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Research Article

Voluntary Vaccination through Perceiving Epidemic Severity in Social Networks

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The severity of an epidemic has a significant impact on individual vaccinating decisions under voluntary vaccination. During the epidemic of a vaccine-preventable disease, individuals in a social network can perceive the infection risks based on global information announced by public health authorities, or local information obtained from their social neighbors. After that, they can rationally decide whether or not to take the vaccine through weighing the relative cost of vaccination and infection (i.e., relative vaccine cost). In this case, both social network structure and individuals' risk perception strategies will affect the final vaccine coverage. In this paper, we focus on the problem of how individuals' perceptions on epidemic severity affect their vaccinating behaviors in the face of flu-like seasonal diseases in social networks, and vice versa. Specifically, we first present three types of static decision-making mechanisms, each of which simulates human vaccinating behaviors based on different local/global information. On this basis, we further present a reinforcement-learning-based mechanism, where individuals can use their historical vaccination experiences to determine what information is more suitable to estimate the severity of the epidemic. Finally, we carry out simulations on three types of social networks to investigate the effects of network structure, source of information, relative vaccine cost, and individual social connections on the final vaccine coverage and epidemic size. The results and findings can provide a new insight for designing incentive-based vaccination policies and intervention strategies for flu-like seasonal diseases.

1. Introduction

Understanding human behavioral response to the spread of vaccine-preventable diseases is critically important for designing effective vaccination policies. Under the voluntary vaccination policy, individuals might decide whether or not to take the vaccine through evaluating the risks from infection [1–4]. In addition, the risk and cost associated with vaccination, such as side effects [5, 6], financial cost [7, 8], and vaccine effectiveness [9], can also affect individuals' vaccinating decisions. Along with this line, great efforts have been made to investigate the dynamics of human voluntary vaccinating behaviors by assuming varying "relative vaccine risk" (i.e., the ratio of the magnitude of vaccination risk to that of infection risk). However, most existing studies do not take into account the differences in individuals' perceptions on their infection risks, which to a great extent depend on the transmission severity of the epidemic in their social contact network. In reality, due to structural heterogeneity of social contact networks, it is extremely difficult for individuals to precisely evaluate their infection risks during an epidemic. Usually, they can estimate the risks based on their awareness of the epidemic severity, such as the disease prevalence and vaccine coverage announced by public health authorities. Accordingly, in this paper, we focus mainly on the problem of how individuals' perceptions on the epidemic severity may affect their self-initiated voluntary vaccinating behaviors in the face of flu-like seasonal diseases. Here, the epidemic severity only indicates the consequences of disease spread in the population (e.g., the scale of the infection), rather than the pathogenicity of a microbial agent to cause disease.

To prevent the epidemic of a vaccine-preventable disease, it would be necessary to understand the complex interactions between disease dynamics and human behavioral response, where a list of reviews about the coupled disease-behavior dynamics from the network science viewpoints has been published [10–13]. On the one hand, individuals' vaccinating behaviors will collectively affect the level of vaccine coverage, and further the final disease prevalence in the whole population. On the other hand, the infection risk, which can be reflected through the disease prevalence, may also affect individuals' vaccinating decisions [14–16]. Once the herd immunity threshold is achieved, individuals' infection risks will be greatly reduced. In this case, self-interested individuals may attempt to refuse to take the vaccine [17–19]. Game theory is the natural framework given that the vaccination strategy of each individual, whose sum defines the vaccine coverage level at the population, as well as the corresponding payoff, will depend on other individuals' decisions. Accordingly, great efforts have been made to characterize such decision-making dilemmas under voluntary vaccination [20–26]. For example, with respect to diseases that require only one-off vaccination (e.g., smallpox), Bauch et al. have presented a vaccination game and revealed that the vaccine coverage level achieved through self-interested individuals may differ from what is best for the population as a whole [20]. While, for flu-like seasonal diseases, Vardavas et al. have proposed a minority-game-inspired human cognition model and found that such diseases cannot be prevented through voluntary vaccination even with risk-free vaccine [23]. Taking into consideration the herd immunity threshold, Shi et al. have introduced an evolutionary threshold game and deduced the stable equilibrium of vaccine coverage in terms of population size, epidemic severity, and the relative vaccine risk [26].

In social networks, the situation becomes more complicated. Many studies have shown that the structure of social contact networks will largely determine disease transmission routes in the population and further affect disease eradicability under voluntary vaccination [27–33]. Moreover, the structure of social networks can also affect individuals' incentive to vaccine, because individuals with heterogeneous social roles may have different risk perceptions on the severity of the epidemic [34–36]. From this viewpoint, a great deal of network-based frameworks have been proposed to simulate human behavioral responses in various social networks [13, 37–40]. Usually, individuals are assumed to act in their own interests and rationally decide whether or not to take the vaccine by evaluating the perceived payoff from vaccination. In addition, individuals' vaccine uptake can also be affected by social learning or social impact, such as imitation [41–45]. Along with this line, Shi et al. have presented a reinforcement learning-based mechanism to investigate individuals' bounded rationality in the face of rational decisions and social influence [46]. However, few of them have focused on how individuals' perceptions on epidemic severity affect their vaccinating behaviors.

Practically, human vaccinating behaviors is usually based on their beliefs, opinions, and awareness of the transmission severity of an epidemic. All these factors can change over time both in an individual level and in the population as a whole [11, 12]. In view of this, a number of belief-based models have been proposed, where the information that individuals base a behavioral change on is not directly relating to disease prevalence [47–50]. In these models, individuals make *subjective* assessment of epidemic severity based on opinions or beliefs that spread independently of current disease prevalence. While, in reality, if the pathogenic characters of disease remain the same, the epidemic severity of the disease can then be predicted through its prevalence. In this case, individuals in a social network can *objectively* perceive the risks of being infected based on their awareness of disease prevalence. During an epidemic, there are two sources of information that individuals can assess: one is the total number of infections (i.e., global prevalence) and vaccine coverage in the whole population, which is announced by public health authorities and available to everyone; the other is the number of infections (i.e., local prevalence) and vaccine coverage in the local communities, which can be obtained from their social neighbors. In socially or spatially structured populations, existing studies have emphasized the impact of locally available information on the dynamics of vaccinating behaviors [30, 31, 51, 52]. Meanwhile, d'Onofrio and coworkers have further studied the interplay between public intervention and private choice against measles and childhood diseases, where vaccinating behavior spreads not only through the diffusion of "private" information but also through public information communicated by the public health authorities [53, 54].

Taking into account the abovementioned considerations and assumptions, in this paper, we aim at exploring human voluntary vaccinating behaviors in the face of a flu-like seasonal disease, where individuals are assumed to be able to perceive the severity of an epidemic based on local and/or global disease-related information. Specifically, we adopt the classical Susceptible-Infected-Recovered (SIR) model to simulate disease transmission in social networks. Specifically, we will later introduce three static decision-making mechanisms, that we will call the *local-*G^1 mechanism, the *local-*G^2 mechanism, and the *global-G* mechanism. Further, to investigate individuals' information preference, we present a reinforcement-learning-based model that allows individuals to strategically make decisions based on either local or global information through learning from their historical decisions and associated utilities. Finally, we conduct simulations in three types of social networks, that is, random regular networks, small-world networks, and scale-free networks, to evaluate the effects of social structures on human vaccinating behaviors.

