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Impact of individual behavior adoption heterogeneity on epidemic transmission in multiplex networks

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In recent years, the impact of information diffusion and individual behavior adoption patterns on epidemic transmission in complex networks has received significant attention. In the immunization behavior adoption process, different individuals often make behavioral decisions in different ways, and it is of good practical importance to study the influence of individual heterogeneity on the behavior adoption process. In this paper, we propose a three-layer coupled model to analyze the process of co-evolution of official information diffusion, immunization behavior adoption and epidemic transmission in multiplex networks, focusing on individual heterogeneity in behavior adoption patterns. Specifically, we investigate the impact of the credibility of social media and the risk sensitivity of the population on behavior adoption in further study of the effect of heterogeneity of behavior adoption on epidemic transmission. Then we use the microscopic Markov chain approach to describe the dynamic process and capture the evolution of the epidemic threshold. Finally, we conduct extensive simulations to prove our findings. Our results suggest that enhancing the credibility of social media can raise the epidemic transmission threshold, making it effective at controlling epidemic transmission during the dynamic process. In addition, improving an individuals' risk sensitivity, and thus their taking effective protective measures, can also reduce the number of infected individuals and delay the epidemic outbreak. Our study explores the role of individual heterogeneity in behavior adoption in real networks, more clearly models the effect of the credibility of social media and risk sensitivity of the population on the epidemic transmission dynamic, and provides a useful reference for managers to formulate epidemic control and prevention policies.

Keywords: multiplex network, epidemic transmission, behavior

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1. Introduction

The impact of infectious diseases has posed many serious threats to the security of society throughout human history. The development of human society has often been accompanied by the threat of sudden epidemics, which hinder social development. In recent years, the highly contagious COVID-19 virus has had a deleterious effect on people's normal productive lives.[1–3] What's more, the COVID-19 pandemic has seen the emergence of many new transmission characteristics that have never occurred before, posing a major obstacle to epidemic prevention and control.[4–6] For this reason, studying the intrinsic transmission patterns of epidemics and exploring the transmission dynamics of the epidemic has received attention from many scholars.

Some traditional studies of epidemic transmission in monolayer networks have provided an important basis for studying the dynamic mechanisms.[7] Bailey proposed the traditional SIS model to describe the transmission process of epidemics.[8] Grabowski extended the SIR model by considering immune individuals.[9] Based on these models, many scholars have studied the mechanisms underlying the spread of epidemics.[10–14] However, traditional studies of diffusion phenomena in single-layer networks often fail to provide a deeper understanding of the coupled effects on complex worlds. For example, epidemic transmission is often accompanied by epidemic-related information diffusion, and different information often affects the strength of the immunization measures in the face of the epidemic. A single exposure network analysis often does not provide a more complete picture of these intricate relationships.[15,16]

In recent years, with the development and popularity of multilayer networks, individuals have become increasingly aware that epidemic transmission is not just simple transmission at the physical contact layer but is also accompanied by epidemic-related information, hence making the study of multilayer networks a popular topic for many scholars.[17–19] The multi-layer network modelling approach has proved to be a better representation of the intricate coupling of relationships in real situations.[20,21] Therefore, it is significant to study epidemic transmission on multi-layered networks. Epidemic transmission is often accompanied by the diffusion of epidemic-related information, and different information often affects individuals' levels of self-protection at the physical contact layer. Therefore, research on information–epidemic coupling effect has great significance for the prevention and control of epidemics. Granell *et al*.[22] proposed a UAU–SIS model that couples a multilayer network with the epidemic transmission process. Later[23] they introduced mass media

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to further analyze the influence of local versus global information on epidemic transmission. Wang and Xia[24] investigated the coupling effect of multiple messages and epidemics on a two-layer network under the influence of mass media and discussed the dynamic effects of different competing messages. Li and Hui[25] studied epidemic transmission in multi-relational networks. Peng *et al.*[26] investigated the effect of messages on a multi-layer network for two competing views on how to influence the scale of epidemic transmission. Guo *et al.*[27] proposed a threshold model, arguing that individuals' behavior adoption usually depends on the state of their neighbors, which can be simply understood by what we describe as the crowd effect, or the standing ovation effect. For example, when the number of neighborhoods around an individual reaches a certain value, the individual tends to accept the message or adopt the same behavior. Xu *et al.*[28] used two threshold models to explore the effects of local versus global awareness on epidemic transmission separately and also considered the heterogeneity of individual responses to risk. Some scholars have also worked on human mobility and spatio-temporal interactions, which are crucial for spreading epidemics. Li *et al.*[29] proved that a local basic reproductive number greater than unity is neither necessary nor sufficient for epidemic outbreaks. Li *et al.*[30] also studied how low population density hinders epidemics. Liu *et al.*[31] revealed general collective patterns behind spatiotemporal interactions between residents and proved that physical contact eventually drives epidemic transmission.

In addition, individuals' behavior patterns are usually influenced by information, resulting in different propagation effects.[32–37] Liu *et al.*[38] argued that individuals' behavior adoption patterns are a nonlinear Markovian process, influenced by time effects and social reinforcement of the number of times they receive information. Moreover, Gao and Tian[39] discussed the pattern of adoption of green behaviors under the combined effect of self-awareness and policies, where coercive policies only act on specific negative individuals. Zhang *et al.*[40] proposed a coupled model of rumor and behavior to study the effect of internode attraction on propagation dynamics. In addition, the behavioral model of vaccination has received much attention,[41–43] especially during the COVID-19 outbreak. Wang *et al.*[44] investigated the impact of multiple vaccination strategies and further discussed the effect of vaccine failure on epidemic transmission. Dai *et al.*[45] discussed the effect of vaccine availability on epidemic transmission in the presence of information. Yin *et al.*[46] proposed a three-level coupled network model to analyze the effect of negative information and vaccination behavior on epidemic transmission dynamics, and considered the combined effect of vaccination cost and flock psychology on the choice of vaccination behavior. Furthermore, higher-order networks provide methods for studying propagation dynamics from the perspective of network heterogeneity. Li *et al.*[47] proposed the coevolution of epidemic–infodemic dynamics on the simplicial complex. Li *et al.*[48] also proposed a competing spread model for two simplicial irreversible epidemics on higher-order networks, and later discussed the immunization strategies for a simplicial irreversible epidemic on the simplicial complex.[49] Other scholars have focused on the effect of individual heterogeneity on dynamics. Nie *et al.*[50] proposed a dynamics model with a homophily effect and heterogeneous populations.

In most cases, these scholars have tended to consider the direct effect of information on the epidemic. In fact, individuals are heterogeneous and usually make different choices when faced with different situations. However, few scholars have discussed the impact of information and an epidemic on behavior adoption patterns under the influence of individual heterogeneity and have assumed that individuals' responses are homogeneous. However, individual behavior adoption patterns are influenced by a combination of information diffusion and epidemic transmission. When individuals select behavior adoption they are often influenced by both epidemic-related information and the epidemic transmission environment. In the dynamic process of epidemic transmission, official information posted on social media often guides individuals to adopt the correct immunization behavior to reduce the probability of infection. However, individual behavior adoption is a complex process that is influenced not only by the credibility of social media but also by the risk sensitivity of the population. For example, when individuals learn about immunization-related official information they often make judgments about the information rather than immediately adopt immunization behaviors; this is often influenced by the credibility of social media. If the credibility of social media is low, even if individuals know the official information they will not adopt the immunization behavior. On the other hand, individuals' immunization behavior adoption processes are also influenced by the risk sensitivity of the population. Individuals who are more sensitive to epidemic risk are more likely to adopt immunization behaviors to protect themselves. For example, during the COVID-19 epidemic some social media sources had lower credibility and individuals preferred not to adopt immunization behaviors, which tended to increase the individual epidemic infection rate. Not only that, when an epidemic is not severe individuals may be less willing to get vaccinated, but when an epidemic is severe most individuals tend to choose to be vaccinated. Thus, the immunization behavior adoption process is not determined by a single adoption process, but by multiple aspects. Based on this phenomenon, we proposed a three-layer coupled model of information–behavior–epidemic to discuss the interaction

effect of information diffusion, individual behavior adoption and epidemic transmission. In particular, we focus on the effect of credibility of social media and risk sensitivity of the population on heterogeneity of behavioral adoption. Our results can provide a reference for exploring the intrinsic connections between official information, immunization behavior and epidemics in multiple ways.

The framework of this paper is as follows: we describe our three-layer coupled model with related assumptions in Section 2. In Section 3, we apply a microscopic Markov chain approach and derive the threshold of epidemic transmission. In Section 4, extensive simulations are performed to demonstrate our theoretical analysis. Finally, in Section 5, our conclusions and outlook are summarized.

