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## Effects of official information and rumor on resource-epidemic coevolution dynamics

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### ABSTRACT

Epidemic-related information and resources have proven to have a significant impact on the spread of the epidemic during the Corona Virus Disease 2019 (COVID-19) pandemic. The various orientation role of information has different effects on the epidemic spreading process, which will affect the individual awareness of resources allocation and epidemic spreading scale. Based on this, a three-layer network is established to describe the dynamic coevolution process among information dissemination, resource allocation, and epidemic spreading. In order to analyze dynamic coevolution process, the microscopic Markov chain (MMC) theory is used. Then, the threshold of epidemic spreading is deduced. Our results indicated that the official information orientation intensity inhibits the epidemics spreading, while rumor orientation intensity promotes epidemic spreading. At the same time, the efficiency of resource utilization restrains the expansion of the infection scale. The two kinds of information are combined with resources respectively. Official information will enhance the inhibitory effect of resources epidemics spreading, while rumor will do the opposite.

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### 1. Introduction

The outbreak of epidemic poses a great threat to the survival of human beings (Varela-Santos and Melin, 2021; Ouyang et al., 2021; Brodeur et al., 2021; Mieczkowska et al., 2021). Take the COVID-19 outbreak, for example, which is causing many problems for economic development, politics, education and people's lives around the world (Nicola et al., 2020; McKibbin and Fernando, 2021; Shi et al., 2021). In order to reduce human losses, we must make a detailed analysis of the spreading mechanism of epidemics.

For a long time, the spreading of epidemics has always been an important subject of research. In 1927, Kermack and Mckendrick established the classical Susceptible Infected Recovered Model (SIR) for the first time, and obtained the threshold theory of epidemic spreading (Ruan, 2020). Many studies of epidemic spreading have been conducted on the classical model. At the end of the 20th century, the discovery of small world network and scale-free net-

work ushered a new era for the study of epidemic spreading (Watts and Strogatz, 1998; Barabási and Albert, 1999). Pastor-Satorras and Vespignani studied the spread of diseases by using complex methods networks earlier (Pastor-Satorras and Vespignani, 2001). The epidemic studies based on complex networks has become a hot topic. Tafreshi and Danziger et al. studied the propagation process of two diseases in multi-layer networks (Azimi-Tafreshi, 2016; Danziger et al., 2019). In order to study the relationship between COVID-19 and large-scale migration in China, Song et al. (Song et al., 2020) constructed a scale-free network with the selected cities as the nodes and found that regional migration can have an impact on the spread of epidemics. By improving Gillespie algorithm, Cota et.al (Cota and Ferreira, 2017) solved the problem of low efficiency of Markov process numerical simulation in classical epidemics spreading model under highly heterogeneous and large network structure. Recently, Mo et al. (Mo et al., 2021) mainly started from public transportation network, believing that public transportation network is the medium of disease spreading. They established time-varying weighted public transit (PT) encounter networks, and they found that shutting down some transportation routes would effectively control the spread of the epidemics.

Researchers of various disciplines are working on how to effectively contain the development of epidemics (Wan et al., 2008; Antulov-Fantulin et al., 2013; Li et al., 2020; Vhatkar and Bhole,

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2022; Nie et al., 2022). Among them, the allocation of resources is the most important way to effectively slow down the spreading of epidemics (Zhao et al., 2019; Preciado et al., 2013; Watkins et al., 2018; Emanuel et al., 2020). For example, in terms of optimal deployment of limited resources, Lokhov et al. (Lokhov and Saad, 2017) settled this problem according to the interaction between network topology and diffusion dynamics. Nowzari et al. (Nowzari et al., 2015) found the disease-free equilibrium point and proposed two solutions to allocation problems with cost budget as constraints. Chen et al. (Chen et al., 2018) mainly considered the influence of social support on the two-layer network composed of social network and connection network. The infection density will undergo mixed phase transition with the support of social resources. After that, they found that global resource allocation had a better inhibitory effect on epidemic spreading (Chen et al., 2019). More resources need to be allocated to hardest-hit areas, and medical resources needed by critically ill patients and health care workers should be given priority (Francis, 2004), which leads to a dynamic process of resource supply. Besides, Bottcher (Böttcher et al., 2015) considered from the perspective of individual disease recovery costs, and found that the uncontrolled spread of disease resulted from the condition that the recovery costs were higher than the key costs.

In addition to resources, information plays an important role and is a factor we cannot ignore in the epidemic spreading. Individuals are very sensitive to information about disease. When they learn about disease information through social media or social network, they will immediately take measures to protect themselves (Sahneh et al., 2012; Verelst et al., 2016; Wang et al., 2021; Zhang et al., 2014; Wang et al., 2015; Zheng et al., 2018; Wang et al., 2019; Pan et al., 2020). Granell et al. (Granell et al., 2013) found that the topology of physical contact network and information dissemination determine the threshold of infectious disease by establishing a multi-layer network model of information and epidemic coupling. Funk et al. (Funk et al., 2009) combined individual awareness with epidemic spreading through a complex network; and found that awareness can hinder the spread of epidemic to some extent; and the spread of awareness has no influence on the critical point of epidemic spreading. Xia et al. (Xia et al., 2019) proposed a coupled two-layer network of epidemic and awareness; and confirmed that awareness related to epidemic can affect the threshold of epidemic spreading. Many studies on information dissemination based on complex networks emerge endlessly (Wang et al., 2021; Huang et al., 2021). Wang et al. (Wang et al., 2021) established a three-layer network model to describe the co-evolution of information; resources and epidemic. They found that information with different recovery rates had different effects on the epidemic spreading. Ye et al. (Ye et al., 2020) proposed a three-layer network to study disease transmission by combining information transmission; behavior change and disease transmission. Their findings suggest that the ability of the media and opinion leaders to spread information should be given equal importance to the ability of disease transmission. Sanchez et al. (Sanchez et al., 2022) constructed two scenario models of July 2020 and August 2020 by using a three-layer network. They looked at the impact of the Hammer and Dance strategy on the spread of COVID-19 in Costa Rica. Their study found that lifting restrictions on population movement after less than three weeks of epidemiological isolation would lead to a sharp increase in cases in July 2020; the results of the August 2020 scenario study showed that the Hammer and Dance strategy would only work for 50 % of the population with movement restrictions.