2. Methods

2.1. Simulating Epidemic Spreading in Social Networks. A social network is represented as a graph $\mathcal{G} = (V, E)$, where

$V = \{1, \cdots, N\}$ stands for the set of individuals and $E = \{e_{ij} \mid i, j \in V\}$ stands for the set of social contacts. If there exists a social contact between individuals i and j, then $e_{ij} = 1$; otherwise, $e_{ij} = 0$. Accordingly, the first-order neighbors of i is denoted as $\mathcal{N}_i = \{j \mid e_{ij} = 1, j \in V\}$. To simulate human group interactions, each individual i treats his/her first-order social neighbors $\{j \mid j \in \mathcal{N}_i\}$ as a locally well-mixed group G_i^1, where individuals directly contact with other members equally often in the group [32, 55]. Moreover, each individual i can obtain information (i.e., disease prevalence and vaccine coverage) in his/her second-order groups $G_i^2 = \{G_j^1 \mid j \in \mathcal{N}_i\}$ from his/her social neighbors $\mathcal{N}_i$, and/or global information from public health authorities. Here, we focus mainly on the problem of how individuals' risk perceptions affect their vaccinating behaviors, where each individual i can perceive the epidemic severity based on (i) the local information in the first-order group G_i^1, (ii) the local information in the second-order groups G_i^2, and (iii) the global information in the whole population.

In this paper, the disease-behavior dynamics is modeled as a two-stage process: (i) the disease transmission dynamics, and (ii) the public vaccination campaign. The two-stage process will go on alternately. To simulate the disease transmission dynamics, the classical Susceptible-Infected-Recovered (SIR) model for epidemic outbreaks is adopted [56, 57]. In the SIR model, individuals are divided into three states: susceptible (S), infected (I), and recovered (R). In a well-mixed population, the fraction of susceptible (S), infected (I), and recovered (R) individuals evolves based on the following deterministic ordinary differential equation:

$$\begin{aligned} \frac{dS}{dt} &= -bSI, \\ \frac{dI}{dt} &= bSI - \gamma I, \\ \frac{dR}{dt} &= \gamma I, \end{aligned} \tag{1}$$

where γ represents the rate of recovery from infection and b represents the number of contacts per unit of time that are sufficient to spread the disease. Specifically, b can be represented as $b = \beta n$, where β is the disease transmission rate and n is the average number of adequate social contacts per unit of time. Moreover, we have $S + I + R = 1$.

A general strategy to simulate stochastic phenomena such as epidemic dynamics on social networks is represented by the Gillespie algorithm [58]. In this paper, to simulate the SIR dynamics in a social network, the following simulation procedure will be repeated until the number of infected individuals is zero. Specifically, at each instant of time step t_k during the simulated epidemic outbreak at season t, the individual whose state should be changed will be determined as follows.

(i) Determine state transition rate of each individual. If an individual i is susceptible, then the rate at which s/he becomes infected is $ST_i(t_k) = \beta \times$ *number of infected neighbors*. Otherwise, if i is infected, the rate at which s/he becomes recovered is $ST_i(t_k) = \gamma$. The total transition rate of all individuals is $\lambda(t_k) = \sum_{i \in V} ST_i(t_k)$.

(ii) After a time period Δt randomly generated from an exponential distribution $f(\Delta t; \lambda) = \lambda \exp(-\lambda \Delta t)$, determine the individual who should change his/her state. Then, generate a random number ν from the uniform distribution $U[0, 1)$. The individual l is chosen if

$$\frac{\sum_{i=1}^{l-1} ST_i(t_k)}{\lambda(t_k)} < \nu < \frac{\sum_{i=1}^{l} ST_i(t_k)}{\lambda(t_k)}. \tag{2}$$

With respect to the SIR model, a susceptible individual can only change state to be infected; an infected individual can only change state to be recovered, while a recovered individual will never change his/her state. Therefore, based on the Gillespie algorithm [58], if the state of individual l is susceptible, s/he will become infected; otherwise, if the state of l is infected, s/he will become recovered.

2.2. Perceiving Epidemic Severity Based on Local/Global Information. In mathematical epidemiology, the basic reproduction number R_0 represents the expected number of cases one primary infected individual caused over the course of its infectious period, in an otherwise uninfected population [59]. With respect to the SIR model in a well-mixed population, R_0 can be calculated as $R_0 = b/\gamma$. In this case, R_0 is also a measure of transmission potential and therefore of the growth speed of cases in the early phase of an epidemic. It should be noted that although both β and γ are known in advance when simulating disease transmission dynamics, it is still impossible for individuals in a large social network to obtain the exact values of disease severity during an epidemic. To deal with this problem, in this paper, we assume that individuals will use the estimated R_0 of the past season as measures of the perceived epidemic severity at the current season. More specifically, we assume that individuals can estimate R_0 based on the local or global prevalence of the disease.

Based on the SIR model with birth and death rates, Bauch and Earn have revealed the probability that an unvaccinated individual eventually becomes infected can be expressed as follows:

$$\pi = 1 - \frac{1}{R_0 (1 - f_V)}, \tag{3}$$

where f_V represents the vaccine coverage level in the population [21]. Moreover, they have also shown that the probability π does not depend on the birth/death rate. Therefore, this result is also applicable to the classical SIR model. To estimate the epidemic severity, in this paper, we first assume that each individual i at epidemic season t will estimate the probability π using the fraction of infected individuals at the previous season $t-1$ (i.e., the disease prevalence $f_{I,t-1}^i$). Then, together with the vaccine coverage $f^i_{V,t-1}$, the epidemic severity R_0 can be perceived as follows:

$$\widetilde{R}^i_0(t) = \begin{cases} \dfrac{1}{\left(1-f^i_{I,t-1}\right)\left(1-f^i_{V,t-1}\right)} & \text{if } 0 \le f^i_{I,t-1} < 1, \\ +\infty & \text{if } f^i_{I,t-1} = 1. \end{cases} \tag{4}$$

Here, the values of $f^i_{I,t-1}$ and $f^i_{V,t-1}$ depend on where individual i gets the disease-related information during the epidemic.

According to the different sources that individuals obtain disease-related information from, in this paper, we present three types of *static* decision-making mechanisms, where all individuals are assumed to perceive the epidemic severity based on the same source of information. The details are as follows.

(i) *Local-G^1 mechanism*: Each individual i only knows the prevalence and vaccine coverage in his/her first-order group G^1_i. Accordingly, the perceived severity of the disease at season t can be estimated based on (4) by setting $f^i_{I,t-1} = f_I(t-1;G^1_i)$ and $f^i_{V,t-1} = f_V(t-1;G^1_i)$, where $f_I(t-1;G^1_i)$ and $f_V(t-1;G^1_i)$ are the prevalence and vaccine coverage in group G^1_i. In this case, we denote $\widetilde{R}^i_0(t)$ as $\widetilde{R}_0(t;G^1_i)$.

(ii) *Local-G^2 mechanism*: Each individual i can interact with his/her social neighbors and obtain disease-related information in the second-order groups G^2_i. At season t, the severity of the epidemic can be perceived as the maximum value of the estimated severity for each group in G^1_i and G^2_i; that is, $\widetilde{R}_0(t;G^2_i) = \max_k\{\widetilde{R}_0(t;G^1_i), \widetilde{R}_0(t;G^1_k) \mid k \in \mathcal{N}_i\}$.

