

Retraction

Retracted: The Evolution Model of Public Risk Perception Based on Pandemic Spreading Theory under Perspective of COVID-19

Complexity

Received 15 August 2023; Accepted 15 August 2023; Published 16 August 2023

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] Y. Zhang, Z. Li, G. Zhou, N. Xu, and J. Liu, "The Evolution Model of Public Risk Perception Based on Pandemic Spreading Theory under Perspective of COVID-19," *Complexity*, vol. 2021, Article ID 1015049, 10 pages, 2021.

Research Article

The Evolution Model of Public Risk Perception Based on Pandemic Spreading Theory under Perspective of COVID-19

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Received 2 September 2021; Accepted 10 November 2021; Published 29 November 2021

Academic Editor: Wei Wang

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After the occurrence of public health emergencies, due to the uncertainty of the evolution of events and the asymmetry of pandemic information, the public's risk perception will fluctuate dramatically. Excessive risk perception often causes the public to overreact to emergencies, resulting in irrational behaviors, which have a negative impact on economic development and social order. However, low-risk perception will reduce individual awareness of prevention and control, which is not conducive to the implementation of government pandemic prevention and control measures. Therefore, it is of great significance to accurately evaluate public risk perception for improving government risk management. This paper took the evolution of public risk perception based on the COVID-19 region as the research object. First, we analyze the characteristics of infectious diseases in the evolution of public risk perception of public health emergencies. Second, we analyze the characteristics of risk perception transmission in social networks. Third, we establish the dynamic model of public risk perception evolution based on SEIR, and the evolution mechanism of the public risk perception network is revealed through simulation experiments. Finally, we provide policy suggestions for government departments to deal with public health emergencies based on the conclusions of this study.

1. Introduction

After the occurrence of public health emergencies, due to the uncertainty of the evolution of events and the asymmetry of pandemic information, the public's risk perception will fluctuate dramatically. The public takes various protective measures, such as collecting relevant information about the pandemic, forwarding and spreading information about the pandemic, producing violent emotional reactions, buying protective goods, and even leaving the pandemic area [1, 2]. In early March 2020, more than 50,000 people across the country were surveyed about their psychological stress and emotional state according to the Shanghai Mental Health Center; the survey showed: about 35% of the interviewees suffered from psychological distress and had obvious emotional stress reaction; about 5.14% of the interviewees suffered from serious psychological distress. During

COVID-19, there has been frantic buying of face masks and disinfectants across the country and around the world. Moreover, public risk perceptions are highly contagious, and excessive risk perceptions by some members of the public can lead to irrational behavior by more members of the public, jeopardizing social harmony and stability. Therefore, we should pay attention to the public's risk perception and emotional guidance, face up to the psychological needs of the public to vent their emotions, and reasonably guide the public's emotional fluctuations and behavioral reactions. These become an important task of COVID-19 pandemic prevention and control [3].

Public risk perception refers to the concern or anxiety expressed by the public about something [4], which reflects the process of the public's subjective evaluation of a specific risk state [5, 6]. When the public is aware of risks, it stimulates the psychological state of coping with risks and

further generates the demand for risk-related information and emergency behavior based on subjective judgment. Too high risk perception often leads the public to overreact to risk events, resulting in a variety of irrational and unnecessary behaviors, which have an unnecessary impact on economic development and social stability. However, when risk perception is too low, the public may give up taking effective self-protection behaviors. Public risk perception is a collection, selection, and understanding of the process of crisis information and response [7, 8]. In the all-media information age dominated by the network, the public's information demand, information channel, and information content are characterized by diversification and complexity. It leads to dynamic change and unpredictability of public risk perception, which further increases the difficulty of health emergency prevention and control.

Therefore, after the occurrence of major public health emergencies, the dynamic evolution law of public risk perception along with the development of the events should be grasped. It is helpful for the government to adopt active and effective risk management policies and measures.

2. Literature Review

2.1. Risk Perception. Scholars generally believe that the public's risk perception is mainly affected by individual characteristics, time, event progress, risk information, and other factors [9]. A questionnaire survey through a psychological scale is the most effective method to study the influencing factors and differences of risk perception. Peacock et al. take hurricane as the research scenario and explore the influencing factors of the formation process of public risk perception from two dimensions of socioeconomic and demographic characteristics [10]. In order to study the characteristics and influencing factors of public risk perception, Slovic carried out a series of empirical studies and summarized 15 different characteristics of risk perception [11].

In the field of behavioral science and psychology, many scholars focus on the important role of memory in individual behavioral decision-making [12]. Most of their research results support that individual memory system has a decisive influence on behavioral decision-making [13]. Welch et al. believed that the information obtained through news media and informal communication channels of social networks all belonged to the information used for behavioral decision-making in the individual memory system [14]. The same conclusion can also be reached when scholars introduce individual memory to build mathematical models. For example, Mullainathan took consumers' memories of previous products and wages as the basis for purchasing decisions and constructed a consumer memory decision model [15]. Mehta et al. studied the relationship between consumers' forgetting rate of brands and purchasing decisions and believed that when consumers are faced with many brands, their memory and perception of these brands play an important role in consumers' choice [16]. Wei et al. constructed an evolution model of individual memory perception and corporate reputation to study the optimal

strategy of CSR activities of enterprises [17]. Wei et al. introduced the recency effect, Lenovo effect, and read-back effect and built the public risk perception evolution model based on crisis information flow. This model uses the crisis information growth model, stakeholder influence model, and stakeholder memory model to measure the process of crisis information release, information diffusion, and information perception. The diffusion coefficient and forgetting coefficient of crisis information are introduced to explain the transmission mechanism of crisis information in the population. It is found that there are lag effect, cumulative effect, and jump phenomenon in the evolution of public risk perception [18].

