

RESEARCH ON INFORMATION INFECTIOUS DISEASE MODEL BASED ON WEIGHTED MULTIPLEX HYPERNETWORK

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ABSTRACT. *With advancements in science and technology, the Internet has complexified social networks, influencing epidemic dynamics through information diffusion. This paper presents a two-layer weighted dynamic evolutionary network model from a hyper-network perspective to analyze the impacts of herd psychology, self-vigilance, and individual immunity on information spread and epidemic transmission. The model incorporates a heterogeneous rewiring rate, proportional to connection strength. Simulation results reveal that rewiring significantly affects epidemic suppression, with maximum infection scale decreasing as information acceptance probability rises and final infection scale decreasing with increased rewiring. Enhanced individual resistance also notably inhibits virus transmission. This study aids in understanding epidemic mechanisms and offers practical strategies for controlling virus spread in real-world scenarios.*

Keywords: Weighted hypergraphs, Mltiplex-hypernetwork, Epidemic transmission, Information diffusion, The dynamic model, Social network

1. Introduction. In the context of the rapid development of science and technology, human society has formed a complex network of relationships. Micro-media platforms, represented by Wechat and Weibo, have become the main channels for acquiring and spreading information in the transmission of epidemic risk, and their interactive communication mode has accelerated the transmission of epidemic information. Different from the past network of mere onlookers, the COVID-19 epidemic involves the vital interests of the public, and everyone is deeply affected. The stagnation of face-to-face social communication and the extreme demand for all kinds of epidemic information, the strong willingness of the public to communicate in the network communication, to a certain extent, has improved the awareness of prevention and control of the public and thus suppressed the spread of the epidemic. Dynamic communication has become one of the core problems of the network structure.

When describing and analyzing the coupling of information diffusion and virus propagation, the study of multi-layer networks becomes more and more important due to the interaction between different real systems [1-4]. In recent years, the influence of information diffusion on epidemic transmission in multi-layer networks has been extensively studied. The emergence and change of information related status affected the transmission process

of the entire epidemic in the social network. Firstly, a single node has two states at the same time, which makes the state of the node more diversified. One describes information related states, and the other describes physical states. The increase of node state leads to the diversity of propagation process. In addition, information diffusion causes individuals to make adaptive behavioral changes in response to epidemic outbreaks. Then, the complex network with static network structure evolves into an adaptive complex network with dynamic physical layer [5].

However, micro-media platform users formed countless network communication nodes, and the connection and forwarding between nodes created countless transmission paths in a short time in a fission way, thus speeding up the update and spread of epidemic information on the network. Traditional complex network models have limitations in accurately depicting the real relationships among multiple nodes. Hypergraph-based hypernetwork is a kind of network that integrates multi-hierarchy and nesting, which can depict the intricate relationship between networks and the interaction characteristics of heterogeneous networks in a more detailed way. In addition, because of the simple structure of the hypernetwork, and the fact that each hyperedge can contain any number of nodes, it can be used to model large and complex multi-structure systems.

At the same time, there are various factors affecting the spread of the epidemic in real life, which has attracted the attention of many scholars. The size and scope of different social groups will lead to different epidemic transmission degrees, and the different prevention and control awareness of individuals will lead to different infection effects. The epidemic risk information obtained and constructed by the public will have great differences due to the differences in herd psychology and self-vigilance awareness, resulting in obvious differences in individual epidemic risk perception and subsequent risk transmission behaviors. In addition, the difference in individual immunity also determines the difference in individual recovery rates. Therefore, it is necessary to study the influence of various factors on the spread of the epidemic and take measures to prevent the spread of the virus.

A weighted multiplex model with multiple time-varying parameters can be used to describe and analyze the above problems. A multi-layer hypernetwork, consisting of an information layer and a physical contact layer, is proposed to describe the dynamic interaction between information and social networks, supporting various dynamic processes. In the information network, individuals exchange disease-related information and define the time-varying acceptance rate based on herd psychology and self-vigilance. In the social physical network, participants exchange biological elements that can spread disease. A healthy individual can actively disconnect from infected groups and reconnect with healthy neighbors. The reconnection rate between infected and healthy nodes changes with the number of infected nodes. Additionally, individual heterogeneity in the physical contact network is considered, with varying immunity levels affecting recovery rates, which impacts the disease spread in the social network.

In this paper, a new average field model is proposed to describe the interaction between information transmission and virus transmission. Suggestions on how to curb the spread of information and effective prevention and control of the epidemic are also put forward. The innovations of this paper are as follows.

- 1) A weighted two-layer dynamic evolutionary network model from a hypernetwork perspective is constructed to describe the interaction between information diffusion in online social networks and epidemic spread in physical contact networks.

- 2) The constructed model takes account of two co-evolutionary processes, namely, the co-evolution of information diffusion and epidemic spread, and the co-evolution of epidemic spread and network structure in physical contact networks.

3) Considering variations in individual connectivity, the model includes heterogeneity in rewiring rates proportional to connection strength, along with factors such as conformity, self-awareness, and individual immunity, to assess their impact on information diffusion and epidemic spread.

4) Monte Carlo (MC) simulation method was used to simulate the weighted coevolutionary multiplex hypernetwork model, and the interaction between information diffusion and epidemic transmission was described and analyzed.