(iii) *Global-G mechanism*: Each individual i can obtain information about global prevalence $f_I(t-1;\mathcal{G})$ and vaccine coverage $f_V(t-1;\mathcal{G})$ in the whole population from public health authorities. In this case, the severity $\widetilde{R}_0(t;\mathcal{G})$ at season t can be perceived based on (4) by setting $f^i_{I,t-1} = f_I(t-1;\mathcal{G})$ and $f^i_{V,t-1} = f_V(t-1;\mathcal{G})$.

Once the epidemic severity is estimated (i.e., $\widetilde{R}^i_0(t)$), each individual i in a social network $\mathcal{G}$ can then perceive the risk of being infected based on the vaccine coverage level in his/her first-order group G^1_i. The infection risk can be formulated as follows:

$$\widetilde{r}_i(t) = 1 - \frac{1}{\widetilde{R}^i_0(t)\left(1 - f^{G^1_i}_{V,t}\right)}. \tag{5}$$

At the beginning of each season, an individual i decides whether or not to take the vaccine by weighting the cost of vaccination c_V and the cost of possible infection c_I. Denote $p_i(t)$ as the vaccinating probability of an individual i at season t. Then, the cost of vaccination is $p_i(t)c_V$, while the estimated cost of infection is $(1-p_i(t))\widetilde{r}_i(t)c_I$. A rational individual should decide to take the vaccine with probability $p_i(t)$ such that $p_i(t)c_V = (1-p_i(t))\widetilde{r}_i(t)c_I$. Therefore, the vaccinating probability of individual i at season t should be

$$p_i(t) = \frac{\widetilde{r}_i(t)}{\widetilde{r}_i(t) + c}, \tag{6}$$

where $c = c_V/c_I$ is the relative cost of vaccination over infection and $\widetilde{r}_i(t)$ is the perceived infection risk based on (5).

2.3. Adjusting Vaccinating Decisions Based on Reinforcement Learning. In reality, different individuals rely on different sources of information to make decisions. Some individuals may prefer local information from their social neighbors, while others may prefer global information from public health authorities. To explore human self-organizing behaviors, we further introduce a reinforcement learning based (*RL-based*) mechanism, which allows individuals to strategically choose local or global information for decision-making based on their historical vaccination experiences. Specifically, the ε-greedy algorithm is adopted: with probability ε, an individual will randomly choose to rely on local or global information, while, with probability $1-\varepsilon$, an individual will choose to rely on the information that generates higher average utility. Here, we focus mainly on how individuals adjust their strategies between the *local-G^2* mechanism and the *global-G* mechanism. Mathematically, the perceived epidemic severity of individual i at season t can be calculated as follows:

$$\widetilde{R}^i_0(t) = \begin{cases} \widetilde{R}^i_0\left(t;G^2_i\right), & \text{with probability } 1-\varepsilon \text{ and } U_i\left(t-1;G^2_i\right) > U_i(t-1;\mathcal{G}), \\ \widetilde{R}^i_0(t;\mathcal{G}), & \text{with probability } 1-\varepsilon \text{ and } U_i\left(t-1;G^2_i\right) \le U_i(t-1;\mathcal{G}), \\ \widetilde{R}^i_0\left(t;G^2_i\right) \text{ or } \widetilde{R}^i_0(t;\mathcal{G}), & \text{with probability } \varepsilon, \end{cases} \tag{7}$$

where $U_i(t-1;G^2_i)$ and $U_i(t-1;\mathcal{G})$ represent the average utility of individual i until season $t-1$, based on local and global information, respectively. The average utilities are updated at season t as follows:

$$U_i\left(t;G^2_i\right) = \begin{cases} \dfrac{U_i\left(t-1;G^2_i\right)\left(n_i\left(t;G^2_i\right)-1\right) + u_i(t)}{n_i\left(t;G^2_i\right)}, & \text{if local-}G^2 \text{ mechanism is used}, \\ U_i\left(t-1;G^2_i\right), & \text{if global-}G \text{ mechanism is used}. \end{cases} \tag{8}$$

$$U_i(t;\mathcal{G}) = \begin{cases} \dfrac{U_i(t-1;\mathcal{G})\left(n_i(t;\mathcal{G})-1\right)+u_i(t)}{n_i(t;\mathcal{G})}, & \text{if global-}G\text{ mechanism is used,} \\ U_i(t-1;\mathcal{G}), & \text{if local-}G^2\text{ mechanism is used.} \end{cases} \quad (9)$$

where $n_i(t;G_i^2)$ (resp., $n_i(t;\mathcal{G})$) are the number of times individual i adopts the *local-G^2* mechanism (resp., the *global-G* mechanism) until the current season t. Specifically, in this paper, the utility $u_i(t)$ of individual i at season t is calculated as follows:

$$u_i(t) = \begin{cases} 1-c, & \text{if } i \text{ is vaccinated,} \\ 0, & \text{if } i \text{ is unvaccinated but infected,} \\ 1, & \text{if } i \text{ is unvaccinated and uninfected.} \end{cases} \quad (10)$$

3. Simulations and Results

3.1. Experimental Settings. In this section, simulations are carried out to investigate how individuals' perceptions on epidemic severity affect their vaccinating decisions in different types of social networks, that is, scale-free networks, small-world networks, and random regular networks. First, the performance of three static decision-making mechanisms is compared in terms of the final vaccine coverage and epidemic size, where all individuals are assumed to adopt the same decision-making mechanism, that is, the *local-G^1* mechanism, the *local-G^2* mechanism, or the *global-G* mechanism. Under such an assumption, the problem of how individuals with different social connections (i.e., node degree) make vaccinating decisions is further investigated with different decision-making mechanisms. Then, taking one step forward, the *RL-based* decision-making mechanism is evaluated, where individuals could adjust their vaccinating decisions based on their historical vaccination experiences. Specifically, the parameters of the simulations are set as follows.

(i) *Social networks*: In our simulations, the scale-free social networks are generated using the Barabsi-Albert(BA) model [60]; the small-world networks are generated using the Watts-Strogatz model with $p = 0.3$ [61]; and the random-regular networks are generated using the method proposed by Kim and Vu [62]. The size of all networks is set to be $N = 10{,}000$, and the average degree is set to be $\langle k \rangle = 4$.

(ii) *Transmission dynamics*: Based on the settings in existing studies [41], in this paper, the disease transmission rate is set to be $\beta = 0.55\,\text{day}^{-1}\,\text{person}^{-1}$, and the recovery rate is set to be $\gamma = 1/3\,\text{day}^{-1}$.

(iii) *Initial parameters*: At the first season, individuals randomly decide whether or not to vaccinate with probability 0.5. Then, 10 individuals are randomly selected to be infected, and the disease starts to spread in corresponding social networks. Later, at the beginning of each season, individuals strategically make vaccinating decisions based on the proposed decision-making mechanisms. With respect to the *RL-based* mechanism, the initial utility of each individual is set to be zero.

To be more rigorous, we randomly generate 100 networks for each type of social networks, while, for each network, the simulations are operated for 10,000 seasons to make sure the dynamics is stable, where the results are averaged over the last 500 seasons. Moreover, the final results are averaged over the 100 networks.