2.2. Communicable Disease Model Network Public Opinion Spread. The infectious disease model is a mathematical model that uses an ordinary differential equation to describe the spread and prevalence of the infectious disease. Consider the similarity between the spread of information and the spread of infectious diseases. Daley et al. applied the infectious disease dynamics model to information transmission, dividing individuals into three categories: susceptible, sprayer, and immune and then constructing the classic DK model [19]. Subsequently, some scholars further refined the communication process and improved the model [20, 21]. However, with the rapid development of information technology and the explosion of social networks, the mode of information transmission has undergone profound changes. The classical infectious disease model can no longer accurately describe the geometric progression fission propagation process of network information [22]. One of the important reasons is that the spread of infectious diseases is unconscious, and the transmission of diseases by infected people is not based on people's subjective will. However, the essence of information communication is social communication, and further research needs to consider the attributes of network information content, public society, and other factors [23–25].

Shang et al. integrated the social network and communication dynamics model and proposed a simulation planning method taking public emergencies as scenarios [26]. Zhu et al. [27] established an infectious disease model based on the transmission rules of the Ebola virus. Wang et al. considered the interdependence of online and offline activities and constructed an information transmission model of a two-layer social network based on complex network theory and communication dynamics [28]. Liu et al. considered the influence of network dynamic evolution and constructed a dynamic network diffusion information transmission model of public emergencies [29]. Wang et al. defined the types of the public and the role of government intervention, and combined with the characteristics of emergency information communication, they constructed a public opinion communication control model under government intervention [30]. Zhong et al. considered the relationship between public status transition and the influence of government intervention, constructed the SEIRS model of public opinion communication control under government intervention, and used control factors to realize effective intervention of online public opinion in emergencies

[31]. Yin et al. [32] considered that users may enter into another related topic after discussing one topic and proposed a multi-information susceptibility discussion immunity (M-SDI) model, effectively predicted the trend of online public opinion communication of public health emergencies through the fitting analysis of COVID-19 public opinion data obtained from China's Sina Weibo. Wang et al. analyzed the mutual influence of multiple public opinion communication and the rule of state transfer among different groups after an emergency occurred and proposed the 3SIR model [33].

So that's all, at present, the research on infectious disease models is relatively mature, and most of them are applied in the field of information dissemination and network public opinion dissemination. However, there are few literature on the evolution of applying the infectious disease model to public risk perception. Therefore, in the context of COVID-19, this paper analyzes the spread characteristics and rules of public risk perception by using the infectious disease model. Considering the propagation properties of the social network, such as social reinforcement effect, containment mechanism, and forgetting mechanism, we constructed the evolution dynamics model of public risk perception based on SEIR, which better delineated the evolution of public risk perception and provided decision-making suggestions for the government in formulating the risk management of public health emergencies.

3. Model Construction

3.1. Characteristics of the Evolution of Public Risk Perception in the COVID-19. The essence of an infectious disease is that the carrier of the pathogen transmits its own germs to the person who comes into contact with it through contact with other individuals. In the context of COVID-19, the spread of public risk perception has the characteristics of infectious disease, and individuals who perceive risk will transmit their perceived risk to other individuals who communicate with them through various communication channels. The transmission of infectious diseases between hosts needs to break a certain threshold, and the spread of the public's perceived risk in the context of COVID-19 also needs certain conditions, as the perceived risk exceeds their own tolerance. Therefore, in the context of COVID-19, the spread of public risk perception has the characteristics of risk sources, transmission media, infectivity, and immunity.

3.1.1. Risk Source. The source of risk is the precondition of risk transmission. If there is no source of risk, there is no risk transmission. Risk sources are equivalent to pathogens in infectious diseases. The public health emergency caused by the COVID-19 outbreak in late December 2019 is a risk source for the spread of public risk perception. As the core of the process of risk communication, the source of risk causes public panic and panic buying of medical equipment depending on the communication media.

3.1.2. Propagation Medium. The transmission medium is the carrier of risk source transmission. After the outbreak of COVID-19, the media of public risk perception are the

Internet, TV, newspapers, Weibo, and other mass media. The pandemic information permeates the entire social cyberspace, and the public receives the pandemic information and transmits the perceived risk incorrectly, thus causing panic among the general public.

3.1.3. Contagious. Infectivity is the most fundamental characteristic of infectious diseases. If there are only pathogens and infectious media, but pathogens do not have infectivity, they do not belong to infectious disease. Risk source of contagion will spread the risk to the environment, when individuals perceive more risk than they can bear, they will spread the risk perception to the outside world through their closely related kinship, work and neighborhood relationships.