The rest of this paper is organized as follows. The relevant work is reviewed in Section 2. In Section 3, the structure of weighted multiplex hypernetwork is described. In Section 4, different network structures are simulated, the influence of network structure characteristics on weighted co-evolutionary multiplex hypernetwork propagation is analyzed and studied, and conclusions are drawn in Section 5.

2. Related Work. Since the real world is a highly complex and interacting non-independent system, scholars simply abstract various complex systems in real life through the study of complex networks, improve the theory of complex networks, and realize that a single network has great limitations compared with a multi-dimensional and multilevel social system. Therefore, they focused their research on higher levels of network complexity. In recent years, the interaction between epidemic transmission and information spread on multiplex networks has gained attention for its role in modeling, predicting, and controlling outbreaks. Based on the multiplex network, Granell et al. [6] took the lead in analyzing the relationship between the two processes of epidemic transmission and the information awareness of infection prevention. Wu and Chen [7] analyzed the interaction between disease spread and disease-based information diffusion in multiplex networks, considering that disease and information can spread concurrently within a single time step. Through probabilistic derivation, they proposed a new individual-based diffusion model and provided the pairwise formulas for the model. Li et al. [8] explored the interplay between epidemic spread and the diffusion of awareness in multiplex networks and found that increased vaccination and improved vaccine efficacy can reduce epidemic spread and delay disease outbreaks.

As information spreads, some risk-conscious individuals tend to change their behavior to avoid being infected, resulting in changes in the structure of the network. Ren et al. [9] proposed an edge-weighting method based on Jaccard similarity to construct weighted networks on the basis of complex networks, and presented a new approach to identify influential spreaders. Song et al. [10] proposed a new weighted co-evolutionary network based on the two-layer network, introduced the heterogeneous rewiring rate proportional to the connection strength, and combined with the adaptive network, described two kinds of coevolutionary processes in the network. Subsequently, more research was done on adaptive networks, and adaptive (weighted) networks became increasingly important.

After the research on complex network has become an upsurge, the research on hypernetwork has gradually come into the attention of researchers, and has been widely used to solve various practical problems. For example, in 2013, Hu et al. [11] built a dynamic evolution model under hypernetwork vision, and introduced the related properties of hypernetwork in detail, such as node hyperdegree and hyperedge hyperdegree, which deepened people's understanding of hypernetwork. In 2023, Sun et al. [12] proposed an SEIR model of dynamic information transmission in social networks considering positive interference and negative interference from the perspective of hypernetwork. By combining the hypernetwork theory with the propagation dynamics equation, the information disturbance function is introduced to establish the information propagation dynamics equation. In 2024, Wang et al. [13] established a susceptible-infected-susceptible (SIS)

transmission model incorporating both collective and individual infection dynamics within a general hypernetwork characterized by high-order interactions. They applied this model to a double uniform hypernetwork to deriving the mean-field representation of the SIS framework. Furthermore, they obtained and dynamically analyzed the threshold for the spread of epidemics within the double uniform hypernetwork. At present, the dynamic communication model under hypernetwork vision has been further developed and is gradually improving, but the information network is always associated with other networks in the social structure. Therefore, the study of hypernetwork is still necessary.

Based on this, this paper establishes a weighted multi-layer hypernetwork model of information diffusion and epidemic transmission, obtains the information dissemination laws related to reality, and analyzes them theoretically and experimentally.

3. Weighted Co-Evolutionary Multiplex Network Model. The mathematical definition of a hypergraph is as follows: Let $V = \{v_1, v_2, \dots, v_n\}$ be the finite node set of the hypergraph, and let $E_i = \{v_{i1}, v_{i2}, \dots, v_{ij}\}$ ($v_{ik} \in V, k \in N^+$) be a nonempty subset of V , $E = \{E_1, E_2, \dots, E_m\}$ be the hyperedge set of the hypergraph, and the binary relation $H = (V, E^h)$ be the hypergraph. It is a generalization of an ordinary graph, which we are familiar with, where an edge can only be connected to two vertices. For hypergraphs, it is generalized to a generalized edge, that is, a hyperedge that can be connected to any number of vertices. Hypergraph was first proposed by Berge [14,15]. In 2006, Estrada and Rodriguez-Velazquez believed that any network that could be represented by a hypergraph was a hypernetwork [16] and gave the definition of a hypernetwork based on a hypergraph.

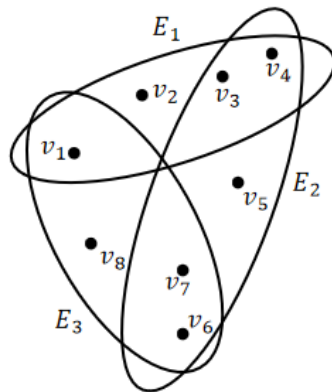


FIGURE 1. Hypergraph

3.1. Two-layer dynamic evolutionary network model. This paper examines a two-layer network in which N nodes are respectively connected by links in each layer. The upper layer network describes the information diffusion network, and the lower layer network describes the individual contact network. The two-layer hypernetwork is used to describe and study the co-evolution of two different dynamic processes and the adaptive change of physical contact network structure.

