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Subsidy policy with punishment mechanism can promote voluntary vaccination behaviors in structured populations

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ABSTRACT

Subsidy policies have been a common way for governments and health organizations to encourage individuals' voluntary vaccination behaviors. However, subsidy policies are often used in combination with punishment policies in reality. So far, few researchers have studied the combination of vaccination subsidy policies and punishment policies. In this study, a new subsidy policy with the punishment mechanism (P-TAR) is first introduced in the vaccination game to explore its impact on voluntary vaccination behaviors. P-TAR selects to subsidize punishers of the last season based on the degree, which is similar to targeted subsidy policy (S-TAR). We first adjust fines and punishment costs to explore how the punishment mechanism of P-TAR influences vaccination coverage and epidemic dynamics. The results show that vaccination coverage can be significantly improved when the fine is high and the punishment cost is low. By comparing P-TAR with S-TAR, we find that P-TAR can more effectively increase the number of vaccinated individuals to control the epidemic size. However, the P-TAR has a higher social cost than S-TAR. Through micro-analyzing the evolution of vaccination behaviors, the P-TAR effectively improves the voluntary vaccination behaviors of non-hub nodes, which is the main reason for P-TAR has more vaccinated individuals than S-TAR. To analyze the model robustness, experiments are conducted with larger network sizes. In addition, we compare the results of unvaccinated individuals who are sequentially punished by their surrounding punishers, as well as those who are punished only once. Finally, we perform the sensitivity analysis on the effectiveness of imperfect vaccine. Current results conclude that implementing strict policies usually incurs significant social costs, while effectively preventing epidemic spreading. We anticipate that this study can offer policymakers valuable insights into the balance between social costs and benefits when formulating vaccination policies.

1. Introduction

Humanity has long struggled with various infectious diseases that not only threaten human life but also cause huge economic losses [1]. It is reported that the COVID-19 pandemic caused millions of confirmed cases and deaths worldwide [2,3]. Therefore, the prevention of worldwide infectious diseases is widely recognized as a major problem that needs to be addressed in modern society. Vaccination has always been considered an important measure for preventing infectious diseases. The vaccination behavior of individual is more of a voluntary behavior. For instance, non-fatal and vaccine-preventable diseases such as influenza, measles and chickenpox usually use voluntary vaccination strategy [4,5]. When individuals make vaccination decisions, they will consider vaccination cost, vaccine side effects, religious beliefs, and the influence of others. In particular, unvaccinated individuals can benefit from herd immunity, as vaccination coverage has reached a sufficient threshold. Hence, individuals may refuse vaccination and rely on their vaccinated neighbors to stay healthy. As a result, the vaccination decision of the population is considered a public goods dilemma [6], which can be effectively informed by evolutionary game theory [7–11].

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Therefore, many researchers have explored the evolutionary dynamics of voluntary vaccination [12–16]. Fu et al. [17] published a pioneering work that used evolutionary game theory to study individual vaccination behavior in different networks. Subsequently, some studies focused on different types of networks, such as classical complex networks (e.g., Barabási–Albert (BA) scale-free networks, Erdős–Rényi (ER) random networks) [17,18], higher-order networks (e.g., simplicial complexes and hypergraph) [19,20] and multiplex networks [21,22] and so on. On the other hand, a great deal of study has also focused on the impact of various factors on individual vaccination behavior, such as perception [23], social influence [15,24], strategy conformity [18,21], memory [25] and so on. In terms of encouraging vaccination, subsidy policy has become a commonly studied method for improving vaccination coverage [26–30]. For instance, Zhang et al. [26] compared random and targeted subsidy policies and discovered that targeted subsidy is more effective than random subsidy when individuals are more willing to imitate the strategies of subsidized individuals. Ding et al. [27] found that the subsidy policy based on one-step history information is significantly effective and could increase the vaccination coverage of non-hub nodes. Tatsukawa et al. [28] proposed a degree-dependent subsidy scheme and found that it is an intermediate policy between the free ticket and flat discount policies.

