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The impact of information dissemination on vaccination in multiplex networks

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Abstract The impact of information dissemination on epidemic control is essentially subject to individual behaviors. Vaccination is one of the most effective strategies against the epidemic spread, whose correlation with the information dissemination should be better understood. To this end, we propose an evolutionary vaccination game model in multiplex networks by integrating an information-epidemic spreading process into the vaccination dynamics, and explore how information dissemination influences vaccination. The spreading process is described by a two-layer coupled susceptible-alert-infected-susceptible (SAIS) model, where the strength coefficient between two layers characterizes the tendency and intensity of information dissemination. We find that the impact of information dissemination on vaccination decision-making depends on not only the vaccination cost and network topology, but also the stage of the system evolution. For instance, in a two-layer BA scale-free network, information dissemination helps to improve vaccination density only at the early stage of the system evolution, as well as when the vaccination cost is smaller. A counter-intuitive conclusion that more information transmission cannot promote vaccination is obtained when the vaccination cost is larger. Moreover, we study the impact of the strength coefficient and individual sensitivity on the fraction of infected individuals and social cost, and unveil the role of information dissemination in controlling the epidemic.

Keywords evolutionary game theory, epidemic modeling, network dynamics

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1 Introduction

The epidemic control has been studied for many decades [1–4], since the outbreak and propagation of virus may cause tremendous damage and bring huge (economic) losses. Various models, such as the susceptible-infected-susceptible (SIS) model [5,6] and the susceptible-infected-recovered (SIR) model [7,8], have been used to describe epidemic spreading processes. The understanding of disease-behavior dynamics motivates more and more efforts to explore the epidemic dynamics beyond such models [9–11]. Individual behaviors, such as wearing masks and washing hands [12], which may reduce the susceptibility to infection, can be triggered by the awareness (information) diffusion. Funk et al. [13] studied how awareness impacts the virus propagation in a well-mixed population, and they found that the awareness diffusion can reduce the virus outbreak range, but cannot affect the epidemic threshold. Similarly, Wu et al. [14] explored the impact of three different kinds of awareness on the epidemic spread in a scale-free networked population. However, single-layer networks provide a limited representation of complex systems [15–17]. The efforts in [13, 14] may fail to involve the realistic scenario where the information and virus spread via different networks simultaneously.

Recently, multiplex networks representing social interactions at different contexts, e.g., individuals transmit information through an online social network, and at the same time an epidemic propagates

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among the individuals on a physical contact network, have been studied in [18–20]. The interactions between layers (networks) may yield the outcomes beyond what isolated layers can capture [21,22]. Wang et al. [23] explored the influence of positive and negative preventive information on epidemic propagation in multiplex networks. Guo et al. [24] introduced a threshold model to describe the awareness cascading phenomenon of human awareness and studied the interplay between the spreading of awareness and epidemic in a multiplex network, which was composed of an awareness spreading network and an epidemic spreading network. However, it assumed that the aware individuals are completely immune to infection, that is, each individual chooses vaccination in response to information. In reality, behavioral adoption or response, especially vaccination, is a complex process [25–27]. On the one hand, vaccination is regarded as one of the most effective and protective behaviors (strategies) against virus propagation [28–30]. On the other hand, vaccination usually comes with a vaccination cost, and the decision of an individual on vaccination depends not only on his trade-off between the vaccination cost and the infection cost, but also on the strategies of other individuals. Vaccination presents a social dilemma since a self-interested individual expects to get benefit from other vaccinated individuals [31–34]. The outbreak of the COVID-19 epidemic seriously threatens public health, and the only long-term solution to this epidemic is to develop effective vaccines [35]. Although there is no vaccine available for the COVID-19 epidemic at the time of writing this paper, understanding the relation between information dissemination and vaccination behavior is critical to epidemic control.

In this study, we construct an evolutionary vaccination game in a multiplex network which is composed of an information layer and a contact layer, and explore the role of information dissemination on vaccination. In order to reflect the reactions of individuals to risk information, we introduce an alert state (A) into the SIS model, and propose a two-layer coupled susceptible-alert-infected-susceptible (SAIS) model to describe the spreading process. Assume the alert individuals are less likely to be infected than the susceptible individuals. We find that different behavioral responses to information have different impacts on epidemic spread. Moreover, we explore the factors that affect the vaccination density, fraction of infected individuals and social cost, which is one of the most important optimization subjects in epidemic control.

The rest of this paper comes as follows. Section 2 formulates the problem of this paper. Section 3 presents a two-layer coupled SAIS model, where the epidemic dynamics are theoretically and numerically analysed. In Section 4, we introduce an evolutionary vaccination game in a multiplex network. Section 5 presents the vaccination performance against the epidemic propagation and the role of information. Section 6 concludes the whole paper.

2 Problem formulation

Vaccination is an effective and preventive strategy against the epidemic propagation. When information and epidemic spread simultaneously, the susceptible individuals may get to know the epidemic status by receiving risk information from their infected neighbors. The qualitative analysis on the impact of information dissemination on vaccination cannot reach a unified conclusion. Consequently, Xia and Liu [30] proposed a belief-based model to study the impact factors of individual vaccination decisions. However, the costs of individuals were not taken into account. Since an unvaccinated individual can benefit from other vaccinated individuals, the vaccination decision-making of an individual depends not only on his trade-off between the vaccination cost and the infection cost, but also on the strategies of other individuals. Therefore, in this study, we propose an evolutionary vaccination game to model the vaccination behaviors of individuals. The correlation between information dissemination and vaccination determines the vaccination density that affects the social cost. By integrating the propagation of information-epidemic into the process of strategic selection and interaction, we explore how information dissemination influences vaccination. Moreover, we illustrate the role of vaccination in epidemic control by analyzing the correlation between the vaccination density and epidemic size, as well as study the impact of the strength coefficient and individual sensitivity on the vaccination density.

In order to study the impact of information dissemination on vaccination, we assume that the vaccinated individuals are completely protected, regardless of the influence of vaccine efficiency. We take the regularity of seasonal diseases and effectiveness of vaccination into account. Individuals who are prone to immunization will be vaccinated before the outbreak of disease. The evolutionary vaccination game model (as illustrated in Figure 1) includes two stages: the decision-making stage (stage 1) and the spreading

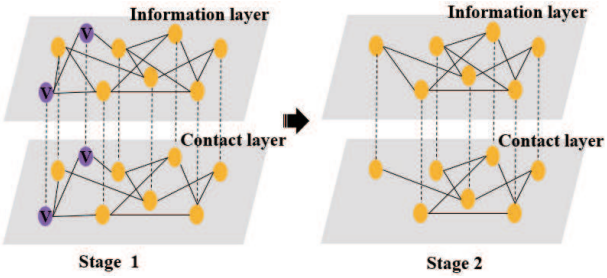

Figure 1 (Color online) A schematic stage illustration of the evolutionary vaccination game model in a multiplex network. This network consists of two layers. The information layer corresponds to a network where risk information spreads, while the epidemic propagates on the contact layer. Individuals labeled by 'V' choose to be vaccinated during the stage 1. During the stage 2, the vaccinated individuals are no longer involved in the epidemiological process which is described by the two-layer coupled SAIS model, while the unvaccinated individuals are at risk of being infected.

stage (stage 2). During stage 2 (epidemic season) the epidemic and information (of the epidemic status) propagate simultaneously at the corresponding layer. Each node (individual) unilaterally decides whether to get vaccinated during stage 1, which is modeled by a vaccination game occurring before the start of an epidemic season. A vaccinated individual will not be infected and no longer gets involved in the next epidemic season, while the unvaccinated individuals have a risk of being infected. When the epidemic process reaches a steady state, each individual will adjust his decision-making with respect to vaccination for the next epidemic season.