2. The three-layer coupled model

During the COVID-19 outbreak, social media played an important role in epidemic control by releasing official information in a timely manner. However, even though some individuals were aware of the official information, they still refused to adopt immunization behaviors. For example, social media emphasized the importance of vaccines and encouraged people to get vaccinated in a timely manner, but some individuals do not think that social media can be trusted and thus were reluctant to adopt immunization behaviors.[51–54] If individuals are more sensitive to epidemic risk, they are more likely to adopt immunization behaviors. In fact, individuals' behavior adoption is not only influenced by the credibility of social media but also by individual risk sensitivity to the severity of the epidemic. To better describe this phenomenon, shown in Fig. 1, in this section, we propose a three-layer coupled model including official information diffusion, immunization behavior adoption and epidemic transmission, in which an individual's immunization behavior adoption process is determined by both the credibility of social media and risk sensitivity of the population to the epidemic.

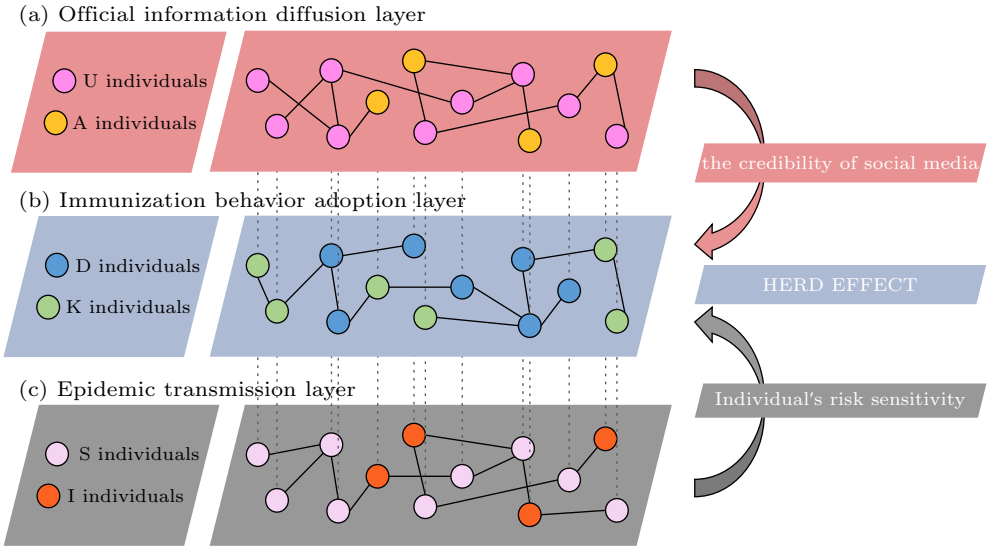


Fig. 1. Structure of the three-layer UAU–DKD–SIS propagation network framework. In the information transmission layer, the purple circles represent individuals U who do not know the official information and the yellow circles represent individuals A who know the official information. In the immunization behavior adoption layer, the blue circles represent individuals D who do not adopt the immunization behavior and the green circles represent individuals K who adopt the immunization behavior. In the epidemic transmission layer, the pink circles represent susceptible individuals S and the orange circles represent infected individuals I.

The model assumptions in this paper are given below.

Assumption 1: Official information diffusion process In the official information diffusion layer, we consider official information diffusion represented by social media. In this layer, the nodes include two states, U (unaware) and A (aware). When an individual in state U who does not know the official information comes into contact with a neighbor in state A who is aware of the official information, the individual in state U will be informed about the official information with probability λ, transform to state A, and start to disseminate the official information. While an individual in state A will forget the official information or lose interest in the official information with probability δ.

Assumption 2: Immunization behavior adoption process In the immunization behavior adoption layer, we mainly consider the adoption of immunization behavior. In this layer, nodes include two states, K (not adopted) and D (adopted). We refer to the wearing of masks, getting vaccinated and taking proper protective measures collectively as immunization behaviors. Considering the impact of the credibility of social media and risk sensitivity of the population to the epidemic on immunization behavior adoption, we define the probability that individual i in the state K decides to adopt immunization behavior as

$$x_i(t) = \zeta \alpha_i(t) + (1-\zeta)\theta_i(t), \tag{1}$$

where $\alpha_i(t)$ is the rate of behavior adoption considering social media at moment t and $\theta_i(t)$ is the rate of behavior adoption considering the sensitivity of the epidemic at moment t. We assume joint influence of the credibility of social media and risk sensitivity of the population to the epidemic on the immunization behavior adoption process. Thus, we use ζ to represent the number of individuals influenced by the credibility of mass media in the immunization behavior adoption process and $\zeta \in [0,1]$ and $1-\zeta$ to represent the number of individuals influenced by risk sensitivity of the population to the epidemic in the immunization behavior adoption process. A larger ζ indicates a greater tendency to be influenced by the credibility of social media in changing behavior, while a smaller ζ indicates a greater tendency to be influenced by risk sensitivity of the population to the epidemic in changing behavior. We introduce the Heaviside step function to characterize the effect of $\alpha_i(t)$ and $\theta_i(t)$ on the immunization behavior adoption process, and the specific explanations for $\alpha_i(t)$ and $\theta_i(t)$ are given in Assumption 4. As illustrated above, individuals in state D who have not adopted immunization behavior will adopt immunization behavior with probability $x_i(t)$. It is worth noting that in the immunization behavior adoption process, we only consider an individual's decision to adopt, and do not consider behavior transmission between neighbors. In addition, an individual who adopts immunization behaviors will face immunization failure with probability η.

Assumption 3: Epidemic transmission process In the epidemic transmission layer, nodes include two states, S (susceptible) and I (infected). The epidemic transmission process follows the classical SIS model where a node in state S comes into contact with a node in state I and will be infected with probability β, while a node in state I will be cured and return to state S with probability μ.

Based on Assumptions 1–3, we can conclude that there are eight node states coupled in the three-layer network, namely UDS, UDI, UKS, UKI, ADS, ADI, AKS and AKI. Here, we assume that once a node receives an infection, it will be informed of the official information as a result of the treatment and communications of the hospital and then adopt immunization behaviors. The individuals with three states, UDI, UKI, AKI, will be transformed into ADI individuals with probability 1. As a result, we can obtain five valid states: UDS, UKS, ADS, AKS and ADI.

Assumption 4: Influence of official information diffusion and epidemic transmission on immunization adoption behavior considering the credibility of social media and risk sensitivity of the population to epidemic In this paper, we focus on the heterogeneity of individuals when engaging in adoption behavior based on the coupled influence of information and the epidemic. The credibility of social media and risk sensitivity of the population to the epidemic are mainly considered. Here, we consider a Heaviside step function to describe the immunization behavior adoption process, i.e., $F(x)=0$, if $x \geq 0$, and $F(x)=1$, if $x<0$.

We hypothesize that individuals' behavior adoption is firstly related to the credibility of social media. In real life, many individuals often choose to disbelieve official information because of the lower credibility of social media. For example, in the early stages of the COVID-19 epidemic, many social media sources promoted the importance of immunization, but there were still individuals who refused to adopt immunization behaviors due to the lower credibility of social media. Also, when the credibility of social media is low, individuals tend to worry about unknown negative impacts of immunization behaviors on health, which also affects individuals' adoption of immunization behaviors. In addition, due to herd mentality, individuals are often reluctant to adopt immunization behaviors when they are surrounded by fewer neighbors who choose to adopt. Therefore, considering the credibility of social media, we calculate the behavior adoption rate $\alpha_i(t)$ as

$$\alpha_i(t) = \alpha_0 F\left[m - \frac{\sum_{j=1}^{N} a_{ij} P_j^{\mathrm{A}}(t)}{k_i^1}\right], \tag{2}$$

where $\sum_{j=1}^{N} a_{ij} P_j^{\mathrm{A}}(t)/k_i^1$ denotes the proportion of individuals who know the official information among the neighbors j of node i at moment t, m represents the credibility of social media, $m \in [0,1]$, with a larger m indicating lower credibility of social media, α_0 is the initial behavior adoption rate under the influence of the diffusion process of official information, α_{ij} are the adjacency matrices that support the official information diffusion process, k_i^1 denotes the degree of node i in the official information diffusion layer and $P_j^{\mathrm{A}}(t)$ is the probability that individual j is in state A at moment t. When $m=1$, social media is completely untrustworthy, and at this point no matter how many neighbors around the individual believe the official information, the individual will not adopt the immunization behavior. When $m=0$, social media is completely trustworthy and at this point individuals will adopt immunization behavior with probability α_0. When $0<m<1$, as the proportion of individuals' neighbors who believe the official information increases and reaches a certain adoption threshold m, individuals will choose to adopt immunization behavior with probability α_0. Specifically, $F\left[m - \frac{\sum_{j=1}^{N} a_{ij} P_j^{\mathrm{A}}(t)}{k_i^1}\right] = 0$, if $m - \frac{\sum_{j=1}^{N} a_{ij} P_j^{\mathrm{A}}(t)}{k_i^1} \geq 0$, and $F\left[m - \frac{\sum_{j=1}^{N} a_{ij} P_j^{\mathrm{A}}(t)}{k_i^1}\right] = 1$, if $m - \frac{\sum_{j=1}^{N} a_{ij} P_j^{\mathrm{A}}(t)}{k_i^1} < 0$.