3.2. Performance of the Static Decision-Making Mechanisms. The main difference between the three static decision-making mechanisms lies in how individuals perceive the severity of an epidemic based on different sources of information. Therefore, the social network structure will highly determine the performance of these decision-making mechanisms. Moreover, the relative vaccine cost c can also greatly affect individuals' vaccinating decisions and further the final vaccine coverage and epidemic size in the whole population. Here, the vaccine coverage is defined as the proportion of individuals who take the vaccine, and the epidemic size is defined as the proportion of individuals who are infected during the epidemic. Figure 1 demonstrates the performance of the three types of decision-making mechanisms in terms of vaccine coverage and epidemic size as the relative cost increases. Simulations are carried out in three types of social networks, that is, scale-free networks ((a) and (b)), small-world networks ((c) and (d)), and random regular networks ((e) and (f)). It can be observed that, for all types of social networks, the vaccine coverage decreases as the relative cost increases under any decision-making mechanism. As a consequence, the epidemic size increases with the decline of vaccine coverage. It is reasonable because individuals need to balance the cost of vaccination and infection. When the relative vaccine cost increases, some of them will refuse to take the vaccine. On the other hand, it can also be observed that, in all these social networks, the *local-G^2* mechanism achieves a relatively higher level of vaccine coverage than that of the *local-G^1* and *global-G* mechanisms. The reason is that each individual with the *local-G^2* mechanism can obtain disease-related information from many groups centered on his/her social neighbors and treat the maximum perceived severity in these groups as his/her own. In doing so, individuals with the *local-G^2* mechanism are more likely to overestimate the severity of the epidemic. Thus, a higher vaccine coverage can be achieved in the whole population. Another observation is that the vaccine coverage of the *local-G^1* mechanism is lower than that of the global-G mechanism. The main reason is that individuals with the *local-G^1* mechanism perceive epidemic severity based only on information from their local neighborhood. In a structured population, most individuals

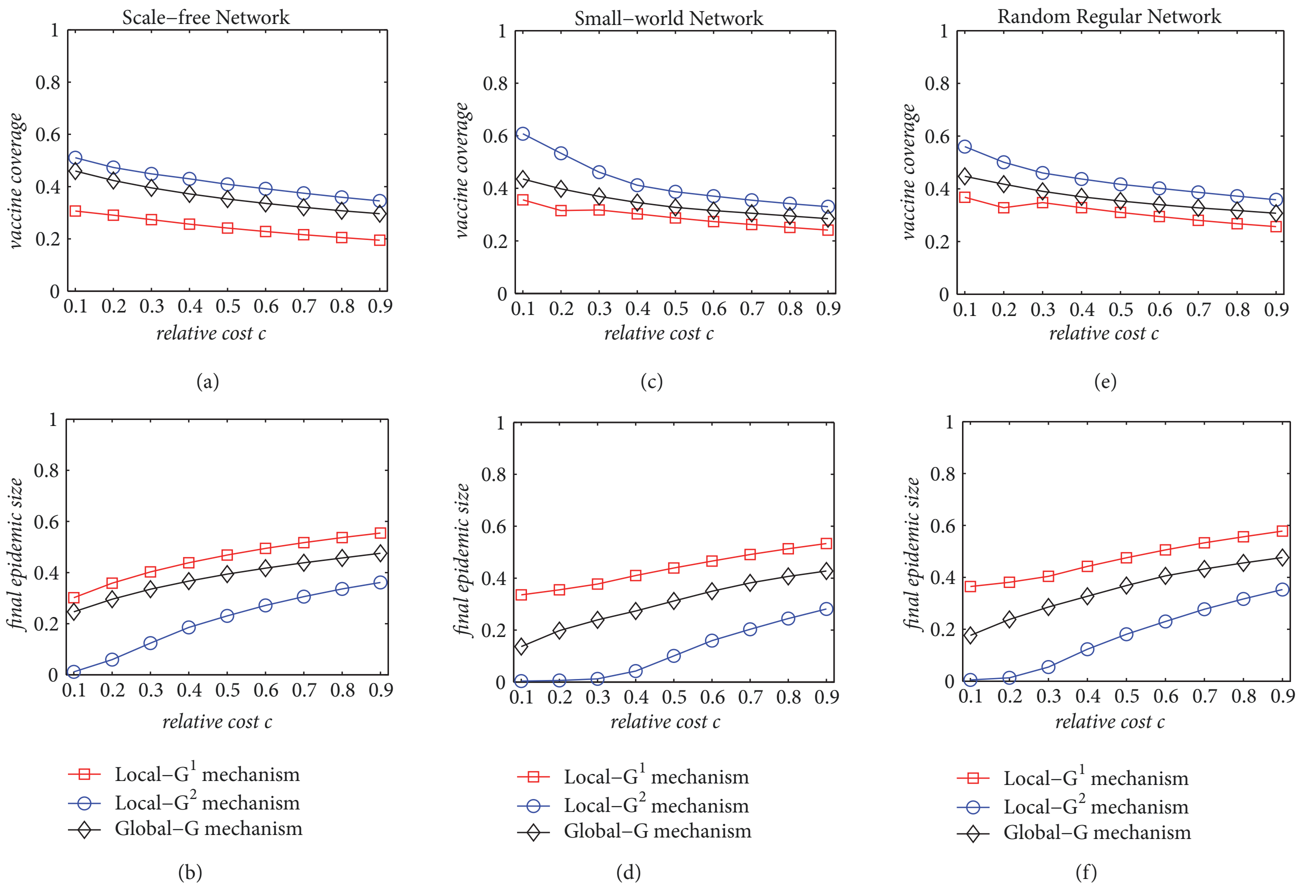


Figure 1: The final vaccine coverage and epidemic size as the relative cost increases under different decision-making mechanisms in three types of social networks. Simulations are carried out on scale-free networks ((a) and (b)), small-world networks ((c) and (d)), and random regular networks ((e) and (f)). The results are averaged over 100 independent network simulations with network size $N = 10,000$ and average degree $\langle k \rangle = 4$.

cannot observe infections (or just a few infections) from their social neighbors when the epidemic is not very serious. In this case, most individuals may underestimate the severity of the epidemic, which results in lower vaccine coverage and larger epidemic size.

3.3. Effects of Social Connections on Individual Decision Making. Because individuals obtain disease-related information through social interactions, the heterogeneous social connections (i.e., degrees) will highly determine what kind of information they can obtain to perceive the epidemic severity and estimate their infection risks. Therefore, we further investigate the effects of individuals' social connections on their vaccinating decisions in scale-free networks. Here, we classify individuals into two groups, that is, the high-degree group and the low-degree group. The high-degree group consists of individuals whose degree k is greater than or equal to 7, while the low-degree group contains individuals whose degree k is less than or equal to 2. The number of individuals in both groups accounts for more than 50% of the population. Figure 2 demonstrates the final vaccine coverage and epidemic size in both groups under different decision-making mechanisms. Simulations are carried out in scale-free networks with network size $N = 10{,}000$ and average degree $\langle k \rangle = 4$. The results are averaged over the last 500 epidemic seasons. It can be observed that both vaccine coverage and epidemic size in the high-degree group are higher than those in the low-degree group under all three static decision-making mechanisms. The reason is that hubs in scale-free networks are more vulnerable to be infected during an epidemic [63, 64]. As a consequence, individuals around hubs are also highly likely to be infected. In this case, it is reasonable that larger epidemic size can be observed in the high-degree group. In this case, high-degree individuals are more likely to overestimate the severity of the epidemic and are then inclined to take the vaccine.