The two layers of the network share the same individuals, that is, each node in one layer has a one-to-one correspondence with a node in the other layer. We assign an activity rate to node i based on definition $b_i(t) = \eta x_i(t)$. As shown in Equation (1), the activity rate $b_i(t)$ and the number of links of node i are proportional to the ratio of the number of links of all nodes at time t .

$$x_i(t) = \frac{h_i(t) + 1}{\sum_i (h_i(t) + 1)}, \quad b_i(t) = \eta \frac{h_i(t) + 1}{\sum_i (h_i(t) + 1)}, \quad (1)$$

where η is the adjustment coefficient and $h_i(t)$ represents the number of hyperedges of the node i at time t . The activity rate $b_i(t)$ is the probability that a node will link to other nodes in unit time, bounded by interval $(0, 1]$. Based on the traditional activity-driven network model [17], we use the hypernetwork theory to improve it. Each layer of network G_t is generated as follows.

- 1) At each discrete time step t , network G_t consists of N isolated nodes.
- 2) Each node i becomes active with probability $b_i(t)$, and the d nodes selected by Equation (2) form d hyperedges. Inactive nodes can also accept connections.

$$\omega_j(t) = \frac{\vartheta_j(t) + 1}{\sum_j (\vartheta_j(t) + 1)}, \quad (2)$$

where $\vartheta_j(t)$ is the degree of the node.

- 3) At the next time step $t + \Delta t$, all edges in the network are removed and the processes 1)-3) are repeated.

3.2. Coupled UAU-SIRS compartment model. In previous studies, UAU (unalert-alert-unalert) model was used for the propagation of consciousness layer and classical SI (susceptible-infected) model and SIR (susceptible-infected-recovered) model were used for physical contact layer. In fact, in the process of virus transmission, individuals who know the virus information are always vigilant, and because of the diversity of virus mutations, individuals in the process of virus transmission, even after recovering from the previous infection, there is still a risk of being infected with other infected people. Therefore, we consider adopting the UA model in the consciousness layer. In the physical contact layer, considering the transition from state R to state S, the SIRS model will better represent the dynamic changes of individual states during the transmission of the virus.

The coupling of multilayer networks introduces numerous interactions between the two layers. Firstly, there is the interplay between information diffusion and epidemic spread. At the early stages of an epidemic, relevant information is scarce and receives little attention. As the virus spreads exponentially, more disease-related information becomes available, providing people with methods and strategies to cope with the epidemic. In this process, the spread of the epidemic promotes information diffusion, while the diffusion of information, in turn, mitigates the spread of the epidemic. The second type of co-evolution involves the interplay between epidemic spread and network structure within the physical contact network. Specifically, individuals, upon receiving information, may alter their behavior to protect themselves if they are aware of the risks. The following section provides a detailed description of the evolutionary processes within the two-layer hypernetwork, including the patterns of state changes in nodes and edges.

3.2.1. UA compartment model. In the information diffusion layer, the UA model is used, where the state of the nodes is unalert (U) or alert (A) of the existence of the epidemic and its prevention. In Figure 2(a), the U state individual does not have information about how to prevent infection, while the A state individual reduces the risk of becoming infected. After communicating with a conscious neighbor, a U-state individual becomes conscious with probability α .

Conformity psychology refers to that individuals give up their own views under the influence of the group, so that their behavior is consistent with the group. This is an act of blind obedience. Individuals who do not understand herd psychology will make bad judgments based on behaviors that are appropriate for their environment, thus putting

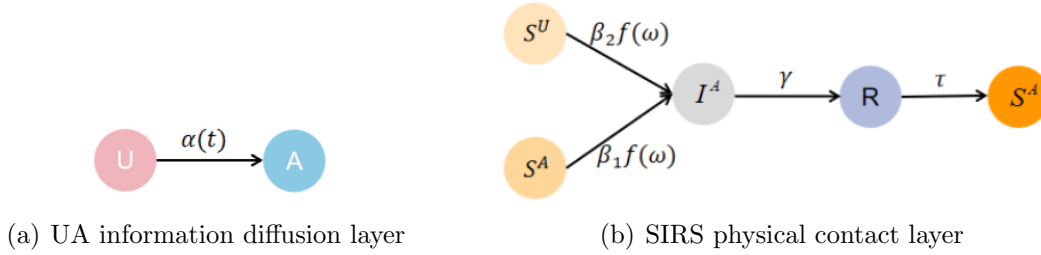


FIGURE 2. Node state transformation process at each layer

individuals at risk of infection. However, the effect of the herd mentality is not 100%. Some individuals may remain unalert even if those around them are alert. Similarly, even if the surrounding individual is not vigilant, it may become cautious because of self-vigilance. Therefore, we use Formula (3) to represent the probability of the node i transitioning from state U to state A at time t .

$$\alpha_i(t) = p_1 \delta_i(t) + \kappa \quad (3)$$

$$\delta_i(t) = \begin{cases} \frac{\sum_j f_{ij} P_j^A(t)}{\sum_j f_{ij}}, & \sum_j f_{ij} \neq 0 \\ 0, & \sum_j f_{ij} = 0. \end{cases} \quad (4)$$

In Formula (3), p_1 represents herd psychology, κ represents self-vigilance, where $p_1 \in [0, 1]$ is an adjustment parameter. Formula (4) is the mathematical interpretation of $\delta_i(t)$, $\delta_i(t)$ is the ratio of the number of nodes in state A connected to node i to the total number of nodes connected to node i , and in the consciousness layer, if node i is connected to node j , then $f_{ij} = 1$; otherwise, $f_{ij} = 0$. $P_j^A(t)$ represents the probability that node j is in state A at time t .