3 The SAIS seasonal epidemics without vaccination

A two-layer multiplex network with different network topologies is illustrated in Figure 1. Both information layer and contact layer have the same number of nodes with the size N. Each node (individual) in one layer corresponds to its counterpart node in another layer. There are three possible states of each node, susceptible (S), alert (A) or infected (I). In the information layer, a susceptible node can perceive the risk information of virus from his infected neighbors, and convert to an alert node. Without loss of generality, we assume that an alert node may ignore or not care about the risk information, and become a susceptible node with rate η. In the contact layer, an infected node infects its susceptible and alert neighbours with infection rates β and β_A, respectively, where $\beta_A = \xi\beta$. Taking into account the complexity of individual decision-making behaviour in reality, we assume that the alert state is different from the immune state, which means $0 < \xi \leqslant 1$. Each infected node recovers with rate μ.

Let $p_i^S(t)$, $p_i^A(t)$ and $p_i^I(t)$ denote the probabilities for node i of being susceptible, alert and infected at time t, respectively. Assume each node has the same sensitivity λ to the risk information. A susceptible node i with degree k_i may receive risk information and become an alert node with a probability $\theta_i(t) = 1 - \prod_{j=1}^{N}(1 - \lambda a_{ji} p_j^I(t))$, where a_{ji} is the element of adjacency matrix $\mathcal{A}$ of the information layer, and $a_{ji} = 1$ if there is a link between nodes i and j. Define the transition probability for node i not being infected by the neighbours as $q_i^S(t)$ if i is a susceptible node, or as $q_i^A(t)$ if i is an alert node. The element of adjacency matrix $\mathcal{B}$ of the contact layer is defined as b_{ji}, and we have

$$\begin{cases} q_i^A(t) = \prod_{j=1}^{N}(1 - b_{ji} p_j^I(t)\beta_A), \\ q_i^S(t) = \prod_{j=1}^{N}(1 - b_{ji} p_j^I(t)\beta). \end{cases} \tag{1}$$

The transition probability diagrams for three states of the coupled SAIS propagation dynamics are illustrated in Figure 2. Here, μ is the transition probability from the infected to the susceptible states, η is the transition probability from the alert to the susceptible states, and the strength coefficient α characterizes the tendency and intensity of information dissemination. For instance, the probability that a susceptible node i remains susceptible at each time step is defined as $\alpha q_i^S(t) + (1-\alpha)(1-\theta_i)$. Specifically, $\alpha = 1$ corresponds to the case in a single-layer network, i.e., only the epidemic propagates in the contact layer. The information and epidemic spreading processes coexist when $0 < \alpha < 1$.

The continuous time Markov approach can provide an exact description of the actual epidemic spreading, however, the infinitesimal generator $Q_{2^N \times 2^N}$ [36] is difficult to obtain, especially for large scale

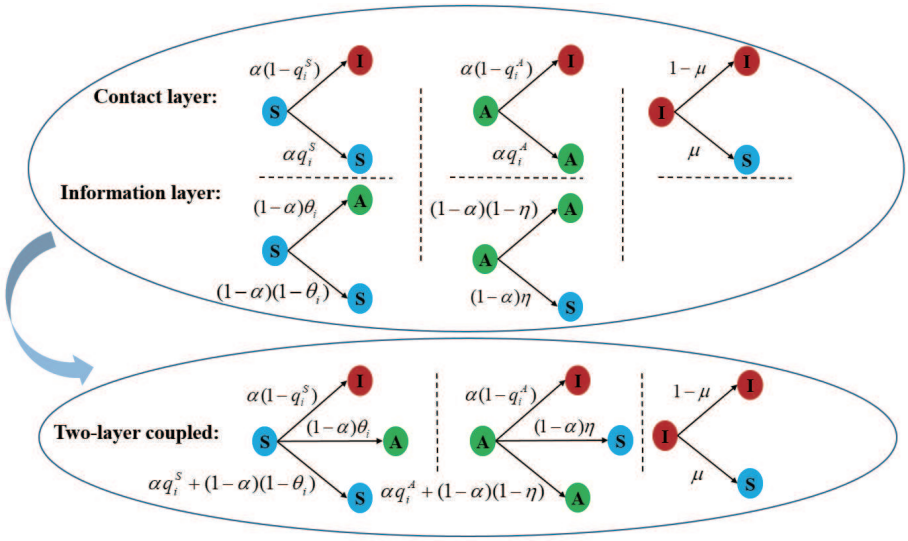

Figure 2 (Color online) Transition probability diagrams for susceptible (S), alert (A), and infected (I) states of the coupled SAIS propagation dynamics. Both susceptible and alert nodes can be infected by their infected neighbors, and the difference is that the alert nodes have been informed. q_i^S is the transition probability for susceptible individual i not being infected by the neighbours; q_i^A is the transition probability for alert individual i not being infected by the neighbours; θ_i is the transition probability for susceptible individual i being informed by the infected neighbours; μ is the transition probability from the infected to the susceptible states; η is the transition probability from the alert to the susceptible states; and α is the strength coefficient.

networks [37], since the Markov chain contains 2^N states. Therefore, we utilize the microscopic Markov chain approach [38] to explore the probability evolution of different states for node i,

$$\begin{cases} p_i^S(t+1) = [\alpha q_i^S(t) + (1-\theta_i(t))(1-\alpha)]p_i^S(t) + \mu p_i^I(t) \\ \qquad\qquad + \eta(1-\alpha)p_i^A(t), \\ p_i^A(t+1) = [\alpha q_i^A(t) + (1-\eta)(1-\alpha)]p_i^A(t) \\ \qquad\qquad + (1-\alpha)\theta_i(t)p_i^S(t), \\ p_i^I(t+1) = \alpha(1-q_i^S(t))p_i^S(t) + \alpha(1-q_i^A(t))p_i^A(t) \\ \qquad\qquad + (1-\mu)p_i^I(t). \end{cases} \tag{2}$$