Figure 3 demonstrates the fraction of vaccinated or infected individuals with various degrees in a scale-free network. The results are based on the last 500 epidemic seasons. It can be observed that, as in Figure 1, individuals with the *local-G*^{2} mechanism (blue dots in Figure 3) are more willing to take the vaccine than the other two mechanisms. As a result, they are less likely to be infected. Moreover, as the degree increases, individuals are inclined to take the vaccine under all three types of decision-making mechanisms. This is consistent with the observation from

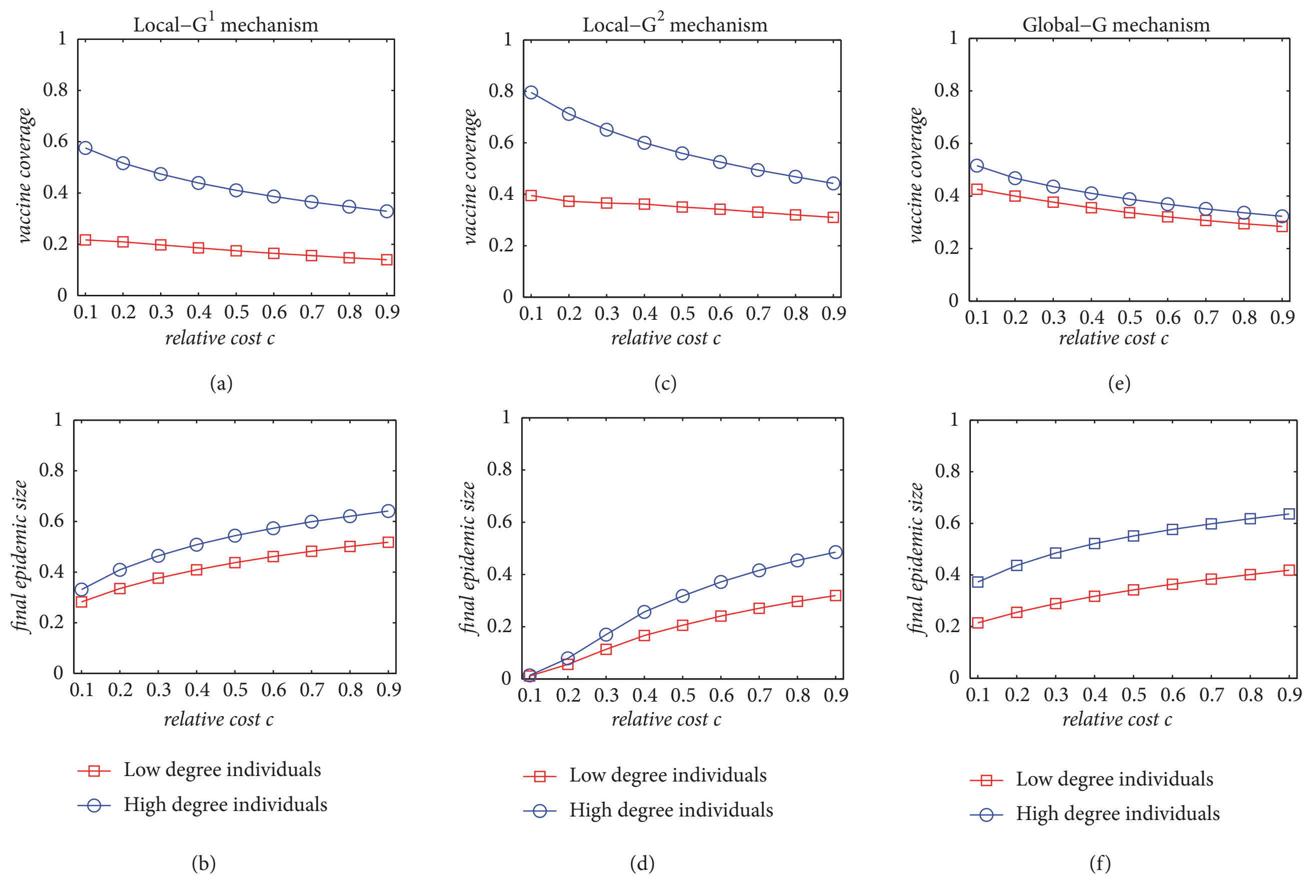


FIGURE 2: The final vaccine coverage and epidemic size in both high-degree and low-degree groups under different decision-making mechanisms. Simulations are carried out in scale-free networks with network size $N = 10,000$ and average degree $\langle k \rangle = 4$. The results are averaged over the last 500 epidemic seasons.

Figure 2. More interestingly, it can be found that there is an intersection in terms of the fraction of vaccinated individuals between the *local-G*^{1} mechanism (red line) and global-*G* mechanism (black line) when the degree is about 6. When the degree is less than 6, the fraction of vaccinated individuals with the *local-G*^{1} mechanism is smaller than those with the global-*G* mechanism. The reason is that the chances of finding infected neighbors around individuals with the small degree are relatively low. Hence, individuals with the *local-G*^{1} mechanism are likely to underestimate the epidemic severity. On the other hand, as the degree increases, individuals themselves and their social neighbors become more and more vulnerable to be infected, which lead them to overestimate epidemic severity. In this case, their willingness for vaccination becomes larger than individuals with the global-*G* mechanism. Consequently, there is also an intersection near the degree $k = 6$ in terms of the fraction of infected individuals between these two mechanisms.

3.4. Effects of Vaccination Experiences on Individual Decision Making. For flu-like seasonal diseases, individuals can accumulate a wealth of vaccination experiences from the past several epidemic seasons. In this case, they can make decisions based on disease-related information (i.e., disease prevalence and vaccine coverage) of the past several seasons. Here, we examine the effects of past vaccination experiences on individuals' vaccinating decisions by comparing the performance of the *local-G*^{2} mechanism that perceives the epidemic severity based on disease-related information of past season(s). The simulations are carried out in a scale-free network with network size $N = 10,000$ and average degree $\langle k \rangle = 4$. The results are based on the last 500 epidemic seasons. Figure 4 demonstrates the average vaccine coverage and perceived epidemic severity under different relative costs. The red lines demonstrate the average vaccine coverage and perceived epidemic severity based on disease-related information of the past one season, while the blue lines demonstrate the performance of the *local-G*^{2} mechanism, which use the average prevalence and vaccine coverage of the past five seasons to estimate the epidemic severity. It can be observed from Figure 4(b) that, with experiences of the past five seasons, the perceived severity of the *local-G*^{2} mechanism is lower than that with experience of the past one season. Consequently, the final vaccine coverage is also relatively lower under different values of relative cost (see Figure 4(a)). Moreover, it can also be found from Figure 4(b) that the perceived severities of the *local-G*^{2} mechanism with five-season experiences are more stable than those