Information orientation affects individuals' attitudes towards epidemic and the act of preventing epidemics. Especially, in a public health emergency, information orientation role is crucial. And official information issued by an authority usually brings the right

information and values to the public and guides the public's consciousness in the right direction (Zhang et al., 2021). While rumors are generally unconfirmed and obscure sources, and often throw the public into a panic (Bavel et al., 2020). Obviously, the two kinds of information bring totally different orientation role to society. Meanwhile, individual resource allocation behavior will also be different under the effect of two opposite orientations. Individuals who know the official information will form a correct awareness of epidemic prevention and actively respond to the call of the official information to donate resources to the infected, while those who know the rumor will snatch resources because of the panic or false epidemic prevention information contained in the rumor. We build a three-layer network model to describe the dynamic development process of information, resources and epidemics, and study the influence of information and resources on epidemic spreading in the dynamic coevolution process of multi-layer networks.

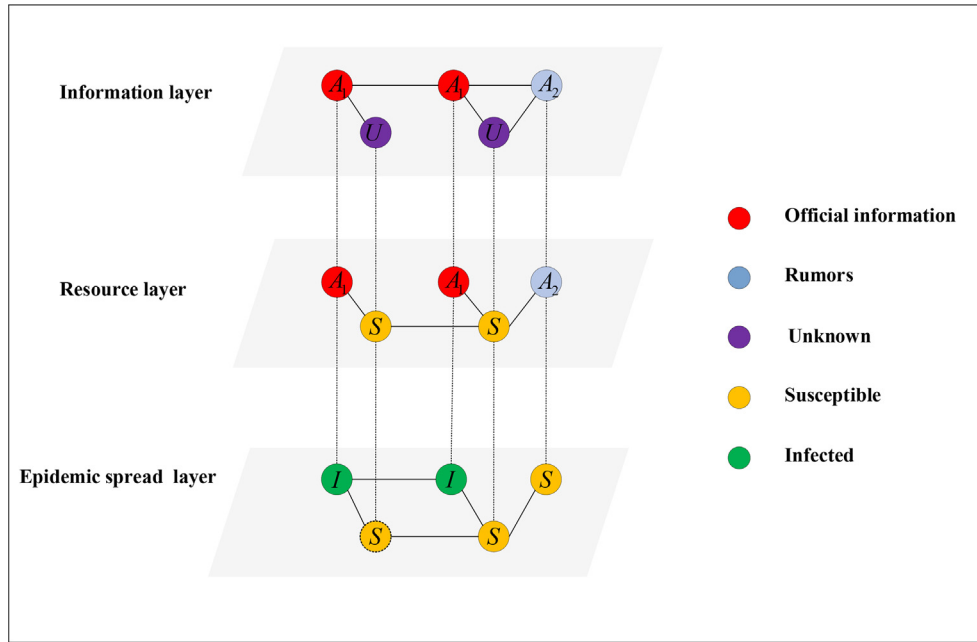
The rest of the paper is structured as follows. In the next section, we will build a three-layer dynamic propagation model, describing in detail the interaction of information, resources, epidemics, and model assumptions. In the third section, we use microscopic Markov chain (MMC) to carry out theoretical analysis on the model. According to the analysis results, numerical simulation is carried out in the fourth section, and conclusions are drawn in the fifth section.

## 2. Information-resource-epidemic coevolution model

During the COVID-19 outbreak, a lot of information about epidemic disseminate far and wide faster. People acquire and disseminate the information through various network media channels, such as Weibo, WeChat, Facebook, Twitter, etc. Some rumors have spread widely. For example, alcohol and high temperatures can kill novel coronavirus, a city has been locked down due to a massive outbreak of COVID-19, antibiotics can effectively protect against viruses, and so on. Rumors of epidemics always cause panic among the masses, and lead to a mass scramble for liquor, drug, masks and other resources, making it more difficult to fight the epidemic. There is also some official information to guide the public in effective epidemic prevention. For example, epidemiologists spread knowledge about effective prevention, authorities released the latest information on the epidemic, and so on. Therefore, we divide information into official information and rumor according to different orientation role to the public. The different orientation role of information has different effect on the actual epidemic spreading process, which will affect the individual allocation of resources and epidemic spreading intensity. As a result, we constructed a multi-layer network to depict the relationship between the allocation of medical resources and the epidemic spreading under the dissemination of official information and rumors. From top to bottom, it's the information layer, the resource layer, and the epidemic layer respectively. Fig. 1 depicts the interaction between information dissemination, resource allocation, and epidemic spreading. There are  $N$  nodes in the system. And there is a one-to-one correspondence between nodes at each layer, and the three-layer network is undirected and unweighted.

### 2.1. Model Assumptions

**Assumptions 1:** After the outbreak of an epidemic, all kinds of information disseminate online. We divide the information into official information and rumors. Individuals can choose to forget the current information state whether they know official information or rumors. Therefore, we adopt unaware-aware-unaware (UAU) communication model to describe the state transition of



**Fig. 1.** Three layers network interaction model. It shows a model diagram of the information-resource-epidemic common transformation. In the model diagram, there are two kinds of information  $A_1, A_2$  in the top layer; individuals will donate or grab, or will not take any action on resources in the middle layer; the bottom layer is the epidemic spreading layer, which contains and two states. The dashed lines above and below represent one-to-one correspondence between nodes on the network.

two kinds of information. The status of the individual who knows neither of the two kinds of information is  $U$ , the status of the individual who knows the official information is  $A_1$ , and the status of the individual who knows the rumor is  $A_2$ . The individuals who do not know any information convert to the state  $A_1$  or  $A_2$  with probability  $\lambda_1, \lambda_2$ , respectively. The individuals who know the official information or rumors ignore current information with probability  $\delta_1, \delta_2$ , and maintain the original information state with probability  $1 - \delta_1, 1 - \delta_2$ , respectively.

**Assumptions 2:** In the course of an epidemic, there is still a possibility of infection after recovery, so the classical Susceptible Infected Susceptible Model (SIS) was established to depict the infection and recovery process of individuals on the network. In the epidemic layer, the status of the susceptible is  $S$ , and that of the infected is  $I$ . Epidemic spreading rates are different under two opposite orientation role information. The epidemic spreading rate for individuals who don't know the two kinds of information is  $\beta^U$  ( $0 < \beta^U \leq 1$ ). If susceptible individuals get official information, individuals may be infected with probability  $\beta^{A_1}$  ( $0 < \beta^{A_1} < 1$ ). If the susceptible individual gets the rumor, the individual may be infected with probability  $\beta^{A_2}$  ( $0 < \beta^{A_2} < 1$ ). The infected recovers with probability  $\mu$ .

