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*Research Article*

# Public Opinion Communication Model under the Control of Official Information

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The rapid development of Internet technology has facilitated the dissemination of information that can threaten national security and public health, and effectively controlling the process of public opinion communication is an important topic in contemporary social network research. This paper establishes an official information-controlled public opinion propagation (OI-SEIR) model based on the delay, latency, and conversion of public opinion communication under the control of official information. According to the influence and importance of the network nodes, we theoretically derive the attitude conversion probability of the nodes, making the model more in line with the actual situation. Through actual cases, we analyzed the important influence of official information on the public opinion communication process and provided a theoretical basis for the government and relevant departments to supervise and correctly guide the public opinion network, which has certain practical significance.

## 1. Introduction

At present, China is in a critical period of economic development and transformation. Major emergencies occur frequently, and public opinion can be shaped by popular Internet platforms. Because of network characteristics such as many ways of formation, fast transmission speed, and wide diffusion range , when emergency occurs, public opinions spread rapidly online. Improper responses to these emergencies by the relevant departments can cause a public opinion crisis and can even affect social stability. Therefore, studying the impact of official information on public opinion communication is important for public opinion supervision and the maintenance of public safety.

Public opinion is formed in complex and interconnected networks [1] and can therefore be considered similar to other complex networks for research purposes [2–5]. The infectious disease model [6–9] is a common method of modeling complex networks, including public opinion networks. The infectious disease model is deployed as a mathematical model that simulates the information dissemination process through the public opinion network [10, 11], enabling detailed analyses of the information dissemination mechanism [12–14]. Therefore, this paper presents a public opinion communication model based on official information control based on a complex network.

## 2. Related Work

Current research on public opinion communication has mainly focused on improving public opinion communication models. The classical SIR [15] and SIS [16] infectious disease models established by Kermack and McKendrick were developed into the SEIR model by Zhao et al. [7] and continue to be widely used and improved based on actual conditions and background changes. In one study [17], the tuberculosis virus was divided into two types: tuberculosis and extrapulmonary tuberculosis, with the latter virus considered not contagious and the former contagious. Another study [18] proposed a time lag consideration, taking the common cold and gonorrhea as examples and analyzing patient recovery at a certain moment in relation to the state of the current moment and the previous state. Several studies [19–21] have stratified the population by age largely because individuals of different ages often have different disease resistances, transmission abilities, and rehabilitation abilities. Bentaleb and Aminie proposed a multistrain SEIR epidemic model with bilinear and nonmonotonic incident functions [22]. Wu et al. proposed a nonlocalized diffusion SEIR model [23], and Liu et al. proposed a new SEIR rumor propagation model that included a hesitation mechanism [24]. Zhang and Cheng established the SETQR model and used the probability theorem to derive the information propagation law [25]. Thus, previous works have significantly improved the node types in the model and thereby more accurately simulated the public opinion communication process, which provides a reference for controlling the public opinion.

In addition, Wang et al. [26] introduced recent progress in the study of coevolution spreading dynamics, emphasizing the contributions from the perspectives of statistical mechanics and network science. The theoretical methods, critical phenomena, phase transitions, interacting mechanisms, and effects of network topology for four representative types of coevolution spreading mechanisms, including the coevolution of biological contagions, social contagions, epidemic-awareness, and epidemic-resources, are presented in detail. Zhang et al. [27] proposed the Media and Interpersonal Relationship-SEIR (MI-SEIR) model based on the SEIR model. The proposed model considers the impact of media transmission and interpersonal relationships on opinion propagation. Their MI-SEIR model divides the propagation nodes into three categories: support, neutral, and opposition. Wang et al. [28] introduced heterogeneous adoption threshold distribution into a non-Markovian spreading threshold model, in which an individual adopts a behavior only when the received cumulative pieces of behavioral information from neighbors exceed his adoption threshold. In order to understand the effects of heterogeneous adoption thresholds quantitatively, an edge-based compartmental theory is developed.

However, none of the above models considered the influence of an external interference mechanism on the public opinion propagation model. In order to solve this problem, Zhong and Sun [29] established a public opinion communication model with a control system under government intervention. However, this system assumed that rumors and official information are simultaneously published, which does not reflect the actual situation. Zhao and Cao [30] established an information diffusion model for the suppression of official information on unofficial information, in which the network nodes are divided into two categories: susceptible and infected. However, this model does not consider the knowledge of the public opinion and does not propagate the existence of information-like nodes for the time being. Zhang et al. [31] established a new model to support external control, but that model did not distinguish between official infected disseminators and false infected disseminators in the network. The model ignores the point that with the injection of official information, false information disseminators may be converted into official information disseminators. The above research results are basically consistent with some of the characteristics and laws of the process of public opinion dissemination, but all have their own shortcomings and deficiencies.

