Research Article

Coevolving Dynamics between Epidemic and Information Spreading considering the Dependence between Vigilance and Awareness Prevalence

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Received 24 February 2021; Accepted 11 May 2021; Published 24 May 2021

Academic Editor: Chenquan Gan

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It has been demonstrated that the propagation of information and awareness regarding a disease can assist in containing the outbreak of epidemics. Previous models for this coevolving usually introduced the dependence between these two processes by setting a lower but time-independent infection rate for individuals with awareness. However, a realistic scenario can be more complicated, as individual vigilance and the adopted protective measures may depend on the extent of the discussion on the disease, whereas individuals may be irrational or lack relevant knowledge, leading to improper measures being taken. These can introduce a time-varying dependence between epidemic dynamics and awareness prevalence and may weaken the effect of spreading awareness in containing a pandemic. To better understand this effect, we introduce a nonlinear dependence of the epidemic infection rate on awareness prevalence, focusing on the effect of different forms of dependence on the coevolving dynamics. We demonstrate that a positive correlation between vigilance and awareness prevalence can enhance the effect of information spreading in suppressing epidemics. However, this enhancement can be weakened if some individuals are irrational. Our results demonstrate the importance of rational behavior in the strategy of containing epidemics by propagation of disease information.

1. Introduction

Fighting a pandemic is a major challenge. Therefore, understanding the dynamics of epidemic spreading and determining an efficient strategy to contain a pandemic have attracted considerable attention in complex networks [1]. Various factors and effects have been discussed, from the network topology and competition between viruses to human behavior and robustness of the health system [2–12]. With the rapid development of modern techniques, the pattern of epidemic spreading has also changed. For instance, the development of modern airline transportation facilitates long-distance travel; however, it also promotes the spread of pathogens, such as the epidemic of SARS [13–15] and the novel influenza A (H_1N_1) [16–18]. High-speed trains are the best choice for intermediate-distance travel in several

countries; however, the high passenger density on these trains can also accelerate the spread of viruses [19]. Cold chain logistics has become one of the most important techniques to ensure food supply. Recently, during the COVID-19 pandemic, it was found that this food transport technique can also carry pathogens and cause local epidemic events [20]. Therefore, there is an increasing demand for more realistic models to better understand epidemic spreading.

One of the characteristics of modern living is the omnipresence of information. Reading news, browsing webpages, and participating in online social networks have become important parts of our daily lives. Messages received through these activities can influence our decision making, can change our behaviors, and, as a result, may also impact the pattern of epidemic spreading [21–24]. Therefore,

understanding the effect of information propagation on the spread of a disease has attracted considerable attention. Models have been proposed to investigate the suppressive effect of spreading awareness on epidemic propagation, focusing on different mechanisms, such as nonlinear coupling [22, 23, 25–29] and competition [30–33].

Recent studies on the coevolution dynamics between information and disease spreading usually assume that the response of individuals to messages is independent of time, and the response to information is manifested by a relatively lower infection rate for individuals with awareness. However, a realistic situation can be more complicated: an individual may not immediately take the highest level of protective measures when he/she receives information regarding the epidemic. The level of protective measures is usually upgraded when individuals become more vigilant or frightened. Recently, it has been demonstrated that this vigilance (or fear) is related to the prevalence of public discussion on epidemics [34–36]. Therefore, it is possible that individuals become more vigilant and upgrade their protective measures when they receive more information regarding the pandemic. That is, there could be a positive correlation between the prevalence of the spreading of awareness of a disease and the protective measures taken by individuals. To better illustrate this, we collected data on COVID-19 in China [37] and the corresponding online discussion on *Sina Weibo*, the largest microblogging system in China. Figure 1 shows a plot of the number of existing cases of COVID-19 (red line), representing the prevalence of the epidemic, and the number of discussions on the epidemic on *Sina Weibo* (green line). As *disinfection* is one of the main protective measures taken by individuals to prevent the spread of epidemics, the prevalence of discussions on disinfection can thus reflect the level of vigilance or fear of the pandemic. Thus, we also indicate the prevalence of discussions on disinfection on *Sina Weibo* (blue line). As shown in Figure 1, the heat of the discussion changes with the prevalence of the epidemic in general; that is, the heat of the discussion increases quickly when the epidemic starts and gradually decreases after the epidemic is contained. However, the short-term fluctuation does not exactly reflect the trend of the epidemic. For instance, there is a peak in the heat of the discussion on *Sina Weibo* around the beginning of April 2020, when the number of existing infected cases continuously decreased. This peak was due to the Qingming day, the traditional tomb-sweeping day in China. A memorial service was held this day; thus, an increase in the discussion on *Sina Weibo* appeared. Nevertheless, the discussion on *disinfection*, which can represent the level of vigilance of individuals, follows the heat of the discussion on the epidemic. This indicates that the vigilance of individuals does not always follow the development of the epidemic but the heat of the discussion. Therefore, the effect of the dependence between individual vigilance and the prevalence of the discussion on the coevolving dynamics of information and epidemic spreading is worth investigating.