**Assumptions 3:** We believe that susceptible individuals are producers and creators of resources. Large manufacturing facilities stop production immediately if an infected person is found. Therefore, only susceptible people are producers of resources, and only susceptible people can transfer goods. During the outbreak of an epidemic, information about the epidemic is pouring in. Under different information, individuals have different attitudes towards resources. In some countries, during the spread of the coronavirus, susceptible individuals have actively contributed to the fight against the pandemic, with official information calling on them to volunteer to help infected people regain their health. At the same time, they actively donate some medical resources, such as medical masks, protective clothing, drugs and so on. Under the influence of rumors, individuals will easily panic and then frantically buy resources to increase the security of their health. For

example, after the nuclear leak in Japan in 2011, rumors about whether "eating salt will prevent radiation" or "determination radiation of Sea salt" were spread widely in some countries near Japan. As a result, people in the country panicked and began to grab salt frantically. Based on these facts, the way for an individual to obtain resources is from susceptible individuals around him. In the meantime, under the impact of two opposite information dissemination, individuals who know the official information will donate resources to the infected if they receive official information guidance and form a correct awareness of epidemic prevention, while individuals who know the rumors receive incorrect epidemic prevention information and panic information will grab resources. A large amount of resources (such as necessary drugs and protective items) are needed in the recovery process of an infected person. If there is a lack of resources, the recovery period of the infected person will be longer, and the possibility of recovery may be reduced due to insufficient resources. Thus, the amount of resources received by infected is one of the crucial factors for recovery.

**Assumptions 4:** In general, there are a total of 6 possible states  $US, UI, A_1S, A_1I, A_2S$  and  $A_2I$ . When an individual is infected, the individual will receive any information about the epidemic. The infected is not ignorant. So  $UI$  is converted to either  $A_1I$  or  $A_2I$  with probability 1. However, the infected will only trust credible official information to help them recover as quickly as possible. Thus,  $A_2I$  is excluded from the model. The infected who knows the official information ( $A_1I$ ) is converted to  $UI$  with probability  $\delta_1$  forgetting the official information. Moreover, susceptible individuals tend to forget information about the epidemic,  $A_1S$  and  $A_2S$  may forget information with probabilities of  $\delta_1$  and  $\delta_2$ , respectively. Furthermore, the infected don't forget the official information before they recover. We use  $\rho^{A_1S}, \rho^{A_2S}, \rho^{A_1I}, \rho^{US}$  to represent the density in these four states respectively.

**Assumptions 5:** Official information usually brings correct orientation effect to the public. With the strengthening of official information orientation, the public will carry out effective epidemic prevention and raise their vigilance, which is conducive to

epidemic prevention and control and slowing down the spreading of epidemic. We set  $\eta_1 (0 < \eta_1 \leq 1)$  to describe official information orientation intensity. The individual knows the official information may be infected with probability  $\beta^{A_1}$ :

$$\beta^{A_1} = \eta_1 \beta^U \quad (1)$$

Rumor is contrary to the orientation effect of official information. Rumor usually brings incorrect orientation effect and panic to the public. With the strengthening of rumor orientation, the public will wrongly judge the epidemic prevention measures brought and form incorrect awareness of epidemic prevention, which is not conducive to epidemic prevention and control. We set  $\eta_2$  to describe rumor orientation intensity. Where,  $\eta_{\max}$  is the maximum that  $\eta_2$  can take. The individual who knows the rumor may be infected with probability  $\beta^{A_2}$ :

$$\beta^{A_2} = \eta_2 \beta^U, \eta_2 \in [1, \eta_{\max}] \quad (2)$$

According to  $\beta^{A_1} = \eta_1 \beta^U$  and  $\beta^{A_2} = \eta_2 \beta^U$ , we can get:  $\beta^{A_1} \leq \beta^U \leq \beta^{A_2}$ .

**Assumptions 6:** In the process of the recovery of infected individuals, a large number of resources are needed. We need to consider the relationship between the use of individual resources and the recovery rate, as well as the effectiveness of resources on the recovery of individual infections. Therefore, the utility of resources and difficulty of epidemic recovery should be took into account in the recovery rate. The infected recovers with probability  $\mu$ :

$$\mu = 1 - \mu_0(1 - \varepsilon)^{R_j(t)}, 0 < \mu_0 < 1, 0 < \varepsilon < 1 \quad (3)$$

Where,  $\mu_0$  is difficulty of epidemic recovery, and  $\varepsilon$  is efficiency of the resources in the recovery process, which is called resource utilization efficiency.  $R_j(t)$  is the amount of resources that individual  $j$  gets at time  $t$ [45]. The definition of parameters are shown in Table 1.

### 3. Theoretical analysis

We use microscopic Markov chain (MMC) theory to analyze the dynamic coupling diffusion dynamics of three-layer networks. In the top-level information layer, both kinds of information are transmitted according to unaware-aware-unaware (UAU) information transmission mode. In the information layer, if there is a con-

nection between individual  $i$  and  $j$ , then there is  $a_{ij} = 1$ , otherwise  $a_{ij} = 0$ . Finally, an adjacency matrix  $A = [a_{ij}]$  is formed. Similarly, we represent the matrix  $B$  as the connection matrix between the resource layer and the epidemic layer, if there is physical contact between individual  $i$  and  $j$ , then there is  $b_{ij} = 1$ ; otherwise,  $b_{ij} = 0$ . Where, the average degree of information layer and epidemic spreading layer is respectively  $\langle k_1 \rangle, \langle k_2 \rangle$ . Both the information layer network and the epidemics spreading network are homogenous networks, and the average degrees are respectively  $\langle k_1 \rangle, \langle k_2 \rangle$ .

Individuals obtain resources from susceptible neighbors at the resource layer. For individual  $i$  in the  $A_1I$  state, he or she can obtain resources from susceptible neighbors, and the denominator on the right indicates that susceptible individual  $J$  allocates resources to himself, himself, and other aware neighbors. For individual  $i$  in state  $A_1S$  or  $A_2S$  state, the resource quantity consists of two parts: the amount of resource received from the susceptible neighbors, and the amount of resource remaining after allocating a unit of resource to every other susceptible individuals. In particular, an individual in the  $A_1S$  will donate  $\phi$  times his or her own resources to an individual in the  $A_1I$ . For individual  $i$  in  $US$  state, the resource amount is the amount remaining after allocating one unit of resources to other aware neighbors. At time step  $t$ , the resource calculation method of individual  $i$  in different states is as follows:

$$GR_i^{A_1I}(t) = (1 + \phi) \sum_j b_{ij} \rho_j^S(t) \frac{1}{\sum_{l \neq i} b_{jl} \rho_l^A(t) + 2} \quad (4)$$

