formula of Pearson correlation coefficient can be seen in the supplement martials. The P-value for each simulation result and its real case was less than 0.05. The specific P-values and Pearson correlation coefficients are shown in the Table 7.

In the Henan ND-PHE double-hazard scenario, the Pearson correlation coefficient between the simulated average for opinion 2 (Fig. 4(C)) and the change of negative public emotions about the rainstorm (Fig. 7(A)) was 0.804. The Pearson correlation coefficient



(A)



(B)

Fig. 9. The spread of negative emotions about the blizzard and COVID-19 epidemic in the Liaoning case. (A) The change in public negative emotions about the blizzard. (B) The change in public negative emotions about the COVID-19 epidemic.

between the simulated average for opinion 4 (Fig. 4(D)) and the change of negative public emotions about the COVID-19 epidemic (Fig. 7(B)) was 0.668. In the Jiangsu ND-PHE double-hazard scenario, the Pearson correlation coefficient between the simulated average for opinion 2 (Fig. 5(C)) and the change of negative public emotions about the typhoon (Fig. 8(A)) was 0.768. The Pearson correlation coefficient between the simulated average for opinion 4 (Fig. 5(D)) and the change of negative public emotions about the COVID-19 epidemic (Fig. 8(B)) was 0.916. In the Liaoning ND-PHE double-hazard scenario, the Pearson correlation coefficient between the simulated average for opinion 2 (Fig. 6(C)) and the change of negative public emotions about the blizzard (Fig. 9(A)) was 0.933. The Pearson correlation coefficient between the simulated average for opinion 4 (Fig. 6(D)) and the change of negative public

Table 7
P-value and pearson correlation coefficient.

ND-PHE double-hazard Case		P-value	Pearson Correlation Coefficient
Henan ND-PHE double-hazard Case	Rainstorm in Henan	$2.792\text{x}10^{-11}$	0.804
	Epidemic in Henan	$5.445\text{x}10^{-7}$	0.668
Jiangsu ND-PHE double-hazard Case	Typhoon in Jiangsu	$1.155\text{x}10^{-10}$	0.768
	Epidemic in Jiangsu	$3.241\text{x}10^{-20}$	0.916
Liaoning ND-PHE double-hazard Case	Blizzard in Liaoning	$6.578\text{x}10^{-14}$	0.933
	Epidemic in Liaoning	$3.133\text{x}10^{-8}$	0.819

emotions about the COVID-19 epidemic (Fig. 9(B)) was 0.819. These results confirmed that the model fit was good.

4.4. Result analysis

The empirical test results for the real-life scenarios basically fitted the simulation results of the DH F-J model, which verifies that the new model can describe the changing pattern of the public opinion to different public safety events in ND-PHE double-hazard scenarios. In the real ND-PHE double-hazard scenarios, there are many different factors which can influence people's opinion, such as the perception of different disasters. These kinds of factors are not captured in existing traditional opinion dynamics, such as the DeGroot model, the F-J model and other extension models based on the F-J model. Therefore, it is difficult to use traditional opinion dynamic models to describe the changing pattern of the public opinion to different public safety events in real ND-PHE double-hazard scenarios. Compared with these traditional opinion dynamic models, the greatest advantage of the DH F-J model is that it can show the impact of disasters on people. It makes the model can reliably describe the specific changing trend and patterns of public opinion to different public safety events in real ND-PHE double-hazard scenarios which traditional models cannot. However, on the other hand, the new model proposed in the study also has some limitations. Some factors that are not related to the disaster itself but affect people's opinion of the disaster cannot be reflected in the model. This means that the results of empirical cases in the real world cannot entirely fit simulation results. Therefore, the potential for the DH F-J model to be improved remains high.

5. Discussion

5.1. Theoretical contributions

From the modeling perspective, the new model proposed in the study makes a meaningful contribution to opinion dynamics research. Traditional opinion dynamic models, such as the Degroot model and the F-J model, always focus on the change of a single opinion (Degroot, 1974; Friedkin, 2001). Compared with traditional opinion dynamics models that focus on a single opinion, the new model proposed in our study focuses on multiple opinions held within human society. It improves on the traditional F-J model to suit the ND-PHE double-hazard scenario constructed in the study. The new model also reflects a logical matrix of relationships between different topics. Compared with some other opinion dynamic models focusing on multiple topics proposed, our new model also has the following two important theoretical implications:

Firstly, the new model proposed in our study can be used to describe the real change patterns of public opinion in real ND-PHE double-hazard scenarios. Traditional opinion dynamics models with logical constraints focusing on multiple topics assume that different opinions held by people will eventually reach a consensus. However, this is only at the theoretical level and cannot describe the specific changes, trends or patterns of people's opinions in the real world. As many specific factors can influence people's opinions in different scenarios in reality, traditional opinion dynamics models can rarely be applied to real scenarios in the real world. After the F-J model with logistic matrix proposed by Friedkin et al. (2016) there are some new extended opinion dynamic models based on this model has been proposed as well. However, these currently existing models consider more theoretical level corrections and extensions. For example, the model proposed by Ye et al. (2018) and the model proposed by He et al. (2022) both focus on the extension of stubborn individual. These models can theoretically analyze and explain the factors that influence the evolution of individuals' opinions, but they are not integrated with reality and cannot be practically applied in real scenarios. This study improved on the F-J opinion dynamics model to make it more applicable to ND-PHE double-hazard scenarios, adding individual sensitivity to hazards and the role of characteristics that represent the extent of hazards. It can quickly identify changing trends in public opinion concerns about two public safety events in ND-PHE double-hazard scenarios in Chinese society based on simple disaster level characterization data. Furthermore, the new model can describe how public opinion on two different public safety events is mutually influential in ND-PHE scenarios in Chinese society. The new model proposed in the study can be correlated with the real ND-PHE double-hazard scenarios. This reflects the real change patterns of people's opinion in these kinds of scenarios in the real world, which extends the research and application of the traditional opinion dynamics models.

Secondly, the new model proposed in the study extends the meaning of the logical matrix proposed in opinion dynamics theory, which is no longer limited to the logical relations among multiple topics but can also describe the logical relations among different events in reality by using the logical relations among different topics. The DH F-J model based on the logical matrix proposed in the study not only reflects the change in people's opinion about different public safety events in ND-PHE double-hazard scenarios but also describes the impact on public opinion when different disasters occur simultaneously under a real ND-PHE double-hazard scenarios by the logic matrix. This finding shows how to use and explore the logical matrix more deeply in future research on opinion dynamics.

To summarize, the new model proposed in this study applies opinion dynamics to the real ND-PHE double-hazard scenarios and can better reflect the patterns of change in public opinion for each disaster in this kind of scenario. It overcomes the problem with traditional opinion dynamics, which cannot be applied in real scenarios and cannot reflect real changes in people's opinions. At the same time, the new model proposed in the study enhances the relevance of the logic matrix in opinion dynamics, which is no longer limited to expressing the logical relationships between topics but can also be extended to express the interaction among different events in reality. This idea of combining the model with realistic scenarios has implications for subsequent research on opinion dynamics and indicates a useful direction for future research.

On the other hand, from the perspective of safety science, studying multi-hazard scenarios is highly meaningful. Real multi-hazard scenarios can cause enormous damage, with greater effect than single-hazard scenarios in the real world. This is due to the coupling effect of different disasters. Therefore, it is important to explore the specific coupling effect of each disaster co-occurring in different kinds of multi-hazard scenario. Double-hazard scenarios involving natural disasters and public health events are among the most typical multi-hazard scenarios. This study is the first to verified the existing coupling effect of natural disasters and public health events in this double-hazard scenario at the information level, which can help society face and respond better to real ND-PHE double-hazard scenarios. Combining information science methods with safety science scenarios, the study explored the changing patterns of public opinion on different types of public safety events in ND-PHE double-hazard scenarios by using opinion dynamics and social media. It combined information science with multi-hazard research scenarios, filling a gap in research, which had not previously examined multi-hazard scenarios at the information level. In addition, this study verified the coupling phenomenon of different disaster species in a multi-hazard scenario at the information level. It showed that at the information level, the final impact of all disasters in the multi-hazard scenario is greater than the simple sum of the impact of each hazard occurring in a single-hazard scenario. Moreover, this study is the first to apply opinion dynamics to study multi-hazard scenarios in the public safety research field.