In order to solve the shortcomings of the above models, this paper establishes the OI-SEIR model to support the control of official information. The model focuses on the following three considerations. (1) *Time Delay*. False information and official information are often not released at the same time. After the false information is generated, the network public opinion is formed, causing adverse effects, before officials can publish the correct information in the network. Therefore, the official information is delayed compared with false information. (2) *Latency*. There are a large number of users in the public opinion network who receive the information but temporarily withhold from propagating it. These users can thus be considered latent nodes, which may more easily change state when the official information is injected, thereby supporting the dissemination of official information. (3) *Conversion*. The injection of official information can convert false information disseminators to official information disseminators. Thus, the OI-SEIR model divides the distributors of official information and false information and may be more suitable for practical situations.

## 3. SEIR Model

The SEIR model is shown in Figure 1. In the SEIR model, the node set is divided into four categories: $S'$ (susceptible node), $E'$ (exposed node), $I'$ (infected node), and $R'$ (recovered node). The susceptible node represents the initial user who has not yet received any message. The exposed node represents the user who receives a message but does not propagate it. The infected node represents the user who receives information and propagates the message. The recovered node represents the user who no longer transmits information or loses interest in the information she/he transmits. The conversion probability between each node is shown in Table 1. The transition probability between node states is in the interval, that is, $0 \le a', b', c', d', e' \le 1$.

Let the total number of nodes in the network be $N$, and the information propagation time is represented by $t$. The information propagation process in the SEIR model is described as follows.

When $t = 0$, false information is generated in the network. When $t \in (0, \infty)$, the susceptible nodes in the network first convert to exposed nodes with the probability of $a'$, and then the exposed nodes convert to the infected node with the probability of $c'$. The susceptible node can also be directly converted to infected nodes with the probability of $b'$. Finally, the infected nodes can be converted into the recovered nodes with the probability of $d'$, and the recovered nodes can be converted into the susceptible nodes with the probability of $e'$.

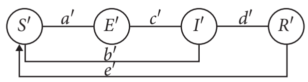


Figure 1: SEIR mode.

Table 1: Conversion probability.

| Symbol | Meaning |
|---|---|
| $a'$ | Probability that a susceptible node is converted into an exposed node |
| $b'$ | Probability that a susceptible node is converted into a infected node |
| $c'$ | Probability that an exposed node is converted into a infected node |
| $d'$ | Probability that a infected node is converted into a recovered node |
| $e'$ | Probability that a recovered node is converted into a susceptible node |

At time $t$, the proportions of susceptible, exposed, infected, and recovered nodes in the network are $S'(t)$, $E'(t)$, $I'(t)$, and $R'(t)$, respectively. Since the total number of users in the network remains unchanged, the following equation can be obtained:

$$S'(t) + E'(t) + I'(t) + R'(t) = 1. \tag{1}$$

The differential form of the SEIR model is shown in the following equation:

$$\begin{cases} \dfrac{dS'}{dt} = -a'(t)S'(t)I'(t) - b'(t)S'(t)I'(t) + e'(t)R'(t), \\ \dfrac{dE'}{dt} = a'(t)S'(t)I'(t) - c'(t)E'(t), \\ \dfrac{dI'}{dt} = c'(t)E'(t) + b'(t)S'(t)I'(t) - d'(t)I'(t), \\ \dfrac{dR'}{dt} = d'(t)I'(t) - e'(t)R'(t), \quad t \in (0, +\infty]. \end{cases} \tag{2}$$

## 4. OI-SEIR Model

*4.1. Network Description.* Let the public opinion network be $G = (V, B, C, F, O)$, where $V$ is the node set in the network, $B$ is the edge set in the network, $C$ is the set of node types, $F$ stands for false information, and $O$ stands for official information.

*4.2. Node Division.* In the OI-SEIR model, the node set is divided into five categories: $S$ (susceptible node), $E$ (exposed node), $I_F$ (false infected node), $I_O$ (official infected node), and $R$ (recovered node), as shown in Table 2.

Table 2: Node status classification.

| Status | Name | Meaning |
|---|---|---|
| $S$ | Susceptible node | User who has not yet received any message |
| $E$ | Exposed node | User who receives a message but does not propagate it |
| $I_F$ | False infected node | User who receives false information and propagates the message |
| $I_O$ | Official infected node | User who receives official information and propagates the message |
| $R$ | Recovered node | User who no longer transmits information or loses interest in the information she/he transmits |

*4.3. Communication Mechanism.* The OI-SEIR model contains an information dissemination layer and an official control layer, as shown in Figure 2. The information control layer includes the susceptible node $S$, the exposed node $E$, the false infected node $I_F$, and the recovered node $R$; the official control layer contains the official infected node $I_O$. The conversion probability between each node is shown in Table 3.