When $p_i^I(t+1) = p_i^I(t) = p_i^I$, we have

$$\begin{cases} p_i^S &= \frac{(1-p_i^I)[\alpha(1-q_i^A)+\eta(1-\alpha)]}{\alpha(1-q_i^A)+(1-\alpha)(\eta+\theta_i)}, \\ p_i^A &= \frac{(1-\alpha)\theta_i(1-p_i^I)}{\alpha(1-q_i^A)+(1-\alpha)(\eta+\theta_i)}, \\ \frac{\mu}{\alpha}p_i^I &= (1-q_i^S)p_i^S + (1-q_i^A)p_i^A. \end{cases} \tag{3}$$

Letting $\beta_A = \xi\beta$, combining (3) with $p_i^S + p_i^A + p_i^I = 1$, the infection probability of node i in the stationary state can numerically be computed by solving

$$p_i^I = \frac{M + \alpha\eta(1-\alpha)(1-q_i^S)}{M + \alpha\mu(1-q_i^A) + (1-\alpha)[\mu(\eta+\theta_i) + \alpha\eta(1-q_i^S)]}, \tag{4}$$

where $M = \alpha(1-q_i^A)[(1-\alpha)\theta_i + \alpha(1-q_i^S)]$. Thus, the infection density ρ^I can be computed as

$$\rho^I = \frac{1}{N}\sum_{i=1}^{N} p_i^I. \tag{5}$$

In a multiplex network with two layers, the topology of each layer is different. For instance, the contact layer of a two-layer BA scale-free network has a power-law degree distribution, and the information layer is the same network with some extra random links. We perform the numerical simulations in a two-layer ER network with network size $N = 500$ and a two-layer BA network with network size $N = 1000$,

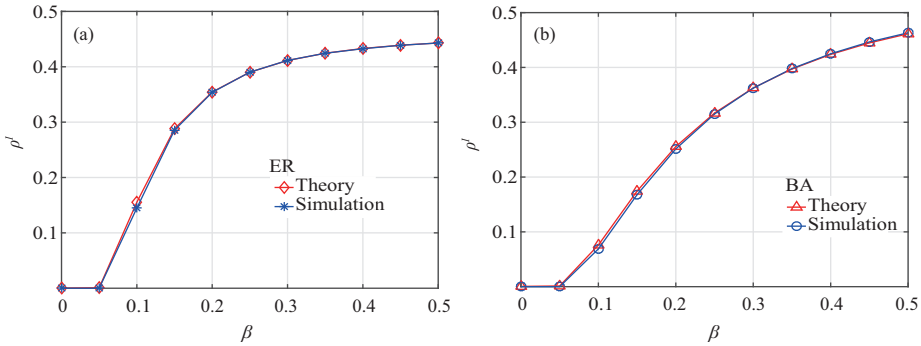

Figure 3 (Color online) Comparison of the infection densities ρ^I obtained by the SAIS model and Monte Carlo simulations as a function of the infection rate β in (a) a two-layer ER network ($N = 500$) and (b) a two-layer BA scale-free network ($N = 1000$), respectively. The result is the average solution of 100 realizations, where $\alpha = 0.5$, $\lambda = 0.3$, $\mu = 0.6$, $\eta = 0.6$, $\xi = 0.5$.

respectively. We find that there is a good agreement between the analytical and simulation results. As illustrated in Figure 3, the infection density ρ^I increases with the increase of infection rate β. When $\beta > \beta_c$, the so-called epidemic threshold, the epidemic outbreaks and the infection density $\rho^I > 0$.

When $\beta \to \beta_c$, the probability $0 \leqslant p_i^I \ll 1$, Eq. (2) can be further simplified as

$$\begin{cases} q_i^A(t) = 1 - \xi\beta \sum_{j=1}^N b_{ji} p_j^I(t), \\ q_i^S(t) = 1 - \beta \sum_{j=1}^N b_{ji} p_j^I(t). \end{cases} \tag{6}$$

Letting $\phi_i = p_i^I$, combining (3) with (6) and omitting the second-order terms of ϕ, we obtain

$$\frac{\mu}{\alpha\beta}\phi_i = (1 - (1-\xi)p_i^A) \sum_{j=1}^N b_{ji}\phi_j. \tag{7}$$

Considering that θ_i is proportional to the sum of p_j^I, we obtain $0 \leqslant p_i^A \ll 1$. Then, Eq. (7) can be reduced to

$$\sum_{j=1}^N \left[b_{ji} - \frac{\mu}{\alpha\beta}\epsilon_{ji} \right] \phi_j = 0, \tag{8}$$

where ϵ_{ji} is the element of the identity matrix. Eq. (8) has non-trivial solutions if and only if $\frac{\mu}{\alpha\beta}$ is the eigenvalue of adjacency matrix $\mathcal{B}$. Therefore, we obtain the epidemic threshold

$$\beta_c = \frac{\mu}{\alpha\Delta_{\max}(\mathcal{B})}, \tag{9}$$

where $\Delta_{\max}(\mathcal{B})$ is the largest eigenvalue of matrix $\mathcal{B}$. Obviously, the epidemic threshold β_c depends on the structure of contact layer $\mathcal{B}$ and the strength coefficient α.

Figure 4 illustrates the impacts of strength coefficient α on the epidemic threshold β_c. We find that the epidemic threshold decreases with the increase of α, regardless of the network topology. Moreover, the epidemic threshold calculated by (9) is in agreement with the one obtained by the MC simulations in a two-layer ER network and a two-layer BA scale-free network, respectively.

Figure 5 shows that the infection density ρ^I depends not only on the network size N but also on the infection rate β. For a two-layer ER network (see Figure 5(a)), when the network size and the infection rate exceed a certain value ($N > 100, \beta > 0.7$), both the network size N and infection rate β will no longer affect the infection density ρ^I. For a two-layer BA scale-free network, the network size N affects the infection density ρ^I only when the infection rate $\beta < 0.3$. When $\beta \geqslant 0.3$, the infection density ρ^I only depends on β.

In order to reveal the role of behavioral response of the alert individuals, we investigate the impact of coefficient ξ on the propagation dynamics. As illustrated in Figure 5(c), ξ does not affect the epidemic threshold β_c, but affects the infection density ρ^I. Moreover, we find that the impact of ξ on the infection density ρ^I is various in different ranges of ξ. When $\xi > 0.3$, the ξ will not affect the infection density ρ^I. The infection density is greatly reduced when $\xi \to 0$, where all the alert individuals are immune to the infection, as the assumption in [38]. However, individuals with risk information do not necessarily choose vaccination in reality.