5.2. Practical implications

This study has important practical implications. It shows the Chinese government that public opinion on natural disasters and public opinion on public health events are positively related and both increase in ND-PHE scenarios in China. It provides a clear direction for the Chinese government's policy formulation in future ND-PHE double-hazard scenarios to face the double hazards, which helps the government to formulate the relevant governances more effectively to respond the ND-PHE double-hazard scenarios. Furthermore, since the study has got that the public opinion of 2 different disasters will both increase in Chinese society in ND-PHE double-hazard scenarios, it means that the negative emotions of public of these 2 different disasters will both increase as well. For examples, the public fears and the rumors of disasters will increase during this period. In the context of the COVID-19 epidemic, it is clear to see that the phenomenon of the amplification of public opinion on disasters will occur more frequently because the probability of simultaneous occurrence of natural disasters and public health events has greatly increased. However, for the government, if there is no effective way that can quickly determine the changing patterns of the amplification of public opinion of the disasters under the ND-PHE double-hazard scenarios, the spread of increased negative public opinion will lose control, which may cause chaos and a negative influence for the stability of the society. Therefore, the government must have a way to determine the specific changing patterns of the disasters in the ND-PHE double-hazard cases. The DH F-J model and the conclusion proposed in this study are good solutions to this dilemma for the Chinese government. It can help Chinese government quickly determine the changing patterns of public opinion on each disaster in ND-PHE double-hazard scenarios according to simple disaster level characterization metrics and the severity of the disaster. To be more specific, based on the new proposed DH F-J model from this study, the government can predict in advance the point in time when public opinion about the disaster amplifies under the ND-PHE double-hazard cases and be able to control the stability of public opinion of the disasters, which assist in maintaining social stability.

On the other hand, the Chinese government can also use the findings of this study as guidance for public opinion resource allocation in ND-PHE double-hazard scenarios. Specifically, it can better direct public sentiment based on the findings of this study. When disasters occur and cause the serious consequences to society, the public will be frightened and panic. In the ND-PHE double-hazard scenarios in China, natural disasters and public health events occur simultaneously and the opinion and panic of the public about both two disasters will increase, creating an unstable society. The Chinese government can use the findings of this study to detect this phenomenon earlier and quickly control any public panic at the right time according to the actual situation. Meanwhile, the spread of rumors related to different disasters will increase a lot during this period as well. The Chinese government also can quickly find the period of proliferation of rumors about the different disasters and effectively eliminate these rumors based on the results of the study. Moreover, it can also coordinate media coverage resources of the official media for different disasters in the ND-PHE double-hazard scenarios. It can use appropriate public opinion resource allocation strategies to alleviate public panic, reducing public anxiety and fear of the simultaneous occurrence of the two different disasters, which can stabilize society and avoid emotional public outbursts.

6. Conclusion and future works

6.1. Conclusive remarks

This study verifies conclusively that in a multi-hazard scenario, there is a coupling effect of different disasters not only at the physical level, but also at the information level. Based on the simulation and empirical results above, the study has found that the trend of change in individual opinion on different types of public safety events in an influence network can represent the changing pattern of public opinion of these two public safety events in ND-PHE double-hazard scenarios. Thus, the DH F-J model proposed in the study can describe the realistic public opinion changes on different disasters in the ND-PHE double-hazard scenarios. We can also get the further conclusion that in Chinese society, when natural disasters and public health events co-occur, these two types of public safety events will both receive more public opinion attention. However, when and how public opinion on these two different types of public safety events increases may be affected by many other factors, such as the sequence of the occurrence of the natural disaster and the public health event and whether there is a period in which both of these two public safety events exist simultaneously. This study contributes to safety science and opinion dynamics researches. It also has important implications for Chinese society. Firstly, this finding fills a gap in multi-hazard research, which is greatly meaningful for multi-hazard studies. Secondly, understanding this pattern of how people's opinion changes in double-hazard scenarios consisting of natural disasters and public health events (ND-PHE double-hazard scenario) can help the government quickly determine public opinion in society regarding these two disasters and swiftly regulate the allocation of public opinion resources as needed. Moreover, as mentioned above, the probability of the simultaneous occurrence of natural disasters and public health events is likely to increase in the future. The government can take advantage of increased public attention to public safety events by increasing the dissemination of public safety culture knowledge. Finally, this study verifies the effectiveness of opinion dynamics at the practical application level and expands the significance of the realistic meanings of opinion dynamics. It also provides new ideas and will make an important contribution to the direction of future research in opinion dynamics.