3.2.2. SIRS compartment model. In the physical contact layer, the SIRS epidemic model is used to simulate the spread process of the epidemic. Nodes have four different states: conscious susceptible (S^A), unconscious susceptible (S^U), infected (I^A), and immune node (R). As shown in Figure 2(b), the probability of a state S^A node being infected by a state I^A neighbor is $\beta_1 f(\omega)$ and the probability of a state S^U node being infected is $\beta_2 f(\omega)$. $f(\omega)$ is a function positively related to connection weights, and it is clear that people without risk awareness are more likely to be infected, so this paper assumes $\beta_1 < \beta_2$. The recovery probability of I^A state is γ . Recovered node (R), after a period of time may lose immunity to the virus with probability τ . Combined with practical considerations, often the more people in the social circle and the closer the social connections of individuals, the faster the spread of the virus, the more difficult to control and quarantine. Here we define the weight of the hyperedge in terms of the excess of the nodes contained in the hyperedge.

Self-recovery rate γ is related to individual resistance VOI . If the individual resistance of infected node is stronger, the probability of it becoming recovery node is higher. Immunity is the body's defense mechanism, responsible for recognizing and eliminating foreign invaders (such as viruses and bacteria). It also helps the body deal with aging, damaged, dying or denatured cells, as well as identifying and dealing with mutated or virus-infected cells.

Suppose that the immunity of different individuals to the same virus follows a normal distribution, that is, $VOI \sim (voi, \sigma_{voi}^2)$. Here, voi is the mean of individual immunity and σ_{voi} is the standard deviation of individual immunity. The larger the VOI , the stronger

the individual's immunity. Therefore, we define the probability that state I^A becomes immune recovery state R as

$$\gamma = \begin{cases} VOI, & VOI < 1 \\ 1, & VOI \geq 1 \end{cases} \quad (5)$$

After a certain period, the recovered nodes (R) do not retransmit the virus, but they may lose their immunity to the virus with a probability of τ and subsequently retain awareness of the virus, thus transitioning to state S^A .

3.2.3. *Dynamic relationship between layers.* Awareness spreading and risk spreading are two processes that influence each other. We assume that as a result of the ongoing spread of the outbreak, status A individuals are still aware of the infection. This awareness can not only reduce the probability of infection, but also make the individual's behavior change and isolate from the infected person. Healthy individuals with risk awareness are likely to sever their connections with infected individuals with a certain probability, denoted as $r_\omega = r(\omega)$. As the link weight increases, the difficulty of disconnection also rises, represented by $r_\omega = p_2 * \frac{1}{\omega}$. In order to ensure the complete function of the network, we assume that healthy people with the network disconnected hyperedge will randomly find other healthy people to connect to form a new hyperedge, as shown in Figure 3. For example, a healthy employee will transfer work tasks from an infected employee to a healthy employee. On this basis, a weighted coevolutionary multilayer hypernetwork model for the interaction between information and virus propagation is established.

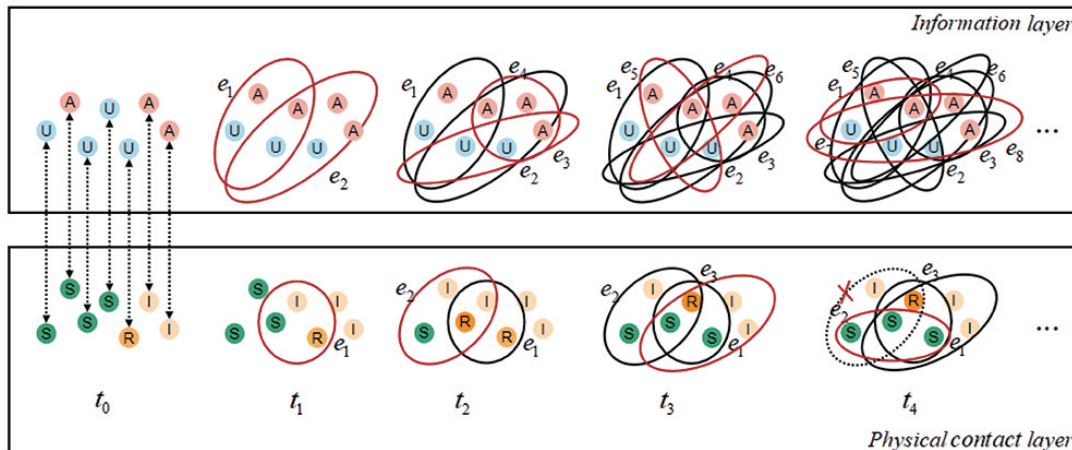


FIGURE 3. Schematic diagram of network state transformation. The upper layer in the figure is the information layer L_1 , and the U-state individual gets the perception with a probability of $\alpha(t)$ after communicating with the sensing neighbor. The lower layer is physical contact layer L_2 . In L_2 , a healthy individual with a sense of risk will disconnect with an infected person with a certain probability $r_\omega = r(\omega)$.

In a weighted co-evolutionary multilayer hypernetwork, unaware healthy nodes can obtain information from their aware neighbors. A healthy node is more likely to be infected by an infected neighbor that interacts with it frequently (that is, a neighbor with a larger link weight). Once a neighbor is infected, the healthy node can observe its erroneous behavior and re-establish connections to bypass the infected neighbor, thereby preventing the spread of attacks or failures. As a result, the topology of the network is constantly changing in response to infection, isolating infected individuals to reduce the probability of infection.

