Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Role of vaccine efficacy in the vaccination behavior under myopic update rule on complex networks

Jiechen Huang\textsuperscript{a,b}, Juan Wang\textsuperscript{c}, Chengyi Xia\textsuperscript{a,b,*}

\textsuperscript{a} Tianjin Key Laboratory of Intelligence Computing and Novel Software Technology, Tianjin University of Technology, Tianjin 300384, PR China
\textsuperscript{b} Key Laboratory of Computer Vision and System (Ministry of Education), Tianjin University of Technology, Tianjin 300384, China
\textsuperscript{c} School of Electrical and Electronic Engineering, Tianjin University of Technology, Tianjin 300384, PR China

A R T I C L E   I N F O

Article history:
Received 1 July 2019
Revised 27 August 2019
Accepted 2 September 2019
Available online 6 September 2019

Keywords:
Imperfect vaccination
Myopic update rule
Regular lattice
Scale-free network

A B S T R A C T

How to effectively prevent the diffusion of infectious disease has become an intriguing topic in the field of public hygienics. To be noted that, for the non-periodic infectious diseases, many people hope to obtain the vaccine of epidemics in time to be inoculated, rather than at the end of the epidemic. However, the vaccine may fail as a result of invalid storage, transportation and usage, and then vaccinated individuals may become re-susceptible and be infected again during the outbreak. To this end, we build a new framework that considers the imperfect vaccination during the one cycle of infectious disease within the spatially structured and heterogeneous population. Meanwhile, we propose a new vaccination update rule: myopic update rule, which is only based on one focal player’s own perception regarding the disease outbreak, and one susceptible individual makes a decision to adopt the vaccine just by comparing the perceived payoffs vaccination with the perceived ones of being infected. Extensive Monte-Carlo simulations are performed to demonstrate the imperfect vaccination behavior under the myopic update rule in the spatially structured and heterogeneous population. The results indicate that healthy individuals are often willing to inoculate the vaccine under the myopic update rule, which can stop the infectious disease from being spread, in particular, it is found that the vaccine efficacy influences the fraction of vaccinated individuals much more than the relative cost of vaccination on the regular lattice. Meanwhile, vaccine efficacy is more sensitive on the heterogeneous scale-free network. Current results are helpful to further analyze and model the choice of vaccination strategy during the disease outbreaks.

© 2019 Elsevier Ltd. All rights reserved.

1. Introduction

Over the past two decades, the outbreak of infectious diseases has been threatening the safety of human lives and properties, such as the severe acute respiratory syndrome SARS [1], H1N1 [2], Ebola [3] and so on. Thus, how to prevent the extensive outbreaks of epidemics has become a challenging topic in the field of public health [4–6]. Meanwhile, the difference of population distribution, religious belief and regional differences may greatly affect the spread of infectious diseases, for example, Refs. [7–10] explore the impact of various topological structures within the population on the infectious diseases spread, and it is convincingly found that heterogeneous networks may quicken the disease spreading within the population, even lead to the absence of epidemic threshold [11].

Meanwhile, the individual reactions to infectious diseases may also substantially influence the diffusion processes of epidemics. One of the most striking cases regarding the outbreaks was H1N1 pandemic in 2009 [12], which induced around 15,000 deaths. During the outbreaks of H1N1, the suppression of epidemic processes can not only be attributed to the public measures, but also through personal and uncoordinated responses, that is, the human behavior has noticeably interfered with the epidemic spreading. In the long run, human behavior has been intricately correlated with the contagion of infectious diseases. In medieval ages, the deadly bubonic plague rendered many people to avoid and flee away from the sick and their close contacts so that their own immunity can be secured [13]. Similarly, the villagers of Yorkshire in Eyam tried to voluntarily quarantine themselves to stop the spread of the plague from that village [14]. In 2003, during the outbreak of SARS, many citizens spontaneously wear the face masks; some schools are temporarily closed and the students are
imperatively required to stay at home so as to avoid the further epidemic infection as much as possible [15]. In addition, protective behavior when confronting the epidemics has also been observed in many other contexts, such as Measles-Mumps-Rubella (MMR) [16], tuberculosis (TB) [17] and HIV [18] etc.

While the impact of human behaviors on the epidemic spreading process has often been mentioned anecdotally, the accurate modeling or quantitative models are relatively fewer regarding their nature, property, or the effect they may have on the spread of the disease. At present, mathematical models have been put forward to study the role of human behavior in the context of social population, such as escape panic [19], pedestrian trails [20], but efforts to quantitatively explore the role of human behavior in the large-scale epidemics generally focus on assessing the effectiveness of various public health measures including the social distancing, school closure etc. In the recent years, there are many fields and methods to help us to study infectious disease [21–32], however, there is an increasing attention about the effect of spontaneous individual action or response strategy on the progression of an infectious disease, in which this kind of spontaneous actions may highly restrain from the further diffusion of epidemics and even change the fate of outbreaks. Thus, it is of great significance to fully understand the interacting mechanisms between the human behavior and disease dynamics within the specified population. It is worth mentioning that Funk et al. [33] systematically summarized the related works and provided a taxonomy framework of behavior-disease models. On the one hand, they classify these models according to source and type of information that individuals base their neighbors on, in which source of information may be local or global and the type of information that individuals change their behaviors are prevalence-based or belief-based. On the other hand, they classify the previous works based on the impact of individual behavior changes on the disease dynamics, which include the following three aspects: (i) the disease state; (ii) model parameters (infection or recovering rate); and (iii) the network contact structure relevant for the spread of epidemics.