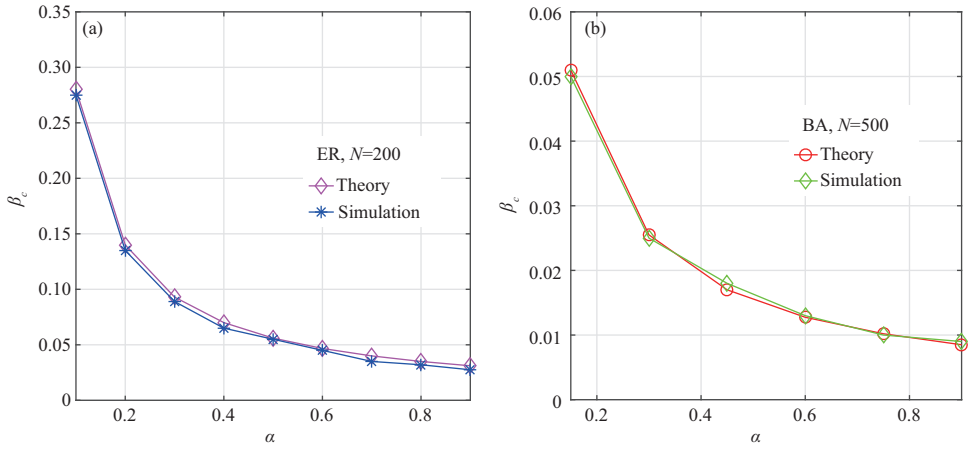

Figure 4 (Color online) Epidemic threshold β_c as a function of the strength coefficient α in (a) a two-layer ER network with $N = 200$ in each layer and (b) a two-layer BA scale-free network with $N = 500$ in each layer, respectively. Parameters $\mu = 0.1$, $\eta = 0.6$, $\xi = 0.5$.

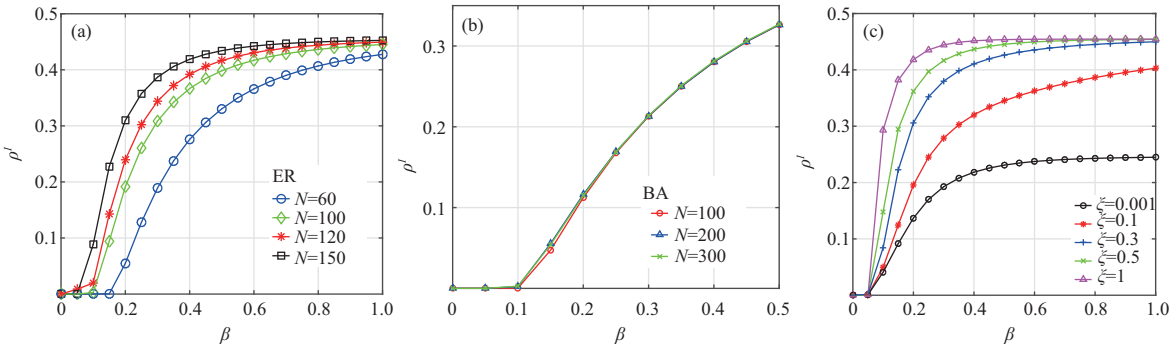

Figure 5 (Color online) Infection density ρ^I as a function of the infection rate β in multiplex networks with different N, where each layer is (a) an ER network and (b) a BA scale-free network, respectively. The strength coefficient $\alpha = 0.5$. (c) The impacts of coefficient ξ on the infection density ρ^I and epidemic threshold β_c.

4 Evolutionary vaccination game

For a network with two layers, although different layers represent social interactions at different contexts, the strategic choices of an individual in one layer may affect that in the other layer. For simplicity, we assume that each node and its counterpart node (which are the same node in different layers) have the same strategy during the same stage.

The decision of an individual may be affected by many factors owing to the infection interactions. We consider that there exists a communication cost T since risk information diffuses in the information layer. In order to promote vaccination, we assume that the unvaccinated individuals have the communication cost $(\frac{1-\alpha}{\alpha})^{\lambda}T$, which is negatively correlated with the strength coefficient α and individual sensitivity λ. An individual choosing vaccination only has the vaccination cost C. Vaccination is completely effective so that a vaccinated individual can fully protect himself and does not participate in the information-epidemic process [39]. In addition to the communication cost, a non-vaccinated individual being infected has the infection cost H. Since the strategy of an individual acts on both layers, the cost of an individual is determined by the total costs of two layers. The cost of an individual i in a two-layer coupled network is therefore denoted by

$$U_i = Cm_s + \left[Hv_i + \left(\frac{1-\alpha}{\alpha}\right)^{\lambda} T\right](1 - m_s), \tag{10}$$

where coefficient $m_s = 1$ if individual i chooses vaccination, otherwise, $m_s = 0$, and $v_i = 1$ or 0 indicates whether individual i is infected or not. Without loss of generality, we assume that the cost C of a vaccinated individual is less than the cost H.

We define the proportion of individuals who choose vaccination as vaccination density, denoted by x.

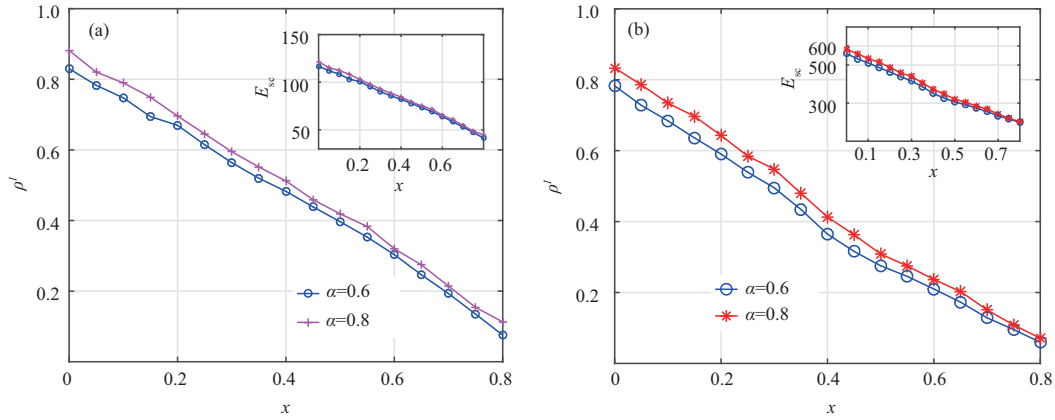

Figure 6 (Color online) The fraction of infected individuals ρ^I and social cost $E_{\rm sc}$ (inset) as a function of the vaccination density x with different strength coefficients α in (a) a two-layer ER network ($N = 100$) and (b) a two-layer BA network ($N = 500$), respectively. Parameters: $\beta = 0.3$, $\mu = 0.1$, $\eta = 0.6$, $C = 0.4$, $T = 0.1$ and $\xi = 0.5$.