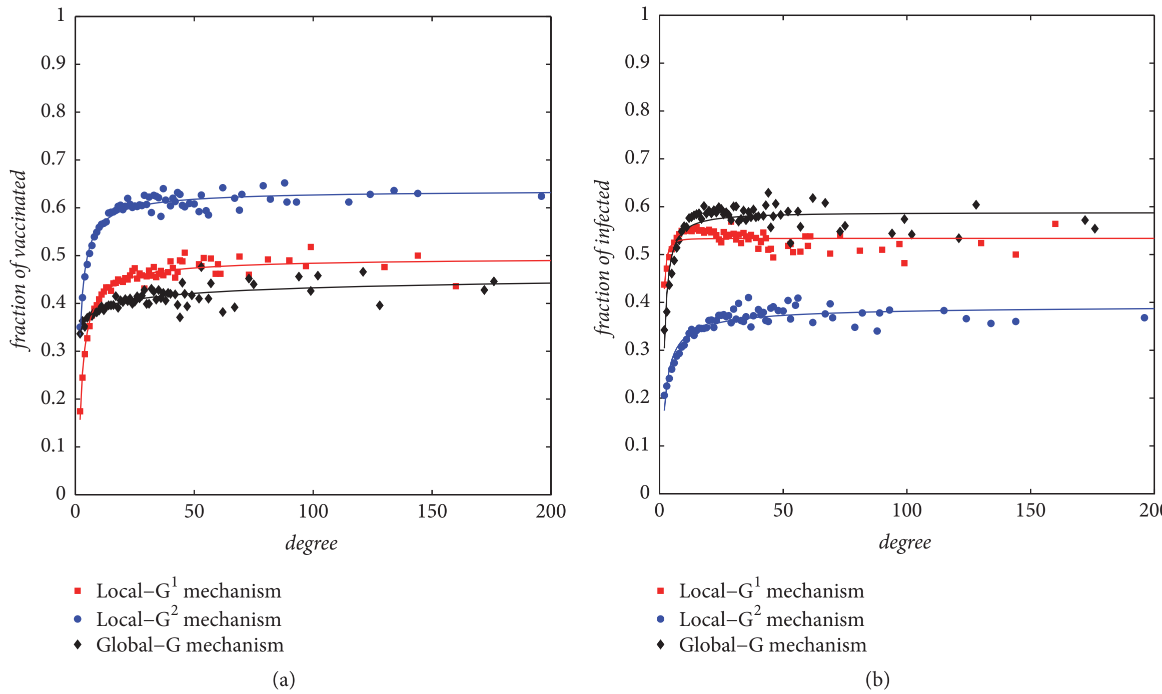


FIGURE 3: The fraction of vaccinated and infected individuals with different degrees under different decision-making mechanisms. The simulations are carried out in scale-free networks with network size $N = 10,000$ and average degree $\langle k \rangle = 4$. The relative cost is set to be $c = 0.5$. The results are based on the last 500 epidemic seasons.

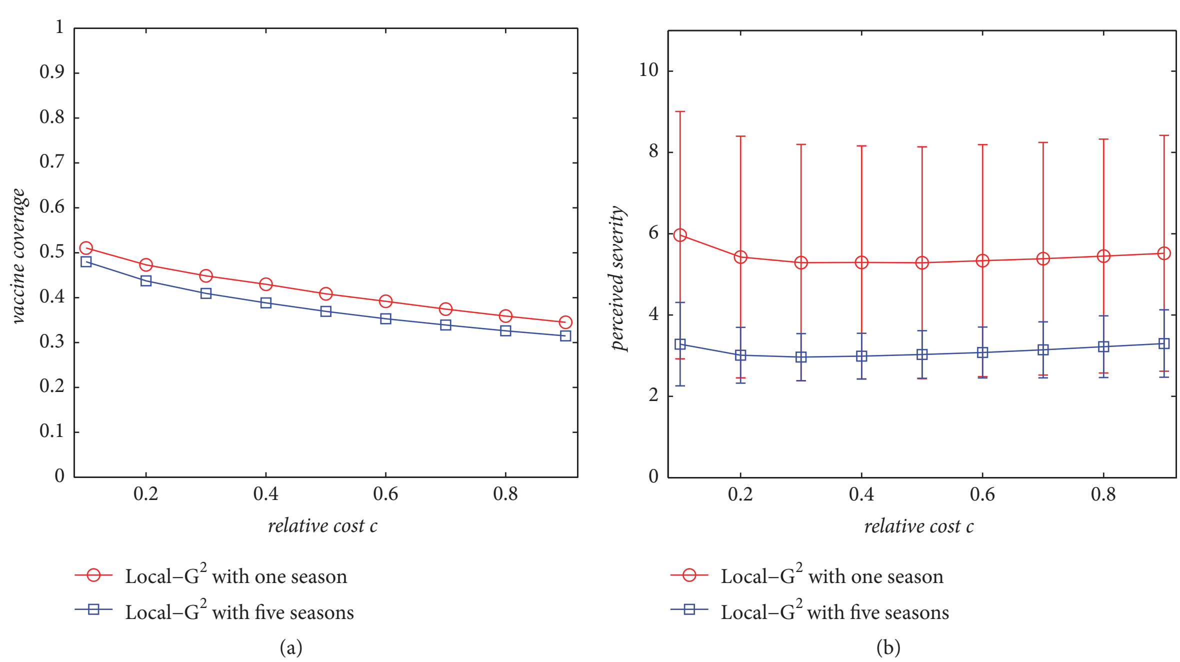


FIGURE 4: The average vaccine coverage and perceived epidemic severity under different values of relative cost. The red lines demonstrate the performance of the *local-G*^{2} mechanism using only disease-related information of the past one season, and the blue lines demonstrate the performance of the *local-G*^{2} mechanism using disease-related information of the past five seasons. The simulations are carried out in a scale-free network with network size $N = 10,000$ and average degree $\langle k \rangle = 4$. The results are based on the last 500 epidemic seasons.