6.2. Limitations

There are still some limitations in this study. Firstly, many factors which are not directly linked to the disaster can also influence the public opinion of public safety events, such as some other hot events not involving disasters that can also distract public opinion. Such factors are not considered in the DH F-J model in the study because they are too complex to include. Additionally, the changing trends of public opinion on disasters in the real ND-PHE double-hazard cases which have been adopted to make the empirical test are from the Internet environment. In our new proposed DH F-J model, we have set the matrix W which represents the allocations of weights to **n** individuals' influence from other individuals in the general human influence network. However, due to the large volume and the complexity of the real Internet environment, the interaction among individuals in the pure Internet environment cannot be completely the same as it is in the general human environment constructed in the simulation. Therefore, it is extremely difficult to consider a clear and explicit rule to show the specific influence of the pure Internet environment in the theoretical model. This will also mean the results of empirical cases in the real world from social media cannot entirely fit simulation results and will generate some errors. Therefore, the potential for the DH F-J model to be improved remains high. Furthermore, because different types of public safety events are inherently not the same, multi-hazard scenarios consisting of different numbers of different types of public safety events are vary greatly. Although the DH F-J model can be adopted in real safety scenarios, this study only verifies that it can be applied in ND-PHE double-hazard scenarios. For the multi-hazard scenarios besides ND-PHE double-hazard scenarios, such as the scenarios where they occur with other types of public safety events, the applicability of the model still needs to be researched further. Also, another limitation is that this study focused on the construction of the new proposed model and it fits to real ND-PHE double-hazard scenarios and did not test the model mathematically. In future research, we will also continue to explore this point.

6.3. Research insights

The pattern proposed in this paper was confirmed in the Chinese setting using our model and a large volume of actual public opinion data from major social networks. However, does this pattern have universal applicability? In other words, does this pattern apply to other countries and societies beyond China? In such cases, does people's attention to natural disasters and public health events in a double-hazard scenario consisting of these two different kinds of public safety events similarly increase compared with the single-hazard scenario? As there is no study related to the change of public opinion on the ND-PHE double-hazard disaster scenario in countries other than China, we conducted brief searches of public opinion data on cases in other countries from Google Trends and other data sources and found the situation to be very complex. For instance, after a simple search for a US-based ND-PHE double-hazard consisting of California mountain fires and the COVID-19 epidemic using "California fire" and "California COVID-19″ as key words in the Google Trends search engine, we found that public attention to the Californian COVID-19 epidemic decreased in this ND-PHE double-hazard scenario. This phenomenon reveals that there are different patterns of public opinion changes for different disasters in ND-PHE double-hazard scenarios in different regions. It can be speculated that there are some important factors which contribute to the result that ND-PHE double-hazard scenarios in different regions will have different forms of changing opinion of different disasters. Therefore, in summary, a preliminary inference is proposed. Among social groups in general, when a public health event co-occurs with a natural disaster, presenting a public health–natural disaster compound double-hazard scenario, the amount of public opinion gained by either one will be (significantly) affected by the other. The public opinion drawn to each public safety event will be influenced by one or more factors, resulting in different trends in different settings. Exploring these specific changing patterns in different ND-PHE double-hazard scenarios in different regions and the main factors that cause the differences will be important tasks to be studied in the future. In more depth, due to this phenomenon, there will also be more in-depth questions to be considered. For example, are there differences in the spread of rumors about different disasters in ND-PHE double-hazard scenarios in different regions? Therefore, based on these considerations, we also have a more defined research plan. In future research, we will continue to explore ND-PHE double-hazard scenarios outside Chinese society. We will try to find the specific performance of the coupling effect of different hazards at the information level in ND-PHE double-hazard scenarios outside Chinese society in order to explore more general conclusions. Meanwhile, we will continue to improve the DH F-J model, increasing its descriptive accuracy and extending its applicability to allow it to be applied to a great number of multi-hazard scenarios.

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CRediT authorship contribution statement

Zilin Xie: Conceptualization, Methodology, Validation, Investigation, Formal analysis, Writing – original draft, Writing – review & editing. **Wenguo Weng:** Project administration, Supervision, Investigation, Writing – review & editing, Funding acquisition. **Yufeng Pan:** Data curation, Visualization, Formal analysis. **Zhiyuan Du:** Methodology, Software. **Xingyi Li:** Data curation, Visualization. **Yijian Duan:** Methodology, Software.

Declarations of Competing Interest

None.

Data availability

Data will be made available on request.

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