The infection rate becomes $(1 - x)\beta$ during the epidemic season [40]. The infection density

$$\rho^I(x) = \frac{1}{N}\sum_{i=1}^{N} p_i^I(x), \tag{11}$$

where $p_i^I(x)$ is the infection probability for node i in the stationary state, which can be obtained in Section 3. The social cost of a multiplex network with N nodes is

$$\begin{aligned} E_{\rm sc} &= N\Bigg[xC + \Bigg[\left(H + \left(\tfrac{1-\alpha}{\alpha}\right)^{\lambda} T\right)\tfrac{\rho^I(x)}{1-x} \\ &\quad + \left(\tfrac{1-\alpha}{\alpha}\right)^{\lambda}\left(1 - \tfrac{\rho^I(x)}{1-x}\right)T\Bigg](1-x)\Bigg] \\ &= N\left[\left(C - \left(\tfrac{1-\alpha}{\alpha}\right)^{\lambda} T\right)x + H\rho^I(x) + \left(\tfrac{1-\alpha}{\alpha}\right)^{\lambda} T\right]. \end{aligned} \tag{12}$$

We study the vaccination dynamics and predict vaccination behavior of individuals through pairwise interactions in a two-layer coupled network. Once the spreading process in this season ends, each individual updates his strategy for the next epidemic season. We adopt the Fermi rule [41, 42] for the strategy updating. At each round, individual i randomly selects a neighbour j in the information layer, compares their costs, and learns the strategy of individual j with the probability,

$$w_{(S_i \leftarrow S_j)} = \frac{k_i^a}{k_i}\frac{1}{1 + \exp[-\kappa(U_j - U_i)]}, \tag{13}$$

where k_i is the degree of individual i, and k_i^a is the number of alert neighbours of individual i. S_i and U_i represent the strategy and the cost of individual i, respectively. Parameter κ represents the selection intensity, measuring how much the selection depends on the cost difference.

5 Vaccination performance and role analysis of information

In order to study the vaccination performance in epidemic control, we consider that a proportion x of individuals chooses to be vaccinated in a two-layer ER network and a two-layer BA network, respectively, and explore the impacts of vaccination on the fraction of infected individuals ρ^I and social cost $E_{\rm sc}$.

As illustrated in Figure 6, the fraction of infected individuals ρ^I, as well as social cost $E_{\rm sc}$, under a smaller strength coefficient α is less than those under a larger strength coefficients α. That is, for a fixed vaccination density x, as the information transmission increases, the fraction of infected individuals ρ^I and social cost $E_{\rm sc}$ decrease, which is consistent with the finding in Section 3. Furthermore, the fraction of infected individuals ρ^I and social cost $E_{\rm sc}$ decrease with the increase of vaccination density x, regardless of the network topology. Therefore, we conclude that the increase of vaccination density can effectively reduce the epidemic size and social cost, and help to control the spreading of epidemics.

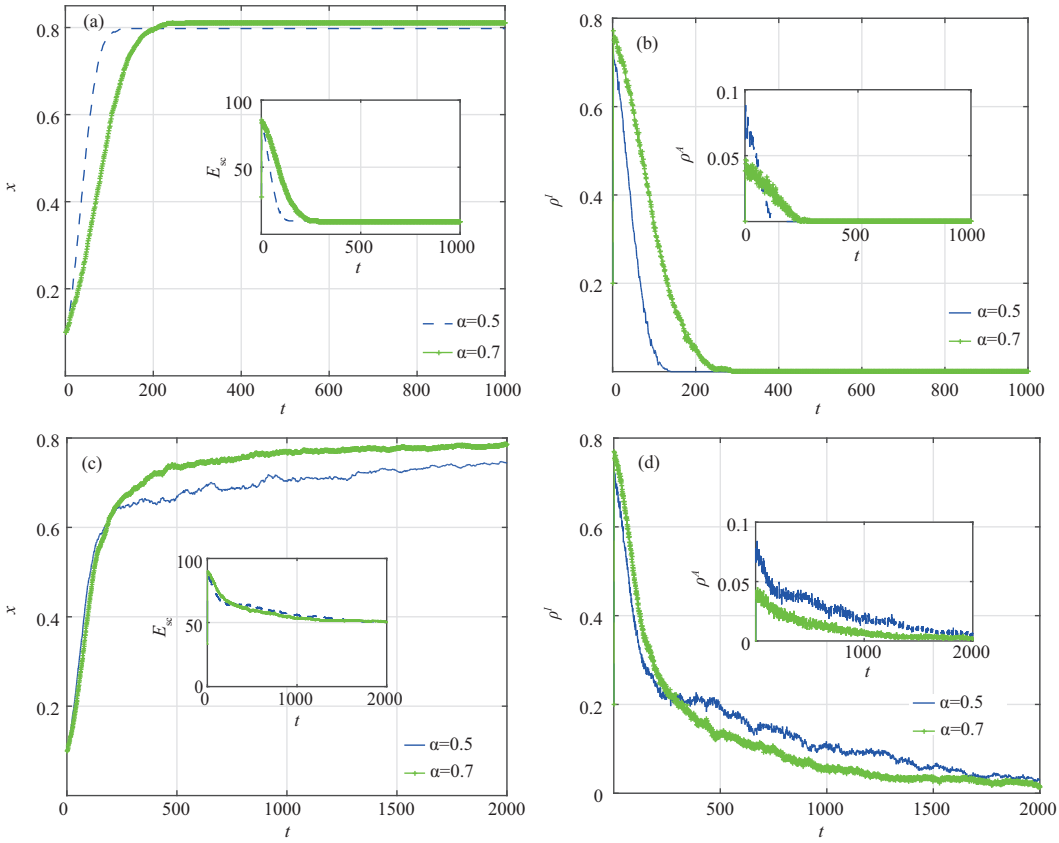

Figure 7 (Color online) (a) and (c) the vaccination density x and social cost $E_{\rm sc}$ (inset), (b) and (d) the fractions of infected individuals ρ^I and alert individuals ρ^A (inset) as a function of time t under different strength coefficients α in a two-layer ER network. Parameters: $N = 100$, $\mu = 0.1$, $\beta = 0.3$, $\eta = 0.6$, $\lambda = 0.3$, $T = 0.1$ and $\xi = 0.5$. (a) and (b): $C = 0.1$, (c) and (d): $C = 0.6$.

How to promote vaccination motivates us to explore the impact factors of vaccination. We first compare the vaccination density x under different strength coefficients α to determine the effect of information dissemination intensity on the vaccination decision-making. Simulations are performed in a two-layer ER network and a two-layer BA scale-free network, respectively. The initial vaccination density x and the fraction of infected individuals ρ^I are set to 0.1 and 0.2, respectively. As illustrated in Figures 7(a) and (c), in a two-layer ER network, vaccination density x increases with the decrease of strength coefficient α at the early stage of the system evolution ($t < 200$). The opposite is true when the system evolution reaches the steady state, regardless of the vaccination cost C. In terms of the fraction of infected individuals ρ^I and social cost $E_{\rm sc}$, the fraction of infected individuals ρ^I and social cost $E_{\rm sc}$ under a smaller strength coefficient α are less than or equal to those under a larger strength coefficient α when the vaccination cost is smaller ($C = 0.1$, see Figure 7(b)). When the vaccination cost is larger ($C = 0.6$, see Figure 7(d)), the comparative result depends on the stage of the system evolution. We conclude that information dissemination can promote vaccination and reduce the epidemic size at the early stage of the system evolution, and the opposite is true when the system evolution reaches the steady state, in the two-layer ER network.