Previous studies on the coevolving dynamics of information and epidemic spreading usually assume that individuals are rational and can take proper protective measures.

However, during a pandemic, not all individuals are rational. Irrational behaviors, such as irrational beliefs [38], irrational antimicrobial prescribing [39], and panic buying [40], cannot protect individuals from the epidemic. On the contrary, these irrational behaviors may facilitate the spread of the epidemic by inducing individuals to take improper protective measures. Therefore, the spread of awareness of the disease can suppress the epidemic when individuals can take proper protective measures. However, it may also facilitate the spread of the disease if individuals are irrational and take inadequate measures. This leads to a negative correlation between the efficiency of individual protective measures and the prevalence of the discussion for irrational individuals.

In this study, based on the framework of the coevolving dynamics of information and disease spreading in two-layer networks, we consider the effect of dependence between individual vigilance and the prevalence of the discussion. Using brief analytics and numerical simulations, we demonstrate that a positive dependence can assist in containing the spread of the epidemic. In some cases, strong individual vigilance can suppress the size of the final outbreak even without increasing the awareness of the population. However, irrational individuals can weaken this suppressive effect. In some extreme cases, when most individuals are irrational, the spreading of information can no longer suppress epidemics.

The remainder of this paper is organized as follows. In Section 2, we introduce the dynamic model. In Section 3, we briefly provide a theoretical analysis. The results for various scenarios are presented in Section 4. The conclusions are presented in Section 5.

2. Model

The model contains two components, as shown in Figure 2. The unaware-aware-unaware (UAU) dynamics describe information spreading. An individual can become aware when (i) he/she is infected by the disease or (ii) through communication with aware neighbors (with probability λ). At each step, each individual becomes unaware with probability δ . In the contagion network, a susceptible-infected-susceptible (SIS) model is used to describe the spread of the disease. The infection rates are β^U and β^A for individuals with and without awareness, respectively. As an individual will take protective measures when he/she becomes aware of the disease, we assume that $\beta^A = \gamma\beta^U$, where $0 \leq \gamma \leq 1$ is related to individual vigilance. The recovery rate for the SIS model is μ .

To incorporate the dependence between individual vigilance and the prevalence of awareness of the disease, we now investigate two specific forms of dependence, where ρ_A is the ratio of the population with awareness:

Dependence 1: $\gamma = (1 - \rho_A)^x$, with $x > 0$

Dependence 2: $\gamma = x^{-\rho_A}$, with $x > 1$

Notably, the dynamics of the model are similar to those of the model in [30]. The difference is that we introduce a dependence between the protective efficiency of individuals

FIGURE 1: (a) Number of existing cases of COVID-19 in China (red line), number of discussions about COVID-19 (M) (green line), and disinfection on *Sina Weibo* (M' , blue line). (b) Smoothed curves in (a) using nonoverlapping windows, $w = 5$.

FIGURE 2: Schematic of the model. The dynamics of information spreading are described using the UAU model in the information network. The epidemic spreading process is described by the SIS model in the contagion network.

and the prevalence of awareness. Therefore, parameter γ is not constant, but it changes with the spreading of awareness.