In particular, for some preventable infectious diseases with the help of vaccines, the epidemic outbreaks are intricately linked with the individual vaccination behavior since the vaccines can help the vaccinators not to be infected by a specific disease. Meanwhile, these vaccinators may indirectly protect their nearest neighbors with whom they contact, and then these neighbors may choose not to vaccinate again (that is, free-ride the vaccinators) so as to avoid the necessary vaccine fees or other potential risk and side effects. Henceforth, the vaccination behavior may dominate the evolutionary process of vaccine preventable diseases. Among them, Bauch and Earn [34] seminally utilized the game theory to model the dilemmatic situation for an individual facing with the epidemics, and they proposed a class of vaccination game to denote the individual decision making and found that, for the well-mixed population, the Nash equilibrium is never to vaccinate if the vaccination cost is higher than that of being infected; but there exists a Nash equilibrium yielding a suboptimal vaccinated fraction if the vaccine cost is lower than that of being infected.

As a further step, complex networks, beyond the well-mixed topology, provide a unified platform to characterize the topology of real-world populations, where the nodes represent individuals and links mimic the contacts among them [35]. Thus, under framework of game theory, many works are devoted to exploring the interplay between contact patterns, behavioral responses and disease dynamics. As an example, Fu et al. [36] found that heterogeneous networks, such as scale-free ones, can induce a broad range of vaccinating actions of many individuals since high-degree hubs with many neighbors become voluntary vaccinators more probably in order to reduce the risk of being infected. After that, Zhang et al. [37] demonstrated that the hubs may largely inhibit the outbreaks of infectious diseases under the voluntary vaccination policy. In the meantime, various subsidy policies on controlling the epidemic spreading have been determined from the socioeconomic perspectives within the well-mixed and networked population [38–43]. Furthermore, most previous works [44–52] often assume that the vaccine has a perfect efficacy, which will endow the complete immunity for the inoculated individuals, but an interesting topic is on how the epidemic spreads when the vaccine is not fully effective for the disease (i.e., 100% efficacy?). Besides, in the vaccination game, whether an individual decides to vaccinate the vaccine or not will be often determined by the estimated payoff, and the vaccinating decision may be transferred from one player to another one inside the population according to a specific role model during the outbreaks. Nevertheless, under some real-world scenarios, some individuals are not willing to imitate the behaviors of others as a result of special belief, religion, opinion and even awareness of a disease.

According to the above description, in the real world, when a new epidemic starts to outbreak, people want to take some measures to protect themselves immediately. Generally, inoculating the vaccine is considered as an effective measure, but the vaccine may fail as result of invalid storage, transportation and usage, and then rendered that the vaccinated individuals may confront the risk of being infected. Henceforth, some individuals make a decision to vaccinate just judge by themselves and don't consider their neighbors. Thus, in order to deeply analyze the role of vaccine efficacy and spontaneous individual decision mechanism in the outbreak of vaccine preventable diseases, we propose a vaccination game model to explore the impact of imperfect vaccine efficacy and myopic update rule in the spatially structure and heterogeneous populations. The rest of this paper is structured as follows. Firstly, we depict the new vaccination game model in Section 2 in detail. Then, Section 3 provides extensive numerical simulation results, which are obtained in the regular lattice and heterogeneous scale-free networks, respectively. Lastly, in Section 4, we end this paper with some conclusions and point out the potential works in the future.

2. The model

As mentioned above, we consider the vaccination game for a class of emerging epidemics within the structured population, where the vaccine can be obtained after the epidemic spreads. Thus, in the current model, all individuals have no chances to vaccinate at the initial time step (t = 0). After that, each time step (t ≥ 1) is divided into two elementary sub-steps: one step is for the decision of inoculating the vaccine; the other one is used to model the process of epidemic spreading. Among them, for the epidemic sub-steps including t = 0, we leverage the frequently used susceptible-infective-recovery (SIR) compartment model to characterize the evolution of epidemics, where each individual may lie in the susceptible (S), infective (I) or recovery (R) state. During the vaccination decision sub-steps, each susceptible individual needs to assess the risk of being infected, and then make the decision whether he will vaccinate or not.

Regarding the SIR model, any susceptible individual may be infected through the contact with infective neighbors and the transmission rate along each infective link is assumed to be β. Meanwhile, the infected individual can be cured with the recovering rate μ, and the recovered one will not be infected again or infect any other healthy ones. Hence, the probability that the susceptible player i without inoculating the vaccine will be infected by all possible infective neighbors can be written as follows,

$$\lambda_i = 1 - (1 - \beta)^{K_{ni}}.$$  (1)
where $k_{i_{inf}}^i$ denotes the total number of infected neighbors of the focal player $i$. The epidemic continues until there are no more newly infected individuals.