In addition, we hypothesize that an individual's behavior adoption is also related to risk sensitivity of the population to the epidemic. When individuals have a high sensitivity to the severity of the epidemic they tend to stay alert and will adopt immunization behaviors. In contrast, individuals with a low sensitivity to the epidemic's severity are more likely not to adopt immunization behaviors by ignoring the prevalence of the epidemic. Therefore, considering the risk sensitivity of

the population to the epidemic, we surmise that the behavior adoption rate $\theta_i(t)$ is

$$\theta_i(t) = \theta_0 F\left[\pi - \frac{\sum_{j=1}^{N} c_{ij} P_j^{\mathrm{I}}(t)}{k_i^2}\right], \tag{3}$$

where π represents the risk sensitivity of the population to the epidemic, $\pi \in [0,1]$, which is used to describe the macroscopic perception of the epidemic by individuals at the level of society, rather than the heterogeneity of perception of the epidemic by different individuals. A larger π indicates that individuals are more sensitive to epidemic severity and less likely to adopt rumor-related behaviors. c_{ij} are the adjacency matrices that support the epidemic transmission process, $\sum_{j=1}^{N} c_{ij} P_j^{\mathrm{I}}(t)/k_i^2$ denotes the proportion of infected individuals among the neighbors j of node i at moment t, θ_0 is the initial rate of behavior adoption under the influence of the epidemic transmission process, k_i^2 denotes the degree of node i in the epidemic transmission layer and $P_j^{\mathrm{I}}(t)$ is the probability that individual j is in state I at moment t. When $\pi = 0$, the individual is completely insensitive to the risk of the epidemic, and the individual does not adopt immunization behavior regardless of the number of neighbors around the individual who are infected. When $\pi = 1$, individuals are extremely sensitive to the risk of an epidemic, and at this point individuals will adopt immunization behavior with probability θ_0. When $0 < \pi < 1$, as the proportion of infected individuals in an individual's neighborhood increases and reaches a certain adoption threshold of risk awareness π, individuals will choose to adopt immunization behaviors with probability θ_0. Specifically, $F[\pi - \frac{\sum_{j=1}^{N} c_{ij} P_j^{\mathrm{I}}(t)}{k_i^2}] = 0$, if $\pi - \frac{\sum_{j=1}^{N} c_{ij} P_j^{\mathrm{I}}(t)}{k_i^2} \geq 0$, and $F[\pi - \frac{\sum_{j=1}^{N} c_{ij} P_j^{\mathrm{I}}(t)}{k_i^2}] = 1$, if $\pi - \frac{\sum_{j=1}^{N} c_{ij} P_j^{\mathrm{I}}(t)}{k_i^2} < 0$.

Assumption 5: Coupling effect of the immunization behavior adoption layer on the epidemic transmission layer We hypothesized that an individual's infection rate in the epidemic transmission layer is influenced by the joint influence of the official information diffusion layer and the immunization behavior adoption layer.

Individual behavioral patterns often play a major role in infection rates in epidemics. Individuals who do not adopt immunization behaviors tend to have a higher infection rate. In addition, when individuals know the official information, they tend to take certain precautions to prevent themselves from getting infected more often than people who do not know the official information. Therefore, we assumed that the infection rates of UKS and AKS individuals is β^{UKS} and β^{AKS}, respectively, are

$$\beta^{\mathrm{UKS}} = \gamma_{\mathrm{UKS}}\beta, \ \ \beta \in [0,1],$$
$$\beta^{\mathrm{AKS}} = \gamma_{\mathrm{AKS}}\beta, \ \ \beta \in [0,1],$$

where γ_{UKS} and γ_{AKS} represent the influence of the UKS and AKS individuals on the infection rate and β is the underlying infection rate independent of other factors.

In addition, we assume that UDS individuals have a lower infection rate than UKS and AKS individuals because they adopt immunization behaviors. Therefore, we assume that the infection rate of UDS individuals is β^{UDS} AKS individuals is β^{UKS} and β^{AKS}, respectively, are

$$\beta^{\mathrm{UDS}} = \gamma_{\mathrm{UDS}}\beta, \ \ \beta \in [0,1],$$

where γ_{UDS} characterizes the influence of the UDS individuals on the infection rate.

Finally, we hypothesized that ADS individuals tend to reinforce some self-protection due to their knowledge of official information, and their infection rate at the epidemic level is relatively lower than that of UDS individuals. Therefore, we hypothesized that the infection rate of ADS individuals would be

$$\beta^{\mathrm{ADS}} = \gamma_{\mathrm{ADS}}\beta, \ \ \beta \in [0,1],$$

where γ_{ADS} represents the influence of the ADS individuals on the infection rate.

We assume that the infection rate of an individual is mainly influenced by behavior adoption and, to a lesser extent, by the receipt of information, thus $\gamma_{\mathrm{UDS}} \leq \gamma_{\mathrm{AKS}}$, and that both the adoption of immunization behavior and knowledge of official information reduces the risk of infection at the epidemic transmission layer, thus $\gamma_{\mathrm{AKS}} \leq \gamma_{\mathrm{UKS}}$. Specifically, an individual has the smallest infection rate if s/he adopts immunization behavior and is aware of official information, while s/he has the highest infection rate if s/he neither adopts immunization behavior nor is aware of official information. Moreover, since behavior has a greater effect on the infection rate than information, we consider that individuals who know the official information but do not adopt immunization behavior have a higher infection rate than those who do not know the information but adopt immunization behavior. In summary, the influencing parameters satisfy $\gamma_{\mathrm{ADS}} \leq \gamma_{\mathrm{UDS}} \leq \gamma_{\mathrm{AKS}} \leq \gamma_{\mathrm{UKS}}$. In addition, in this paper, we argue that an individual's state in the immunization behavior adoption layer has a direct effect on the epidemic transmission process, while an individual's state in the information diffusion layer influences their immunization behavior adoption process and then affects the epidemic transmission process indirectly. Therefore, to simplify the model, we let $\gamma_{\mathrm{AKS}} = \gamma_{\mathrm{UKS}} = 1$, $\gamma_{\mathrm{UDS}} = \varphi$ and $\gamma_{\mathrm{ADS}} = \varphi^2$, and then we have $\beta^{\mathrm{A}} = \varphi\beta^{U} = \varphi^2\beta^{K} = \varphi^2\beta$. The simplified parameters are as follows:

$$\beta^{X} = \begin{cases} \beta, & X = \text{UKS and AKS}, \\ \varphi\beta, & X = \text{UDS}, \\ \varphi^2\beta, & X = \text{ADS}, \end{cases} \tag{4}$$

where $X \in \{\mathrm{UKS}, \mathrm{AKS}, \mathrm{UDS}, \mathrm{ADS}\}$. φ is used to characterize the attenuation factor of the infection rate in individuals with different status, $\varphi \in [0,1]$.

Based on the above discussion, we can obtain the propagation model of the three-layer network as follows:

(i) Official information diffusion

$$\mathrm{UDS} \xrightarrow{\lambda} \mathrm{ADS}, \quad \mathrm{UKS} \xrightarrow{\lambda} \mathrm{AKS},$$
$$\mathrm{ADS} \xrightarrow{\delta} \mathrm{UDS}, \quad \mathrm{AKS} \xrightarrow{\delta} \mathrm{UKS}.$$

(ii) Immunization behavior adoption

$$\mathrm{UDS} \xrightarrow{x_i} \mathrm{UKS}, \quad \mathrm{ADS} \xrightarrow{x_i} \mathrm{AKS},$$
$$\mathrm{UKS} \xrightarrow{\eta} \mathrm{UDS}, \quad \mathrm{AKS} \xrightarrow{\eta} \mathrm{ADS}.$$

(iii) Epidemic transmission

$$\mathrm{UDS} \xrightarrow{\varphi\beta} \mathrm{ADI}, \quad \mathrm{UKS} \xrightarrow{\beta} \mathrm{ADI},$$
$$\mathrm{ADS} \xrightarrow{\varphi^2\beta} \mathrm{ADI}, \quad \mathrm{AKS} \xrightarrow{\beta} \mathrm{ADI}, \quad \mathrm{ADI} \xrightarrow{\mu} \mathrm{ADS}.$$