3. Model Analysis

In the model, each individual can be unaware (U) or aware (A) and susceptible (S) or infected (I). According to the dynamics, three states are possible in the system: US , AS , and AI . We note that the UI state is erroneous because an individual will become aware of the disease immediately when he/she is infected. Here, we only include the correlation between ρ_A and γ ; the transition trees for the possible states in our model are the same as those in [30], as shown in Figure 3. Therefore, we can also apply the microscopic Markov chain approach (MMCA) to analyze the coevolution dynamics between information spreading and disease spreading [30, 41–43].

We denote by a_{ij} and b_{ij} the adjacency matrices of the information- and disease-spreading networks, respectively. The probability that node i is in one of the three states at time

t is denoted by $p_i^{AI}(t)$, $p_i^{AS}(t)$, and $p_i^{US}(t)$. The transition probability for node i from unaware to aware is $r_i(t)$. The probabilities for the transition from susceptible to infected are $q_i^A(t)$ and $q_i^U(t)$ for nodes with and without awareness, respectively. These probabilities can be estimated as

$$r_i(t) = \prod_j [1 - a_{ij} p_j^A(t) \lambda], \quad (1)$$

$$q_i^A(t) = \prod_j [1 - b_{ij} p_j^{AI}(t) \beta^A], \quad (2)$$

$$q_i^U(t) = \prod_j [1 - b_{ij} p_j^{AI}(t) \beta^U], \quad (3)$$

where $p_j^A(t) = p_j^{AI}(t) + p_j^{AS}(t)$. Therefore, according to the transition trees shown in Figure 3 and the transition probabilities calculated using equations (1)–(3), the microscopic Markov chains for the dynamics of each node can be obtained as

$$\begin{aligned} p_i^{US}(t+1) &= p_i^{AI}(t) \delta \mu + p_i^{US}(t) r_i(t) q_i^U(t) + p_i^{AS}(t) \delta q_i^U(t), \\ p_i^{AS}(t+1) &= p_i^{AI}(t) (1 - \delta) \mu + p_i^{US}(t) (1 - r_i(t)) q_i^A(t) + p_i^{AS}(t) (1 - \delta) q_i^A(t), \\ p_i^{AI}(t+1) &= p_i^{AI}(t) (1 - \mu) + p_i^{US}(t) \{ [1 - r_i(t)] [1 - q_i^A(t)] + r_i(t) [1 - q_i^U(t)] \} \\ &\quad + p_i^{AS}(t) \{ \delta [1 - q_i^U(t)] + (1 - \delta) [1 - q_i^A(t)] \}. \end{aligned} \quad (4)$$

The stationary state of the system can be estimated by the stationary state in equation (4). The populations of infected nodes and nodes with awareness are defined as $\rho_I = (1/N) \sum_i p_i^I$ and $\rho_A = (1/N) \sum_i p_i^A$, respectively.

4. Results

To quantitatively study the effect of different forms of dependence between individual vigilance and the prevalence of the discussion on the spread of the epidemic, we now focus on the two functional forms by comparing the results of a simulation with the theoretical estimation from equation (4). The simulation results were obtained by averaging the results from 30 independent realizations, based on Erdős–Rényi (ER) random networks, with $N = 1000$ nodes, and average degree $\langle k \rangle = 12$ for the information network and $\langle k \rangle = 10$ for the disease network. The recovery rates were set to $\delta = 0.6$ and $\mu = 0.4$. The theoretical estimation was obtained by iterating equation (4) until a stationary state was reached. For simplicity, we define $\beta^U = \beta$. The reproduction rate $R_0 = (\beta \langle k_b \rangle / \mu)$ is the key factor that determines the spread of the disease. Thus, we focus on the spreading pattern for different R_0 .