As for the individual vaccination decision, each susceptible one will evaluate the risk of being infected and compare the difference between the vaccine cost ($C_V$) and the potential expenses once he has been infected. Without loss of generality, we fix the infection cost $C_I = 1$, while the vaccine cost is usually lower than $C_I$ and then its relative cost can be re-scaled as $0 < c = C_V / C_I < 1$. In order to quantitatively perform the decision, by borrowing from the terms in game theory, we assume that the decision process is based on the comparison between the perceived payoffs of vacci-
nation $\Pi^i_V$ and the perceived payoffs of being infected $\Pi^i_{NV}$, if he is not vaccinated, which can be expressed as follows, respectively,

$$\Pi^i_V = -c_V = -c,$$

$$\Pi^i_{NV} = -\lambda_i c_i = -\lambda_i,$$  \(2\)

where $\lambda_i$ denotes the potential infection probability that can be calculated according to Eq. (1). Then, the susceptible agent $i$ will independently decide to inoculate the vaccine with the following Fermi-like probability,

$$\rho_{i\text{vac}} = \frac{1}{1 + e^{-\lambda_i c_i}},$$  \(4\)

where $K$ represents the impact of the noise or its reverse $1/K$ means the strength of strategy selection, which reflects the uncertainty of vaccination strategy adoption. Here, we term this vaccination decision as the myopic update rule just based on one player’s own perception, which is different from imitating the vaccination strategy of others in many previous works [37,38,43–47]. When $K \to 0$, agent $i$ is totally rational and whether he will vaccinate or not is fully determined by comparing $\Pi^i_V$ and $\Pi^i_{NV}$.

that is, agent $i$ will vaccinate if $\Pi^i_V \geq \Pi^i_{NV}$ and not vaccinate if $\Pi^i_V < \Pi^i_{NV}$. On the contrary, when $K \to \infty$, agent $i$ will randomly perform the vaccination choice.

In addition, we consider the imperfect vaccination program, that is, the vaccine efficacy is not 100% and the vaccination may fail as a result of incorrect transportation, storage, and usage of vaccine. Thus, we introduce an independent parameter $\theta$ to characterize the vaccine failure rate, which implies that the susceptible individual to choose the vaccination is still kept in the susceptible state with the probability $\theta$, while the probability changing from $S$ into $V (S \to V)$ state is set to be $(1 - \theta)$. Once the healthy individual decides to vaccinate, he will have a chance to enter into the vaccinated ($V$) state, the SIR epidemic dynamics will evolve into the SIRV model as illustrated in Fig. 1, in which the successfully vaccinated individual will be equivalent to the R-type one at the next time step, that is, the successfully vaccinated ($V$-type) agent does not get the infection or infect others, either. We do not know when does vaccine fails, so that at each propagating time step, inoculation individuals are judged whether the vaccine is fails or not. To be noted, the vaccinated healthy individuals will not be vaccinated again during this epidemics even if the vaccine lost its effect.

In order to further explore the impact of network topology on the evolutionary process under the imperfect vaccination, we simulate the current mechanism on $L \times L$ regular lattices and scale-free networks with $N = L^2$ nodes, respectively. Initially, we stochastically choose $I_0 = 10$ individuals as the infective seeds within the population, and other $(N - I_0)$ individuals are kept in the susceptible state, and thus there have no vaccinators. At $t = 0$ step, the system starts the evolution according to the SIR model. After that, from $t = 1$, each susceptible agent has the opportunity to receive the vaccination and then the system carries out the evolution of epidemics based on the above-mentioned two elementary steps. The system continuously evolves until there are no infective individuals. In addition, the current results are averaged over 1000 independent runs so that the large fluctuations can be removed. In all the numerical simulations, the population size is fixed to be $N = 10000$. In the homogenous topology, we use the regular lattice satisfying the periodic boundary with the size $L = 100$ as the underlying networks, and each individual has 4 nearest neighbors (that is, the von-Neumann neighborhood). As for the heterogeneous topology, we generate the scale-free network by using the configuration model, in which the average degree is fixed to be $< k >= 4$ and the power exponent is set to be $\gamma = 3$.

3. Results and analyses

In this section, we conduct extensive numerical simulations to demonstrate the vaccination behavior on the regular lattices and scale-free networks, respectively. Among them, we mainly discuss the influence of vaccine cost $c$ and failure rate $\theta$ on the collective vaccination level within the population. Without loss of generality, we set the value of parameters in the SIR model as $\beta = 0.46$ and $\gamma = 1/3$, which are identical with those in Ref. [36].