$$R_i^{A_1S}(t) = \sum_j b_{ij} \rho_j^S(t) \frac{1}{\sum_{l \neq i} b_{jl} \rho_l^A(t) + 2} - \phi R_i^{A_1I}(t) \quad (5)$$

$$R_i^{A_2S}(t) = \frac{1}{\sum_j b_{ij} \rho_j^{A_2}(t) + 1} + \sum_j b_{ij} \rho_j^S(t) \frac{1}{\sum_{l \neq i} b_{jl} \rho_l^A(t) + 2} \quad (6)$$

$$R_i^{US}(t) = \frac{1}{\sum_j b_{ij} \rho_j^A(t) + 1} \quad (7)$$

We have completed resource allocation in resource layer. At time step  $t$ , if individual  $i$  is unaware of the existence of epidemic, then the probability that this person is not infected by any neighbor with an infectious disease is defined as  $q_i^U(t)$ ; otherwise, the probabilities that individual  $i$  will not be infected by any infective neighbors are expressed as  $q_i^{A_1}(t)$  or  $q_i^{A_2}(t)$ , when being aware of official information or rumors at time step  $t$ , respectively. The probability of individual  $i$  not being notified by any known official information or rumors neighbor is  $r_i^{A_1}$  or  $r_i^{A_2}$ . At time- $t$ ,  $q_i^U(t), q_i^{A_1}(t), q_i^{A_2}(t), r_i^{A_1}(t)$  and  $r_i^{A_2}(t)$  can be described by the following:

$$r_i^{A_1}(t) = \prod_j [1 - a_{ji} \rho_j^{A_1}(t) \lambda_1] \quad (8)$$

$$r_i^{A_2}(t) = \prod_j [1 - a_{ji} \rho_j^{A_2}(t) \lambda_2] \quad (9)$$

$$q_i^{A_1}(t) = \prod_j [1 - b_{ji} \rho_j^{A_1I} \beta^{A_1} e^{R_i^{A_1S}(t)}] \quad (10)$$

$$q_i^{A_2}(t) = \prod_j [1 - b_{ji} \rho_j^{A_1I} \beta^{A_2} e^{R_i^{A_2S}(t)}] \quad (11)$$

$$q_i^U(t) = \prod_j [1 - b_{ji} \rho_j^{AI}(t) \beta^U] \quad (12)$$

**Table 1**  
Definition of parameters.

Parameter	Definition
$N$	Number of nodes in the network
$\lambda_1$	The probability that an individual who does not know anything converts to knowing official information
$\lambda_2$	The probability that an individual who does not know anything converts to knowing rumor
$\delta_1$	The probability of an individual forgetting or ignoring official information
$\delta_2$	The probability of an individual forgetting or ignoring rumor
$\eta_1$	The intensity of official information orientation
$\eta_2$	The intensity of rumor orientation
$\eta_{\max}$	The maximum value that $\beta^U$ can reach in the interval $[0,1]$
$\beta^U$	The probability that an individual who doesn't know either information will be infected
$\beta^{A_1}$	The probability that an individual who knows official information will become infected
$\beta^{A_2}$	The probability that an individual who knows the rumor will get infected
$\mu$	Recovery rate of the infected
$\mu_0$	the infected recovery difficulty
$\varepsilon$	efficiency of the resources in the recovery process



According to Fig. 2, the densities of the four states at time  $t + 1$  can be obtained:

$$\begin{aligned} \rho_i^{A_1 I}(t+1) &= \rho_i^{US}(t)r^{A_1}r^{A_2}(1-q^U) + \rho_i^{US}(t)(1-r^{A_2})(1-q^{A_2}) \\ &+ \rho_i^{US}(t)[1-r^{A_1} - (1-r^{A_1})(1-r^{A_2})](1-q^{A_1}) \\ &+ \rho_i^{A_1 I}(t)\{\delta_1(1-\mu) + (1-\delta_1)(1-\mu)\} \\ &+ \rho_i^{A_2 S}(t)\{\delta_2(1-q^U) + (1-\delta_2)(1-q^{A_2})\} \\ &+ \rho_i^{A_1 S}(t)\{\delta_1(1-q^U) + (1-\delta_1)(1-q^{A_1})\} \end{aligned} \quad (13)$$

$$\begin{aligned} \rho_i^{A_1 S}(t+1) &= \rho_i^{US}(t)\{1-r^{A_1} - (1-r^{A_1})(1-r^{A_2})\}q^{A_1} \\ &+ \rho_i^{A_1 S}(t)(1-\delta_1)q^{A_1} + \rho_i^{A_1 I}(t)(1-\delta_1)\mu \end{aligned} \quad (14)$$

$$\rho_i^{A_2 S}(t+1) = \rho_i^{A_2 S}(t)(1-\delta_2)q^{A_2} + \rho_i^{US}(t)(1-r^{A_2})q^{A_2} \quad (15)$$

$$\begin{aligned} \rho_i^{US}(t+1) &= \rho_i^{A_1 S}(t)\delta_1q^U + \rho_i^{A_1 I}(t)\delta_1\mu + \rho_i^{A_2 S}(t)\delta_2q^U \\ &+ \rho_i^{US}(t)r^{A_1}r^{A_2}q^U \end{aligned} \quad (16)$$

If the densities of the four states at  $t + 1$  do not change significantly attr, it shows that the multi-layer network system is stable.

$$\rho_i^{A_1 I}(t+1) = \rho_i^{A_1 I}(t) = \rho_i^{A_1 I}\rho_i^{A_2 S}(t+1) = \rho_i^{A_2 S}(t) = \rho_i^{A_2 S} \quad (17)$$

$$\rho_i^{US}(t+1) = \rho_i^{US}(t) = \rho_i^{US}, \rho_i^{A_1 S}(t+1) = \rho_i^{A_1 S}(t) = \rho_i^{A_1 S} \quad (17)$$

Meanwhile,

$$\rho^{A_2 S} \approx \rho^{A_2}\rho^{A_1 S} + \rho^{A_1 I} \approx \rho^{A_1}\rho^{US} = 1 - \rho^{A_1} - \rho^{A_2} \quad (18)$$