3. The theoretical analysis

3.1. Probability transition tree and equations

Let a_{ij}, b_{ij} and c_{ij} denote the adjacency matrices that support the official information diffusion process, immunization behavior adoption process and epidemic transmission process, respectively. Any individual has five overall states (UDS, UKS, ADS, AKS, ADI) and the probability of node i being in the five states at time t is assumed to be $P_i^{\mathrm{UDS}}(t)$, $P_i^{\mathrm{UKS}}(t)$, $P_i^{\mathrm{ADS}}(t)$, $P_i^{\mathrm{AKS}}(t)$, and $P_i^{\mathrm{ADI}}(t)$, respectively, satisfying the normalization condition $P_i^{\mathrm{UDS}}(t) + P_i^{\mathrm{UKS}}(t) + P_i^{\mathrm{ADS}}(t) + P_i^{\mathrm{AKS}}(t) + P_i^{\mathrm{ADI}}(t) = 1$. We use $r_i(t)$ to represent the probability of node i not being informed by any neighbor at time t, $\alpha_i(t)$ to represent the probability of node i not adopting immunization behavior at time t due to the credibility of social media, $\theta_i(t)$ to represent the probability of node i not adopting immunization behavior at time t due to the risk sensitivity of the population to epidemic, $x_i(t)$ to represent the probability of node i not adopting immunization behavior at time t, $q_i^{\mathrm{U}}(t)$ to represent the probability of a UDS node not being infected by any neighbor at time t, $q_i^{\mathrm{K}}(t)$ to represent the probability of a UKS and AKS node not being infected by any neighbor at time t and $q_i^{\mathrm{A}}(t)$ to represent the probability of a ADS node not being infected by any neighbor at time t, respectively. We obtain the following:

$$r_i(t) = \prod_j \left[1 - a_{ji} P_j^{\mathrm{A}}(t) \lambda\right], \tag{5}$$

$$\alpha_i(t) = \alpha_0 F\left[m - \frac{\sum_{j=1}^{N} a_{ij} P_j^{\mathrm{A}}(t)}{k_i^1}\right], \tag{6}$$

$$\theta_i(t) = \theta_0 F\left[\pi - \frac{\sum_{j=1}^{N} c_{ij} P_j^{\mathrm{I}}(t)}{k_i^2}\right], \tag{7}$$

$$x_i(t) = \zeta \alpha_i(t) + (1-\zeta)\theta_i(t), \tag{8}$$

$$q_i^{\mathrm{U}}(t) = \prod_j \left[1 - c_{ji} P_j^{\mathrm{ADI}}(t) \beta^{\mathrm{U}}\right], \tag{9}$$

$$q_i^{\mathrm{K}}(t) = \prod_j \left[1 - c_{ji} P_j^{\mathrm{ADI}}(t) \beta^{\mathrm{K}}\right], \tag{10}$$

$$q_i^{\mathrm{A}}(t) = \prod_j \left[1 - c_{ji} P_j^{\mathrm{ADI}}(t) \beta^{\mathrm{A}}\right], \tag{11}$$

where $P_j^{\mathrm{A}}(t) = P_j^{\mathrm{ADS}}(t) + P_j^{\mathrm{AKS}}(t)$ and $P_j^{\mathrm{I}}(t) = P_j^{\mathrm{ADI}}(t)$.

According to the scheme in Fig. 2, the microscopic Markov chain approach[55,56] for each state can be proposed as follows:

$$\begin{aligned} P_i^{\mathrm{UDS}}(t+1) &= P_i^{\mathrm{UDS}}(t) r_i(t) x_i(t) q_i^{\mathrm{U}}(t) + P_i^{\mathrm{UKS}}(t) r_i(t) \eta q_i^{\mathrm{U}}(t) \\ &\quad + P_i^{\mathrm{ADS}}(t) \delta x_i(t) q_i^{\mathrm{U}}(t) + P_i^{\mathrm{AKS}}(t) \delta \eta q_i^{\mathrm{U}}(t), \end{aligned} \tag{12}$$

$$\begin{aligned} P_i^{\mathrm{UKS}}(t+1) &= P_i^{\mathrm{UDS}}(t) r_i(t) [1 - x_i(t)] q_i^{\mathrm{K}}(t) \\ &\quad + P_i^{\mathrm{UKS}}(t) r_i(t) (1-\eta) q_i^{\mathrm{K}}(t) \\ &\quad + P_i^{\mathrm{ADS}}(t) \delta [1 - x_i(t)] q_i^{\mathrm{K}}(t) \\ &\quad + P_i^{\mathrm{AKS}}(t) \delta (1-\eta) q_i^{\mathrm{K}}(t), \end{aligned} \tag{13}$$

$$\begin{aligned} P_i^{\mathrm{ADS}}(t+1) &= P_i^{\mathrm{UDS}}(t) [1 - r_i(t)] x_i(t) q_i^{\mathrm{A}}(t) \\ &\quad + P_i^{\mathrm{UKS}}(t) [1 - r_i(t)] \eta q_i^{\mathrm{A}}(t) \\ &\quad + P_i^{\mathrm{ADS}}(t) (1-\delta) x_i(t) q_i^{\mathrm{A}}(t) \\ &\quad + P_i^{\mathrm{AKS}}(t) (1-\delta) \eta q_i^{\mathrm{A}}(t) + P_i^{\mathrm{ADI}}(t) \mu, \end{aligned} \tag{14}$$

$$\begin{aligned} P_i^{\mathrm{AKS}}(t+1) &= P_i^{\mathrm{UDS}}(t) [1 - r_i(t)] [1 - x_i(t)] q_i^{\mathrm{K}}(t) \\ &\quad + P_i^{\mathrm{UKS}}(t) [1 - r_i(t)] (1-\eta) q_i^{\mathrm{K}}(t) \\ &\quad + P_i^{\mathrm{ADS}}(t) (1-\delta) [1 - x_i(t)] q_i^{\mathrm{K}}(t) \\ &\quad + P_i^{\mathrm{AKS}}(t) (1-\delta)(1-\eta) q_i^{\mathrm{K}}(t), \end{aligned} \tag{15}$$

$$\begin{aligned} P_i^{\mathrm{ADI}}(t+1) &= P_i^{\mathrm{UDS}}(t) r_i(t) \\ &\quad \times \left\{x_i(t)[1 - q_i^{\mathrm{U}}(t)] + [1 - x_i(t)][1 - q_i^{\mathrm{K}}(t)]\right\} \\ &\quad + P_i^{\mathrm{UDS}}(t) [1 - r_i(t)] \\ &\quad \times \left\{x_i(t)[1 - q_i^{\mathrm{A}}(t)] + [1 - x_i(t)][1 - q_i^{\mathrm{K}}(t)]\right\} \\ &\quad + P_i^{\mathrm{UKS}}(t) r_i(t) \\ &\quad \times \left\{\eta[1 - q_i^{\mathrm{U}}(t)] + (1-\eta)[1 - q_i^{\mathrm{K}}(t)]\right\} \\ &\quad + P_i^{\mathrm{UKS}}(t) [1 - r_i(t)] \\ &\quad \times \left\{\eta[1 - q_i^{\mathrm{A}}(t)] + (1-\eta)[1 - q_i^{\mathrm{K}}(t)]\right\} \\ &\quad + P_i^{\mathrm{ADS}}(t) \delta \\ &\quad \times \left\{x_i(t)[1 - q_i^{\mathrm{U}}(t)] + [1 - x_i(t)][1 - q_i^{\mathrm{K}}(t)]\right\} \\ &\quad + P_i^{\mathrm{ADS}}(t) (1-\delta) \\ &\quad \times \left\{x_i(t)[1 - q_i^{\mathrm{A}}(t)] + [1 - x_i(t)][1 - q_i^{\mathrm{K}}(t)]\right\} \\ &\quad + P_i^{\mathrm{AKS}}(t) \delta \\ &\quad \times \left\{\eta[1 - q_i^{\mathrm{U}}(t)] + (1-\eta)[1 - q_i^{\mathrm{K}}(t)]\right\} \\ &\quad + P_i^{\mathrm{AKS}}(t) (1-\delta) \\ &\quad \times \left\{\eta[1 - q_i^{\mathrm{A}}(t)] + (1-\eta)[1 - q_i^{\mathrm{K}}(t)]\right\} \\ &\quad + P_i^{\mathrm{ADI}}(t)(1-\mu). \end{aligned} \tag{16}$$