Subsidy policy is used to incentivize vaccination behaviors, which in essence uses reward mechanisms to promote cooperation in public goods game (PGG), and reward can be understood as an incentive for cooperative behavior that directly promotes cooperative behavior in the population [7–9,31–33]. For example, Szolnoki et al. [8] found that moderate rewards are an effective way to promote cooperation when the synergy factor is low. Likewise, punishment is resistance to defective behavior and indirectly promotes cooperative behavior in the population, which is also commonly used to promote cooperation in PGG [34–38]. For instance, Wang et al. [37] proposed two methods of punishment: slight intensity of punishment and severe intensity of punishment, and found that both methods significantly promoted cooperation. Perc et al. [38] showed how adaptive punishment may increase public cooperation by activating spatial reciprocity or giving people who sanction antisocial behavior an advantage in competition. Lee et al. [39] proposed a punisher similar to a police officer or mercenary who monitored the population and punished defectors, finding that the maximum average outcome could be reached at an intermediary punishment cost. It is worth mentioning that reward and punishment coexist as management measures in the context of actual social management. Thus, Zhang et al. [40] showed that network reciprocity can be combined with reward–punishment mechanisms in order to achieve the co-evolution of network structure and individual behavior. It was found that the right combination of reward and punishment to promote cooperation is more effective.

During the ongoing COVID-19 pandemic, subsidy has emerged as a successful strategy to incentivize individuals to get vaccinated. For example, some countries have implemented government measures to encourage vaccination, such as offering free vaccines [41,42]. Meanwhile, some countries have also taken punishment measures, such as banning unvaccinated individuals from traveling by public transportation, refusing entry, or restricting access to public places [43,44]. The two incentives are commonly implemented together. As far as we know, although many studies have explored the impact of subsidy policies on individual vaccination behavior, there has been no research to study subsidy policies with punishment mechanisms. In this study, we construct a vaccination game model that combines the punishment mechanism and the subsidy policy in the BA scale-free network. The results show that preventing the epidemic is more effective when the fine is higher and the cost of punishment is lower. Moreover, we contrast the P-TAR with the previous target subsidy policy (S-TAR) and find that the P-TAR is more effective in preventing disease spread. Through micro-analysis, we conclude that P-TAR is more effective by increasing vaccination coverage for non-hub nodes. To analyze the model robustness, we perform experiments on larger network sizes and found that the results of the two network sizes are nearly consistent. Furthermore, additional experiments are conducted to investigate the impact of different punishment methods on individual vaccination behaviors. This experiment demonstrates that unvaccinated individuals who are punished sequentially by the surrounding punisher are more effective than those who are only punished once. Lastly, when introducing the vaccine failure rate, we observe that fewer susceptible individuals chose to vaccinate as the vaccine failure rate increases. Thus, vaccine failure rate almost entirely dominates the fraction of vaccinated and infected individuals.

The remaining content of this article is as follows: Section 2 introduces the model in detail and describes the P-TAR vaccination game model process. Section 3 compares and analyzes P-TAR and S-TAR through a series of simulations. Finally, Section 4 summarizes the findings of this study.

2. Model

We propose a vaccination game model consisting of a subsidy policy with punishment mechanisms. As shown in Fig. 1, the vaccination game model is divided into two stages: vaccination decision-making and epidemics spreading [17]. Because some studies have demonstrated that the degree distribution of many networks follows a power-law distribution [45], the whole vaccination process is conducted on a BA scale-free network. In the network, each node represents an individual, and the edges between nodes represent the neighborhood relationship between individuals. During the vaccination decision stage, we introduce a punisher strategy in which punishers impose punishment on unvaccinated individuals around them. The punisher's power to punish can be regarded as punitive behavior performed through monitoring and reporting. Then, the punishers are determined whether to subsidize according to its degree. Next, individuals decide whether to get vaccinated based on the previous season's payoffs. The classical susceptible–infected–removed (SIR) model is used to simulate disease transmission in the epidemic spreading stage. To simplify the model, the vaccination is assumed to provide perfect immunity, meaning that individuals will not become infected during the period in which they are vaccinated. The model's details are described below.

2.1. Payoff structure

This model includes punishers in contrast to previous studies that focused only on subsidy policies. A punisher monitors all of his/her neighbors, and punishes surrounding unvaccinated individuals from the last season. The payoff of the punished individual is reduced by fine β, and the punisher needs to pay the punishment cost $\gamma\beta$. The multiplication factor γ ($0 \leq \gamma \leq 1$) is introduced to represent the relationship between fine and punishment cost. Specifically, if $\gamma = 0$, punishers do not have to pay the cost of punishment. If $\gamma = 1$, which means the punishment cost paid by the punisher equals the fine paid by the punished individual. Thus, a punisher i pays the punishment cost proportional to the number of unvaccinated individuals $N_{nov,i}(t-1)$ around him/her. The total punishment cost of individual i is represented by

$$F_i(t) = N_{nov,i}(t-1) \cdot \gamma\beta \tag{1}$$

An penalized unvaccinated individual j need to pay the fine correlated to the number of punishers $N_{pv,j}(t-1)$ in his/her neighbors. In particular, an unvaccinated individual may avoid punishment if there are no punishers around. The total fine of individual j is given as

$$W_j(t) = N_{pv,j}(t-1) \cdot \beta \tag{2}$$

Besides punishment cost and fine, the payoff of individual i also needs to consider his/her strategy and healthy state from last season. If