3.3. Theoretical analysis. Each node i has a certain probability of being in one of three states at time t , represented by $[S^A]$, $[S^U]$, and $[I^A]$, respectively. We give definitions of symbols used in the model in Table 1, including node density, edge density in different states, and relevant parameters in the model.

TABLE 1. Definition of key parameters

Term	Definition
$(S^A I^A)_\omega$	The weight of ω is the proportion of hyperedges containing (not only) conscious susceptible nodes and infected nodes.
$[S^A]_\omega$	The proportion of conscious susceptible nodes in the hyperedge with weight ω .
$[S^U]_\omega$	The proportion of unconscious susceptible nodes in the hyperedge with weight ω .
$[S^U]$	The proportion of unconscious susceptible nodes.
$[S^A]$	The proportion of conscious susceptible nodes.
$[I^A]$	The proportion of infected nodes.
$[R]$	Proportion of recovered immunizers.
$\beta_1 f(\omega)$	An unconscious susceptible node is infected by an infected neighbor through a hyperedge with a weight of ω .
$\beta_2 f(\omega)$	A conscious susceptible node is infected by an infected neighbor through a hyperedge with a weight of ω .
$\alpha(t)$	The rate at which an unconscious node receives information and becomes a conscious node.
r_ω	The rewiring rate proportional to the hyperedge weight ω .

- Change the process of node state over time:

$$\frac{d[S^A]}{dt} = \tau[R] - \sum_{\omega} \beta_1 f(\omega) [S^A]_{\omega} + \alpha [S^U], \quad (6)$$

$$\frac{d[S^U]}{dt} = - \sum_{\omega} \beta_2 f(\omega) [S^U]_{\omega} - \alpha [S^U], \quad (7)$$

$$\frac{d[I^A]}{dt} = \sum_{\omega} \beta_2 f(\omega) [S^U]_{\omega} + \sum_{\omega} \beta_1 f(\omega) [S^A]_{\omega} - \gamma [I^A], \quad (8)$$

$$\frac{d[R]}{dt} = \gamma [I^A] - \tau [R]. \quad (9)$$

The system of Equations (6)-(9) is called the node state change model. On the right side of Equation (6), the first term indicates that recovered node R loses immunity to the virus with probability τ but retains virus awareness to state S^A . The second entry represents the infection process, where an S^A -state node is infected by an I^A -state neighbor at a rate of $\beta_1 f(\omega)$ through a ω -weighted link. The third entry represents the information diffusion process, in which an S^U -state individual receives information from an A -state neighbor at a rate of α and converts its state to S^A . On the right side of Formula (7), the first item is the infection process. The S^U -state node is infected by the I^A -state neighbor at a rate of $\beta_2 f(\omega)$ through a ω -weighted link. Apparently, $\beta_2 > \beta_1$ indicates that people

who are not aware of the risks are more likely to be infected. The second is the process of information diffusion. On the right side of Formula (8), the first and second items represent the infection process, and the third item indicates that the node in state I^A recovers to the immune state R with probability γ . The first item on the right of Formula (9) is the recovery process, and the second item is the process of losing immunity and becoming S^A state.

- Change the process of link state over time:

$$\frac{d(S^A I^A)_\omega}{dt} = -r_\omega (S^A I^A)_\omega. \tag{10}$$

In this paper, the change of hyperedge over time is not considered, but only the disconnection and reconnection of hyperedge. When a susceptible individual S^A with awareness and an infected individual I^A are within the same social circle, this social circle will disconnect with a probability r_ω to prevent further spread of the infectious disease.

Specifically, in the steady state, all nodes are eventually risk conscious due to the propagation of information, so there are only three states left in the network, namely $[S^A]$, $[I^A]$, and R. In addition, all nodes and links in different states achieve dynamic stability, that is, $\left(\frac{d[S^A]}{dt}, \frac{d[I^A]}{dt}, \frac{d[R]}{dt}, \frac{d(S^A I^A)_\omega}{dt}\right) = (0, 0, 0, 0)$, and the steady-state equation satisfies

$$\tau[R] - \sum_\omega \beta_1 f(\omega) [S^A]_\omega = 0, \tag{11}$$

$$\sum_\omega \beta_1 f(\omega) [S^A]_\omega - \gamma [I^A] = 0, \tag{12}$$

$$\gamma [I^A] - \tau[R] = 0, \tag{13}$$

$$-r_\omega (S^A I^A)_\omega = 0. \tag{14}$$

In the stable state, all nodes have developed risk awareness. It can be observed from the equations that the probability of information reception does not affect the final stable state of the network. In other words, the analysis results indicate that the probability of information reception does not influence the ultimate infection size. However, due to the isolation effect of the rewiring process on infected and susceptible nodes, the rewiring rate exhibits a significant impact on the network's final infection outcome.

In the stable state, all nodes possess risk awareness, and the probability of information reception does not influence the network's final stable state or ultimate infection size. However, the rewiring rate significantly affects the network's final infection outcome due to its isolating effect on infected and susceptible nodes.