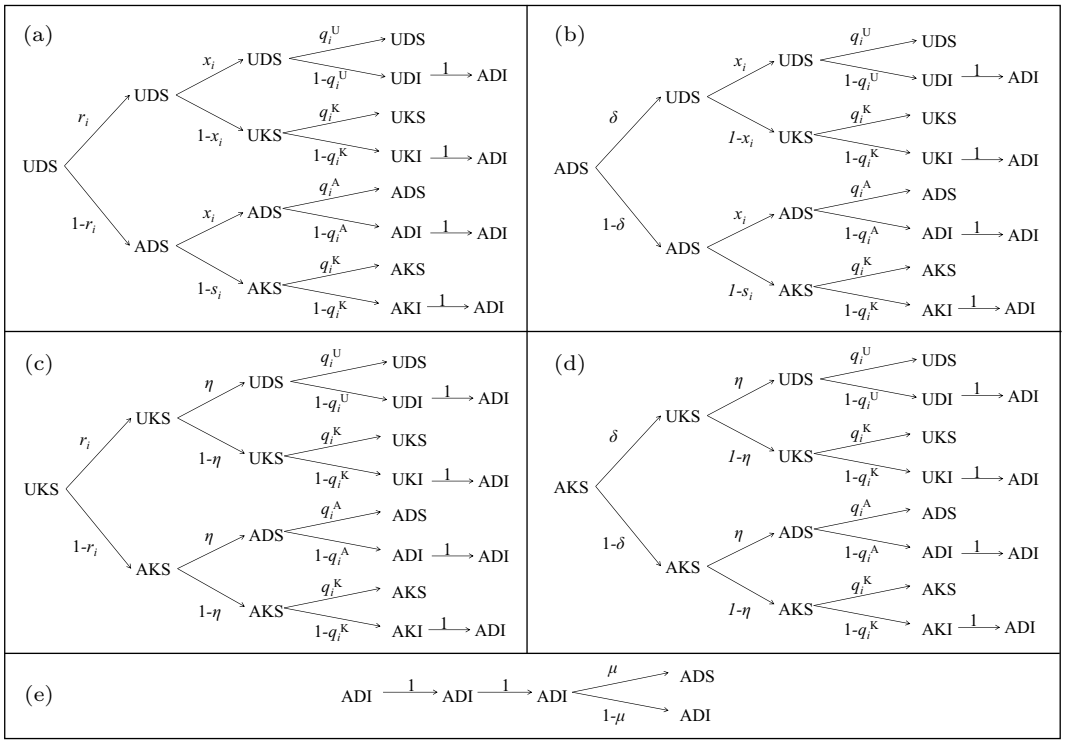


Fig. 2. The probability transmission trees for five possible states (including UDS, UKS, ADS, AKS, and ADI).

3.2. Critical epidemic threshold of the system

Using the transformation equations derived from the probability transmission tree above, we can summarize the epidemic threshold β_c of the model. When the system tends to a steady state, we can obtain that $P_i(t+1) = P_i(t) = P_i$ holds for any node i and all possible states. The number of infected individuals in the system approaches 0 near the epidemic threshold, that is, $P_i^{\mathrm{I}} = P_i^{\mathrm{ADI}} = \varepsilon_i \ll 1$. Accordingly, equations (9), (10) and (11) can be approximated as

$$q_i^{\mathrm{U}}(t) = \prod_j [1 - c_{ji} P_j^{\mathrm{ADI}}(t) \beta^{\mathrm{U}}] \approx 1 - \beta^{\mathrm{U}} \sum_j c_{ji}\varepsilon_{ji} = 1 - \varphi\sigma_i, \quad (17)$$

$$q_i^{\mathrm{K}}(t) = \prod_j [1 - c_{ji} P_j^{\mathrm{ADI}}(t) \beta^{\mathrm{K}}] \approx 1 - \beta^{\mathrm{K}} \sum_j c_{ji}\varepsilon_{ji} = 1 - \sigma_i, \quad (18)$$

$$q_i^{\mathrm{A}}(t) = \prod_j [1 - c_{ji} P_j^{\mathrm{ADI}}(t) \beta^{\mathrm{A}}] \approx 1 - \beta^{\mathrm{A}} \sum_j c_{ji}\varepsilon_{ji} = 1 - \varphi^2\sigma_i, \quad (19)$$

where

$$\sigma_i = \beta \sum_j c_{ji}\varepsilon_{ji}, \quad (20)$$

and equation (16) in the steady state becomes

$$\begin{aligned}
\varepsilon_i = {} & (1-\mu)\varepsilon_i + P_i^{\mathrm{UDS}} \Big\{ r_i \left[x_i \varphi\sigma_i + (1-x_i)\sigma_i \right] \\
& + (1-r_i) \left[x_i \varphi^2\sigma_i + (1-x_i)\sigma_i \right] \Big\} \\
& + P_i^{\mathrm{UKS}}(t) \Big\{ r_i \left[\eta\varphi\sigma_i + (1-\eta)\sigma_i \right] \\
& + (1-r_i) \left[\eta\varphi^2\sigma_i + (1-\eta)\sigma_i \right] \Big\} \\
& + P_i^{\mathrm{ADS}}(t) \Big\{ \delta \left[x_i \varphi\sigma_i + (1-x_i)\sigma_i \right] \\
& + (1-\delta) \left[x_i \varphi^2\sigma_i + (1-x_i)\sigma_i \right] \Big\} \\
& + P_i^{\mathrm{AKS}}(t) \Big\{ \delta \left[\eta\varphi\sigma_i + (1-\eta)\sigma_i \right] \\
& + (1-\delta) \left[\eta\varphi^2\sigma_i + (1-\eta)\sigma_i \right] \Big\}. \quad (21)
\end{aligned}$$

This is equivalent to

$$\mu\varepsilon_i = P_i^{\mathrm{UDS}}\varphi\sigma_i + P_i^{\mathrm{ADS}}\varphi^2\sigma_i + \left(P_i^{\mathrm{UKS}} + P_i^{\mathrm{AKS}} \right) \sigma_i. \quad (22)$$

Since $P_i^{\mathrm{I}} = P_i^{\mathrm{ADI}} = \varepsilon_i \ll 1$, similarly, removing $O(\varepsilon_i)$ terms in the stationary state of Eqs. (12)–(15) we get

$$P_i^{\mathrm{UDS}} = P_i^{\mathrm{UDS}} r_i x_i + P_i^{\mathrm{UKS}} r_i \eta + P_i^{\mathrm{ADS}} \delta x_i + P_i^{\mathrm{AKS}} \delta\eta, \quad (23)$$

$$\begin{aligned}
P_i^{\mathrm{UKS}}(t+1) = {} & P_i^{\mathrm{UDS}} r_i (1-x_i) + P_i^{\mathrm{UKS}} r_i (1-\eta) \\
& + P_i^{\mathrm{ADS}} \delta (1-x_i) + P_i^{\mathrm{AKS}} \delta (1-\eta), \quad (24)
\end{aligned}$$

$$\begin{aligned}
P_i^{\mathrm{ADS}} = {} & P_i^{\mathrm{UDS}} (1-r_i) x_i + P_i^{\mathrm{UKS}} (1-r_i)\eta \\
& + P_i^{\mathrm{ADS}} (1-\delta) x_i + P_i^{\mathrm{AKS}} (1-\delta)\eta, \quad (25)
\end{aligned}$$

$$\begin{aligned}
P_i^{\mathrm{AKS}} = {} & P_i^{\mathrm{UDS}} (1-r_i)(1-x_i) + P_i^{\mathrm{UKS}} (1-r_i)(1-\eta) \\
& + P_i^{\mathrm{ADS}} (1-\delta)(1-x_i) + P_i^{\mathrm{AKS}} (1-\delta)(1-\eta). \quad (26)
\end{aligned}$$

Substituting $P_i^{\mathrm{UDS}}(t) + P_i^{\mathrm{UKS}}(t) + P_i^{\mathrm{ADS}}(t) + P_i^{\mathrm{AKS}}(t) = 1$ into Eq. (19) leads to

$$\begin{aligned}
\varepsilon_i = {} & (1-\mu)\varepsilon_i + P_i^{\mathrm{UDS}}\varphi\sigma_i + P_i^{\mathrm{ADS}}\varphi^2\sigma_i + \left(P_i^{\mathrm{UKS}} + P_i^{\mathrm{AKS}} \right) \sigma_i \\
= {} & (1-\mu)\varepsilon_i \\
& + \left[P_i^{\mathrm{UDS}}\varphi + P_i^{\mathrm{ADS}}\varphi^2 + \left(P_i^{\mathrm{UKS}} + P_i^{\mathrm{AKS}} \right) \right] \beta \sum_j c_{ji}\varepsilon_{ji}, \quad (27)
\end{aligned}$$

which can be written as

$$\sum_j \{[1-P_i^{\mathrm{UDS}}(1-\varphi)-P_i^{\mathrm{ADS}}(1-\varphi^2)]c_{ji}-\frac{\mu}{\beta}\}\varepsilon_j=0. \quad (28)$$

Let $h_{ji}=[1-P_i^{\mathrm{UDS}}(1-\varphi)-P_i^{\mathrm{ADS}}(1-\varphi^2)]c_{ji}$, and $C=[c_{ji}]$, so

$$h_{ji}=[1-P_i^{\mathrm{UDS}}(1-\varphi)-P_i^{\mathrm{ADS}}(1-\varphi^2)]C, \quad (29)$$

where the maximum eigenvalue of matrix H is a non-microscopic solution of Eq. (28) and the threshold of the epidemic is determined by the maximum eigenvalue of matrix H,

$$\beta_{\mathrm{c}}^{\mathrm{U}}=\frac{\mu}{\Lambda_{\max}(H)}, \quad (30)$$

where $\Lambda_{\max}(H)$ is the maximum eigenvalue of matrix H, and matrix H depends on the solutions of Eqs. (23) and (25), which are also solved by iteration.