Let the total number of nodes in the network be $N$, $N = [1, \ldots, i, \ldots, j, \ldots, n, \ldots]$, and $N$ will remain unchanged for the given network. The transition probability between node states is in the interval $[0, 1]$; that is, $0 \leq a, b, c, d, e, \varepsilon, \eta, \theta \leq 1$. The information propagation time is represented by $t$. At time $t \in (0, +\infty)$, the information propagation process in the OI-SEIR model is described as follows:

(1) $t = 0$: False information is generated in the network.

(2) $t \in (0, T)$: There is only false information in the network. The susceptible nodes in the network first convert to exposed nodes, and then the exposed nodes convert to the false infected node $I_F$, according to the respective probabilities. Susceptible nodes can also be directly converted to false infected nodes, false infected nodes can be converted into the recovered nodes, and recovered nodes can be converted into susceptible nodes, again following the respective probabilities.

(3) $t = T$: The false information spreads in the public opinion network for a period of time before government departments release official information to guide public opinion and avoid the further spread of false information. In this article, this time is denoted by $T$.

(4) $t \in (T, +\infty]$: The false information and the official information coexist in the network. The various types of network nodes begin to be converted to official infected nodes, according to the probabilities presented in Table 2. Among these, the probability of converting susceptible nodes to official infected nodes is called the direct immunization rate; the probability of converting exposed nodes to official infected nodes is called the latent immunization rate, and the probability of converting false infected nodes

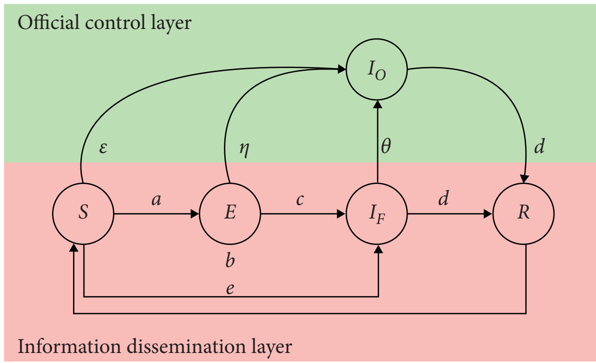


Figure 2: OI-SEIR model.

to official infected nodes is called the infection immunization rate. If the government successfully guides public opinion, only official infected nodes will be in the network over time, whereas if the government fails, only false infected nodes will persist.

At time $t$, the proportions of susceptible, exposed, false infected, official infected, and recovered nodes in the network are $S(t)$, $E(t)$, $I_F(t)$, $I_O(t)$, and $R(t)$, respectively. Because the total number of users in the network is assumed to remain unchanged,

$$S(t) + E(t) + I_F(t) + I_O(t) + R(t) = 1. \tag{3}$$

At $t = 0$, that is, at the initial moment of information dissemination, each node occupies the following proportions in the network:

$$\begin{cases} S(0) \approx 1, \\ E(0) = 0, \\ I_F(0) \approx 0, \\ I_O(0) \approx 0, \\ R(0) = 0. \end{cases} \tag{4}$$

The differential form of the OI-SEIR model is as follows:

$$\begin{cases} \dfrac{\mathrm{d}S}{\mathrm{d}t} = -[a(t) + b(t)]S(t)I_F(t) - \varepsilon(t-T)S(t-T)I_O(t-T) + e(t)R(t), \\ \dfrac{\mathrm{d}E}{\mathrm{d}t} = a(t)S(t)I_F(t) - c(t)E(t) - \eta(t-T)E(t-T)I_O(t-T), \\ \dfrac{\mathrm{d}I_F}{\mathrm{d}t} = c(t)E(t) + bS(t)I_F(t) - d(t)I_F(t) - \theta(t-T)I_F(t-T)I_O(t-T), \\ \dfrac{\mathrm{d}I_O}{\mathrm{d}t} = \varepsilon(t-T)S(t-T)I_O(t-T) + \eta(t-T)E(t-T)I_O(t-T) + \theta(t-T)I_F(t-T)I_O(t-T) - d(t-T)I_O(t-T), \\ \dfrac{\mathrm{d}R}{\mathrm{d}t} = d(t)I_F(t) + d(t-T)I_O(t-T) - e(t)R(t), \quad t \in (0, +\infty]. \end{cases} \tag{5}$$

The above analysis shows that the proportion of official infected nodes in the network is an important factor in evaluating the effect of official information on the control of public opinion communications. Because the number of official infected nodes is affected by the direct immunization rate $\varepsilon$, the latent immunization rate $\eta$, and the infection immunization rate $\theta$, the remainder of this analysis focuses on these three types of immunization rate.