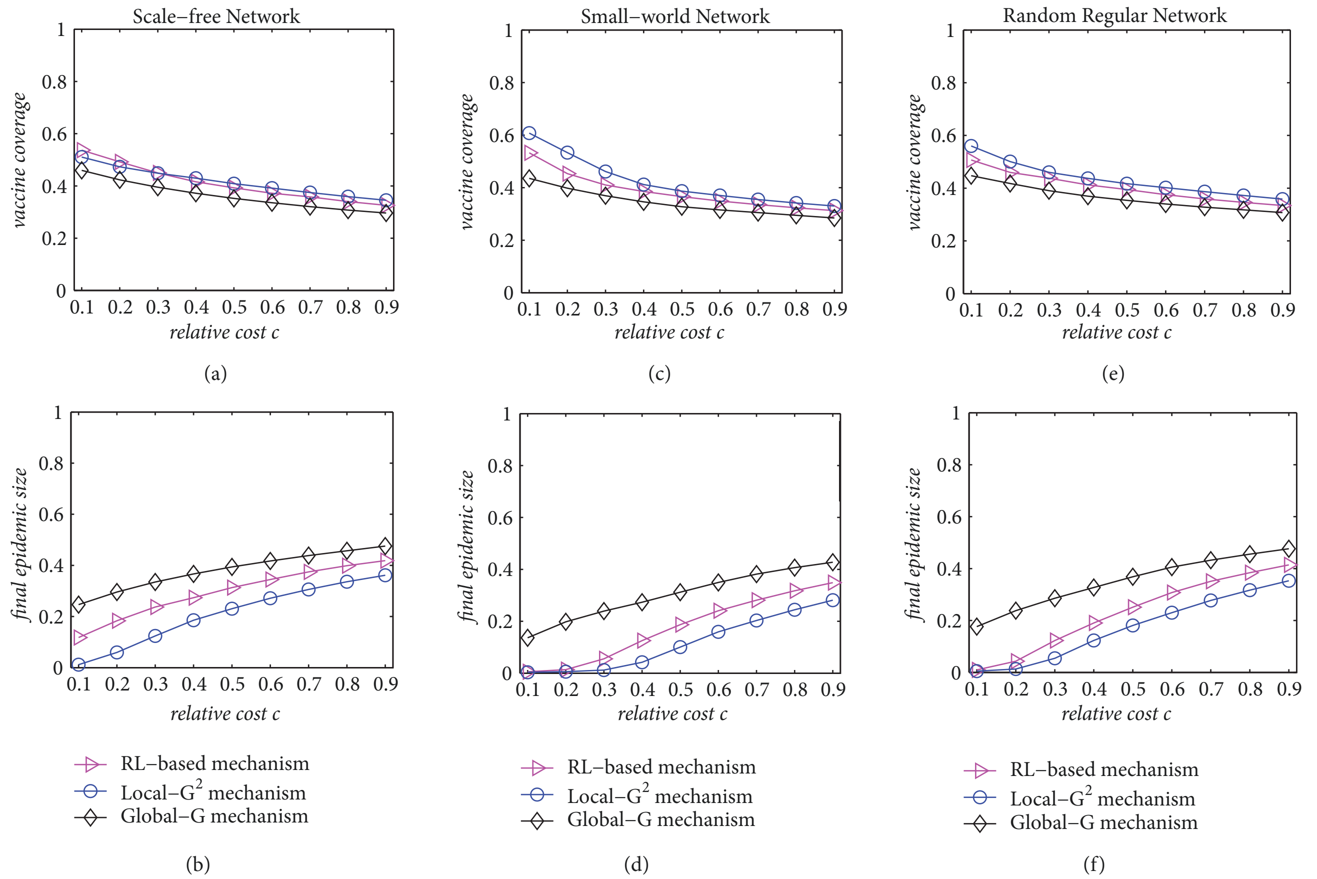


Figure 5: The final vaccine coverage and epidemic size of the *RL-based* mechanism compared with the local and global mechanisms in three types of social networks. Simulations are carried out on scale-free networks ((a) and (b)), small-world networks ((c) and (d)), and random regular networks ((e) and (f)). The results are averaged over 100 independent network simulations with network size $N = 10{,}000$ and average degree $\langle k \rangle = 4$.

with one-season experience because it has relatively smaller variance in terms of the perceived severity during the last 500 epidemic seasons. This is reasonable because, with the *local-*G^2 mechanism, individuals are more likely to overestimate the epidemic severity because they use the maximum value of estimated severities from their neighbors. When the disease-related information of the past five seasons is averaged, both the estimated severity and its variance will be reduced. It seems that the more past information individuals rely on, the more stable their vaccinating decisions are. With respect to the *RL-based* mechanism, individuals' utilities will be updated based on those of all past seasons.

3.5. Performance of the Adaptive RL-Based Mechanism. Different from the static decision-making mechanisms, the *RL-based* mechanism allows individuals to adaptively decide what type of information they use to estimate the epidemic severity based on their historical vaccination experiences. In this section, the performance of the *RL-based* mechanism is evaluated by comparing the final vaccine coverage and epidemic size with those of the *local-*G^2 and the *global-G* mechanism. Figure 5 demonstrates the simulation results in three types of social networks with network size $N = 10{,}000$ and average degree $\langle k \rangle = 4$. Unsurprisingly, it can be observed that, in all these networks, the effect of the *RL-based* mechanism is somewhere between the other two mechanisms with respect to both vaccine coverage and epidemic size. This is because, during the vaccination campaign, individuals can adaptively adjust their risk perception method between the *local-*G^2 and the *global-G* mechanisms through reinforcement learning. When the severity is overestimated through information from individuals in second-order groups (i.e., the *local-*G^2 mechanism), the unnecessary vaccination cost will enable individuals to choose global information as an alternative, and vice versa. As shown in Figure 6(a), when the *RL-based* mechanism is used (the red dots), individuals' perceptions on epidemic severity vary greatly with their degrees. When the degree is smaller than 6, individuals' perceptions seem to be stable with no variation. However, as the degree increases, individuals' perceptions begin to differentiate. Especially, as the degree is larger than 50, some individuals choose to use local information (i.e., red dots around the blue line), while the others prefer to use global information (i.e., red dots around the black line). The results reveal that high-degree individuals are more sensitive to the disease-related information for making vaccination decisions.