4. The numerical simulations

In this section, we perform a number of simulations to validate the applicability of our proposed model. We mainly describe the role of different parameters by discussing the epidemic outbreak threshold β_{c} and the final number of infected individuals ρ^{I}. Here, we assume a three-layer scale-free network including 3000 nodes in each layer, where the number of edges to attach from a new node to existing nodes is 6. Each point in the figures of size 40×40 is obtained by 50 simulations. For simplicity, we assume $\theta_0=\alpha_0$. In addition, the initial numbers of nodes A, K, and I were each assumed to be 0.1. In order to make the simulation data more reliable, the parameter settings in this paper are based on the references shown in Table 1.

Table 1. Definition of parameters and related references.

Parameter	Definition	References
λ	The rate of diffusion of official information	[22,26,28]
δ	The rate of forgetting official information	[22,24–26]
α_0	The initial behavior adoption rate under the influence of the diffusion of official information	[32–34,46,57]
θ_0	The initial behavior adoption rate under the influence of the epidemic transmission process	[32–34,46,57]
m	The credibility of social media	[32,34,37]
π	The risk sensitivity of the population to the epidemic	[33,34,39]
ζ	The weight of individuals influenced by the credibility of mass media in the immunization behavior adoption process	[41–43]
η	The immunization failure rate	[41–43,46]
β	The epidemic transmission rate	[22–25]
φ	The attenuation factor of the infection rate	[22,24,27]
μ	The epidemic recovery rate	[22–25]

We first discuss the effect of the credibility of social media m on the final number of infected individuals ρ^{I} for different information diffusion rates λ in Fig. 3. As we hypothesized in Eq. (2), a larger m indicates a lower credibility of social media. Therefore, we can see from the figure that the final number of infected individuals increases as m increases, while the epidemic threshold β_{c} exhibits a two-stage change as m increases. When m is small, changing m has little effect on the epidemic threshold, and when m is large the epidemic threshold gradually decreases as m increases. It is worth noting that at this point only two variables, m and β, are available and all other variables are fixed. In addition, the epidemic threshold β_{c} increases and the final number of infected individuals ρ^{I} decreases as the information diffusion rate λ increases. In real life, the phenomenon of social governance chaos caused by the public's loss of trust in social media occurs from time to time. Therefore, in the prevention and control of an epidemic, social media should build a credible social image and at the same time increase efforts to publish and diffuse the official information, which increases the epidemic transmission threshold and effectively reduces the chances of epidemic outbreaks.

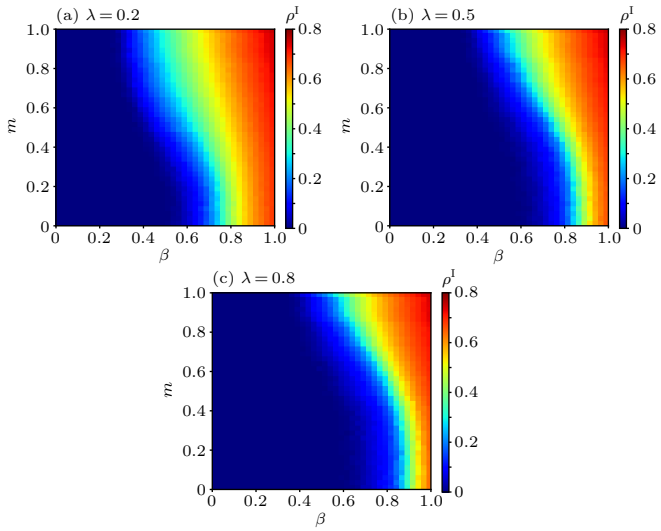


Fig. 3. The influence of β and m on ρ^{I}. λ is set as follows: (a) $\lambda=0.2$, (b) $\lambda=0.5$, (c) $\lambda=0.8$. Other parameters are set to be $\alpha_0=0.4$, $\delta=0.6$, $\eta=0.4$, $\mu=0.8$, $\varphi=0.5$, $\pi=0.5$, $\zeta=0.5$.

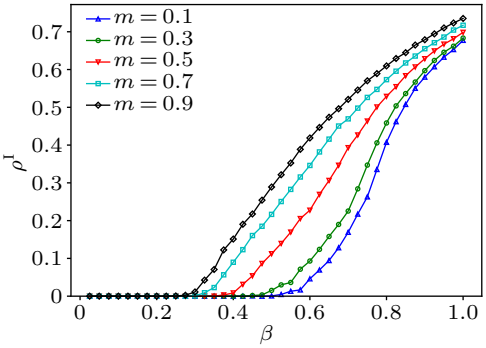


Fig. 4. The ρ^{I} as a function of β for different values of m. Other parameters are set as follows: $\lambda=0.5$, $\alpha_0=0.4$, $\delta=0.6$, $\eta=0.5$, $\mu=0.8$, $\varphi=0.5$, $\pi=0.5$, $\zeta=0.5$.

In Fig. 4, we further discuss the effect of the credibility of social media on the epidemic threshold β_c. The trend between the different lines similarly illustrates that that for smaller m (high credibility of social media), the epidemic threshold increases significantly and the final number of infected individuals decreases, which is consistent with our conclusion in Fig. 3. It is worth noting that increasing trust in social media can be effective in curbing epidemic transmission. For $\beta > \beta_c$, when epidemic transmission is out of control, as β increases the credibility of the media has little impact on the final number of infected individuals. At this moment, the government's control policy should focus more on control of physical contact rather than the diffusion of information via social media. Therefore, in the embryonic stage of disease transmission, increasing the credibility of social media is to a certain extent important for controlling epidemic transmission.

In Fig. 5, we analyze the effect of risk sensitivity of the population to the epidemic on the final number of infected individuals ρ^I for different information diffusion rates λ. As we can see in Fig. 5(a), as the risk sensitivity of the population π increases, the epidemic threshold β_c decreases and the final number of infected individuals ρ^I increases. It is worth noting that at this point only two variables, π and β, are available and all other variables are fixed. Similarly, the same can be observed in Figs. 5(b) and 5(c). The reason for this phenomenon is that as π increases, individuals become more sensitive to risk and therefore are more likely to be aware of the threat of the epidemic and thus adopt immunization behaviors. Moreover, by comparing the different subplots, we find that the final number of infected individuals keeps increasing as the information diffusion rate decreases, especially for smaller π. This shows that increasing the awareness of the population about the importance of taking precautions and always maintaining good immunization behaviors can facilitate the epidemic control process.

To more clearly illustrate the impact of risk sensitivity of the population to the epidemic on the epidemic threshold, we show the changes of ρ^I under different β and π in Fig. 6. We can observe a more pronounced two-stage effect: increasing π has a strong effect on raising the epidemic threshold, while for $\beta > \beta_c$ the impact of increasing risk sensitivity of the population to the epidemic on the epidemic threshold gradually diminishes and increasing π still reduces the final number of infected individuals. For the different colored lines in Fig. 6, the variables are also only π and β. This likewise suggests that, within the controllable range of epidemic transmission, increasing risk sensitivity of the population to the epidemic facilitates raising the epidemic threshold. Therefore, the government should strengthen science education and raise the risk sensitivity of the population to the epidemic, which plays an essential role in epidemic control. In addition, it is important for individuals to maintain a state of moderate tension in the face of epidemic transmission so that they can take effective measures to reduce their risk.

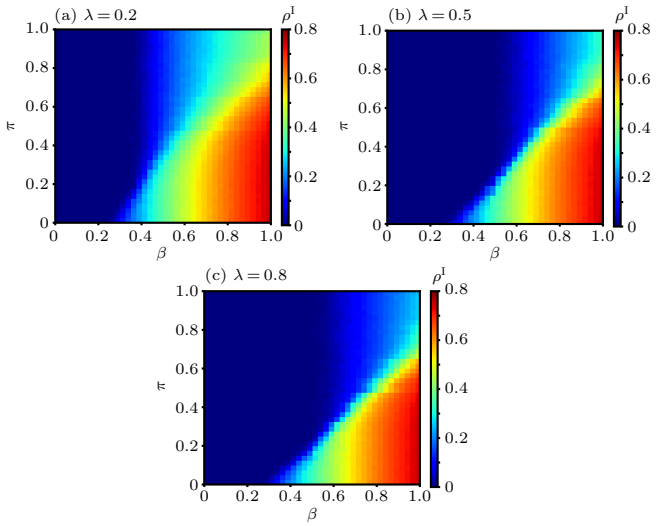


Fig. 5. The influence of β and π on ρ^I. λ is set as follows: (a) $\lambda = 0.2$, (b) $\lambda = 0.5$, (c) $\lambda = 0.8$, from left to right. Other parameters are set to be $\alpha_0 = 0.4$, $\delta = 0.6$, $\eta = 0.6$, $\mu = 0.8$, $\varphi = 0.5$, $m = 0.5$, $\zeta = 0.5$.