In a two-layer BA scale-free network, the impacts of information dissemination on vaccination and epidemic control are related to the vaccination cost C. Figures 8(a) and (b) show that when the vaccination cost is smaller ($C = 0.1$), the results of comparison between the vaccination density x, the fraction of infected individuals ρ^I and social cost $E_{\rm sc}$ under different strength coefficients α are similar to those in a two-layer ER network. Information dissemination helps to improve vaccination density x and reduce the epidemic size ρ^I at the early stage of the system evolution. When the vaccination cost is larger ($C = 0.6$, see Figure 8(c)), vaccination density x increases with the increase of strength coefficient α, which indicates that information dissemination cannot promote vaccination. In terms of the fraction of infected individuals ρ^I, we find that the fraction of infected individuals ρ^I under a smaller strength coefficient α is less than that under a larger strength coefficient α at the early stage of the system evolution ($t < 200$).

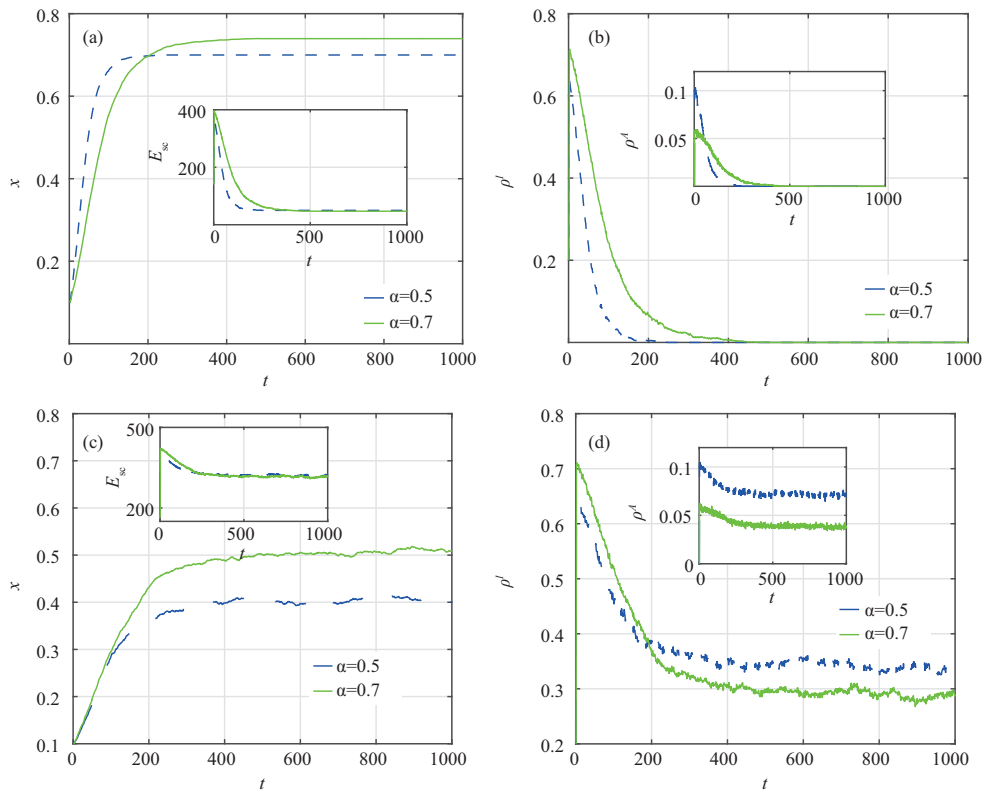

Figure 8 (Color online) (a) and (c) the vaccination density x and social cost $E_{\rm sc}$ (inset), (b) and (d) the fractions of infected individuals ρ^I and alert individuals ρ^A (inset) as a function of time t under different strength coefficients α in a two-layer BA network. Parameters: $N = 500$, $\mu = 0.1$, $\beta = 0.3$, $\eta = 0.6$, $\lambda = 0.3$, $T = 0.1$ and $\xi = 0.5$. (a) and (b): $C = 0.1$, (c) and (d): $C = 0.6$.

This may be because the fraction of alter individuals ρ^A under a smaller strength coefficient α is more than that under a lager strength coefficient α, and some basic protection behavior, such as wearing masks and washing hands, triggered by information dissemination, can reduce the effective infectivity. In this case, information dissemination helps to control the epidemics. The opposite is true when the system evolution reaches the steady state. In summary, the impact of information dissemination on collective vaccination behavior depends on not only the vaccination cost C and network topology, but also the stage of the system evolution.

We further explore the effect of sensitivity coefficient λ on vaccination. For the sake of simplicity, we assume that each individual has the same sensitivity λ to the information. We perform simulations on a two-layer ER network and a two-layer BA scale-free network, respectively. We find that vaccination density x increases with the increase of sensitivity coefficient λ at the early stage of the system evolution ($t < 200$) in a two-layer ER network (see Figures 9(a) and (c)). The opposite is true when the system evolution reaches the steady state, regardless of the vaccination cost C. That is, information dissemination contributes to improving vaccination density x and reducing the epidemic size ρ^I at the early stage of the system evolution. In a two-layer BA scale-free network, vaccination density x increases with the decrease of sensitivity coefficient λ when the vaccination cost is larger ($C = 0.6$, see Figure 10(c)). In this case, increased individual sensitivity to information does not promote vaccination.

Above all, we conclude that the impact of information dissemination on individual vaccination behavior depends on not only the vaccination cost C and network topology, but also the stage of the system evolution. In a two-layer ER network, information dissemination helps to improve vaccination density and reduce the epidemic size at the early stage of the system evolution. The opposite is true when the system evolution reaches the steady state, regardless of the vaccination cost C. In a two-layer BA scale-free network, information dissemination can promote vaccination only at the early stage of the system evolution, as well as when the vaccination cost is smaller. When the vaccination cost is larger, vaccination density decreases with the increase of information dissemination.