3.1.4. Immunity. Some people are immune to certain infections because they have antibodies or have been vaccinated against them. In the process of risk transmission caused by the outbreak of COVID-19, some individuals show different immunity based on their psychological quality and knowledge. For example, individuals with poor mental health and inadequate knowledge of novel coronavirus and the spread of the virus have much lower immunity than individuals with high mental health and abundant protective behaviors against COVID-19. At the same time, the individual's gender, personality, and living environment will affect their immune ability.

Therefore, in the context of COVID-19, the transmission process of public risk perception has the characteristics of the transmission process of infectious diseases. The infectious disease model is used to analyze and simulate the transmission process of risk perception so as to understand the principle of risk perception transmission and provide a reference for the formulation of risk perception control measures.

3.2. Factors Influencing the Evolution of Public Risk Perception. Public risk perception is widely spread through the Internet, TV, newspapers, Weibo, and other mass media in the social network space such as the circle of relatives, neighbors, and friends who are closely related to individuals. The dissemination of public risk perception is a complex process, which is not only affected by individual factors such as inter-individual intimacy, knowledge background, and life experience [34–36] but also affected by social factors such as information memory effect, social reinforcement effect, interest attenuation effect, containment mechanism, authority effect, broken window effect, and responsibility dispersion effect [37–40]. This paper focuses on the influence of the forgetting mechanism, social reinforcement effect, and containment mechanism on public risk perception transmission.

3.2.1. Forgetting Mechanism. German psychologist Ebbinghaus revealed the nonlinear attenuation of information value with the passage of time through the method of relearning. It reflects the significant impact of

attenuation characteristics on information dissemination. Relevant literature call this phenomenon a forgetting mechanism [41], and it is proved by simulation that this mechanism can inhibit information diffusion and reduce the scale of information dissemination [42]. Scholars have shown that the rate of forgetting has a significant impact on the density of spreaders and immunizers in rumor-spreading experiments. The higher the forgetting probability or the faster the forgetting speed, the weaker the spreading power of rumors [43]. Then, in major public health emergencies, the public risk perception transmission characteristics will be the same.

3.2.2. Social Reinforcement Effect. In the process of information transmission, individuals tend to be skeptical of information, and the probability of transmitting information after receiving it only once is very limited. However, if the neighbor repeatedly prompts the same information so that the individual receives the same information many times, the probability of the individual believing the information and spreading it will greatly increase. In social networks, information is dense, and a lot of information is mixed with truth and false. It is difficult for ordinary people to make a reasonable judgment. At this time, most people will use others' judgment to form their own opinions. Therefore, the social reinforcement effect is very obvious in the information dissemination of social networks.

Literature [44] constructed a rumor propagation model with social reinforcement effect and interest attenuation effect based on the social network and believed that the social reinforcement effect and interest attenuation effect would simultaneously act on the propagation state node, which would be converted into the connected state by interest attenuation effect, and the connected state would be converted into the propagation state by the social reinforcement effect. Therefore, this paper defines the propagation probability function of public risk perception in the social network caused by the social reinforcement effect as follows:

$$\lambda(m) = 1 - (1 - \beta)e^{-b(m-1)}, \quad (1)$$

where β is the initial transmission rate, which represents the probability that an individual will transmit the pandemic information after receiving it only once; b is the strengthening factor; and m is the number of messages received when $m = 1$ and $\lambda(1) = \beta$.

Figure 1 shows that under the action of different reinforcement coefficient b , the propagation probability of individual risk perception changes with the change of m . Initial value $\lambda(1) = \beta = 0.5$ represents the transmission probability of risk perception of susceptible individuals receiving information of an pandemic.

Based on the above considerations, this paper focuses on the local environment of individuals to describe the forgetting mechanism, social reinforcement effect, and containment mechanism of the spread of public risk perception and analyzes how these factors affect the spread of risk perception through simulation.

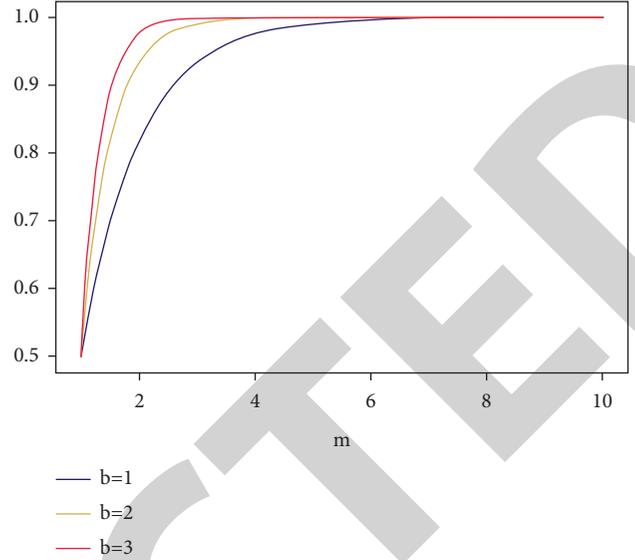


FIGURE 1: Influence of different reinforcement coefficients on propagation probability.