3.1. Regular lattices

First, we investigate the equilibrium fraction of both vaccinated ($\rho_V$) and recovered ($\rho_R$) state individual size for different values of relative cost of vaccination $c$ and vaccine failure rate $\theta$. Fig. 2 plots
the fraction of vaccinated (upper panel) and recovered (bottom panel) in as a function of relative cost $c$ for three different vaccine failure rates $\theta$. In each panel, we consider the impact of three different vaccine failure rates $\theta = 0.04$ (red square), $0.05$ (blue circle), $0.06$ (yellow triangle), respectively. On the one hand, for a specific vaccine failure rate $\theta$, $\rho_V$ declines with the increase of the relative vaccination cost $c$, while $\rho_R$ increases as $c$ augments, which means that the vaccination cost will markedly affect the willingness of individuals to inoculate the vaccine. As an example, when $c \leq 0.5$, $\rho_V$ and $\rho_R$ can almost keep the similar vaccination level as $c$ increases; However, $c > 0.5$ leads to the substantial reduction of $\rho_V$ and the continuous rising of $\rho_R$ since the vaccination cost is comparable to the infection cost. In particular, $\rho_V$ will be dramatically reduced when $c$ is up to 0.95, even tends to zero as the vaccination cost is too high, especially for $c = 0.95$. On the other hand, under the same vaccination cost $c$, $\rho_V$ decreases as the vaccine failure rate becomes higher, for instance, the fraction of adopting the vaccination strategy under $c = 0.06$ is much less than that with $c = 0.05$, which implies that the vaccinated fraction within the whole population will be a little more sensitive to the vaccine failure rate.

Then, we discuss the influence of the noise factor $K$ on the vaccination behavior within the population in Fig. 3, where we set $\sigma = \frac{1}{R}$, termed as the strength of selection ($0 < \sigma < \infty$), as 2 and 2.5, which are slightly different from that in Fig. 2. Likewise, it can be clearly shown that $\rho_V$ declines and $\rho_R$ increases slowly when the relative cost of vaccination $c$ lies between 0 and 0.4. Afterwards, when the relative cost of vaccination $c$ is more than 0.5, the greater the noise selection strength, the more rapidly the varying trend of $\rho_V$ and $\rho_R$. In fact, as the strength of selection increases, individuals become much more rational and will not tend to take the vaccination strategy since they will take their own economic cost and the related interests, say, free-riding behavior, into account. In particular, the relative cost $c$ is beyond 0.5, or the vaccine loss rate is higher (i.e., $\theta = 0.06$), the un-vaccination behavior of rational individuals become much more prominent, and thus it is unable to prevent the outbreaks of epidemics, which can be observed from the larger $\rho_R$ as $c > 0.5$ or $\theta = 0.06$.

Next, in order to fully check the impact of relative vaccination cost $c$ and the vaccine failure rate $\theta$ on the vaccination behavior, Fig. 4 illustrates the evolution of $\rho_V$ and $\rho_R$ within the broader ranges of $c$ and $\theta$. It is clearly indicated that at the lower vaccine failure rates (say, $\theta < 0.04$), the fraction of vaccinated individuals is often more than half of the total population, even if relative cost of vaccination $c$ is large (e.g., 0.9); Meanwhile, a plethora of vacci-
nated individuals further prevent the outbreak of epidemics so that the percentage of recovered individuals is very low within the population. On the contrary, at the high vaccine failure rates ($\theta > 0.06$), $\rho_v$ is very slow and it indicates that there are few healthy individuals to choose the vaccination strategy after performing the infection risk assessment, which further leads to the potential outbreak of epidemics. In particular, when the vaccine failure rate is beyond 0.09 (i.e., $\theta \geq 0.09$), the whole population is almost recovered regardless of the value of $c$, which means the real outbreak of epidemics. The current results strongly demonstrate that the vaccine failure rate $\theta$ dramatically affect the evolution of vaccination behavior in our model, the equilibrium fraction vaccinated and recovered individuals is almost dominated by the vaccine failure rate, while the impact of the vaccine cost $c$ can play an important role just under the intermediate value of vaccine failure rate (say, $\theta = 0.04 - 0.06$). Thus, creating the high quality vaccine is significant, which greatly determines the individual vaccination inclination.

Furthermore, to deeply understand individual state change in the lattice as SIRV model evolves, we record the evolutionary snapshots of individual states at various time steps for $\theta = 0.03$, $c = 0.3$ and $\theta = 0.08$, $c = 0.8$ in Fig. 5. Among them, the upper eight panels denote the snapshots under $\theta = 0.03$ and $c = 0.3$, while the lower eight panels represent the ones for $\theta = 0.08$ and $c = 0.8$. At time step $t = 0$, there are no vaccinated individuals on the lattice and only $I_0 = 10$ randomly infected seeds, and then the epidemic starts to propagate at this time. After that ($t \geq 1$), the susceptible individuals have the opportunity to determine whether they will inoculate the vaccine or not. It is clearly observed that most individuals choose to vaccinate under these two cases when epidemic begins to spread. However, when $\theta = 0.03$ is lower, there is fewer vaccinated individuals to become susceptible, and then most of vaccinated individuals are immunized, in which the epidemic is hard to spread and finally tends to be extinct. Reversely, for the higher vaccine failure rate (i.e., $\theta = 0.08$), the vaccine is easy to be invalid, many vaccinated individuals become susceptible due to the loss of vaccine efficacy. Therefore, the epidemic can be pandemic and then most of individuals enter the recovered state in the end. All these results again demonstrate that the vaccine efficacy plays the significant role in the evolution of vaccination behavior of epidemic outbreaks within the structured population.