## 5. Immunization Rate Based on Attitude Value

*5.1. Attitude Value.* The node attitude value $a_p(t)$ indicates the degree to which the node recognizes the received official information at time $t$, and its value changes with time, as expressed by (4):

$$a_p(t+1) = a_p(t) + \gamma_{p\leftarrow q}(t). \tag{6}$$

Here, $a_p(t+1)$ represents the attitude value $a_p(t) \in [-1, 1]$ of the node at time $t+1$. When $a_p(t) = -1$, node $i$ completely rejects the received information; when $a_p(t) = 1$, node $i$ completely accepts the received information. $\gamma_{p\leftarrow q}$ represents the attitude influence between nodes, where the attitude value $\gamma_{p\leftarrow q}$ at a certain moment is affected by other nodes in the network at that moment.

$$\gamma_{p\leftarrow M}(t) = \frac{\sum M(t) \cdot a_M(t)}{p(t) + M(t)}. \tag{7}$$

Here, $M$ is the set of node types that affect the attitude value of node $p$ at time $t$, referred to as the impact set. The impact set $M$ includes the false infected node $I_F$ and the official infected node $I_O$, that is, $M \in (I_F, I_O)$. $a_M(t)$ indicates the attitude value of $M$ at time $t$. $p(t)$ represents the proportion of the state of node $p$ in the network at time $t$.

Table 3: Conversion probability.

| Symbol | Meaning |
|---|---|
| $a$ | Probability that a susceptible node S is converted into an exposed node E |
| $b$ | Probability that a susceptible node S is converted into a false infected node $I_F$ |
| $c$ | Probability that an exposed node $E$ is converted into a false infected node $I_F$ |
| $d$ | Probability that a false infected node $I_F$ is converted into a recovered node R<br>Probability that an official infected node $I_O$ is converted into a recovered node R |
| $e$ | Probability that a recovered node $R$ is converted into a susceptible node S |
| $\varepsilon$ | Probability that a susceptible node S is converted into an official infected node $I_O$ |
| $\eta$ | Probability that an exposed node $E$ is converted into an official infected node $I_O$ |
| $\theta$ | Probability that a false infected node $I_F$ is converted into an official infected node $I_O$ |

*5.2. Immunization Rate.* With government intervention after the time delay $T$, various types of nodes in the public opinion network begin to switch to official infected nodes. Below, we define the direct immunization rate $\varepsilon(t)$, the latent immunization rate $\eta(t)$, and the infection immunization rate $\theta(t)$, respectively.

The direct immunization rate $\varepsilon(t)$ is as follows:

$$\varepsilon(t+1) = \varepsilon(t) \cdot \left[1 + \frac{a_S(t+1)+1}{2}\right]. \tag{8}$$

Combining (6)–(8),

$$\begin{cases} \varepsilon(t+1) = \varepsilon(t) \cdot \left\{1 + \frac{1}{2} \cdot \left[\left(a_S(t) + \frac{I_F(t) \cdot a_{I_F}(t) + I_O(t) \cdot a_{I_O}(t)}{I_F(t) + I_O(t) + S(t)}\right) + 1\right]\right\}, \\ t \in [0, +\infty). \end{cases} \tag{9}$$

The latent immunization rate $\eta(t)$ is as follows:

$$\eta(t+1) = \eta(t) \cdot \left[1 + \frac{a_E(t+1)+1}{2}\right]. \tag{10}$$

Combining (6), (7), and (10),

$$\begin{cases} \eta(t+1) = \eta(t) \cdot \left\{1 + \frac{1}{2} \cdot \left[\left(a_E(t) + \frac{I_F(t) \cdot a_{I_F}(t) + I_O(t) \cdot a_{I_O}(t)}{I_F(t) + I_O(t) + E(t)}\right) + 1\right]\right\}, \\ t \in [0, +\infty). \end{cases} \tag{11}$$

Infection immunization rate $\theta(t)$ is as follows:

$$\theta(t+1) = \theta(t) \cdot \left[1 + \frac{a_{I_F}(t+1)+1}{2}\right]. \tag{12}$$

Combining (6), (7), and (12),

$$\begin{cases} \theta(t+1) = \theta(t) \cdot \left\{1 + \frac{1}{2} \cdot \left[\left(a_{I_F}(t) + \frac{I_F(t) \cdot a_{I_F}(t) + I_O(t) \cdot a_{I_O}(t)}{I_F(t) + I_O(t)}\right) + 1\right]\right\}, \\ t \in [0, +\infty). \end{cases} \tag{13}$$

## 6. Simulation Verification and Analysis

A simulation was conducted to analyze the public opinion communication process under the control of official information. The case is introduced and analyzed as follows.

*6.1. Case Introduction.* The case of the alleged kidnapping of the female master of Peking University in the United States was taken as an example to study the control effect of official information on the public opinion communication process and the influence of different intervention points and intervention intensity on the control effect.

On June 12, 2017, many official Weibo accounts such as People's Daily, Headline News, CCTV News, and others released a microblog entry titled "Female master of Peking University lost in the United States and suspected of being kidnapped by 'fake police'." The release of this headline on Weibo quickly caused intense discussions among thousands of Weibo users, who expressed different attitudes toward this incident. On June 15, 2017, after a lapse of three days, many official Weibo accounts posted another microblog entry entitled "FBI categorizes this lost case as kidnapping." At this point, the various speculations of Weibo users gradually subsided under the control of official information, opening a new round of discussions based on verified information.