For the epidemic model of SIS, if  $\beta^U > \beta_c^U$ , infectious epidemics will continue to spread and persist for a long time; otherwise, the infection will disappear quickly. Therefore, it can be assumed that  $\rho_i^{A_1 I} = \theta_i \ll 1$ . According to (10), (11) and (12), higher-order terms can be ignored and the following approximations can be obtained:

$$q_i^{A_1}(t) = 1 - \beta^{A_1} \varepsilon_i^{R^{A_1 S}(t)} \sum_j b_{ij} \theta_j \quad (19)$$

$$q_i^{A_2}(t) = 1 - \beta^{A_2} \varepsilon_i^{R^{A_2 S}(t)} \sum_j b_{ij} \theta_j \quad (20)$$

$$q_i^U(t) = 1 - \beta^U \sum_j b_{ij} \theta_j \quad (21)$$

To simplify the formula (19)-(21), let

$$\alpha_i^{A_1} = \beta^{A_1} \varepsilon_i^{R^{A_1 S}(t)} \sum_j b_{ij} \theta_j \quad (22)$$

$$\alpha_i^{A_2} = \beta^{A_2} \varepsilon_i^{R^{A_2 S}(t)} \sum_j b_{ij} \theta_j \quad (23)$$

$$\alpha_i^U = \beta^U \sum_j b_{ij} \theta_j \quad (24)$$

Substitute formula (22)-(23) into formula (19), (20), and (21) to obtain:

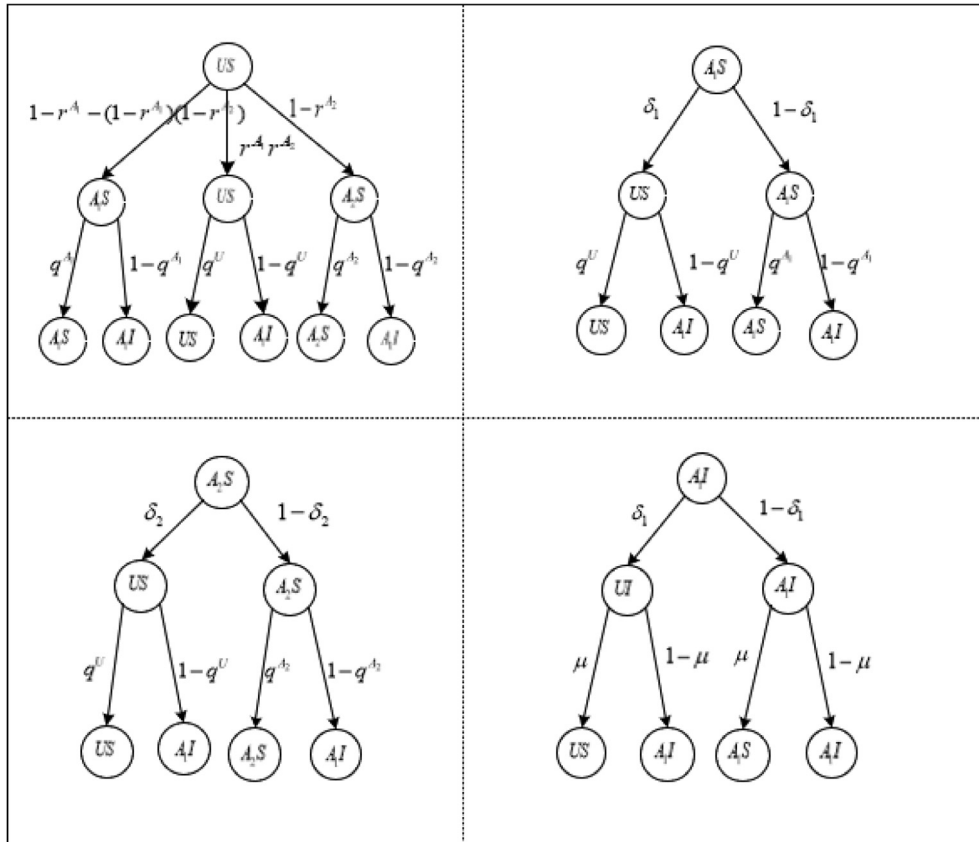


Fig. 2. Probability tree of four state changes. The individual state is first affected by the information layer and forgets the official information with a probability of  $\delta_1$ , with the probability of  $\delta_2$  forget rumors; the probability that  $i$  is not notified by any neighbor that knows  $A_1$  is  $r_i^{A_1}$ , the probability of not being notified by any neighbor who knows  $A_2$  is  $r_i^{A_2}$ ; in the epidemic layer, it is affected by the resources possessed by the individual. The individual knows official information, knows rumors or does not know two kinds of information, the probability of not being infected are  $q_i^{A_1}$ ,  $q_i^{A_2}$ , and  $q_i^U$  respectively.

$$\begin{aligned} \rho_i^{A_1 I} &= \rho_i^{A_1 S} \left\{ \delta_1 \alpha_i^U + (1 - \delta_1) \alpha_i^{A_1} \right\} + \rho_i^{A_1 I} (1 - \mu) + \rho_i^{A_2 S} \left\{ \delta_2 \alpha_i^U + (1 - \delta_2) \alpha_i^{A_2} \right\} \\ &\quad + \rho_i^{US} \left\{ r^{A_1} r^{A_2} \alpha_i^U + (r^{A_2} - r^{A_1} r^{A_2}) \alpha_i^{A_1} + (1 - r^{A_2}) \alpha_i^{A_2} \right\} \end{aligned} \quad (25)$$

$$\begin{aligned} \rho_i^{A_1 S} &= \rho_i^{A_1 S} (1 - \delta_1) (1 - \alpha_i^{A_1}) + \rho_i^{A_1 I} (1 - \delta_1) \mu + \rho_i^{US} (r^{A_2} \\ &\quad - r^{A_1} r^{A_2}) (1 - \alpha_i^{A_1}) \end{aligned} \quad (26)$$

$$\rho_i^{A_2 S} = \rho_i^{A_2 S} (1 - \delta_2) (1 - \alpha_i^{A_2}) + \rho_i^{US} (1 - r^{A_2}) (1 - \alpha_i^{A_2}) \quad (27)$$

$$\begin{aligned} \rho_i^{US} &= \rho_i^{A_1 S} \delta_1 (1 - \alpha_i^U) + \rho_i^{A_1 I} \delta_1 \mu + \rho_i^{A_2 S} \delta_2 (1 - \alpha_i^U) \\ &\quad + \rho_i^{US} r^{A_1} r^{A_2} (1 - \alpha_i^U) \end{aligned} \quad (28)$$

By ignoring the higher-order terms of formula (26), (27) and (28), it can be obtained:

$$\rho_i^{A_1 S} = \rho_i^{A_1 S} (1 - \delta_1) + \rho_i^{US} (r^{A_2} - r^{A_1} r^{A_2}) \quad (29)$$

$$\rho_i^{A_2 S} = \rho_i^{A_2 S} (1 - \delta_2) + \rho_i^{US} (1 - r^{A_2}) \quad (30)$$

$$\rho_i^{US} = \rho_i^{A_1 S} \delta_1 + \rho_i^{A_2 S} \delta_2 + \rho_i^{US} r^{A_1} r^{A_2} \quad (31)$$