As described in the model, individuals with awareness will take protective measures, leading to a reduced infection rate $\beta^A = \gamma \beta^U$ with $\gamma \leq 1$. Therefore, the reproduction rate R_0 for individuals with awareness is also reduced. As individual vigilance can change with the prevalence of the discussion

about the epidemic, we introduce a function for the dependence between γ and ρ_A . Figure 4(a) shows a plot of the first function $\gamma = (1 - \rho_A)^x$. As x increases, ρ_A decreases faster with an increase in ρ_A , indicating a faster increase in individual vigilance. As a result, a larger x results in a lower ratio of infected nodes, as well as a lower ratio of nodes with awareness, as shown in Figures 4(b)–4(d). Notably, for large R_0 , ρ_A saturates and does not increase; however, a larger x can suppress the spread of the epidemic owing to the increase in the individual vigilance. Figures 4(e) and 4(f) show the dependence of the critical infection rate R_{0c} on x and λ . As in [30], increasing the information propagation rate λ holds back the outbreak of the epidemic. In addition, a smaller x can also significantly delay the outbreak of the epidemic, indicating that a positive correlation between individual vigilance and the prevalence of discussion can indeed suppress the outbreak of the epidemic.

Regarding the second form of $\gamma = x^{-\rho_A}$, Figure 5(a) shows that the level of vigilance also increases with x , as is the case with the first form in Figure 4. Thus, a larger x also leads to a lower ratio of infected population (Figures 5(b)–5(d)) and a larger critical infection rate R_{0c} (Figures 5(e) and 5(f)). Combining the results of the different forms of dependence between γ and ρ_A (Figures 4 and 5), we can conclude that a positive correlation between individual vigilance and the prevalence of discussion can significantly assist in containing the epidemic. In addition, when ρ_A saturates for large β , increasing individual vigilance can further suppress the epidemic.

FIGURE 3: Probability trees for the transition for the possible states at each time step for the model. The four possible states are aware-infected (AI), aware-susceptible (AS), unaware-infected (UI), and unaware-susceptible (US). The transition probabilities are r_i from U to A, q_i^A from S to I if node i is aware, q_i^U from S to I if node i is unaware, δ from A to U, and μ from I to S.

Figures 4 and 5 show an intersection of ρ_A in the middle range of R_0 . For small R_0 , the population with awareness ρ_A for high vigilance (larger x in Figures 4 and 5) is lower than that for low vigilance, and it reverses when R_0 becomes large. This implies that high vigilance has a stronger suppressive effect on the spread of the epidemic but does not always result in a lower ratio of ρ_A owing to the containment of the epidemic. For small R_0 , high vigilance can suppress the spread of both epidemic and information, whereas, for large R_0 , high vigilance can suppress the epidemic but can slightly facilitate the spread of information. This can be understood from the first equation in equation (4). The stationary state $p_i^{US}(t+1) = p_i^{US}(t)$ yields $p_i^{US} = ((p_i^{AI}\delta\mu + p_i^{AS}\delta q_i^U)/(1 - r_i q_i^U))$. In the case of a low infection rate, the infected population is small ($\rho_I \ll 1$), and $p_i^{AI} \ll p_i^{AS}$ leads to $p_i^{US} \approx ((p_i^{AS}\delta q_i^U)/(1 - r_i q_i^U))$. The term $r_i q_i^U$ in the denominator is a high-order small quantity compared with the numerator, and the fluctuation of p_i^{US} primarily depends on the fluctuation of p_i^{AS} and q_i^U . When vigilance increases, ρ_I tends to decrease, leading to higher p_i^{AS} and q_i^U (estimated from equation (3)). Therefore, a higher vigilance level can lead to a higher p_i^{US} , resulting in a decrease in ρ_A because of the relation $\rho_A = 1 - \sum_i p_i^{US}$. In the case of a high infection rate, $p_i^{AI} \gg p_i^{AS}$ and thus $p_i^{US} = (p_i^{AI}\delta\mu/(1 - r_i q_i^U))$, where the fluctuation of p_i^{US} primarily depends on the fluctuation of p_i^{AI} . For a higher vigilance level, p_i^{AI} tends to decrease, resulting in a decrease in p_i^{US} and, thus, an increase in ρ_A . These different behaviors for small and large R_0 underlie the observed intersection of ρ_A for different vigilance levels in the intermediate range of the infection rate.