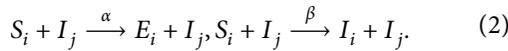
3.3. Dynamic Evolution Model of Public Risk Perception in COVID-19. The individual in the social network is represented as the node in the network, and the relationship between individuals is represented by the connection between nodes, so the social network is represented as a concrete network structure. The individuals in the social network are represented as nodes in the network, and the relationships between individuals are represented by the links between nodes, thus representing the social network as a specific network structure. In the process of risk perception propagation, it can only be propagated between neighboring nodes. When a node propagates risk perception to its neighboring nodes, if the neighboring nodes choose to believe and accept the information, then the neighboring nodes continue to propagate risk perception to its neighbors. If the neighboring node does not accept the risk perception, the neighboring node does not propagate it again.

When the risk perception spreads from the risk source to the whole network, there will be different psychological states for the same information due to the different interests and knowledge of nodes in the network. Therefore, nodes have different attitudes on whether to accept the spread of risk perception and ultimately lead to different trends in the spread of risk perception. So that, the nodes in the social network can be divided into four states: the susceptible state (S), the latent state (E), the onset state (I), and the recovering state (R). Among them, the susceptible state refers to the public who has not received the pandemic information. The latent status refers to receiving information but not disseminating risk perception. In other words, it refers to receiving pandemic information for the first time and perceiving risk but not breaking one's maximum risk tolerance. The onset state refers to the state of panic and anxiety when receiving information, which is spreading risk perception. The recovery status refers to the public who rationally see the pandemic and do not spread it.

The proportions of these four groups in the total population at time t are, respectively, $S(t)$, $E(t)$, $I(t)$, $R(t)$, and $S(t) + E(t) + I(t) + R(t) = 1$.

Considering the social reinforcement effect, forgetting mechanism, and containment mechanism of public risk perception, the following risk perception communication rules are proposed:

- (1) When the susceptible individual S_i receives the information transmitted from an infected individual I_j , the susceptible individual S_i may change to the latent state E_i with probability α or may change to the onset state I_i with the initial rate of transmission β and transmit the pandemic information to other individuals. The state transition can be expressed as follows:



- (2) The nodes in the latent state are suspicious of the pandemic information and will receive the information transmitted from the nodes in the neighboring pandemic state many times. Under the influence of the social reinforcement effect, the nodes in the latent state E_i will be transformed into the onset state I_i with the probability of transmission λ . The latent node E_i that has not been transformed into the disease state may be transformed into the recovering state R_i with probability θ . The E_i transition process of the latent state can be expressed as follows:



- (3) Since the onset node has already believed the pandemic information and spread it, the transmission state will not be affected by the social strengthening effect. However, the onset state I_i is affected by the social containment mechanism, the nodes in the onset state I_i will be transformed into the recovery state R_i with the probability of transmission ϵ . The I_i transition process of the onset state can be expressed as follows:



- (4) With the passage of time, the recovering state R_i was affected by the amnesia mechanism and changed to the susceptible state S_i with a probability of δ . The R_i transfer process of the healing state can be expressed as follows:



According to the above analysis, the evolution model of the public risk perception network in COVID-19 is shown in Figure 2.

In summary, the public risk perception communication dynamics model is as follows:

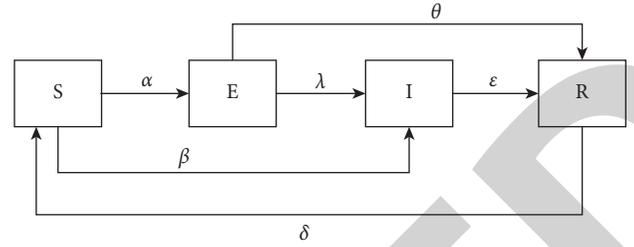


FIGURE 2: State transition diagram of social network nodes.

$$\begin{aligned} \frac{dS(t)}{dt} &= -\alpha S(t)I(t) - \beta S(t)I(t) + \delta R(t), \\ \frac{dE(t)}{dt} &= \alpha S(t)I(t) - \lambda E(t) - \theta E(t), \\ \frac{dI(t)}{dt} &= \beta S(t)I(t) + \lambda E(t) - \epsilon I(t), \\ \frac{dR(t)}{dt} &= \theta E(t) + \epsilon I(t) - \delta R(t). \end{aligned} \quad (6)$$

3.4. Analysis of the Basic Reproduction Number of the Model.

In this paper, the next-generation matrix method is used to calculate the basic reproduction number R_0 .