### 3.2. Scale-free networks

In the real world, many networks are often heterogeneous, and thus it is necessary to understand the mechanics of myopic update rule better on heterogeneous topology. To this end, we formulated the game of taking the vaccine on the scale-free network. Here, we generate the scale-free network with 10,000 node under the configuration model, where the average degree of the whole network is equal to 4 and the power exponent 3. After the fundamental networks are created, the system evolves according to the SIRV model, which is identical with the iteration procedure on regular lattices, and the epidemic continues until there are no more newly infected individuals.

First of all, we plot the time courses of fraction of susceptible, vaccinated and recovered individuals for different the relative cost of vaccination $c$ and vaccine failure rate $\theta$ in Fig. 6. In all panels, the red, blue and yellow lines denote the evolution of susceptible, recovered and vaccinated individuals, respectively. It can be found that the vaccinated individuals increase rapidly in a very short time, and then reach a peak. Vaccinated individuals are rarely become susceptible because of the vaccine failure $\theta$ is lower (as shown in Fig. 6a,c) so that the number of recovered ones increases a little and arrives at the equilibrium quickly, which states clearly that the epidemic is eliminated and has not become pandemic. Due to the vaccine failure rate, the fraction of vaccinated individuals goes down and then tends to be zero after reaching the peak. However, when the value of vaccine failure rate $\theta$ is raised (as shown in Fig. 6b,d), even though the vaccinated individuals increase rapidly, they become susceptible quickly due to the high vaccine failure rate $\theta$, it can’t prevent the epidemic spread so that the number of recovered individuals increases. Additionally, we found that for the value of vaccine failure rate $\theta = 0.03$, whatever the values of relative cost of vaccination $c$, the number of recovered agents is the same as that at the equilibrium. Generally, when the epidemic starts to spread, many susceptibles take the vaccine in the population at a short due to the perception of infection risk. Also, this vaccination behavior is almost widespread regardless of the values of relative cost of vaccination $c$ and vaccine failure rate $\theta$. At the lower vaccine failure rate, vaccinated individuals are hard to become susceptible, which leads to the disease propagates difficulty and be eliminated as soon as possible. These results are also consistent with the work of Zhang et al. [37], since the hub nodes are often vaccinated immediately after the disease starts to spread. But for the higher vaccine failure rate, the vaccinated individuals become susceptible quickly, the disease can outbreak.

We also consider the equilibrium fraction of both vaccinated ($\rho_v$) and recovered ($\rho_R$) state individual size for different values of
Fig. 5. Snapshots of the system on lattice. In the diagram, the population is divided into susceptible individuals (gray), infected individuals (red), recovery individuals (green) and vaccinated individuals (blue). The upper eight subplots denotes $\theta = 0.03$ and $c = 0.3$ condition, the lower eight subplots denotes $\theta = 0.08$ and $c = 0.8$ condition. The results are depicted for $\beta = 0.46$, $K = 0.4$ and $\mu = 1/3$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

relative cost of vaccination $c$ and vaccine failure rate $\theta$. We present different strategies: one is random vaccination (RAND), and the other one is the hub vaccination (HUB). Here, only several highest degree nodes have a chance to vaccinate in the HUB scheme; however, we randomly select unvaccinated susceptible ones to inoculate the vaccine at each time step in the RAND one. Fig. 7 (HUB) and Fig. 8 (RAND) plot the fraction of vaccinated (upper panel) and recovered (bottom panel) ones as a function of relative cost $c$ for three different vaccine failure rates $\theta$, respectively. According to Fig. 6, we can find that the vaccinated individuals increase rapidly in a short time when the epidemic starts to spread, which leads to the elimination of epidemics quickly. In Figs. 7 and 8, from left to right, the vaccinated proportion is set to be 0.1, 0.2, 0.3 at each time step, receptively. As the vaccinated proportion enhances, $\rho_V$ increases while $\rho_R$ declines whatever the way of vaccination is. It is natural that when the vaccinated proportion grows, there are more unvaccinated susceptible individuals, who can choose to vaccinate and obtain the immunity so that the epidemic can not spread. We can find that under the HUB scheme, when the vaccinating proportion increases, the value of vaccine failure $\theta = 0.008$ and the values of relative cost of vaccination $c < 0.6$, the fraction of vaccinated individuals
increases. As the value of vaccine failure is raised, the vaccinated individuals become susceptible more easily and the epidemic can outbreak, the risk of infection of unvaccinated susceptible ones also grows, which renders that the payoffs of being infected $\Pi_{NV}$ are increased. Thus, even the value of relative cost of vaccination $c$ rises, unvaccinated susceptible individuals are more likely to choose the vaccination strategy, which is different from results on regular lattices. When the value of relative cost of vaccination $c > 0.6$, due to the higher cost, unvaccinated susceptible individuals are unwilling to choose the vaccination, and then the number of vaccinated individuals declines. The $\rho_R$ under the RAND is enhanced with the increase of the relative vaccination cost $c$, but is different from those under the HUB, which is related to the variation of $\rho_V$. As the relative cost of vaccination $c$ and vaccine failure rates $\theta$ increases, the $\rho_V$ declines rapidly under the RAND at each propagating time step. Meanwhile, the vaccine failure rate $\theta$ has little effect on the $\rho_R$ regardless of the vaccination scheme.