Substitute formula (29), (30) and (31) into formula (25) to obtain:

$$\begin{aligned} \theta_i &= \rho_i^{A_1 S} \left\{ \delta_1 \alpha_i^U + (1 - \delta_1) \alpha_i^{A_1} \right\} + \theta_i (1 - \mu) + \rho_i^{A_2 S} \left\{ \delta_2 \alpha_i^U + (1 - \delta_2) \alpha_i^{A_2} \right\} \\ &\quad + \rho_i^{US} \left\{ r^{A_1} r^{A_2} \alpha_i^U + (r^{A_2} - r^{A_1} r^{A_2}) \alpha_i^{A_1} + (1 - r^{A_2}) \alpha_i^{A_2} \right\} \end{aligned} \quad (32)$$

$$\mu \theta_i = \rho_i^{US} \alpha_i^U + \rho_i^{A_1 S} \alpha_i^{A_1} + \rho_i^{A_2 S} \alpha_i^{A_2} \quad (33)$$

Substituting formula (18), formula (22)-(24), formula (1)-(2) to formula (33) can be written as:

$$\begin{aligned} \mu \theta_i &= (1 - \rho_i^{A_1} - \rho_i^{A_2}) \beta^U \sum b_{ij} \theta_j + \rho_i^{A_1} \eta_1 \beta^U \varepsilon^{R_i^{A_1 S}} \sum b_{ij} \theta_j \\ &\quad + \rho_i^{A_2} \eta_2 \beta^U \varepsilon^{R_i^{A_2 S}} \sum b_{ij} \theta_j \end{aligned} \quad (34)$$

$$\mu \theta_i = \beta^U \left\{ (1 - \rho_i^{A_1} - \rho_i^{A_2}) + \rho_i^{A_1} \eta_1 \varepsilon^{R_i^{A_1 S}} + \rho_i^{A_2} \eta_2 \varepsilon^{R_i^{A_2 S}} \right\} \sum b_{ij} \theta_j \quad (35)$$

$$\sum_j \left\{ \left[ 1 - (1 - \eta_1 \varepsilon^{R_i^{A_1 S}}) \rho_i^{A_1} - (1 - \eta_2 \varepsilon^{R_i^{A_2 S}}) \rho_i^{A_2} \right] b_{ji} - \frac{\mu}{\beta^U} \right\} \theta_j = 0 \quad (36)$$

Leth<sub>ji</sub> = [1 - (1 - η<sub>1</sub>ε<sup>R<sub>i</sub><sup>A<sub>1</sub>S</sup>)ρ<sub>i</sub><sup>A<sub>1</sub></sup> - (1 - η<sub>2</sub>ε<sup>R<sub>i</sub><sup>A<sub>2</sub>S</sup>)ρ<sub>i</sub><sup>A<sub>2</sub></sup>]b<sub>ji</sub>, we can set H matrix,</sup></sup>

$$H = \left[ 1 - (1 - \eta_1 \varepsilon^{R_i^{A_1 S}}) \rho_i^{A_1} - (1 - \eta_2 \varepsilon^{R_i^{A_2 S}}) \rho_i^{A_2} \right] B \quad (37)$$

$$\beta_c^U = \frac{\mu}{\Lambda_{\max}(H)} \quad (38)$$

$$\beta_c^U = \frac{1 - \mu_0 (1 - \varepsilon)^{R_i^{A_1}}}{\left[ 1 - (1 - \eta_1 \varepsilon^{R_i^{A_1 S}}) \rho_i^{A_1} - (1 - \eta_2 \varepsilon^{R_i^{A_2 S}}) \rho_i^{A_2} \right] \Lambda_{\max}(B)} \quad (39)$$

where the maximum eigenvalues of H and B are Λ<sub>max</sub>(H) and Λ<sub>max</sub>(B) separately, and Λ<sub>max</sub>(H) = Λ<sub>max</sub>(B) ≈ < k<sub>2</sub> >.

$$\beta_c^U = \frac{1 - \mu_0 (1 - \varepsilon)^{R_i^{A_1}}}{\left[ 1 - (1 - \eta_1 \varepsilon^{R_i^{A_1 S}}) \rho_i^{A_1} - (1 - \eta_2 \varepsilon^{R_i^{A_2 S}}) \rho_i^{A_2} \right] \langle k_2 \rangle} \quad (40)$$

#### 4. Model simulation

A multi-layer dynamic propagation model is established under scale-free network, and the model is analyzed by using MMC theory. In the coevolution process of simulation, we consider the interrelationships among information, resources and epidemic, and explain the role of information dissemination and resource allocation in the spreading of epidemics. 2000 nodes were used for numerical simulation, and the information layer and the epidemic layer were homogeneous networks with an average degree of <k<sub>1</sub>> = 6, <k<sub>2</sub>> = 3 respectively. The output results of each simulation were averaged over 50 iterations.

We studied the relationship between resource utilization efficiency and infection scale under different difficulty of epidemic recovery. From Fig. 3, we can clearly see that with the increase of ε, the infection density decreases. At the same time, we found that the lower difficulty of epidemic recovery, the lower the infection density. It has given us a lot of inspiration for epidemic prevention and control, we should enhance the resource utilization efficiency to maximize the value of existing resources, and appeal to the public to save and allocate resources rationally, and help the public form a right awareness of resource allocation behavior. In order to prevent epidemic infection density reached the scope of the uncontrolled, epidemic recovery difficulty should be reduced through a variety of methods.