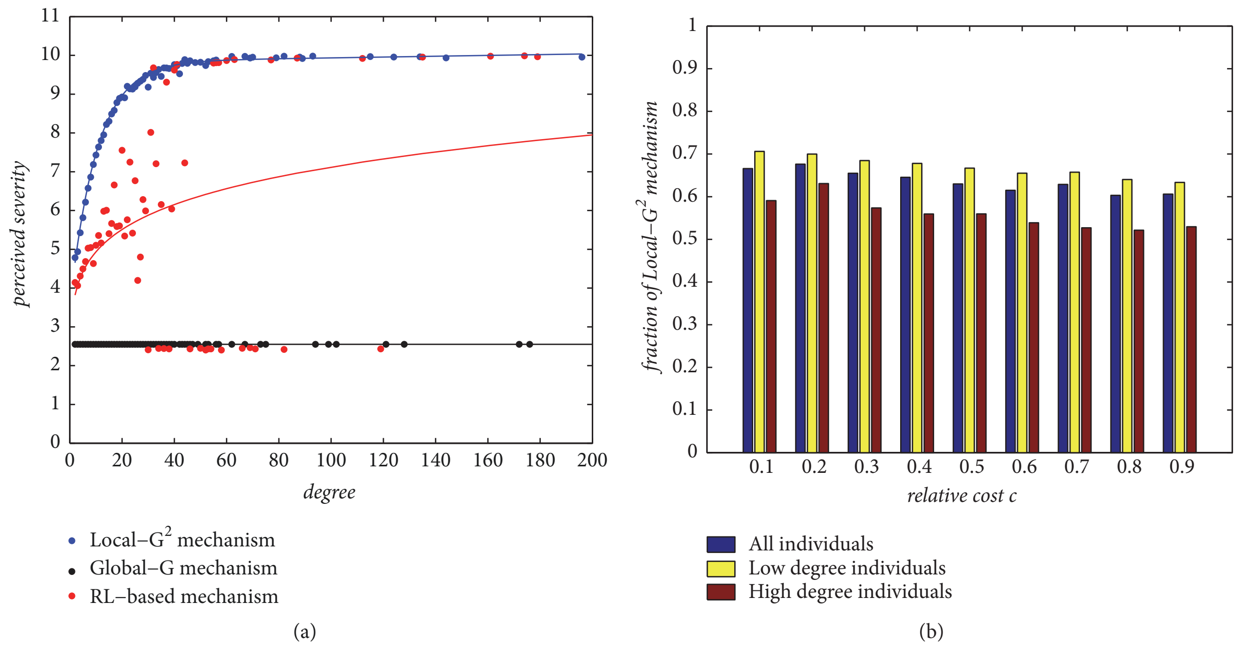


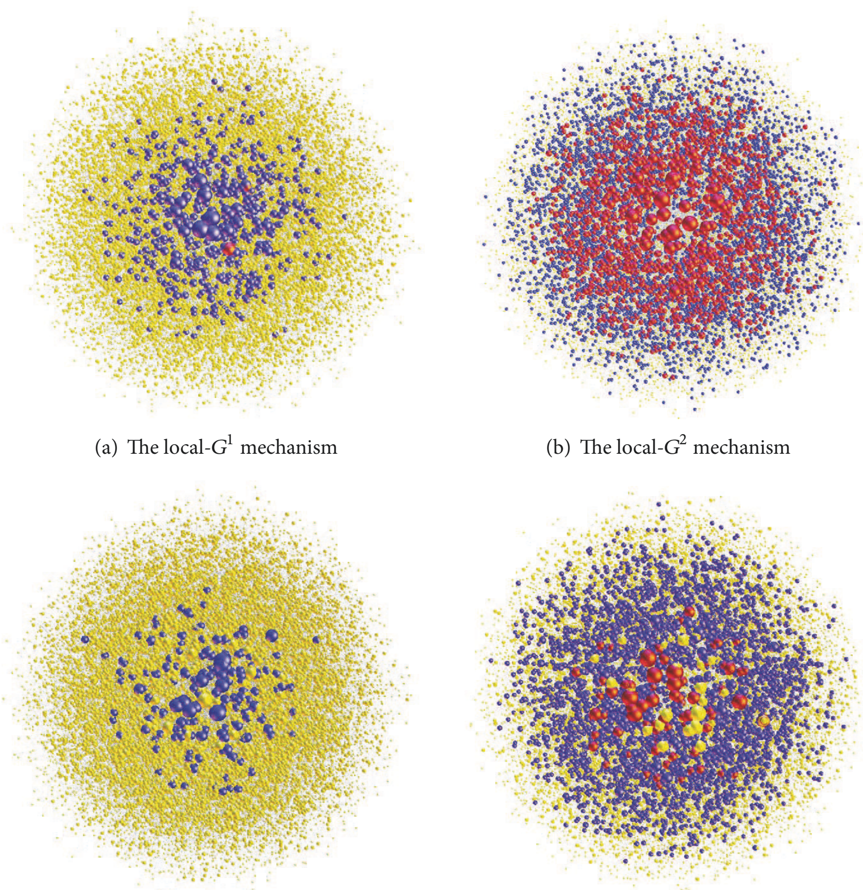
Figure 6: The individual performance of the *RL-based* decision-making mechanism. (a) The perceived epidemic severity for individuals with different social connections under different decision-making mechanisms when the relative cost $c = 0.5$. (b) The fraction of individuals who adopt the *local-*G^2 mechanism in different groups. Simulations are carried out on a scale-free network with network size $N = 10{,}000$ and average degree $\langle k \rangle = 4$. The results are averaged over the last 500 epidemic seasons.

Figure 6(b) demonstrates the proportion of individuals who use the *local-*G^2 mechanism in the whole population, as well as in the low-degree and high-degree groups. It can be observed that, under different relative cost c, more than half of the population adopts the *local-*G^2 mechanism, while, as the relative cost increases, the proportion decreases slightly because overestimation of severity may reduce individuals' utility when the cost of vaccination is relatively high. Such an observation can also be observed in both low-degree and high-degree groups. Moreover, the results show that the proportion of individuals using the *local-*G^2 mechanism in the low-degree group is higher than that in the high-degree group. This is consistent with the results in Figure 6(a), where the perceived severity of low-degree individuals using the *RL-based* mechanism is closer to the perception using the *local-*G^2 mechanism, while in the high-degree group, some individuals may adopt the *global-G* mechanism to avoid overestimation. Figure 7 demonstrates the snapshots of individuals' vaccinating probabilities in a scale-free network under four different decision-making mechanisms. Nodes with larger size represent individuals with higher degrees. The yellow nodes stand for individuals with low vaccinating probability (i.e., $p \le 0.4$), the blue nodes stand for individuals with middle vaccinating probability (i.e., $0.4 < p \le 0.5$), and the red nodes stand for individuals with high vaccinating probability (i.e., $p > 0.5$). It can be clearly observed that individuals with higher degrees in three static mechanisms are more likely to take the vaccine than those with lower degrees. Through visualization, it confirms the results when the relative cost $c = 0.5$ in Figure 2, while, for the *RL-based* mechanism, it can be found in Figure 7(d) that some high-degree individuals have a high probability to take the vaccine (i.e., the big red nodes), while the others have a low probability (i.e., the big yellow nodes). This verifies our observations in Figure 6.

4. Conclusion

In this paper, we have focused on investigating human voluntary vaccinating behaviors through perceiving epidemic severity of a flu-like seasonal disease in social networks. Based on the source of information individuals can base their severity perception on, we have presented three static decision-making mechanisms: (i) the *local-*G^1 mechanism allows individuals to perceive the epidemic severity based only on the prevalence and vaccine coverage in their first-order neighborhood; (ii) the *local-*G^2 mechanism allows individuals to make decisions based on information from their second-order social groups; and (iii) the *global-G* mechanism allows individuals to utilize the global information announced by public health authorities. Under a static decision-making mechanism, all individuals can only adopt the same information to estimate the severity of the epidemic. To reflect the real-world situations, we have further presented a reinforcement-learning-based mechanism, where individuals are allowed to adaptively adjust their strategies based on their historical vaccination experiences.

We have carried out simulations on three types of social networks to evaluate the performance of the proposed mechanisms. Simulation results on three types of static mechanisms have shown that individuals with the *local-*G^1 mechanism (respectively, the *local-*G^2 mechanism) are



(a) The local-G^1 mechanism

(b) The local-G^2 mechanism

(c) The global-G mechanism

(d) The RL-based mechanism

Figure 7: The snapshots of individuals' vaccinating possibilities in a scale-free network under (a) the *local-G^1* mechanism, (b) the *local-G^2* mechanism, (c) the *global-G* mechanism, and (d) the *RL-based* mechanism. Nodes with larger size represent individuals with higher degrees. The yellow nodes stand for individuals with low vaccinating probability ($p \leq 0.4$), the blue nodes stand for individuals with middle vaccinating probability ($0.4 < p \leq 0.5$), and the red nodes stand for individuals with high vaccinating probability ($p > 0.5$). The results are averaged over the last 500 epidemic seasons with the relative cost $c = 0.5$.

more likely to underestimate (respectively, overestimate) the epidemic severity, which may result in a relatively larger (respectively, smaller) epidemic size in the whole population. Moreover, we have revealed that high-degree individuals in a scale-free network are more inclined to take the vaccine than low-degree individuals under any of these three decision-making mechanisms. However, under the *RL-based* mechanism, the information preference of high-degree individuals has differentiated. Some of them prefer to use the local information from their second-order neighborhoods, while the others would like to base global information from public health authorities. The observations and findings provide a new perspective for designing incentive-based vaccination policies: how can we motivate and guide high-degree individuals to understand the real epidemic situation and avoid underestimating the epidemic severity? The key challenge lies in that we need to take into account the complicated disease-behavior dynamics during the policy-making process.

Data Availability

The simulation data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no competing financial interests.

Authors' Contributions

Benyun Shi and Hongjun Qiu designed research, Benyun Shi, Guangliang Liu, Hongjun Qiu, Yu-Wang Chen, and Shaoliang Peng conceived the experiments, Benyun Shi and Guangliang Liu conducted the experiments, Benyun Shi, Guangliang Liu, Hongjun Qiu, Yu-Wang Chen, and Shaoliang Peng analysed the results. Benyun Shi wrote the manuscript and all authors reviewed the manuscript.

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