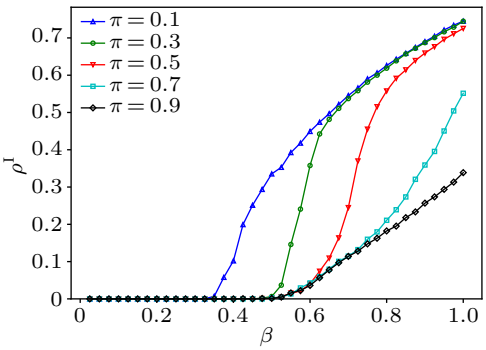


Fig. 6. The ρ^I as a function of β for different values of π. Other parameters are set as follows: λ =0.5, $\alpha_0 = 0.4$, $\delta = 0.6$, $\eta = 0.6$, $\mu = 0.8$, $\varphi = 0.5$, $m = 0.5$, $\zeta = 0.5$.

Subsequently, we focus on exploring the effect of different epidemic attenuation factors φ on the final number of infected individuals. By comparing Figs. 7(a)–7(c) we can see that the reduction of φ has a beneficial effect on epidemic control. As φ decreases, the adoption of immunization measures intensifies, which in turn reduces the infection rate. Therefore, during epidemic transmission people should strengthen their self-protection, raise their awareness of self-prevention and take more effective measures to prevent disease, measures which have a high inhibitory effect on the spread of infectious diseases.

Next, we demonstrate the impact of different epidemic attenuation factors φ on the epidemic threshold in Fig. 8. Unsurprisingly, increase in φ will lead to expansion of the epidemic, the same conclusion as in Fig. 7. What's more, the influence of φ on the final number of infected individuals is gradually decreasing. Therefore, the government can control the epidemic by encouraging people to adopt good protective measures.

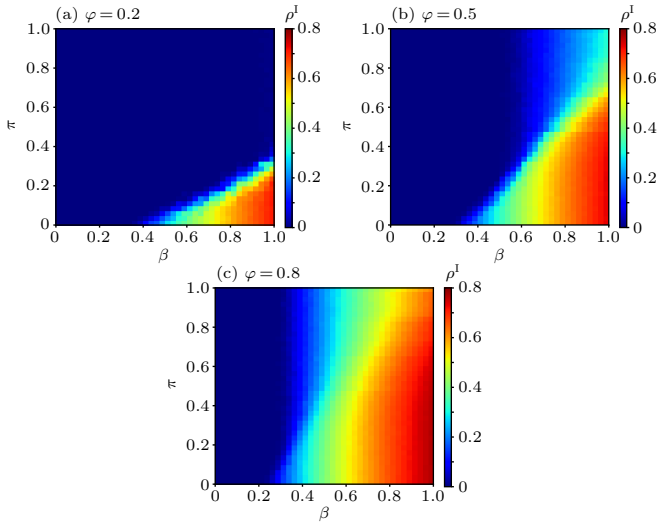


Fig. 7. The influence of β and π on ρ^{I}. φ is set as follows: (a) $\varphi = 0.2$, (b) $\varphi = 0.5$, (c) $\varphi = 0.8$. Other parameters are set to be $\lambda = 0.5$, $\alpha_0 = 0.4$, $\delta = 0.6$, $\eta = 0.5$, $\mu = 0.8$, $m = 0.5$, $\zeta = 0.5$.

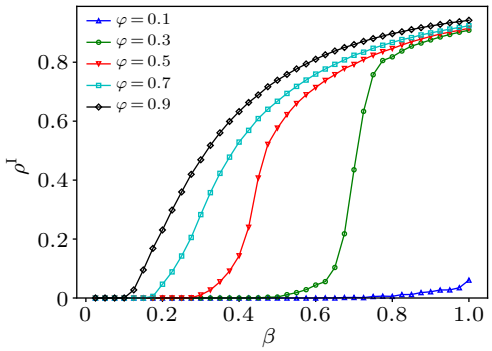


Fig. 8. The ρ^{I} as a function of β for different values of φ. Other parameters are set as follows: $\lambda = 0.5$, $\alpha_0 = 0.4$, $\delta = 0.6$, $\eta = 0.4$, $\mu = 0.8$, $m = 0.5$, $\pi = 0.5$, $\zeta = 0.5$.

In Fig. 9, we investigate the effect of behavior adoption preference on the final number of infected individuals, where a larger ζ represents a greater tendency for individuals to be influenced by the information layer and choose to adopt immunization behavior. As can be seen from Fig. 9, the epidemic threshold increases and the final number of infected individuals decreases as ζ increases. The reason for this phenomenon is that for larger ζ individuals adopt immunization behavior when there are sufficient neighborhoods that know the official information, while for smaller ζ individuals only adopt immunization behavior when the epidemic outbreak reaches a certain level. Thus, when ζ is small individuals pay more attention to effects originating from the information diffusion layer, and when ζ is large individuals pay more attention to effects originating from the epidemic transmission layer. In this regard, relevant managers should aim to diffuse official information in a timely manner at the early stage of the epidemic to raise individuals' awareness, and also make a great effort after the outbreak to increase people's perception of danger and encourage them to adopt immunization behaviors, which is a good reference for epidemic control. Furthermore, by comparing Figs. 9(a)–9(c), we can see that epidemic transmission is well suppressed with increasing α_0. Therefore, when faced with immunization behavior, individuals should also maintain good self-judgment, improve their own hygiene and actively choose to adopt the right behavior, which is also conducive to the control of the epidemic.

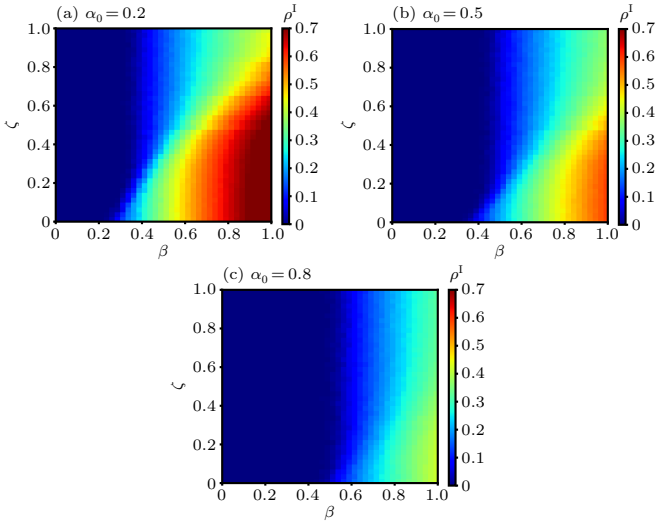


Fig. 9. The influence of β and ζ on ρ^{I}. α_0 is set as follows: (a) $\alpha_0 = 0.2$, (b) $\alpha_0 = 0.5$, (c) $\alpha_0 = 0.8$. Other parameters are set to be $\lambda = 0.2$, $\delta = 0.6$, $\eta = 0.5$, $\mu = 0.8$, $\varphi = 0.5$, $m = 0.5$, $\pi = 0.5$.

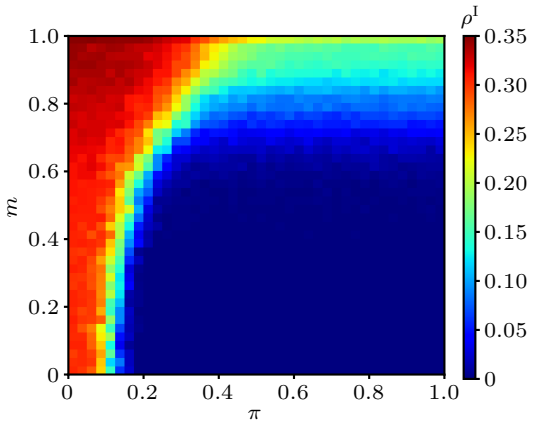


Fig. 10. The influence of π and m on ρ^{I}. Other parameters are set to be λ =0.5, α_0 =0.4, δ =0.6, $\eta = 0.5$, $\mu = 0.8$, $\varphi = 0.5$, $\beta = 0.5$, $\zeta = 0.5$.

Finally, to investigate the joint effect of the credibility of social media m and risk sensitivity of the population to epidemic π on the final number of infected individuals ρ^{I}, we perform the simulations shown in Fig. 10. We explore the effect of individual heterogeneity in the information diffusion layer and individual heterogeneity in the epidemic transmission layer on adoption of immunization behavior. When the effect of the credibility of social media is not considered ($m = 0$), the two-stage effect of π occurs at about 0.225. As m increases (credibility of social media decreases), the epidemic threshold gradually decreases. In addition, when the

risk sensitivity of the population to the epidemic is not considered ($\pi = 1$) the two-stage effect of m occurs at around 0.425. As π decreases (an individual's risk sensitivity decreases), the epidemic threshold gradually decreases. What's more, the results show that increasing π makes a more significant contribution to epidemic control than decreasing m. In reality, facing limited resources for fighting epidemics, should put more effort into epidemic control rather than a single propaganda source for official information.