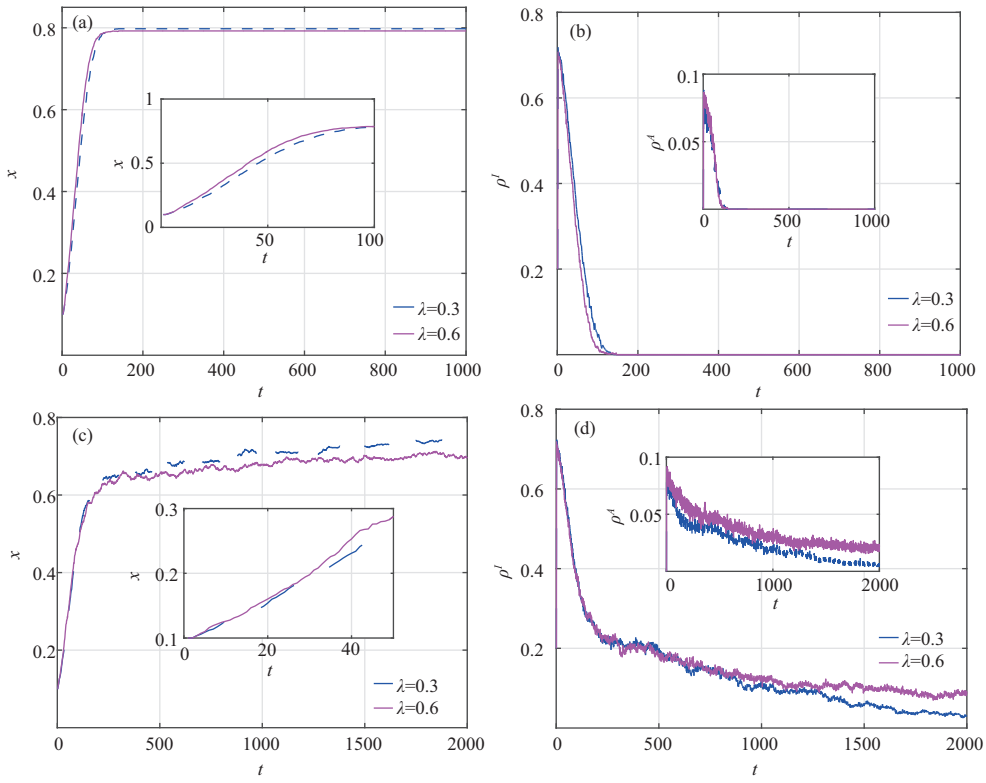

Figure 9 (Color online) (a) and (c) the vaccination density x, (b) and (d) the fractions of infected individuals ρ^I and alert individuals ρ^A (inset) as a function of time t under different sensitivity coefficients λ in a two-layer ER network. Parameters: $N = 100$, $\beta = 0.3$, $\mu = 0.1$, $\eta = 0.6$, $\alpha = 0.5$, $T = 0.1$, $\xi = 0.5$, $\kappa = 20$. (a) and (b): $C = 0.1$ (c) and (d): $C = 0.6$.

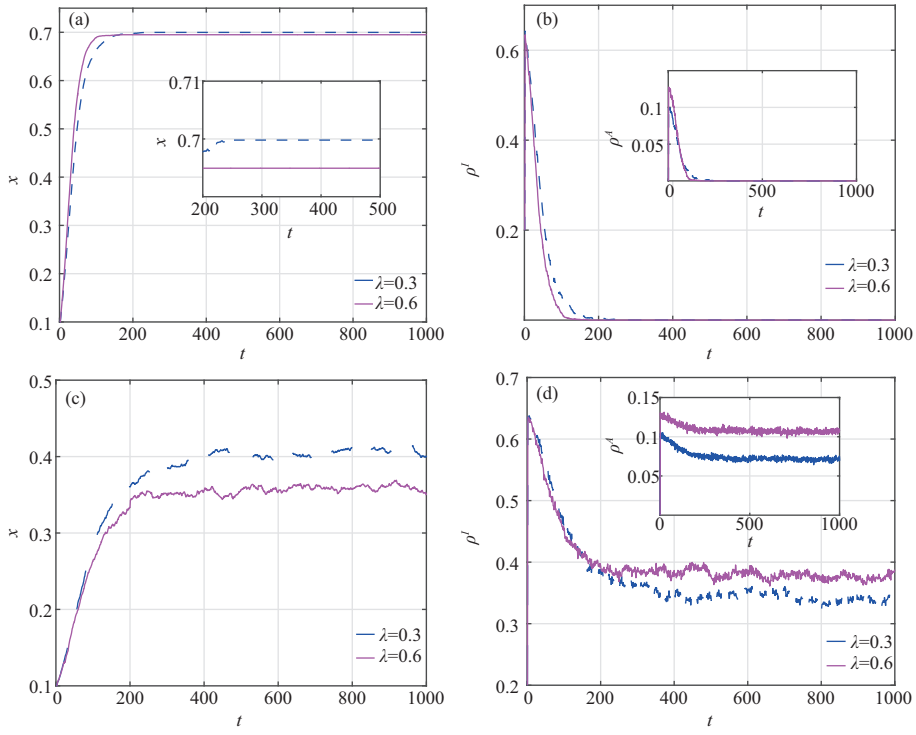

Figure 10 (Color online) (a) and (c) the vaccination density x, (b) and (d) the fractions of infected individuals ρ^I and alert individuals ρ^A (inset) as a function of time t under different sensitivity coefficients λ in a two-layer BA network. Parameters: $N = 500$, $\beta = 0.3$, $\mu = 0.1$, $\alpha = 0.5$, $\eta = 0.6$, $T = 0.1$, $\xi = 0.5$, $\kappa = 20$. (a) and (b): $C = 0.1$, (c) and (d): $C = 0.6$.

6 Conclusion

Individuals behavioral responses to information dissemination determine the influence of information on epidemic control. Taking into account the complexity of decision-making of individuals in vaccination, we have presented an evolutionary vaccination game model by incorporating the information-epidemic propagation process into the vaccination dynamics, and explored the influence of information dissemination on vaccination. We find that the impact of information dissemination on vaccination decision-making depends on not only the vaccination cost and network topology, but also the stage of the system evolution. In a two-layer ER network, information dissemination helps to improve vaccination density and reduce the epidemic size at the early stage of the system evolution, and the opposite is true when the system evolution reaches the steady state. Compared with a two-layer ER network, the same result can be obtained in a two-layer BA network when the vaccination cost is smaller, and information dissemination cannot promote vaccination when the vaccination cost is larger. Since information dissemination is inevitable during the epidemic, the correlation between information dissemination and vaccination may provide a guidance for the authorities to implement information regulation for epidemic control. However, the stochastic fluctuations that lead to the extinction of infection in finite networks [43] have not been considered in this paper, which may be of interest in multiplex vaccination games in the future.