States 1, 2, 3, and 4 represent the states of E , I , S , and R , respectively. The density of class 4 node states is denoted by x_i , that is $x = (x_1, x_2, x_3, x_4)^T$. Constructor $F(x)$: $F_i(x)$ represents the probability of new diseased nodes in state i ; according to the above information, when $i = 1$, the probability of new diseased node in latent state E is αSI ; when $i = 2$, the probability of new diseased node in onset state is βSI ; and when $i = 3, 4$, there were no new disease nodes in susceptible nodes and recovered nodes. Therefore,

$$F(x) = \begin{bmatrix} F_1(x) \\ F_2(x) \\ F_3(x) \\ F_4(x) \end{bmatrix} = \begin{bmatrix} \alpha SI \\ \beta SI \\ 0 \\ 0 \end{bmatrix}. \quad (7)$$

Constructor $V(x)$: $V_1(x)$, $V_2(x)$, $V_3(x)$, and $V_4(x)$, respectively, represents the probability of change of state nodes of E , I , S , and R ; hypothesis $V_i(x) = V_i^-(x) - V_i^+(x)$, where $V_i^+(x)$ represents the probability of changing from another state node to the i state and $V_i^-(x)$ represents the probability of transition from the i state node to another state; therefore,

$$V(x) = \begin{bmatrix} V_1(x) \\ V_2(x) \\ V_3(x) \\ V_4(x) \end{bmatrix} = \begin{bmatrix} \lambda E + \theta E \\ \epsilon I - \lambda E \\ \alpha SI + \beta SI - \delta R \\ \delta R - \theta E - \epsilon I \end{bmatrix}. \quad (8)$$

Obviously, when there is no diseased node in the network system, all nodes are susceptible to infection, that is, $E_0 = (0, 0, S^*, 0)$ is the equilibrium point of the system, The derivative of $F(x)$ and $V(x)$ at E_0 is as follows:

$$\begin{cases} DF(E_0) = \begin{pmatrix} F & 0 \\ 0 & 0 \end{pmatrix}, \\ DV(E_0) = \begin{pmatrix} V & 0 \\ J_3 & J_4 \end{pmatrix}, \end{cases} \quad (9)$$

where

$$\begin{cases} F = \begin{pmatrix} 0 & \alpha \\ 0 & \beta \end{pmatrix}, \\ V = \begin{pmatrix} \lambda + \theta & 0 \\ -\lambda & \varepsilon \end{pmatrix}. \end{cases} \quad (10)$$

Therefore, we calculated that

$$FV^{-1} = \begin{bmatrix} \frac{\alpha\lambda}{(\lambda + \theta)\varepsilon} & \frac{\alpha}{\varepsilon} \\ \frac{\beta\lambda}{(\lambda + \theta)\varepsilon} & \frac{\beta}{\varepsilon} \end{bmatrix}. \quad (11)$$

The spectral radius of FV^{-1} is expressed as $\rho(FV^{-1})$, that is, the basic regeneration number R_0 is

$$R_0 = \rho(FV^{-1}) = \frac{\alpha\lambda + \beta(\lambda + \theta)}{\varepsilon(\lambda + \theta)}. \quad (12)$$

In the analysis of the network information transmission process, the basic regeneration number R_0 is an important parameter to measure whether network information can be spread on a large scale. It represents the average number of people affected by introducing a disease state node when all the network space is susceptible to infection without intervention. When $R_0 < 1$, the network information will not be widely diffused. When $R_0 > 1$, the network information will present a large-scale diffusion trend.

It can be seen from equation (12) that the basic regeneration number is closely related to the social effects of public risk perception, and these social effects have an important influence on whether the public risk perception spreads on a large scale. Among them, when other factors remain unchanged, the initial transmission rate of public risk perception keeps increasing, so that the basic regeneration number R_0 gradually changes from a value less than 1 to a value greater than 1, and the public panic gradually spreads. With the increase of the basic regeneration number R_0 , the diffusion scale becomes larger and larger.

4. Numerical Simulation and Analysis

This part will verify the rationality and stability of the evolutionary model of public risk perception through simulation experiments and analyze the propagation mechanism of risk perception. In the simulation experiments, the initial conditions given are: $S(0) = 1$, $E(0) = 0.00$, $I(0) = 0.00$, and $R(0) = 0.00$.

4.1. Analysis of the Density of State Nodes in the Network. Set the initial parameter to $\alpha = 0.2, \beta = 0.5, \lambda = 0.5, \theta = 0.3, \varepsilon = 0.2, \delta = 0.1$ and substitute into equation (12); the calculation gives the basic regeneration number R_0 as 3.125, The theory suggests that public risk perceptions undergo mass diffusion, which is consistent with the results in the figure.

From Figure 3, it can be seen that the node density of the susceptible state decreases rapidly at the initial stage and eventually tends to stabilize; the node density of the latent state increases rapidly to a peak of 0.31, then gradually decreases, and eventually tends to 0; the node density of the pathogenic state increases rapidly at the early stage of propagation and reaches a peak of 0.63, after which the node density gradually decreases and eventually stabilizes at 0.32; the node density of the healed state rapidly increases during the propagation process and eventually reaches a stable at 0.61. The density of nodes in the healed state increased rapidly during propagation and eventually reached a stable level of 0.61.