It can be found that in the Figs. 7 and 8, whatever the ways of vaccination, the epidemic can outbreak and vaccinated individuals are more sensitive to the vaccine failure rate. Therefore, except $\beta = 0.46$, we consider the epidemic evolution of SIRV model under the lower transmission rate $\beta = 0.3$. Meanwhile, we set the $I_0 = 10$ initial infective seeds as the top 10 largest degree nodes, which is here termed as the hub infection scheme. Correspondingly, we call the randomly selecting one for the generous case as the random infection.

Fig. 9 plots the fraction of vaccinated (left) and recovered (right) individuals as a function of the relative cost of vaccination $c$ with the vaccine failure rate $\theta$ for different infection mechanism and transmission rate $\beta$. The upper panels present the results under the random infection, while the lower panels denote the results for hub infection. Within each panel, the solid symbols provide the results under the lower transmission rate $\beta = 0.3$, while the empty symbols denote the evolution of transmission rate $\beta = 0.46$. It is obvious that under the lower transmission rate, the fraction of vaccinated individuals is higher than that under the high transmission rate. On the contrary, the fraction of recovered individuals under the lower transmission rate is less than those under the higher transmission rate. The trends of $\rho_V$ under the random infection is similar to the hub infection. However, the number of recovered individuals under the hub infection is still higher than those under the random infection when the values of relative cost of vaccination $c < 0.6$. In addition, regardless of infection mechanism and the values of $c$, the vaccine failure rate has little effect on the $\rho_R$. 

Fig. 6. The time courses of different state size for relative cost of vaccination $c = 0.3$ (upper), $c = 0.8$ (lower) and vaccine failure rate $\theta = 0.003$ (left), $\theta = 0.03$ (right). The red, blue and yellow lines denotes susceptible, recovered and vaccinated state respectively. The results are depicted for $\beta = 0.46$, $\mu = 1/3$ and $K = 0.4$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
Fig. 7. The fraction of vaccinated (upper) and recovered (lower) state shown as functions of the relative cost of vaccination $c$ with hub vaccine. The red square curve indicates vaccine failure rate $\theta = 0.002$, the round blue curve indicates vaccine failure rate $\theta = 0.005$, the yellow triangle curve indicates vaccine failure rate $\theta = 0.008$. At each propagating time step, the vaccinate proportion from left to right is 0.1, 0.2, 0.3. The results are depicted for $\beta = 0.46$, $\mu = 1/3$ and $K = 0.4$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 8. The fraction of vaccinated (upper) and recovered (lower) state shown as functions of the relative cost of vaccination $c$ with random vaccine. The red square curve indicates vaccine failure rate $\theta = 0.002$, the round blue curve indicates vaccine failure rate $\theta = 0.005$, the yellow triangle curve indicates vaccine failure rate $\theta = 0.008$. At each propagating time step, the vaccinate proportion from left to right is 0.1, 0.2, 0.3. The results are depicted for $\beta = 0.46$, $\mu = 1/3$ and $K = 0.4$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
4. Conclusions

In summary, based on the SIR epidemic dynamics, we investigate the imperfect vaccine immunity under the myopic update rule in different foundation topology including the regular lattice and scale-free networks, where the focal player makes the vaccination decision just according to his own judgement about the epidemic situation. Extensive numerical simulations show that most unvaccinated susceptible individuals are willing to inoculate the vaccine under the myopic update rule, whatever the type of network is, in particular for the lower vaccine cost ($c \leq 0.5$) and failure rate ($\theta \leq 0.06$). After the epidemic starts to propagate, and most of individuals change their strategies to adopt the vaccine in a short time since the individual can estimate the infection risk at the early stage, which leads the epidemics to be hard to spread within the population. However, due to the failure of vaccine or the free-riding behavior of susceptible individuals, vaccinated individuals become susceptible again and then confront the risk of being infected, which creates the potential epidemics situation.