We have demonstrated that the dependence of γ on ρ_A can assist in suppressing the spread of the epidemic, assuming that all individuals are rational—higher prevalence of the discussion about the disease leads to a higher level of vigilance. However, in reality, not all individuals are rational. Irrational behaviors, such as irrational beliefs [39], irrational antimicrobial prescribing [39], and panic buying [40], may facilitate the spread of the epidemic by inducing individuals to take improper protective measures. Therefore, we now consider cases in which a part of the population is irrational. As irrational behavior can lead to the opposite effects of those by rational behavior, in our model, these two types of individuals are defined as follows:

Dependence 1: $\gamma = (1 - \rho_A)^x$ for rational individuals, and $\gamma = (1 + \rho_A)^x$ for irrational individuals

Dependence 2: $\gamma = x^{-\rho_A}$ for rational individuals, and $\gamma = x^{\rho_A}$ for irrational individuals

Accordingly, disease awareness can reduce the infection rate for rational individuals but increase the infection rate for irrational individuals.

Figure 6 shows the effect of irrational individuals on the spread of the epidemic for the first form of dependence. As the irrational population increases, the final infected population increases, whereas the critical infection rate decreases. This indicates that irrational individuals can facilitate the spread of the epidemic by introducing a negative correlation between vigilance and awareness prevalence. In extreme cases in which irrational individuals become the majority of the system, the spread of information can no longer suppress the epidemic. As shown in Figures 6(d) and 6(f), if most individuals are irrational and take improper measures, a larger population with awareness leads to more serious outbreaks of the epidemic. A similar conclusion can also be obtained for the second form of dependence, as shown in Figure 7. Heterogeneity is an important characteristic of real contagion networks, and different spatial distributions may impact the effect of irrational individuals. Thus, we also performed numerical simulations on BA networks. Figure 8 shows the result of the first form of dependence for three different infection rates: $R_0 = 1.25, 2.5$, and 3.75 . The irrational individuals are distributed on nodes with the highest degree, nodes with the lowest degree, and randomly chosen nodes. It can be concluded that, in the second case, the epidemic is not significantly worsened by a small fraction of irrational individuals. When the irrational individuals are randomly distributed or placed on nodes with a high degree, the final infected population increases. This effect of irrational individuals is more pronounced for smaller values of R_0 . Figure 8(d) shows the dependence of the critical infection rate on the ratio of irrational individuals for various scenarios. Again, we observe that an increased ratio of irrational individuals can facilitate the spread of the epidemic. A similar effect is observed for the second form of independence in Figure 9.

FIGURE 4: (a) Plots of the function $y = (1 - \rho_A)^x$ for different x values. The dependence of prevalence ρ_A and ρ_I on the infection rate R_0 is shown in (b) for $\lambda = 0.1$, (c) for $\lambda = 0.3$, and (d) for $\lambda = 0.8$. Solid lines represent the ratio of awareness nodes ρ_A and dashed lines represent the ratio of infected nodes. Symbols represent the simulation results and different colors correspond to different x values. (e) Dependence of the critical infection rate R_{0c} for the epidemic outbreak on parameter x . (f) Dependence of R_{0c} on λ , with $\delta = 0.6$ and $\mu = 0.4$.

FIGURE 5: (a) Plots of the function $y = x^{-\rho_A}$ for different x values. The dependence of prevalence ρ_A and prevalence ρ_I on the infection rate R_0 is shown in (b) for $\lambda = 0.1$, (c) for $\lambda = 0.3$, and (d) for $\lambda = 0.8$. Solid lines represent the ratio of awareness nodes ρ_A and dashed lines represent the ratio of infected nodes. Symbols represent the simulation results and different colors correspond to different x values. (e) Dependence of the critical infection rate R_{0c} for the epidemic outbreak on parameter x . (f) Dependence of R_{0c} on λ , with $\delta = 0.6$ and $\mu = 0.4$.

FIGURE 6: For the first form of dependence, where $\gamma = (1 - \rho_A)^x$ for rational individuals and $\gamma = (1 + \rho_A)^x$ for irrational individuals, the dependence of prevalence ρ_A and prevalence ρ_I on the infection rate R_0 is calculated for (a) 0%, (b) 20%, (c) 50%, (d) 80%, and (e) 100% irrational individuals. Solid lines represent the ratio of awareness nodes ρ_A and dashed lines represent the ratio of infected nodes. Symbols represent the simulation results and different colors correspond to different x values. (f) Comparison between cases of different ratios of irrational individuals, with $x = 0.8$. All calculations are based on $\delta = 0.6$ and $\mu = 0.4$.