4.2. Impact of Initial Propagation Rate on the Evolution of Public Risk Perception. The node density of the morbidity state represents the active degree of risk perception transmission; the node density of the healing state represents the degree of risk perception transmission final state. Therefore, the impact of public health pandemics on public risk perception is investigated by analyzing the change in node density of morbidity and healing states with the initial transmission rate β . Figures 4 and 5 depict how public risk perceptions vary over time in terms of the density of morbidity status and healing status under the influence of different initial transmission probabilities. Set the initial parameter $\alpha = 0.2, \lambda = 0.5, \theta = 0.3, \varepsilon = 0.2, \delta = 0.1$; take three cases $\beta = 0.2, \beta = 0.5$, and $\beta = 0.8$; and substitute into equation (12); the calculation can get the basic regeneration number R_0 as 1.625, 3.125, and 4.625, respectively; theoretically, the public risk perception will carry out large-scale diffusion, which is consistent with the results in the figure. As can be seen in Figures 4 and 5, both the onset state and the healing state R density maxima increase with increasing initial transmission probability β . That is, the greater the initial probability of transmission, the more the public is inclined to spread risk perceptions, and the shorter the time it takes to reach the peak. After the node density of the disease state reaches its peak, as the government's emergency work advances, such as the effective implementation of pandemic prevention and control measures, some members of the public believe that the pandemic is temporarily controllable, and the number of publics spreading information about the pandemic begins to decrease, and eventually, all change to the disease state. Therefore, the greater the initial rate of transmission of public risk perception, the faster the network transmission that is not only fast but also on a large scale.

4.3. The Impact of Social Reinforcement Effects on the Evolution of Public Risk Perceptions. Set the initial parameter to $\alpha = 0.2, \beta = 0.5, \theta = 0.3, \varepsilon = 0.2, \delta = 0.1$ and take the three cases $b = 1, m = 1, b = 1, m = 2$, and $b = 2, m = 2$. Figure 6 depicts the change in the density of morbidity status nodes

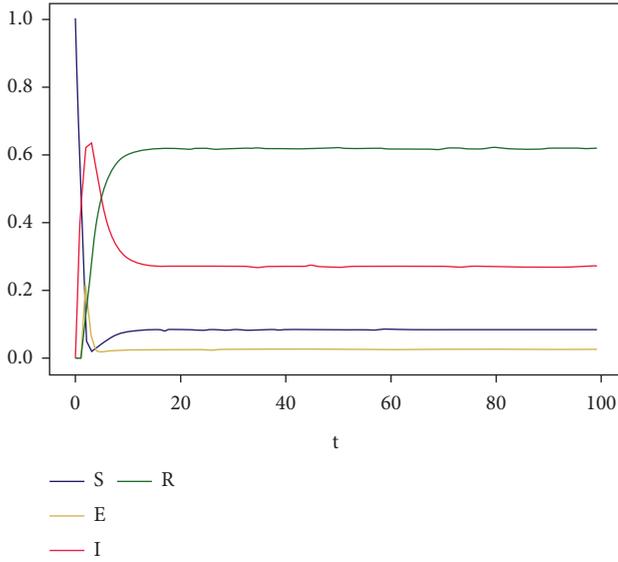


FIGURE 3: Trend of state changes of various nodes in the SEIR model.

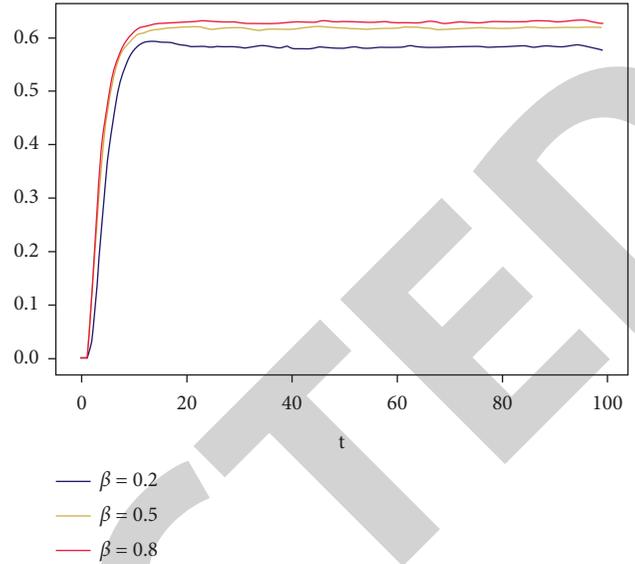


FIGURE 5: Effect of initial propagation rate on node density in the healed state.

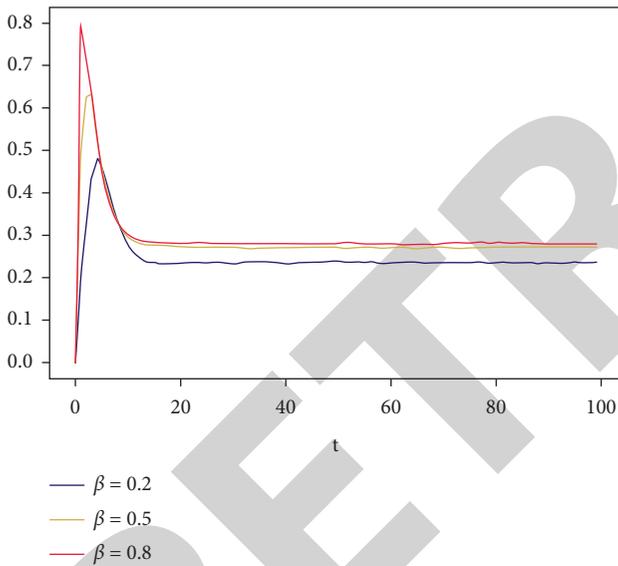


FIGURE 4: Effect of initial transmission rate on the density of nodes in the onset state.