*6.2. Control Effect of Official Information on Public Opinion Communication.* To obtain the initial parameters for this case, the whole process of the public opinion propagation must be tracked in real time, and detailed statistical analyses must be conducted on the state changes of all users in the microblog client, which is highly complex. In order to reduce the complexity and still ensure the accuracy of the data, this study selected the official Weibo account of the People's Daily, which has a high number of Weibo fans and stimulates many fan interactions, which was the object of these statistical analyses. The initial node ratio and the conversion rate were self-set values, and the initial attitude value, initial immunization rate, and delay were statistical results obtained after using the professional crawler tool for data crawling.

First, the information dissemination process in the SEIR model is analyzed, that is, the process of public opinion dissemination under unofficial control. The initial parameter settings in the experiment are shown in Table 4, and the simulation results are shown in Figure 3, where the abscissa indicates the time of information propagation in days and the ordinates indicate the proportion (%) of various types in the network as predicted by the SEIR model. The blue solid line indicates the change in the proportion of susceptible nodes in the process of information dissemination. The yellow and green dotted lines indicate the changes in the proportion of exposed and infected nodes in the process of information dissemination, respectively. The red dotted line indicates the change in the proportion of recovered nodes in the process of information dissemination.

The following can be obtained from Figure 3:

(1) $t \in (0, 1)$

TABLE 4: Initial parameter setting of the SEIR model.

| Initial node ratio | | | | |
|---|---|---|---|---|
| $S'(0)$ | $E'(0)$ | $I'(0)$ | $R'(0)$ | |
| 0.96 | 0 | 0.04 | 0 | |
| Conversion rate | | | | |
| $a'$ | $b'$ | $c'$ | $d'$ | $e'$ |
| 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |

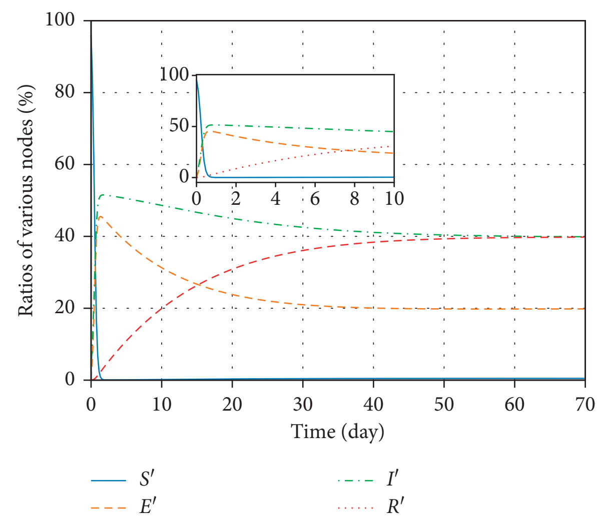

FIGURE 3: Public opinion communication map of the SEIR model.

The number of susceptible nodes in the network changes linearly and decreases rapidly, transforming into exposed nodes and infected nodes. Therefore, the number of information exposed nodes and infected nodes increases rapidly. At the same time, the number of recovered nodes increases slightly from 0.

(2) $t = 1$

The number of susceptible nodes is close to 0, and the number of exposed and infected nodes has reached the maximum, accounting for about 50% and 45% of the entire network, respectively. At the same time, the number of recovered nodes continues to increase. This shows that when public opinion just broke out, it spreads very fast.

(3) $t \in (1, 60)$

After $t = 1$, the number of susceptible nodes continues to decrease, until $t \approx 2$; the number of susceptible nodes is 0. At the same time, the number of exposed and infected nodes slowly decreases and eventually stabilizes. The proportions of exposed and infected nodes in the entire network are about 40% and 20%, respectively. When $t = 30$, the number of recovered nodes continues to increase and eventually stabilizes after $t = 60$. The number of recovered nodes in the entire network accounts for about 40%. The entire public opinion dissemination network stabilizes after $t = 60$.

Through the changes of the number of various nodes in the process of information dissemination, it can be seen that, in the absence of government interference, it took as long as 60 days to stabilize the distribution of the Internet public opinion on the case of a female student from Peking University who was abducted by “false police” in the United States, which means that people does not pay attention to the network incident and the online public opinion will basically be stable when the time of public opinion dissemination is long enough.

Then, the information dissemination process in the OI-SEIR model is analyzed, that is, the process of public opinion dissemination under official control. The initial parameter settings in the experiment are shown in Table 5. The simulation results are shown in Figure 4, where the abscissa indicates the time of information propagation in days and the ordinates indicate the proportion (%) of various types in the network as predicted by the OI-SEIR model. The blue solid line indicates the change in the proportion of susceptible nodes throughout the information dissemination process. The green and red dotted lines indicate the changes in the proportion of exposed and false infected nodes, respectively, and the curves with the green boxes and purple stars indicate the changes in the proportions of official infected nodes and recovered nodes, respectively.