It can be seen from the equation that information diffusion changes the law of epidemic transmission and also changes the network structure. In turn, the spread of the epidemic affects the probability of receiving information, that is, the law of information diffusion. Therefore, information diffusion, epidemic dynamics, and network structure interact. In the next section, we will simulate the above processes using Monte Carlo (MC) method to further explore the relationship between them.

4. Simulation Results. In this section, simulation is used to analyze the propagation dynamics of the proposed multi-layer dynamic network model. This paper describes how to use MATLAB to simulate information diffusion and virus propagation processes to obtain data. The results show the correctness of theoretical analysis and provide effective suggestions for epidemic prevention and control. The initial settings of relevant parameters of hypernetwork are shown in Table 2.

TABLE 2. Hypernetwork parameters for initial settings

Hypernetwork parameters	Parametrization	Value
Total number of nodes in the network	N	1000
Adjustment coefficient	η	100
The social layer has a hyperedge to select the number of nodes	u_1	8
The number of nodes in a hyperedge of the physical contact layer	u_2	5
A node forms the number of hyperedges	m	3
Herd psychology coefficient	p_1	0.2
Adjustment coefficient of the disconnected link	p_2	0.03
Individual resistance	μ	0.4
Standard deviation of individual resistance	σ	0.15
The probability of the recovered person becoming susceptible	τ	0.1
The probability of an unconscious susceptible person being infected	β_1	0.4
The probability of a conscious susceptible person being infected	β_2	0.2
Node density of the alert state at the initial moment	$P^A(0)$	0.1
Node density of the infected state at the initial time	$P^I(0)$	0.05

MC is a method of stochastic simulation of dynamic process by computer. The left diagram of Figure 4 depicts the proportions of the U and A states as a function of time steps, and the right diagram depicts the proportions of the S, I and R states as a function of time steps t .

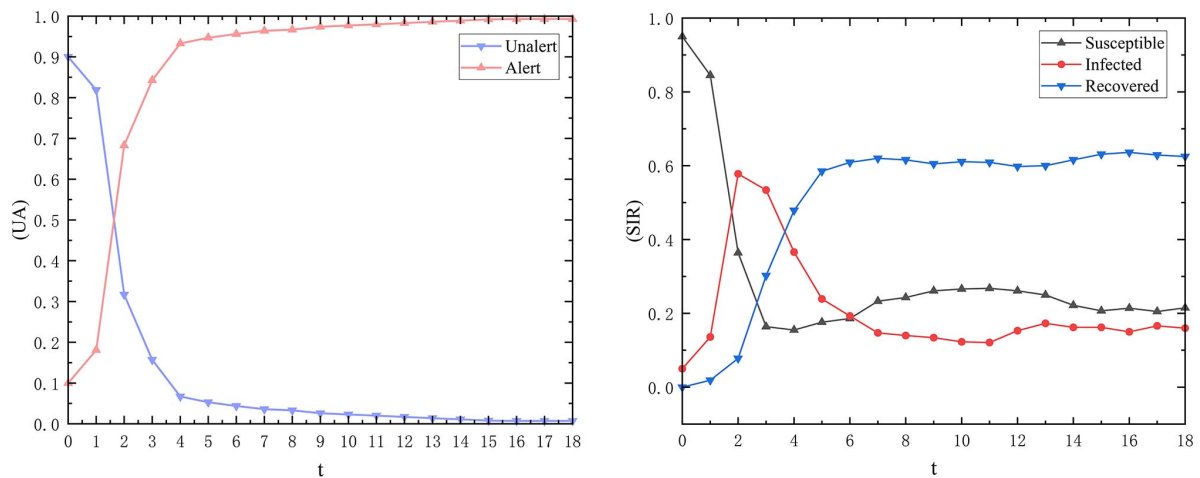


FIGURE 4. UA-SIRS Monte Carlo (MC) simulation

The purpose of this paper is to study the interaction between propagation processes in multilayer networks. As described in the previous section, we used the UA model to describe the spread of information and the SIRS model to describe the spread of outbreaks. Positive receptivity of epidemic-related information was closely related to epidemic infection. Suppose the probability that a non-sensing node receives information from a sensing neighbor is $\alpha_i(t) = p_1 \delta_i(t) + \kappa$. In a physical contact network, the rewiring rate is set to $r(\omega) = p_2 * \frac{1}{\omega}$, $p_2 \in (0, 1)$. p_1 and p_2 are the adjustment parameters of $\alpha(t)$ and $r(\omega)$, respectively. The larger the p_1/p_2 , the higher the information acceptance probability/rewiring rate. We explore the relationship between information transmission and the process of epidemic transmission through the changes of p_1 and p_2 .

Firstly, the impact of information diffusion on epidemic transmission was studied, as shown in Figure 5. The curve shows the change in the proportion PI of infected individuals