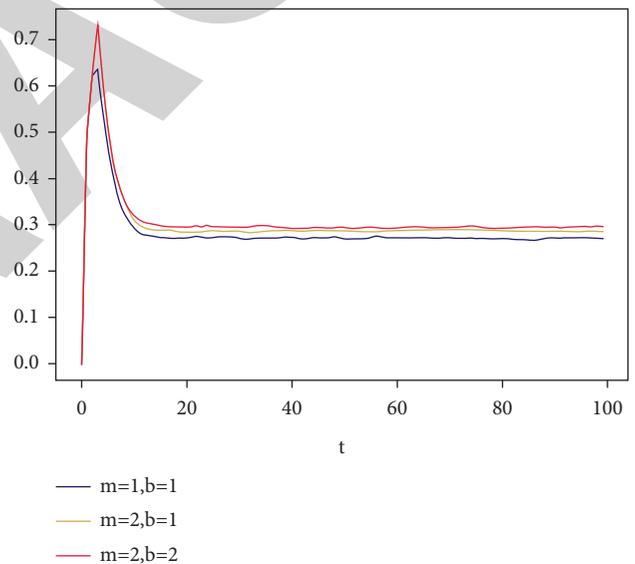


FIGURE 6: Effect of reinforcement effects on the density of nodes in the onset state.

over time for different social reinforcement effects on public risk perception. As can be seen in Figure 6, the greater the number of times an individual receives information about a pandemic, the greater the density of morbidity status nodes, for the same reinforcement factor. Similarly, the higher the reinforcement factor, the higher the density of onset nodes, given the same number of times an individual received information about the pandemic. This suggests that the public is more inclined to disseminate risk perceptions in the presence of social reinforcement effects.

4.4. Impact of Containment Mechanisms on the Evolution of Public Risk Perceptions. Set the initial parameter to $\alpha = 0.2$, $\beta = 0.5$, $\lambda = 0.5$, $\theta = 0.3$, $\delta = 0.1$ and take the three cases

$\varepsilon = 0.2$, $\varepsilon = 0.4$, and $\varepsilon = 0.6$. Substituting into equation (12), the corresponding basic regeneration numbers R_0 are 3.125, 1.56, and 1.04, respectively, and the nodal densities of onset states when public risk perception transmission reaches stability are 0.27, 0.16, and 0.1, respectively. From Figure 7, it can be seen that the maximum value of the onset state node density decreases with the increase of the containment mechanism ε . Since ε represents the strength of the containment mechanism, this means that the stronger the containment mechanism, the easier it is for the onset state nodes to be influenced by other nodes and stop spreading, the faster the network reaches a stable state, and the smaller the density of onset state nodes after the network is stable. Therefore, the containment

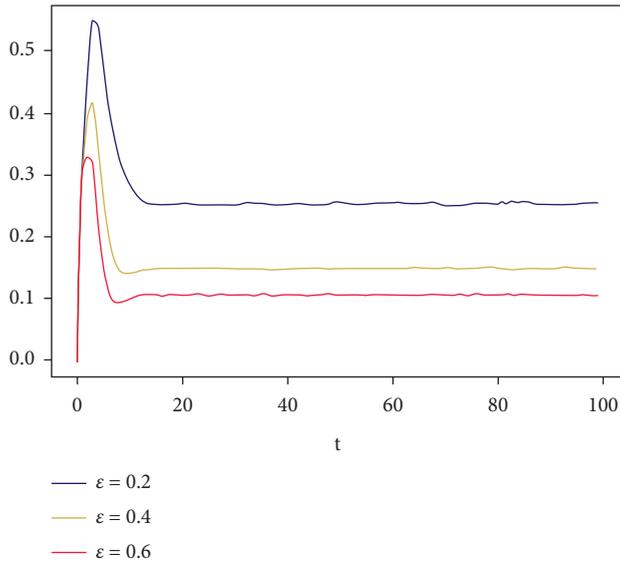


FIGURE 7: Effect of containment mechanisms on node density in the onset state.

mechanism curbs the spread of public risk perception to a certain extent, reducing the speed and scope of transmission.

4.5. The Impact of Forgetting Mechanisms on the Evolution of Public Risk Perception. Set the initial parameter to $\alpha = 0.2, \beta = 0.5, \lambda = 0.5, \theta = 0.3, \varepsilon = 0.2$; take the three cases of $\delta = 0.1, \delta = 0.4$, and $\delta = 0.7$, and substitute into (12); the corresponding basic regeneration numbers are all 3.125. The node densities of onset states when network propagation is stable are 0.28, 0.52, and 0.61, respectively.

As can be seen from Figure 8, the maximum value of the onset state node density increases with the increase of the forgetting rate δ . Since δ represents the intensity of forgetting, this means that the greater the degree of forgetting, the easier it is for sick state nodes to forget the received pandemic information and the easier it is for them to become susceptible nodes again to receive pandemic information and propagate risk perceptions, making the density of sick state nodes greater when the network is stable.