The following can be obtained from Figure 4:

(1) $t \in (0, 1)$

The number of susceptible nodes decreases linearly and rapidly, while the number of exposed and false infected nodes increases linearly and rapidly. At the same time, the number of recovered nodes increases slightly.

(2) $t = 1$

The number of susceptible nodes is close to 0, while the number of exposed and false infected nodes has reached the maximum, accounting for about 50% and 45% of the entire network.

(3) $t \in (1, 3)$

The number of susceptible nodes continues to decrease, until $t = 2$, and the number of susceptible nodes is 0. The number of false infected nodes is almost stable. The number of exposed nodes is slowly decreasing. The number of recovered nodes continues to increase slightly.

Before the intervention of government information, comparing the SEIR model and the OI-SEIR model in the first three days after the outbreak of public opinion, the changing trend of each node in the two models is basically the same, which means that the trend of public opinion dissemination is basically the same, and the spread speed is very fast.

(4) $t \in (3, +\infty)$

When $t = 3$, with the injection of official information, the direction of public opinion changes. The number of susceptible nodes is 0. The number of false infected nodes drops rapidly. When $t \approx 5$, The number of false infected nodes is 0 and finally disappears in the network. Similarly, the number of exposed nodes drops rapidly. When $t \approx 4.5$, the number of exposed nodes is 0 and finally disappears in the network. The number of recovered nodes continues to increase linearly. However, compared with Figure 3, the number of information infected nodes slowly decreases and finally stabilizes after $t = 60$. When $t \in (3, 40)$, the number of exposed nodes slowly decreases, and after $t = 40$, it stabilizes. Comparing the SEIR model and the OI-SEIR model, it can be seen that 3 days after the outbreak of public opinion, due to government intervention, the number of susceptible, exposed, and false infected nodes in the OI-SEIR model decreases rapidly, while the number of recovered and official infected nodes increases rapidly, and the epidemic has quickly stabilized. Since the SEIR model has no government

Table 5: Initial parameter setting of the OI-SEIR model.

| Initial node ratio | | | | |
|---|---|---|---|---|
| $\eta(0)$ | $\eta(0)$ | $\theta$ | $\theta(0)$ | $\theta'(0)$ |
| 0.95 | 0 | 0.04 | 0.01 | 0 |
| Conversion rate | | | | |
| $\theta$ | $\theta(0)$ | $\theta(0)$ | $\theta$ | $\varepsilon(0)$ |
| 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Initial attitude value | | | | |
| $a_S(T)$ | $a_E(T)$ | | $a_{I_F}(T)$ | |
| 0.8 | 0.7 | | 0.6 | |
| Initial immunization rate | | | Delay | |
| $\varepsilon(0)$ | $\eta(0)$ | $\theta(0)$ | $T$ | |
| 0.6 | 0.4 | 0.2 | 3 | |

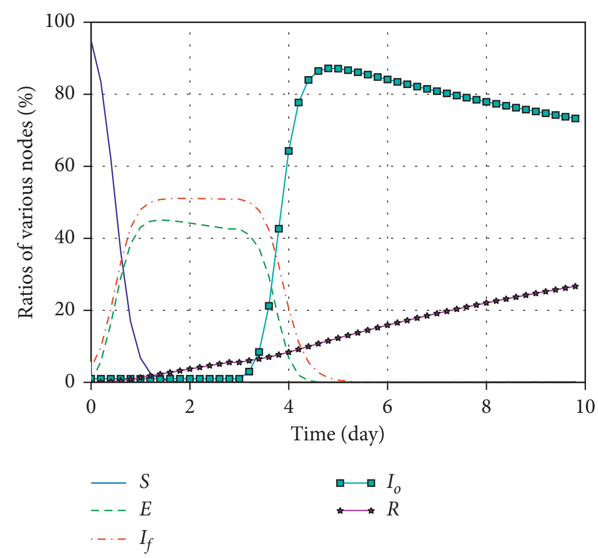


Figure 4: Public opinion communication map of the OI-SEIR model.

intervention, it will take a relatively long time to stabilize.

Based on the SEIR model and OI-SEIR model, it can be seen that it is very important and effective for the government and other relevant departments to control and guide the public opinion network. The injection of official information successfully changes the direction of the public opinion network and guides it to the right direction to avoid the further spread of false information.