To be of great interest, we find that the impact of vaccine failure rate on the vaccination coverage becomes much higher, when compared to the role of the relative cost of vaccine. For example, the value of vaccine failure rate $\theta$ is usually assumed to be no more than 10%, or else most vaccinated individuals become re-susceptible again. At a fixed $\theta$, the fraction of vaccinated individuals almost keep unchanged when the relative vaccine cost is not beyond $c = 0.5$, but this value will become lower and lower after $c$ is more than 0.5, which is basically consistent with the reality of vaccine usage. On the contrary, on the scale-free networks, the number of vaccinated individuals is more sensitive to the effect on vaccine failure rate $\theta$.Hub nodes have a stronger inclination to adopt the vaccine under the myopic update rule, which can effectively prevent the diffusion of epidemics. Hence, the disease will be eliminated quickly in heterogeneous topology. However, when the values of vaccine failure rate increase a little bit, hub nodes become susceptible and cannot prevent the epidemic spread, which leads to the epidemic outbreak. Meanwhile, when the relative cost of vaccination $c$ increases, unvaccinated susceptible individuals are not willing to choose the vaccination strategy, which can not stop the outbreak of infectious diseases. When the vaccine failure rate further increases, such as 0.03, the number of vaccinated individuals decays to zero before the epidemic is eliminated, which
is almost equivalent with the classic SIR model. Anyway, current results are conducive to better understanding the individual vaccination behaviors when confronting the real epidemics.

Declaration of Competing Interest

The authors declare that they do not have any financial or non-financial conflict of interests.

Acknowledgments

This project is financially supported by the National Natural Science Foundation of China (NSFC) (Grant nos. 61773286 and 71401122).