5. Conclusion

In this paper we propose a three-layer coupled model that considers the influence of official information diffusion and adoption of immunization behavior on epidemic transmission. Behavior adoption by individuals is influenced by both the official information diffusion layer and the epidemic transmission layer, and individual heterogeneity in behavior adoption is related to the credibility of social media and the risk sensitivity of the population to epidemic. We investigated the influence of the factors described by the model, focussing on epidemic transmission dynamics and the epidemic threshold, by using the microscopic Markov chain approach. At the same time, we conducted a large number of simulations to demonstrate the feasibility and realism of our model. Through this research we found that increasing the credibility of social media can raise the epidemic transmission threshold, which has an important impact in increasing the epidemic transmission threshold and effectively reducing the chances of epidemic outbreaks. In addition, increasing the risk sensitivity of the population to an epidemic is equally beneficial in epidemic prevention and can reduce the number of infected individuals and delay epidemic outbreak. At this stage of COVID-19 development, due to low risk sensitivity of the population to the epidemic and lack of knowledge about COVID-19, many people may simply regard some symptoms as a common cold and not choose to go for further treatment, which in turn hinders epidemic control. Therefore, increasing the ability of individuals to perceive risks and encouraging them to adopt immunization behaviors can reduce the size of an epidemic. The optimal control of an epidemic can be achieved by understanding the coupling effects of multiple factors.

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References

[1] Yang L, Liu S S, Liu J Y, Zhang Z X, Wan X C, Huang B, Chen Y H and Zhang Y 2020 *Signal Transduction and Targeted Therapy* **5** 1
[2] Le T T, Andreadakis Z, Kumar A, Román R G, Tollefsen S, Saville M and Mayhew S 2020 *Nat. Rev. Drug Discov.* **19** 305
[3] Yuki K, Fujiogi M and Koutsogiannaki S 2020 *Clin. Immunol.* **215** 108427
[4] Velavan T P and Meyer C G 2020 *Trop. Med. Int. Health* **25** 278
[5] Daniel S J 2020 *Prospects* **49** 91
[6] Burki T K 2022 *Lanc. Resp. Med.* **10** e17
[7] Berkman L F and Kawachi I 2014 *Social Epidemiology* (New York: Oxford University Press) pp. 304–309
[8] Bailey N T J 1975 *The Mathematical Theory of Infectious Diseases and Its Applications* (High Wycombe: Bucks HP13 6LE) pp. 85–87
[9] Grabowski A and Kosiński R A 2004 *Phys. Rev. E* **70** 031908
[10] El-Dessoky M M and Khan M A 2022 *Alex. Eng. J.* **61** 729
[11] Vassallo L, Perez I A, Alvarez-Zuzek L G, Amaya J, Torres M F, Valdez L D and Braunstein L A 2022 *Math. Biosci.* **346** 108664
[12] El Hajji M and Albargi A H 2022 *Math. Biosci. Eng.* **19** 2853
[13] Chang L, Gao S and Wang Z 2022 *J. Theor. Biol.* **536** 111003
[14] Nourbakhsh S, Fazil A, Li M, Mangat C S, Peterson S W, Daigle J and Champredon D 2022 *Epidemics* **39** 100560
[15] Vosoughi S, Roy D and Aral S 2018 *Science* **359** 1146
[16] Pastor-Satorras R, Castellano C, Van Mieghem P and Vespignani A 2015 *Rev. Mod. Phys.* **87** 925
[17] Zhan X X, Liu C, Zhou G, Zhang Z K, Sun G Q, Zhu J J, and Jin Z 2018 *Appl. Math. Comput.* **332** 437
[18] Kabir K M A and Tanimoto J 2019 *Commun. Nonlinear Sci.* **72** 565
[19] Zeng Q, Liu Y, Tang M and Gong J 2021 *Knowledge-Based Systems* **229** 107365
[20] Buldyrev S V, Parshani R, Paul G, Stanley H E and Havlin S 2010 *Nature* **464** 1025
[21] Hong X, Han Y, Tanaka G and Wang B 2022 *Knowledge-Based Systems* **252** 109413
[22] Granell C, Gómez S and Arenas A 2013 *Phys. Rev. Lett.* **111** 128701
[23] Granell C, Gómez S and Arenas A 2014 *Phys. Rev. E* **90** 012808
[24] Wang Z and Xia C 2020 *Nonlinear Dyn.* **102** 3039
[25] Li R, Tang M and Hui P M 2013 *Acta Phys. Sin.* **62** 168903 (in Chinese)
[26] Peng K, Lu Z, Lin V, Lindstrom M R, Parkinson C, Wang C and Porter M A 2021 *Mathem. Mod. Meth. Appl. Sci.* **31** 2455
[27] Guo Q, Jiang X, Lei Y, Li M, Ma Y and Zheng Z 2015 *Phys. Rev. E* **91** 012822
[28] Xu H, Zhao Y and Han D 2022 *Nonlinear Dyn.* **110** 901
[29] Li R, Wang W and Di Z 2017 *Physica A* **467** 30
[30] Li R, Richmond P and Roehner B M 2018 *Physica A* **510** 713
[31] Liu C, Yang Y, Chen B, Cui T, Shang F, Fan J and Li R 2022 *Chaos* **32** 081105
[32] Fan C J, Jin Y, Huo L A, Liu C, Yang Y P and Wang Y Q 2016 *Physica A* **461** 523
[33] Zhu L, Liu W and Zhang Z 2021 *Math. Comput. Simulat.* **188** 268
[34] Liu Q H, Wang W, Tang M and Zhang H F 2016 *Sci. Rep.* **6** 25617
[35] Liu Q H, Wang W, Cai S M, Tang M and Lai Y C 2018 *Phys. Rev. E* **97** 022311
[36] Zuo C, Wang A, Zhu F, Meng Z and Zhao X 2021 *Complexity* **2021** 6680135
[37] Ventura P C, Aleta A, Rodrigues F A and Moreno Y 2022 *Chaos, Solitons & Fractals* **156** 111849
[38] Liu L, Wang X, Tang S, Zheng H and Zheng Z 2021 *J. Stat. Mech.: Theory Experiment* **2021** 063402
[39] Gao X and Tian L 2019 *Physica A* **514** 226
[40] Zhang Y, Su Y, Weigang L and Liu H 2019 *Chaos, Solitons & Fractals* **121** 168
[41] Boslaugh S 2007 *Encyclopedia of Epidemiology* (New York: Sage Publications) pp. 125–126
[42] Weinberg G A and Szilagyi P G 2010 *J. Infect. Dis.* **201** 1607
[43] Osterholm M T, Kelley N S, Sommer A and Belongia E A 2012 *Lancet Infect. Dis.* **12** 36
[44] Wang Z, Moreno Y, Boccaletti S and Perc M 2017 *Chaos, Solitons & Fractals* **103** 177
[45] Dai X, Zhu P, Guo Y and Wang Z 2019 *IEEE Access* **7** 61558

[46] Yin Q, Wang Z, Xia C and Bauch C T 2022 *Commun. Nonlinear Sci.* **109** 106312
[47] Li W, Cai M, Zhong X, Liu Y, Lin T and Wang W 2023 *Chaos, Solitons & Fractals* **168** 113102
[48] Li W, Nie Y, Li W, Chen X, Su S and Wang W 2022 *Chaos* **32** 093135
[49] Li W, Ni L, Zhang Y, Su S, Peng B and Wang W 2022 *Frontiers in Physics* 946
[50] Nie Y, Zhong X, Lin T and Wang W 2022 *Appl. Math. Comput.* **432** 127380
[51] Shi H J, Duan Z S, Chen G R and Li R 2009 *Chin. Phys. B* **18** 3309
[52] Fu F, Rosenbloom D I, Wang L and Nowak M A 2011 *Proceedings of the Royal Society B: Biological Sciences* **278** 42
[53] Wang Z, Bauch C T, Bhattacharyya S, d'Onofrio A, Manfredi P, Perc M and Zhao D 2016 *Phys. Rep.* **664** 1
[54] Ruan Z, Tang M and Liu Z 2012 *Phys. Rev. E* **86** 036117
[55] Gómez S, Arenas A, Borge-Holthoefer J, Meloni S and Moreno Y 2010 *Europhys. Lett.* **89** 38009
[56] Wang Y, Chakrabarti D, Wang C and Faloutsos C 2023 *In* 22*nd International Symposium on Reliable Distributed Systems* 25–34
[57] Sun M, Tao Y and Fu X 2021 *Chaos* **31** 093134