### 6.3. Factors Influencing Official Information Control Effects

*6.3.1. Effect of Delay T on the Control Effect of Official Information.* The influence of the delay $T$ on the control effect of the official information was analyzed by changing the delay $T$, as shown in Figure 5, where the axes and legend are the same as in Figure 4. Figure 5 shows that the delay $T$ does not change the overall trend of diffusion through the public opinion network although the delay increases the time over which false information propagates in the network. Therefore, the smaller the delay $T$ is, that is, the earlier the official information is injected into the public opinion network, the faster the false information disappears from the network and the faster the public opinion network is stabilized.

*6.3.2. Effect of Direct Immunization Rate ε on the Control Effect of Official Information.* The effect of the direct immunization rate $\varepsilon$ on the control effect of official information was analyzed by changing the initial direct immunization rate $\varepsilon(0)$, as shown in Table 6. The simulation results are shown in Figure 6, where the axes and legend are the same as in Figure 4. Figure 6 shows that the initial direct immunization rate $\varepsilon(0)$ is reduced. After the delay $T$, the proportion of official infected nodes in the network shows a wave pattern where the peak value decreases with each cycle and eventually stabilizes. The proportion of false infected nodes in the network is gradually reduced but appears repeatedly until the final stabilization. Thus, the direct immunization rate $\varepsilon(0)$ has a significant influence on the guidance effect of the official information on the public opinion network. An insufficient initial direct immunization rate $\varepsilon(0)$ will greatly weaken the control effect of the official information, allowing the reappearance of false infected nodes in the network and reducing the guiding role of the official messages and prolonging the time for the release of public opinion.

*6.3.3. Effect of Latent Immunization Rate η on the Control Effect of Official Information.* The influence of the latent immunization rate $\eta$ on the control effect of the official information was analyzed by changing the initial latent immunization rate $\eta(0)$, as shown in Table 7. The simulation results are shown in Figure 7, where the axes and legend are the same as in Figure 4. Figure 7 shows that reducing the initial latent immune rate $\eta(0)$ reduces the rate of decrease in latent nodes in the network but has little effect on the

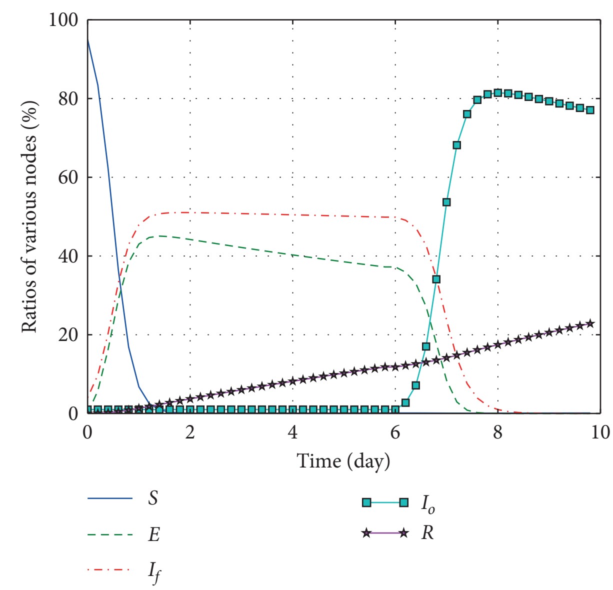


Figure 5: Effect of delay $T$ on control effect.

Table 6: Initial direct immunization rate $\varepsilon(0)$.

| Initial direct ]immunization rate | Initial direct immunization rate after change |
|---|---|
| $\varepsilon(0)$ | $\varepsilon\prime(0)$ |
| 0.6 | 0.001 |

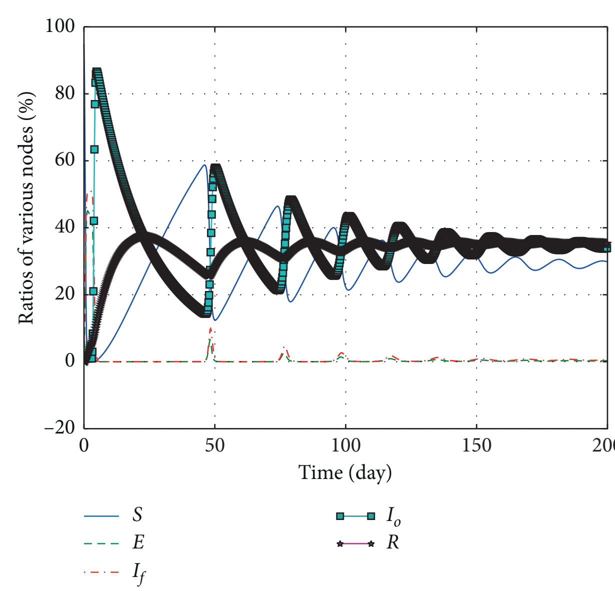


Figure 6: Effect of initial direct immunization rate on control effect.