References

[1] Riley S, Fraser C, Donnelly CA, Ghani AC, Abu-Raddad LJ, Hedley AJ, Leung CM, Ho LM, Lam TH, Thach TQ, Chau P, Chan KP, Lo SV, Leung PY, Tsang T, Ho W, Lee KH, Lau EM, Ferguson NM, Anderson RM. Transmission dynamics of the etiological agent of SARS in hong kong: impact of public health interventions. Science 2003;300:1061–6.
[2] Jamieson DJ, Honen MA, Rasmussen SA, Williams JL, Swerdlow DL, Biggerstaff MS, Lindstrom S, Louie JK, Christ CM, Rohn SR, Fonseca VP, Ridger KA, Kuhles DJ, Eggers P, Bruce H, Davidson HA, Lutterloh E, Harris ML, Burke C, Cocornescu N, Finelli L, Macfarlane KT, Shi R, Olsen SJ. Novel influenza a (H1N1) pregnancy working group. H1N1 influenza virus infection during pregnancy in the usa. Lancet 2009;374:451–8.
[3] Okware S, Omaswa FG, Zaramba S, Opio A, Lutwama JK, Kamugisha J. Singapore TB and Influenza A(H1N1). Proc Natl Acad Sci 2010;107:22020–5.
[4] Ferguson N. Capturing human behaviour. Nature 2007;446(7173):733.
[5] Jones NH, Salathé M. Early assessment of anxiety and behavioral response to novel swine-origin influenza A(H1N1). PLoS ONE 2009;4(12):e8032.
[6] McNeill WH, Plagues and peoples. Health Care Manage Rev. 1997;2:99–100.
[7] Scott S, Duncan CJ. Biology of plagues: evidence from historical populations. Cambridge UK: Cambridge University Press: 2001.
[8] Liu JY, Yang X, Fang E, Tsui HY, Wong E, Wing YK. SARS-Related perceptions in hong kong. Emerg Infect Dis. 2005;11:417–24.
[9] Stratton K, Gable A, Shetty P, McCormick M, editors. Institute of medicine (US) immunization safety review committee. Immunization safety review: measles-mumps-rubella vaccine and autism, Washington DC: National Academies Press: 2001.
[10] Raja A. Immunology of tuberculosis. Med Clinics North Am 1993;77:1235–51.
[11] Abitua A, Hotz VJ, Philipson T. The responsiveness of the demand for condoms to the local prevalence of AIDS. J Hum Resour 1996;31:896–97.
[12] Helbing D, Parkas I, Vicsek T. Simulating dynamical features of escape panic. Nature 2000;407:487–90.
[13] Helbing D, Keltisch J, Molnár P. Modelling the evolution of human traffic systems. Nature 1997;385:47–50.
[14] Bu Z, Li HJ, Wang Z, Gao G. Dynamic cluster formation game for attributed graph clustering. IEEE Trans Cybern 2019;49(1):328–41.
[15] Li HJ, Bu Z, Li AH, Liu ZD, Shi Y. Fast and accurate mining the community structure: integrating center locating and membership optimization. IEEE Trans XDE 2016;22(8):2349–62.
[16] Cao J, Bu Z, Wang YY, Yang H, Jiang J, Li HJ. Detecting consumer-community groups in smart grids from the multilayer perspective. IEEE Trans Syst Man Cybern Syst 2019;49(8):1632–64.
[17] Li HJ, Bu Z, Wang Z, Cao J, Shi Y, Wang H. Enhance the performance of network computation by a tunable weighting strategy. IEEE Trans Emerg Top Comput Intelli 2018;2(3):214–23.
[18] Chen Y, Ding S, Xu Z, Zheng HD, Yang SL. Blockchain-based medical records secure storage and medical service framework. J Med Syst 2019;43(1):5.
[19] Ding S, Li ZM, Liu X, Huang H, Yang SL. Diabetic complication prediction using a similarity-enhanced latent Dirichlet allocation model. Inf Sci 2019;499:12–24.
[20] Ding S, Li L, Li ZM, Wang H, Zhang YC. Smart electronic gastroscopic system using a cloud–edge collaborative framework. Future Gener Comput Syst 2019;100:395–407.
[21] Matažić P, Ozer M, Hofijnik J. Social and juridical challenges of artificial intelligence. Palgrave Commun 2019;5:61.
[22] Wang ZS, Guo QT, Sun SW, Xie CY. The impact of awareness diffusion on SIR-like epidemics in multiplex networks. Appl Math Comput 2019;349:134–47.
[23] Xie CY, Wang ZS, Zheng CY, Guo QT, Shi YT, Dehmer M, Chen QZ. A new coupled disease-aware spreading model with mass on multiplex networks. Inf Sci (Ny) 2019;471:185–200.
[24] Wang J, Li C, Xie CY. Improved centrality indicators to characterize the nodal spreading capability in complex networks. Appl Math Comput 2018;334:388–400.
[25] Zheng CY, Xie CY, Guo QT, Matthews D. Interplay between SIR-based disease spreading and awareness diffusion on multiplex networks. J Parallel Distrib Comput 2018;115:289–8.
[26] Funk S, Salathé M, Jansen VA. Modelling the influence of human behavior on the spread of infectious diseases: a review. J R Soc Interf 2010;7:1247–56.
[27] Bauch CT, Earn D. Vaccination and the theory of games. Proc Natl Acad Sci 2004;101:13239–44.
[28] Zhou T, Fu ZQ, BH W. Epidemic dynamics on complex networks. Prog Nat Sci 2005;16:452–7.
[29] Fu F, Rosenbloom DI, Wang L, Nowak M. Imitation dynamics of vaccination behavior on social networks. Proc Biol Sci 2011;278:42–9.
[30] Zhang HF, Zhang J, Zhou CS, Small M, Wang B. Hub nodes inhibit the outbreak of epidemic under voluntary vaccination. New J Phys 2010;12(2):023015.
[31] Ohkusa Y. Policy evaluation for the subsidy for influenza vaccination in elderly. Vaccine 2005;23:2256–60.
[32] Kondo M, Hoshi SL, Okubo I. Does subsidy work? Price elasticity of demand for influenza vaccination among the elderly in japan. Health Policy 2009;91:269–76.
[33] Zhang HF, Zhang J, Liu ZQ, Shi Y, Xu P. Shetty X.ruc. Preferential imitation can invalidate targeted subsidy policies on seasonal-influenza infections. Appl Math Comput 2017;294:31–42.
[34] Ding H, Xu JH, Wang Z, Ren YZ, Cui GH. Subsidy strategy based on history information can stimulate voluntary vaccination behaviors on seasonal diseases. Phys A 2018;503:390–59.
[35] Zhang HF, Wu ZX, Xu XX, Small M, Wang L, Wang BH. Impacts of subsidy policies on vaccination decisions in contact networks. Phys Rev E 2013;88(1):012813.
[36] Xue J, Chikwa M, Deguchi H. Simulation analysis of vaccination subsidy with ABM approach. In: Agent-Based Approaches in Economic and Social Complex Systems VIII Springer Japan, Vol. 13; 2015. p. 103–14.
[37] Zhang HF, Shu PP, Wang Z, Tang M, Small M. Preferential imitation can invalidate targeted subsidy policies on seasonal-influenza infections. J Biol Math 2016;31:233–72.
[38] Bauch CT, Galvani AP, Earn DJ. Group interest versus self-interest in smallpox vaccination policy. Proc Natl Acad Sci 2013;100:10564–7.
[39] Bauch CT. Imitation dynamics predict vaccinating behavior. Proc Biol Sci 2005;272:1669–75.
[40] Liu XT, Wu ZX, Zhang L. Impact of committed individuals on vaccination behavior. Phy Rev E 2012;86(5):051932.
[41] Nefeso Mbah ML, Liu J, Bauch CT, Tekel YI, Medlock J, Meyers LA, Galvani AP. The impact of imitation on vaccination behavior in social contact networks. PLoS Comput Biol 2012;8(4):e1002469.
[42] Oraby T, Thampi V, Bauch CT. The influence of social norms on the dynamics of vaccinating behavior for paediatic infectious diseases. Proc Biol Sci 2014;281(1780):20133172.
[43] Fukushima E, Koboko S, Tanimoto J, Wang Z, Hagishima A, Ikegaya N. Risk assessment for infectious disease and its impact on voluntary vaccination behavior in social networks. Chaos Solitons Fract 2014;68:1–9.
[44] Vardavas R, Breban R, Blower S. Can influenza epidemics be prevented by voluntary vaccination? PLoS Comput Biol 2007;3(5):e85.