We studied the difference between official information and rumor dissemination on epidemic spreading. It can be seen from Fig. 4 (a), that in the process of increasing the spread rate of official information, the scale of the infected gradually shrinks, and official information inhibits the epidemics spreading. It can be found in Fig. 4 (b), that the infected scale keeps expanding with the rumor dissemination rate. Rumor dissemination promotes the expansion of the infected scale, and has a positive promoting effect on epidemic. During plague prevention, official information brings correct and effective information to the public and helps the public form correct awareness of epidemic prevention. The authorities concerned should actively publicize knowledge and information about the epidemic and guide people to form a correct awareness of epidemic prevention. This has a positive effect on the epidemic prevention. Rumor control and refuting mechanisms are particularly important during the epidemic period. Rumors generally cause social panic, which is not conducive to the correct and effective plague prevention, and may also cause large-scale gathering phenomenon. When refuting rumors, positive official information

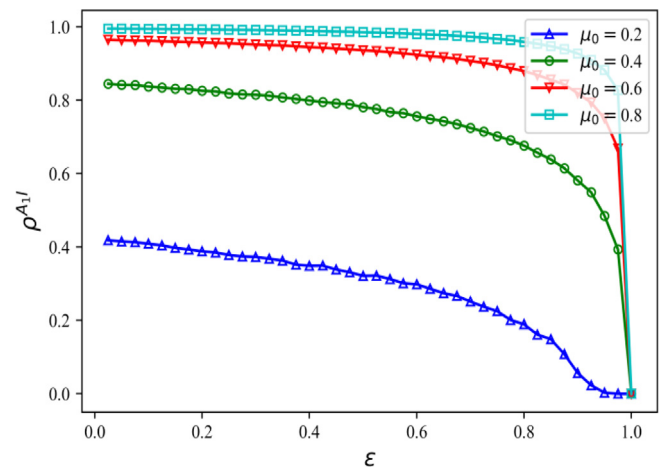
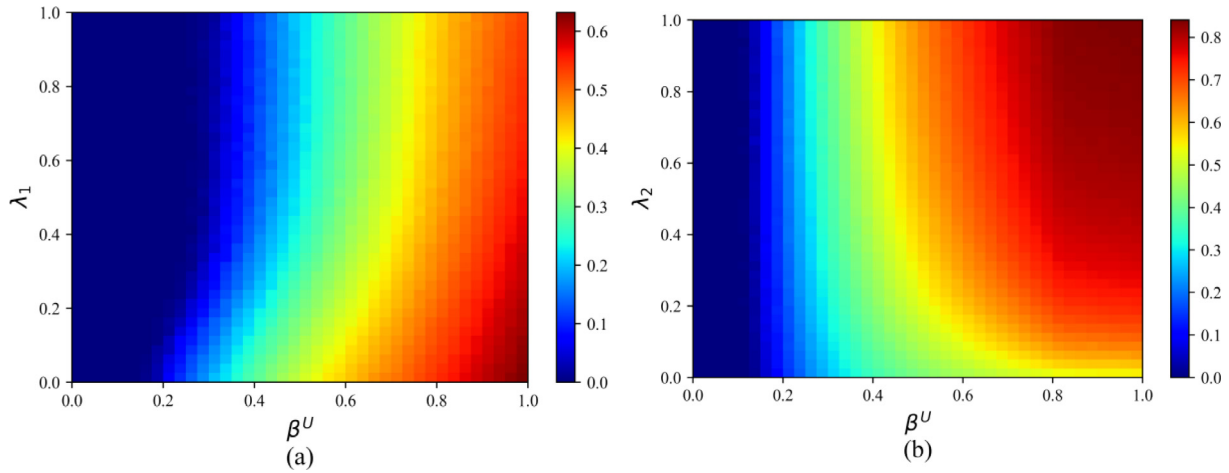


Fig. 3. The relationship between resource utilization efficiency and epidemic spreading scale under different difficulty of epidemic recovery. Where, N = 2000, β<sup>U</sup> = 0.6, λ<sub>1</sub> = λ<sub>2</sub> = 0.4, η<sub>1</sub> = η<sub>2</sub> = 1, φ = 0.5.

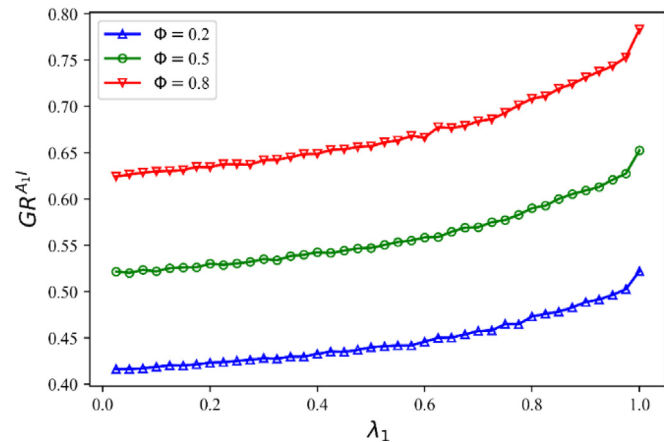


**Fig. 4.** The difference between the official information dissemination and rumor on epidemic infection scale. Where, Figure (a),  $\lambda_2 = 0.2, \mu_0 = 0.8, \varepsilon = 0.2, \eta_1 = 0.7, \eta_2 = 1.3, \phi = 0.1$ ; Figure (b),  $\lambda_1 = 0.4, \mu_0 = 0.8, \varepsilon = 0.2, \eta_1 = 0.7, \eta_2 = 1.1, \phi = 0.1$ .

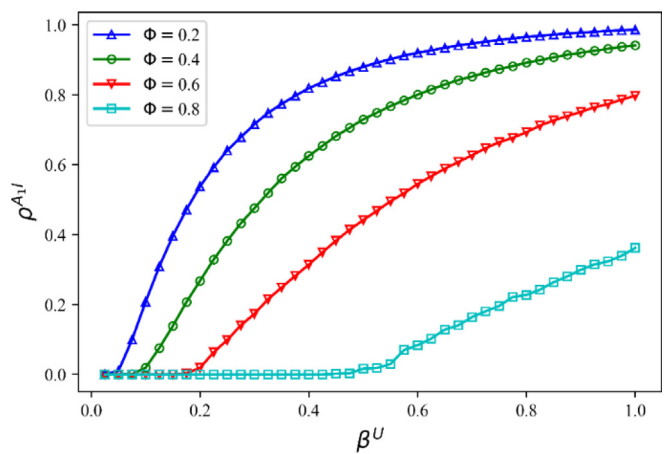
should be publicized to guide the society to develop in a correct direction of public opinion.

We studied the amount of resources available to the infected at different donation rates as official information dissemination. From Fig. 5, we can see that the amount of resources acquired by the infected increases with the dissemination of official information. It indicates that the dissemination of official information is more likely to arouse public concern about the infected. We should increase the intensity of official information dissemination, so that positive orientation can be conveyed to the public. It's conducive to attracting the public attention to the epidemic and guiding the correct prevention behavior.

We examined how the scale of infection varies with the rate of epidemic spreading at different rates of resource donation. As can be seen from Fig. 6, as the rate of infection continues to increase, so does the scale of infection. But at the same infection rate, the higher the donation rate, the lower the infection scale. When the resource donation rate keeps increasing, the amount of resources obtained by the infected will increase, which will greatly improve the recovery rate of the infected and reduce the density of the infected. From this, it can be concluded that resources have an inhibitory impact during the epidemic spreading. Resource donation rate can affect the infected density. Thus, we should strengthen the dissemination of official information through mass



**Fig. 5.** Under different donation rates, the amount of resources acquired in  $A_{1I}$  state. Where,  $\beta^U = 0.6, \lambda_2 = 0.4, \mu_0 = 0.2, \eta_1 = 0.8, \eta_2 = 1.1, \varepsilon = 0.2$ .