Table 7: Initial latent immunization rate $\eta(0)$.

| Initial latent immunization rate | Initial latent immunization rate after change |
|---|---|
| $\eta(0)$ | $\eta\prime(0)$ |
| 0.4 | 0.001 |

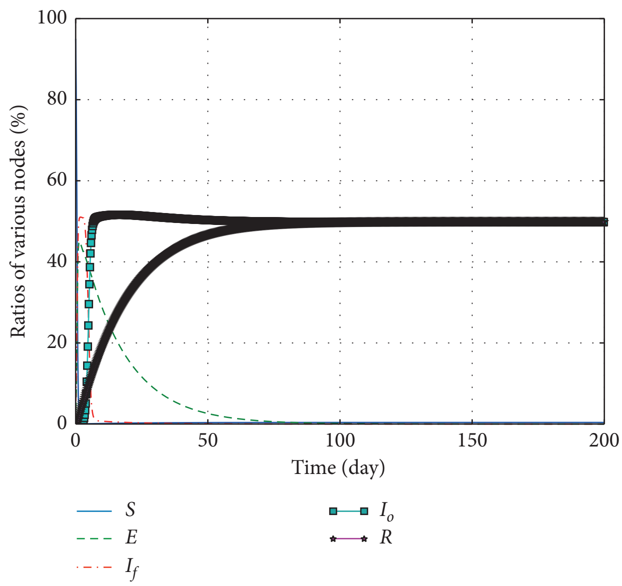


Figure 7: Effect of initial latent immunization rate on control effect.

Table 8: Initial infection immunization rate $\theta(0)$.

| Initial infection immunization rate | Initial infection immunization rate after change |
|---|---|
| $\theta(0)$ | $\theta'(0)$ |
| 0.2 | 0.001 |

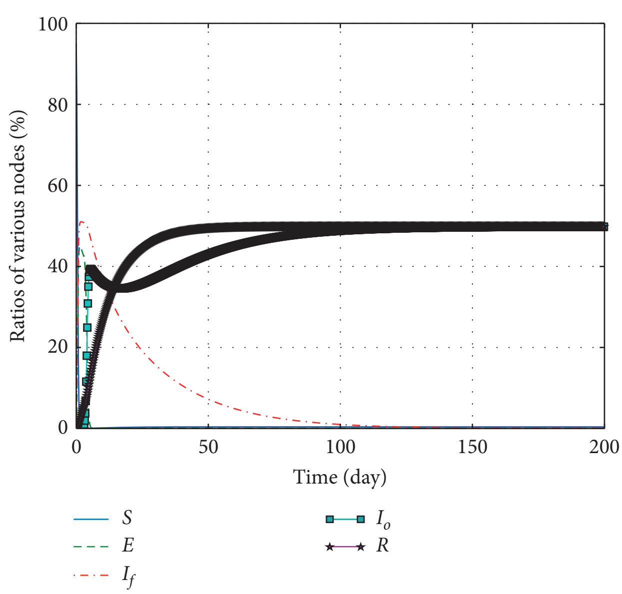


Figure 8: Effect of initial infection immunization rate on control effect.

speed at which false infected nodes disappear during information propagation. Therefore, the initial latent immunization rate $\eta(0)$ can increase the time required for the network to reach equilibrium and reduce the efficiency of information guidance.

*6.3.4. Effect of Infection Immunization Rate $\theta$ on the Control Effect of Official Information.* The influence of the infection immunization rate $\theta$ on the control effect of the official information was analyzed by changing the initial infection immunization rate $\theta(0)$, as shown in Table 8. The simulation results are shown in Figure 8, where the axes and legend are the same as in Figure 4. Figure 8 shows that reducing the initial infection immunity rate $\theta(0)$ seriously reduces the speed at which false infected nodes disappear during the information dissemination process. Thus, although the infection immunization rate does not cause false infected nodes to reappear in the network, the infection immunization rate increases the difficulty of guiding the information propagation direction. Therefore, the infection immunization rate $\theta$ has a significant influence on the guidance effect of the official information on the public opinion network, with a low initial direct immunization rate $\varepsilon(0)$ weakening the control effect and allowing false infected nodes to persist in the network for a longer period of time.

## 7. Conclusions

This paper proposed a model that considered the characteristics of time delay, latency, and conversion in the process of information dissemination, with official information inputs. The direct immunization rate, latent immunization rate, and infection immunization rate of the OI-SEIR model were derived according to the node attitude value. We selected a salient news topic on Weibo as a practical case to verify the proposed model by simulation. The simulation results showed the control effect of official information on public opinion transmission as predicted by the OI-SEIR model and demonstrated that the direct, latent, and infection immunization rates affect the guidance effect of official information, with the direct immunization rate having the greatest impact, followed by the infection immunization rate and then the latent immunization rate. The research work in this paper demonstrates the important role of official information in guiding public opinion, and the research on the effects of different types of immunization rates can elucidate information dissemination behavior in complex networks and improve the efficiency of information guidance.

## Data Availability

No data were used to support this study.

## Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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