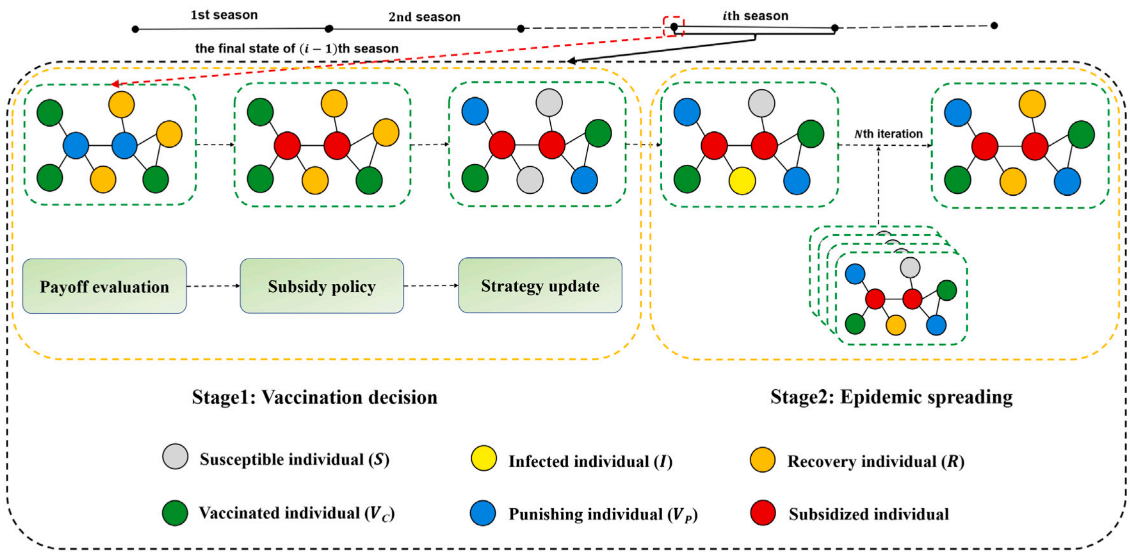

Fig. 1. Schematic diagram of the vaccination game model for subsidy policy with punishment mechanism. The two stages (vaccination decision stage and epidemic spreading stage) in a period are sequenced.

individuals chose to be vaccinated in season $t-1$, they need to pay vaccination cost C_v, which includes monetary expenses, perceived vaccine risks, and potential side effects. The punisher also requires vaccination, and needs to pay the vaccination cost C_v. In addition, unvaccinated individuals who are infected also have to pay the infection cost C_I. Without loss of generality, we set $C_I = 1$ and let $c = C_v/C_I$ $(0 \le c \le 1)$ describe the relative cost of vaccination [46]. A successful "free-rider" can avoid getting the disease, just consider whether he or she is fined. The payoff of a subsidized punisher is $-C_v$ (as detailed in the subsidy policy in Section 2.2). According to the above description, the payoff $\pi_i(t)$ of individual i in season t are as follows:

$$\pi_i(t) = \begin{cases} -C_v, & vaccinator\ and\ subsidized punisher, \\ -F_i(t) - C_v, & un-subsidized\ punisher, \\ -W_i(t) - 1, & punished\ non-vaccinator, \\ -W_i(t), & free-rider. \end{cases}$$

2.2. Subsidy policy

The target subsidy policy (S-TAR) [26] distributes the total subsidy amount pc to nodes with higher degrees of the proportion p, and the subsidized individuals remain unchanged in all seasons. To make the model comparisons, we use the same model of total subsidy amount to subsidize punishers in P-TAR. In contrast to the S-TAR, the P-TAR chooses punishers for subsidies each season. More specifically, the degree of each node is used to rank it, and the punisher can be subsidized for the whole cost (including punishment cost and vaccination cost). If the remaining subsidy amount is not enough to cover the whole cost of the punisher i, the next punisher j is successively chosen to be subsidized until the remaining subsidy amount is not enough to cover the whole cost of any punisher. From the neighbor's perspective, a subsidized punisher is regarded as an individual vaccinated voluntarily [27]. Thus, the payoff of subsidized punisher is $-C_v$. As with other subsidy policies [26,27], subsidized punishers do not need to make the vaccination decision in this season and continue to be punishers.