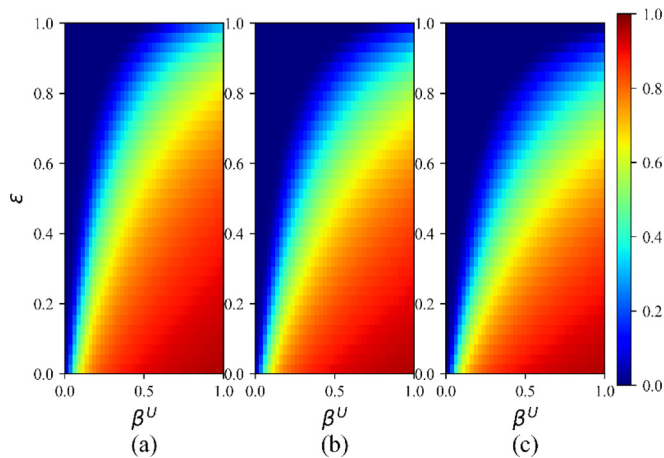
**Fig. 6.** Variation of epidemic infection scale under different resource donation rates. Where,  $\lambda_1 = 0.5, \lambda_2 = 0.2, \mu_0 = 0.4, \eta_1 = 0.8, \eta_2 = 1.1, \varepsilon = 0.2$ .

media, guide correct public opinion and correct behavior, and appeal to the masses to donate resources rationally.

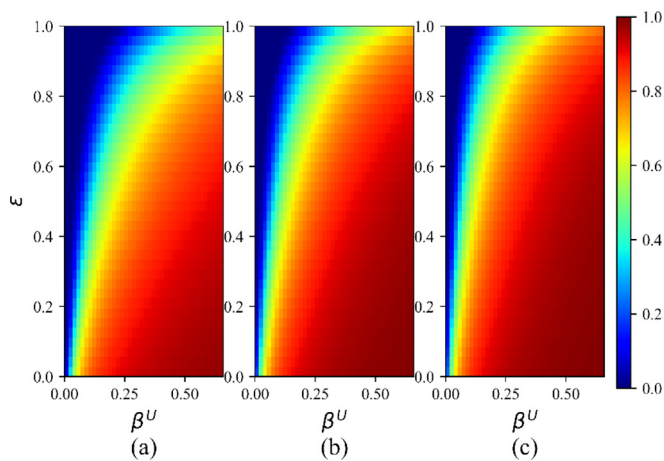
As can be seen from Fig. 7, infection scale keeps decreasing with the increase of resource utilization efficiency and epidemic spreading rate. By comparing the above three heat maps, we found that as official information orientation intensity increased, infection scale decreased. Under different official information orientation intensity, infection scale decreases with the increasing efficiency of resource utilization. We can conclude that the efficiency of resource utilization has an inhibitory impact on infection scale, and the inhibitory impact keeps enhancing with the increasing official information orientation intensity. The official information orientation intensity and resource utilization efficiency have the same inhibitory effect on epidemic spreading, and the greater official information orientation intensity, the stronger the resource utilization efficiency inhibitory effect. Under the joint role of official information and resources, we should maximize the inhibitory effect of resources on diseases, and improve the utilization efficiency of resources. It can not only make rational use of resources during the epidemic period, but also dissemination positive information to the masses to promote correct epidemic prevention behaviors and form correct epidemic prevention awareness.

It can be seen from Fig. 8 that with the increasing rumor orientation intensity, the scale of epidemic infection shows an expanding trend. As the efficiency of resource utilization increases, the





**Fig. 7.** Scale of epidemic infection under different official information orientation intensity. Where,  $\lambda_1 = 0.3, \lambda_2 = 0.4, \mu_0 = 0.9, \phi = 0.1$ . FIG. (a).  $\eta_1 = 0.2$ , FIG. (b).  $\eta_1 = 0.5$ , FIG. (c).  $\eta_1 = 0.8$ .



**Fig. 8.** Scale of epidemic infection under different rumor orientation intensity. Where,  $\lambda_1 = 0.4, \lambda_2 = 0.7, \phi = 0.2, \mu_0 = 0.9$ . FIG. (a).  $\eta_2 = 1.1$ , FIG. (b).  $\eta_2 = 1.3$ , FIG. (c).  $\eta_2 = 1.5$ .

scale of the epidemic has increased. By comparing the three heat maps above, the scale of epidemic infection varies with the rumor orientation intensity, and the stronger the rumor orientation intensity, the larger the scale of epidemic infection. At the same time, with the increasing of resource utilization efficiency, the trend of expanding epidemic infection scale gradually slows down. But, the scale of epidemic infection is also increasing as the intensity of rumor orientation and the resource utilization efficiency increase. It indicates that resource utilization efficiency can restrain epidemic infection scale, and rumor orientation intensity will weaken the effect of resource utilization efficiency on suppressing epidemic spreading. Therefore, during an epidemic outbreak, it is important to strictly control the dissemination of rumors and improve the resource utilization efficiency.

## 5. Conclusion

In the study of the coupling dynamic coevolution process of information, resources and epidemic, we used the three-layer network model and analyzed the model with MMC theory. Based on this, we investigated how two different orientation information affect individual resource allocation, and individual resource allo-

cation can influence the spread of an epidemic. How the scale of epidemic infection develops under the combined effect of information and resources was also studied. We found that information orientation plays a key role in the development of epidemic trend. Official information inhibits the spreading of epidemics and rumors promote the spreading of epidemics. Besides, resource utilization efficiency also has an inhibiting effect on the development of epidemics.

In practice, in the absence of effective treatment for epidemics, controlling the orientation role of information and rational resources allocation will be an effective method to restrain the spreading of epidemics. Mainstream media play an critical role in the coevolution process of information dissemination, and make full use of the powerful influence of mainstream media to actively publicize the correct orientation information and timely refute rumors. While promoting the correct information guidance function, the rational allocation of resources and improving the resource utilization efficiency also get enough attention. Because the combination of positive office information guidance and higher resource utilization will effectively control the expansion trend of the epidemic.

## Data availability statement

All data, models, and code generated or used during the study appear in the submitted article.

## Declaration of Competing Interest

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

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