FIGURE 7: For the second form of dependence, where $\gamma = x^{-\rho_A}$ for rational individuals and $\gamma = x^{\rho_A}$ for irrational individuals, the dependence of prevalence ρ_A and prevalence ρ_I on the infection rate R_0 is calculated for (a) 0%, (b) 20%, (c) 50%, (d) 80%, and (e) 100% irrational individuals, respectively. Solid lines represent the ratio of awareness nodes ρ_A and dashed lines represent the ratio of infected nodes. Symbols represent the simulation results and different colors correspond to different x values. (f) Comparison between cases of different ratios of irrational individuals, with $x = 2$. All calculations are based on $\delta = 0.6$ and $\mu = 0.4$.

FIGURE 8: For the first form of dependence, where $\gamma = (1 - \rho_A)^x$ for rational individuals and $\gamma = (1 + \rho_A)^x$ for irrational individuals, the dependence of epidemic prevalence ρ_I on the ratio of irrational individuals on the BA scale-free network for (a) $R_0 = 1.25$, (b) $R_0 = 2.5$, and (c) $R_0 = 3.75$. Irrational individuals are distributed according to three different strategies: on nodes with the highest degree (red line), on nodes with the lowest degree (green line), and randomly distributed (blue line). (d) The critical infection rate R_{0c} for epidemic outbreak in different situations. The parameters are the same as those in Figures 4 and 6.

FIGURE 9: For the first form of dependence, where $\gamma = x^{-\rho_A}$ for rational individuals and $\gamma = x^{\rho_A}$ for irrational individuals, the dependence of epidemic prevalence ρ_I on the ratio of irrational individuals in the BA scale-free network for (a) $R_0 = 1.25$, (b) $R_0 = 2.5$, and (c) $R_0 = 3.75$. Irrational individuals are distributed according to three different strategies: on nodes with the highest degree (red line), on nodes with the lowest degree (green line), and randomly distributed (blue line). (d) The critical infection rate R_{0c} for epidemic outbreak in different situations. The parameters are the same as those in Figures 4 and 6.

These results demonstrate the importance of maintaining rationality in containing epidemics, as the efficiency of the strategy of inducing individuals to become aware of the disease and take protective measures depends on the ratio of individuals who can take proper measures. If most individuals cannot take proper protective measures, the spread of awareness cannot assist in containing the epidemic. Thus, irrational population is also a factor that may affect the spread of the pandemic.

5. Conclusion

In modern society, online communication and social media have become important sources of information. Accordingly, relevant information can be spread faster during a pandemic. Individuals can become vigilant about the spread of the disease and take protective measures. Therefore, the process of information propagation can suppress epidemics to a certain extent. In a more realistic scenario, the vigilance of individuals who are aware of the disease is not constant. The level of vigilance and protective measures may change with awareness prevalence. Therefore, investigating the effect of the dependence of individual vigilance on awareness prevalence may lead to a deeper understanding of the coevolution dynamics between epidemic spreading and information spreading.

In this study, we investigated the effect of various forms of dependence between individual vigilance and the spread of awareness of a disease. For rational individuals, vigilance and the level of protective measures increase with the prevalence of discussion. We demonstrated that this positive dependence can enhance the effect of information spreading in suppressing epidemics, as shown in Figures 4 and 5. However, individuals may not be rational and may not take proper protective measures. These irrational behaviors may weaken the effect of information spreading in the containment of the epidemic. In extreme cases where most individuals are irrational, information propagation may even facilitate the spread of the disease, as shown in Figures 6–9. Thus, our results demonstrate the importance of rational behaviors in containing epidemics. Information propagation can efficiently suppress epidemics only when most individuals remain rational and can take proper protective measures.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This study was supported by the National Social Science Foundation of China, “Risk Communication and Effectiveness Evaluation in Public Crises” (20AXW008).

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