2.3. Strategy updating

Except for subsidized punishers, the remaining individuals updated their strategies based on payoff differences. In detail, a non-subsidy individual i randomly selects an individual j from its neighbors, and the probability of adopting the neighbor j's strategy is determined by the following Fermi function:

$$f(\pi_j(t) \to \pi_i(t)) = \frac{1}{1 + exp((\pi_j(t) - \pi_i(t))/K)} \tag{3}$$

Here, $1/K$ represents the strength of strategy selection $(0 < 1/K < \infty)$. If $1/K \to \infty$, individuals will be more sensitive to the payoff difference. We set $K = 1$ in this study because the uncertainty has been discussed in previous studies [17,47,48].

2.4. Epidemic season

Every unvaccinated individual can be infected at this stage. We simulate this process modeling SIR epidemic dynamics. At the initial time step, the number of initial infection seeds I_0 is randomly selected from a susceptible population. A susceptible individual (S) will be infected at a rate of λ through contact with an infected individual (I). Infected individuals can become recovering individuals (R) at a rate of μ and will not be infected again during this season. The epidemic continues until there are no new infected individuals. We implement the evolution of the SIR model through the Gillespie algorithm [49].

2.5. Simulation procedure

The simulation is conducted on the BA scale-free network with a population of 1000 and an average degree of 4. Everyone is initially assigned a vaccination strategy of being vaccinated or not with equal probability. In particular, we select half of the vaccinated individuals as punishers [50]. After that, the seasonal epidemic starts to spread according to initial infected individuals, assuming $\lambda = 0.55$ and $\mu = 1/3$ [17]. To ensure the evolution process reaches a steady state, we collect data after discarding enough transient time steps. The total number of Monte Carlo (MC) steps is 3000 and the equilibrium results represent the average of the last 100 MC steps of 200 independent experiments. In addition, the V (vaccination coverage), R (final epidemic size), and SC (social cost) are calculated as follow:

$$\begin{aligned} V &= V_C + V_P = N_V/N \\ R &= N_R/N \\ SC &= N_R \cdot 1 + N_V \cdot c + \gamma \cdot \beta\ \cdot N_{nop} \end{aligned} \tag{4}$$

V_C and V_P denote the proportion of pure vaccinators and punishers, respectively. Here, pure vaccinators are individuals who vaccinate

Table 1
Summary of main parameters.

Symbol	Description	Value
N	Size of networks	$N = 1000$
$\langle k \rangle$	Average degree of networks	$\langle k \rangle = 4$
λ	Transmission rate	$\lambda = 0.55$
μ	Recover rate	$\mu = 1/3$
C_v	Cost of vaccination	$0 \leq C_v \leq 1$
C_I	Cost of infection	$C_I = 1$
c	Relative cost of vaccination (C_v/C_I)	$0 \leq c \leq 1$
p	Proportion of subsidized individuals	$p = 0.04$
γ	Punishment cost related multiplication factor	$0 \leq \gamma \leq 1$
β	Fine	$0 \leq \beta \leq 1$
$W_i(t)$	The penalty cost of individual i in period t	
$F_i(t)$	Fine for individual i in period t	
$N_{nov,i}(t)$	Number of unvaccinated individuals around Punisher i in period t	
$N_{pv,i}(t)$	Number of punishers around unvaccinated individual i in period t	

without becoming punishers. N_R and N_V represent the numbers of infected and vaccinated individuals. Additionally, N_{nop} represents the number of penalties. Table 1 summarizes the main parameters in our model.

3. Results

In this part, we first investigate and explain the impacts of fine β and punishment cost-related multiplication factor γ on vaccination behavior. Then, a comparative study of the targeted subsidy policy (S-TAR) and the subsidy policy with punishment mechanism (P-TAR) is conducted to investigate the impact of these two policies on voluntary vaccination behavior. At last, we perform a series of sensitivity analyses on the model, including: network size, punishment approach, and vaccine effectiveness.