5. Research Conclusions and Policy Recommendations

5.1. Research Conclusions. In this paper, based on COVID-19, first, we analyzed the infectious characteristics of public risk perception in public health emergencies. Second, according to the characteristics of public risk perception transmission in social networks, we established the evolution dynamics model of public risk perception and solved the basic regeneration number. Finally, we revealed the evolution mechanism of the public risk perception network through parameter selection and simulation experiments. Therefore, the significance of this study is reflected in the following three aspects:

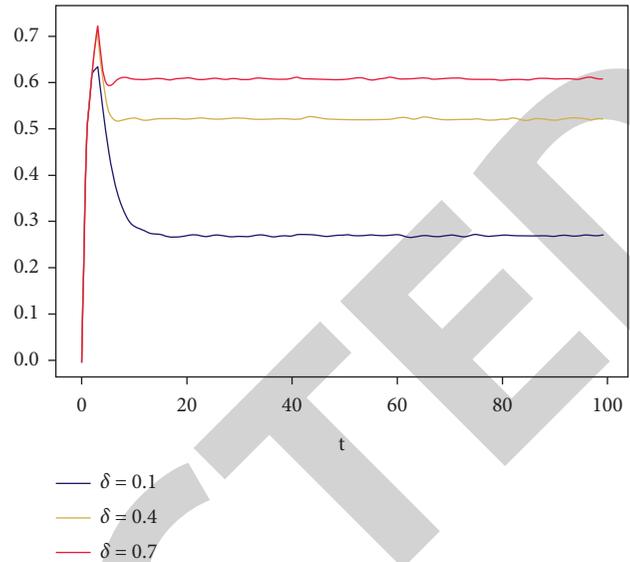


FIGURE 8: Effect of forgetting mechanisms on the density of nodes in the onset state.

- (1) Systematically summarize the characteristics of public risk perception of infectious diseases in public health emergencies, including risk sources, transmission media, infectivity, and immunity. It provides a theoretical basis for the establishment of a public risk perception model.
- (2) Systematically analyze the influencing factors of public risk perception of public health emergencies. From two dimensions of individual and social factors, we focused on analyzing the influence of the forgetting mechanism, social reinforcement effect, and containment mechanism on the spread of risk perception and established the evolution dynamics model of the public risk perception based on SEIR. The stability of the model is proved theoretically by solving the basic regeneration number.
- (3) The infectious disease model is applied to the evolution model of risk perception of public health emergencies; through simulation experiments, we revealed the evolution mechanism of public risk perception network. The greater the initial rate of diffusion, the greater the speed and scope of network diffusion; the stronger the social reinforcement effect, the greater the speed and scope of network diffusion; the stronger the rate of forgetting, the greater the speed and scope of network diffusion; and the stronger the rate of containment, the weaker the speed of network diffusion and the smaller the scale of network diffusion.

5.2. Policy Recommendations. The conclusions of this study can provide the following suggestions for relevant government departments to deal with major public health emergencies:

- (1) The government should immediately launch the emergency plan to rescue the affected public, shrink the scope of the emergency, reduce the level of the emergency, cut down the influence of the emergency, and weaken the public risk perception so as to reduce the negative impact of the online public opinion of the emergency and maintain social harmony and stability.
- (2) The government should undertake the responsibility of supervision, regulation, and management. First, on the premise of satisfying the public's right to know, gradually relax the control on news media, and standardize the system of information disclosure and dissemination. In the process of information disclosure, the government should establish two-way communication channels: on the one hand, timely inform the public of the truth of the incident and, on the other hand, invite experts to objectively analyze and release authoritative information. Second, the government has a responsibility to know the source of the public's fear and respect the public's perception of risk. The risk that may be overestimated by the public through various ways has to be reduced, so as to reduce the public's risk perception level and relieve the public's panic.
- (3) News media should abide by professional ethics and report objectively and fairly, which will help reduce the risk perception of the public. The media is the reporter of the risk information of public health emergencies, the interpreter of dynamic information, and the guide of the public's risk perception. After the occurrence of public health emergencies, the public relies more on media reports because of asymmetric information. Therefore, the media should report information objectively, accurately and timely so that the potential risks can be recognized by the public so as to cut down the public's risk perception and panic and ultimately reduce the change from vulnerable groups to latent groups or disease groups.
- (4) The public should maintain a positive and optimistic attitude, collect emergency information rationally and objectively, and reduce the overestimated risk perception because of information insufficient. Instead of passively receiving information, the public should actively acquire and screen information. The analysis must be rational and objective so as to avoid herd behavior.

In a word, in the face of public health emergencies, the government should establish an early warning and response mechanism for public risk perception. The media should report the emergency objectively and fairly in order to guide public opinion correctly. The public should remain positive and optimistic, enhance the awareness of discrimination, reduce unnecessary panic, and improve the confidence to overcome difficulties.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This research was funded by the Research Funds of Anhui Xinhua University under Grant no. 2018kyqd01 and Anhui Provincial Quality Project in Colleges and Universities under Grant no. 2018ylzy074.

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