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References

1 Pastor-Satorras R, Vespignani A. Epidemic spreading in scale-free networks. Phys Rev Lett, 2001, 86: 3200–3203
2 Theodorakopoulos G, Le Boudec J Y, Baras J S. Selfish response to epidemic propagation. IEEE Trans Automat Contr, 2013, 58: 363–376
3 Chen S, Wang K, Sun M, et al. Spread of competing viruses on heterogeneous networks. Phil Trans R Soc A, 2017, 375: 20160284
4 Pastor-Satorras R, Castellano C, van Mieghem P, et al. Epidemic processes in complex networks. Rev Mod Phys, 2015, 87: 925–979
5 Zhang Y Q, Li X. When susceptible-infectious-susceptible contagion meets time-varying networks with identical infectivity. Europhys Lett, 2014, 108: 28006
6 Li C, van de Bovenkamp R, van Mieghem P. Susceptible-infected-susceptible model: a comparison of N-intertwined and heterogeneous mean-field approximations. Phys Rev E, 2012, 86: 026116
7 Wang J B, Wang L, Li X. Identifying spatial invasion of pandemics on metapopulation networks via anatomizing arrival history. IEEE Trans Cybern, 2016, 46: 2782–2795
8 Wang Y, Cao J D. Final size of network epidemic models: properties and connections. Sci China Inf Sci, 2021, 64: 179201
9 Wang Z, Andrews M A, Wu Z X, et al. Coupled disease-behavior dynamics on complex networks: a review. Phys Life Rev, 2015, 15: 1–29
10 Li X J, Li C, Li X. Minimizing social cost of vaccinating network SIS epidemics. IEEE Trans Netw Sci Eng, 2018, 5: 326–335
11 Li X J, Li C, Li X. Vaccinating SIS epidemics in networks with zero-determinant strategy. In: Proceedings of IEEE International Symposium on Circuits Syst, 2017. 2275–2278
12 Iwamura Y, Tanimoto J, Fukuda E. Effect of intermediate defense measures in voluntary vaccination games. J Stat Mech, 2016, 2016: 093501
13 Funk S, Gilad E, Watkins C, et al. The spread of awareness and its impact on epidemic outbreaks. Proc Natl Acad Sci USA, 2009, 106: 6872–6877
14 Wu Q, Fu X, Small M, et al. The impact of awareness on epidemic spreading in networks. Chaos, 2012, 22: 013101
15 de Arruda G F, Rodrigues F A, Moreno Y. Fundamentals of spreading processes in single and multilayer complex networks. Phys Rep, 2018, 756: 1–59
16 Li C, Wang H, de Haan W, et al. The correlation of metrics in complex networks with applications in functional brain networks. J Stat Mech, 2011, 2011: P11018
17 Wang Z, Wang C Y, Gao C, et al. An evolutionary autoencoder for dynamic community detection. Sci China Inf Sci, 2020, 63: 212205
18 Buldyrev S V, Parshani R, Paul G, et al. Catastrophic cascade of failures in interdependent networks. Nature, 2010, 464: 1025–1028
19 Sahneh F D, Scoglio C, van Mieghem P. Generalized epidemic mean-field model for spreading processes over multilayer complex networks. IEEE/ACM Trans Networking, 2013, 21: 1609–1620
20 Zhou Y, Zhou J, Chen G, et al. Effective degree theory for awareness and epidemic spreading on multiplex networks. New J Phys, 2019, 21: 035002
21 Bauch C T, Galvani A P. Social factors in epidemiology. Science, 2013, 342: 47–49
22 Li Y Y, Zou X F. Identifying disease modules and components of viral infections based on multi-layer networks. Sci China Inf Sci, 2016, 59: 070102
23 Wang Z S, Xia C Y, Chen Z Q, et al. Epidemic propagation with positive and negative preventive information in multiplex networks. IEEE Trans Cybern, 2021, 51: 1454–1462
24 Guo Q, Jiang X, Lei Y, et al. Two-stage effects of awareness cascade on epidemic spreading in multiplex networks. Phys Rev E, 2015, 91: 012822
25 Young H P. The dynamics of social innovation. Proc Natl Acad Sci USA, 2011, 108: 21285–21291
26 Centola D. The spread of behavior in an online social network experiment. Science, 2010, 329: 1194–1197
27 Bauch C T, Earn D J D. Vaccination and the theory of games. Proc Natl Acad Sci USA, 2004, 101: 13391–13394

28 Fu F, Rosenbloom D I, Wang L, et al. Imitation dynamics of vaccination behaviour on social networks. Proc Biol Sci, 2011, 278: 42–49
29 Reluga T C, Bauch C T, Galvani A P. Evolving public perceptions and stability in vaccine uptake. Math Biosci, 2006, 204: 185–198
30 Xia S, Liu J. A belief-based model for characterizing the spread of awareness and its impacts on individuals' vaccination decisions. J R Soc Interface, 2014, 11: 20140013
31 Bauch C T, Galvani A P, Earn D J D. Group interest versus self-interest in smallpox vaccination policy. Proc Natl Acad Sci USA, 2003, 100: 10564–10567
32 Galvani A P, Reluga T C, Chapman G B. Long-standing influenza vaccination policy is in accord with individual self-interest but not with the utilitarian optimum. Proc Natl Acad Sci USA, 2007, 104: 5692–5697
33 Hilbe C, Wu B, Traulsen A, et al. Cooperation and control in multiplayer social dilemmas. Proc Natl Acad Sci USA, 2014, 111: 16425–16430
34 Zhang H F, Wu Z X, Tang M, et al. Effects of behavioral response and vaccination policy on epidemic spreading-an approach based on evolutionary-game dynamics. Sci Rep, 2014, 4: 5666
35 Tizard I R. Vaccination against coronaviruses in domestic animals. Vaccine, 2020, 38: 5123–5130
36 van Mieghem P, Omic J, Kooij R. Virus spread in networks. IEEE/ACM Trans Netw, 2009, 17: 1–14
37 Wang W, Tang M, Stanley H E, et al. Unification of theoretical approaches for epidemic spreading on complex networks. Rep Prog Phys, 2017, 80: 036603
38 Granell C, Gómez S, Arenas A. Dynamical interplay between awareness and epidemic spreading in multiplex networks. Phys Rev Lett, 2013, 111: 128701
39 Trajanovski S, Hayel Y, Altman E, et al. Decentralized protection strategies against SIS epidemics in networks. IEEE Trans Control Netw Syst, 2015, 2: 406–419
40 Anderson R M, May R M. Infectious Diseases of Humans: Dynamics and Control. Oxford: Oxford University Press, 1992
41 Szabó G, Tőke C. Evolutionary prisoner's dilemma game on a square lattice. Phys Rev E, 1998, 58: 69
42 Zhu P C, Wang X Y, Jia D Y, et al. Investigating the co-evolution of node reputation and edge-strategy in prisoner's dilemma game. Appl Math Comput, 2020, 386: 125474
43 Hindes J, Schwartz I B, Shaw L B. Enhancement of large fluctuations to extinction in adaptive networks. Phys Rev E, 2018, 97: 012308