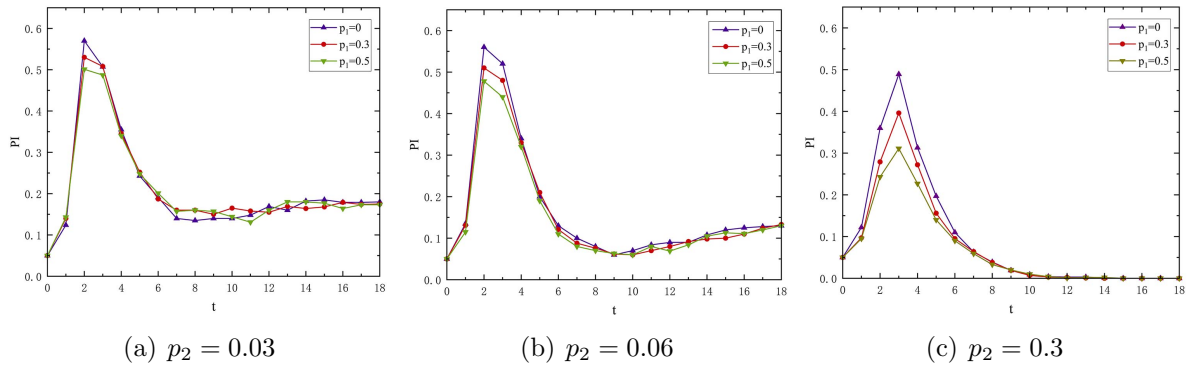


FIGURE 5. Influence of information diffusion on epidemic transmission under different parameters p_2 and rewiring rate r_ω . The curve shows the change in the number of infected persons $I(t)$ over time t with the increase of p_1 .

with different p_1 in each subgraph over time t . From each subgraph, we can see that as p_1 increases, the maximum infection size, i.e., the peak of the curve, decreases. When p_1 increases, the probability of information acceptance increases. At this time, the number of S^A -state nodes increases, and consciously susceptible individuals reduce the infection probability and slow down the infection rate through prevention and control behaviors. However, each subgraph shows that the information acceptance probability does not affect the network’s final infection, which aligns with our theoretical analysis in Section 3.

It is worth noting that each curve in Figure 5 shows an infection peak due to the risk awareness of all infected individuals, i.e., I^A state, and I^A state nodes return to R state with a recovery probability of γ . Therefore, the number of S^A -state nodes in the network continues to increase, and the infection rate in the network gradually slows down until it reaches a stable state. When the recovery process disappears, i.e., $\gamma = 0$, the peak disappears, as shown in Figure 6 (circle curve).

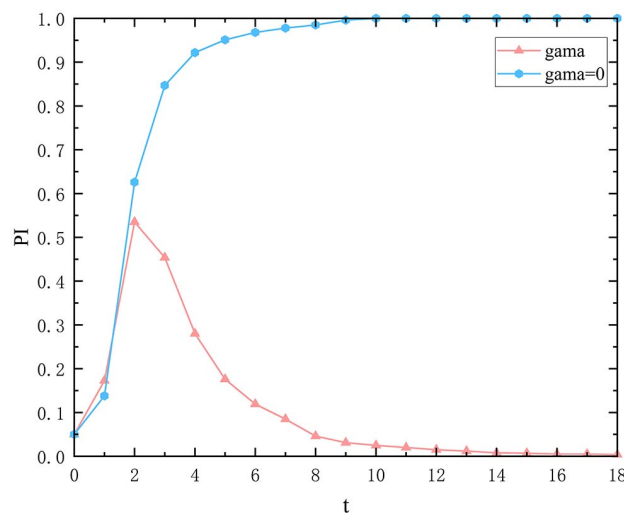


FIGURE 6. Comparison of recovery process during infection. Here, we set $p_1 = 0.2$, $p_2 = 0.08$.

We can also see from Figure 5 that with the increase of rewiring parameter p_2 , disease transmission in the hypernetwork is greatly improved. As can be seen from Figures 5(a)-5(c), with the increase of p_2 , the peak value of state I^A decreased significantly, and the final infection decreased significantly. When $p_2 = 0.03$, the final infection probability is

20%, at $p_2 = 0.06$, the final infection probability is 10%, and at $p_2 = 0.3$, the final infection probability approaches zero. In addition, this paper will continue to study the influence of rewiring behavior on the course of epidemic transmission. Figure 7 shows the influence of rewiring behavior on epidemic transmission under different information acceptance probabilities. The curve shows the change of infection ratio PI with time t as p_2 increases. As you can see from each subgraph, the size of the infection in the network decreases as p_2 increases. This act of rewiring effectively suppresses the spread of the virus because it blocks the route of infection. In the early stages of infection, the higher the rewiring rate, the easier it is for the infection to eventually disappear.

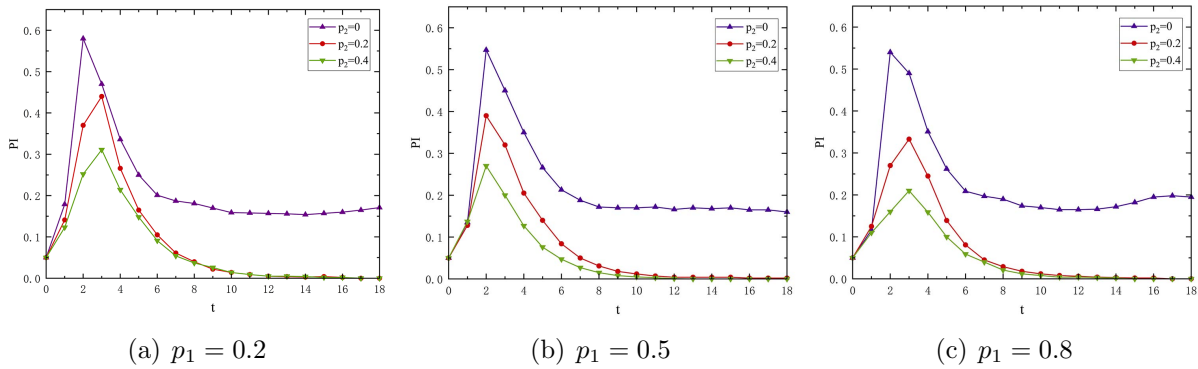


FIGURE 7. Influence of rewiring behavior on epidemic transmission under different parameters p_1 of information acceptance rate. The curve shows the change of the number of infected persons $I(t)$ with time t as p_2 increases.

Compared with the influence of information transmission on the infection process, the rewiring behavior has a greater impact on the final infection scale, as shown in Figure 8. With the increase of rewiring parameter p_2 , the final infection scale decreases. As shown in Figure 8, when $p_2 > 0.08$, the final infection of the network approaches 0.

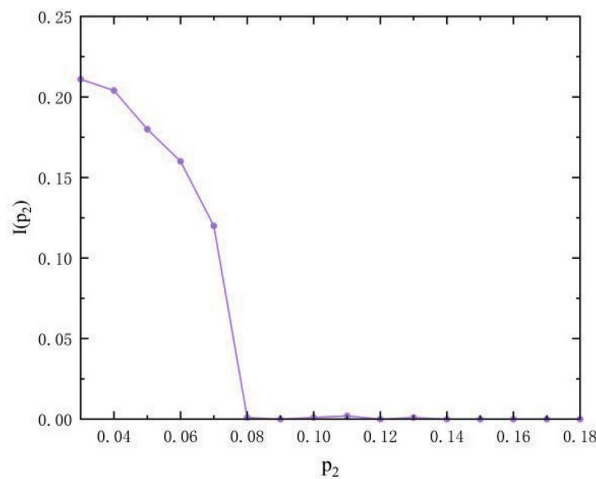


FIGURE 8. Influence of rewiring rate pair (steady state)

Figure 9 shows the change curve of density of susceptible node S , infected node I and recovered node R over time when individual resistance is different in the hypernetwork. In the process of virus transmission, individual resistance has an important impact on the speed and scope of virus transmission. With the gradual increase of individual resistance, the density of susceptible nodes increases gradually when the resistance tends to steady

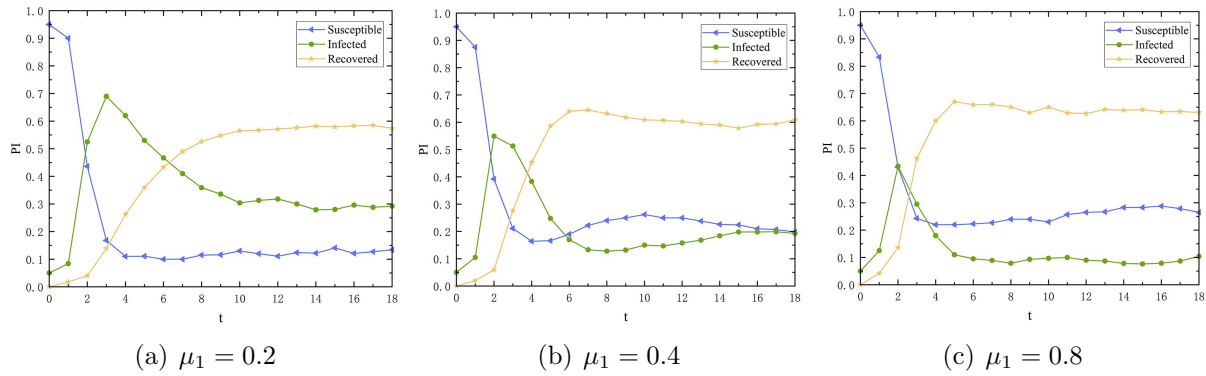


FIGURE 9. Trend curve of infectious diseases under different resistance

state. The peak value of infected nodes decreased gradually. The density of restored nodes reaching steady state gradually increases. Therefore, improving the individual resistance of the population can effectively narrow the scope of infectious diseases and help reach the homeostasis earlier.

5. Conclusions. The spread of information significantly impacts epidemic transmission, and vice versa. This paper employs a two-layer hypernetwork model to analyze this interaction, considering herd mentality, self-vigilance, and individual immunity. A heterogeneous rewiring rate, proportional to connection strength, is introduced. Simulation results reveal that rewiring effectively inhibits epidemic spread. The maximum infection scale decreases with higher information acceptance and increased rewiring. Self-vigilance interacts with infection scale, while herd mentality and individual immunity also influence it. Stronger herd mentality and individual immunity both reduce the maximum infection scale. Effective epidemic control should leverage herd mentality to disseminate prevention information and encourage individual immunity enhancement.

The weighted multilayer hypernetwork model proposed by us only describes the dynamic interaction between information diffusion and epidemic transmission, which is more diverse and complex in real life. Therefore, we hope to have a more realistic model on the basis of this model, so as to deepen the research on the dynamic interaction of communication in real systems. For example, we can start with government intervention, vaccination, and the implementation rate of prevention and control measures, or try to collect actual social network data to further verify the authenticity of the model, or consider a more dynamic evolutionary process to complete the network environment.

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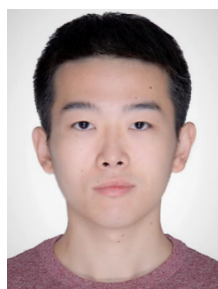
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