3.1. Vaccination behaviors under P-TAR

First, we investigate the effect of vaccination coverage (V), final epidemic size (R), and social cost (SC) with vaccination relative cost c for different fines β in Fig. 2. By setting $\gamma = 1$, we ensure that punishment cost paid by the punishers is equal to the fine paid by the punished. For $\beta = 0$, the P-TAR policy is similar to the S-TAR policy, it is an interesting phenomenon. The difference is that the P-TAR policy provides subsidies to punishers with higher degrees every season, and the S-TAR policy offers free vaccination to individuals with higher degrees and remains constant in all seasons. As shown in Fig. 2(a) and (b), for some vaccination costs c (e.g., $c = 1$), the vaccination coverage V is higher, and the final epidemic size R is lower when $\beta = 0$. And the social cost SC of $\beta = 0$ is always lower than other β because punishers do not have to pay the punishment cost in Fig. 2(c).

For another specific β, V decreases gradually and R increases steadily as c increases because the cost of vaccination is almost as high as the cost of infection. It implies that a lower vaccination cost can encourage individuals to get vaccinated. For example, when $c \leq 0.6$, V is almost 1 and R is close to 0. As the vaccination cost rises ($c > 0.6$), leading to the continuous decrease of V and the significant increase of R. The social cost SC increases with the punishment cost paid by punishers since the cost of punishment is included in the calculation of the social cost. Under the same vaccination cost c, the vaccination coverage V increases and the epidemic size R decreases with the rise of β. For instance, the fraction of individuals adopting the vaccination strategy under $\beta = 1$ is higher than with other β, implying that the vaccinated fraction within the overall population will be more sensitive to the fines β. The SC does not change significantly. In particular, we further analyze V and find the proportion of punishers V_P is very high in Fig. 2(d) and (e). This phenomenon is attributed to the subsidized vaccination of punishers, which encourages more individuals to become punishers. As shown in Fig. 2, the prevention of epidemics becomes more effective with the increase of β, except for $\beta = 0$. However, in reality, governments and regulators often adopt restrictive policies for unvaccinated individuals, such as banning them from entering public places or taking public transport. Punishing unvaccinated individuals is less costly for governments and regulators. Therefore, setting $\gamma = 1$ is stricter. The following experiments will explore the impact of different punishment cost-related multiplication factors γ on vaccination behavior.

Fig. 3 plots the punishment cost-related multiplication factor γ as functions of the vaccination relative cost c under the P-TAR policy. It is evident that γ has a more obvious effect on improving vaccination behavior. As shown in Fig. 3(a), when γ is smaller ($\gamma \leq 0.6$), all individuals can be effectively encouraged to be vaccinated regardless of the value of c. However, larger γ ($\gamma > 0.6$) have a negative impact on vaccination behavior. Specifically, the effect of improving vaccination coverage became less effective as γ increased. This is because individuals consider their economic costs and associated benefits, leading to a decrease in the number of punishers (Fig. 3(e)). The proportion of pure vaccinators increased. Thus, the probability of unvaccinated individuals being punished decreases, which cannot prevent the outbreak of epidemics. However, there is no significant difference in SC (Fig. 3(c)). This is because smaller γ increases vaccination costs, while larger γ improves punishment costs. To compare the significant differences between P-TAR and S-TAR, the values of β and γ are fixed at 1 and 0.8, respectively.

3.2. Compare P-TAR with S-TAR

We compare the effects of different policies on voluntary vaccination behavior. As shown in Fig. 4, both S-TAR and P-TAR policies can effectively prevent pandemic outbreaks when compared to the No policy. However, as the vaccination cost c increases, the vaccination coverage of the P-TAR policy remains 1. Diseases can be completely eliminated when $c < 0.9$ (As shown in Fig. 4(b)). When $c \geq 0.9$, individuals take into account the relevant benefits, and the number of free riders increases. Due to the prevalence of sanctioning behavior in the network, very few free riders can escape punishment. From the point of view of group interests, the social cost of P-TAR is slightly higher than that of the No policy. In contrast, S-TAR has the lowest social cost but is not as effective as P-TAR in promoting individual vaccination and preventing epidemic spread.

To analyze the co-effects of vaccination cost c and the fraction of subsidized individuals p on vaccination behavior, Fig. 5 illustrates the evolution of V, R, and SC within the broader ranges of c and p. It is clearly indicated that as c decreases and p increases, the fraction of the vaccination coverage V increases, and the final epidemic size R decreases. Compared to S-TAR results in the top panel, areas with higher vaccination coverage in Fig. 5(d) are wider than in Fig. 5(a), and areas with lower epidemic size in Fig. 5(e) are wider than in Fig. 5(b), meaning that P-TAR policy is more effective than S-TAR policy on promoting vaccination coverage. However, when c is high

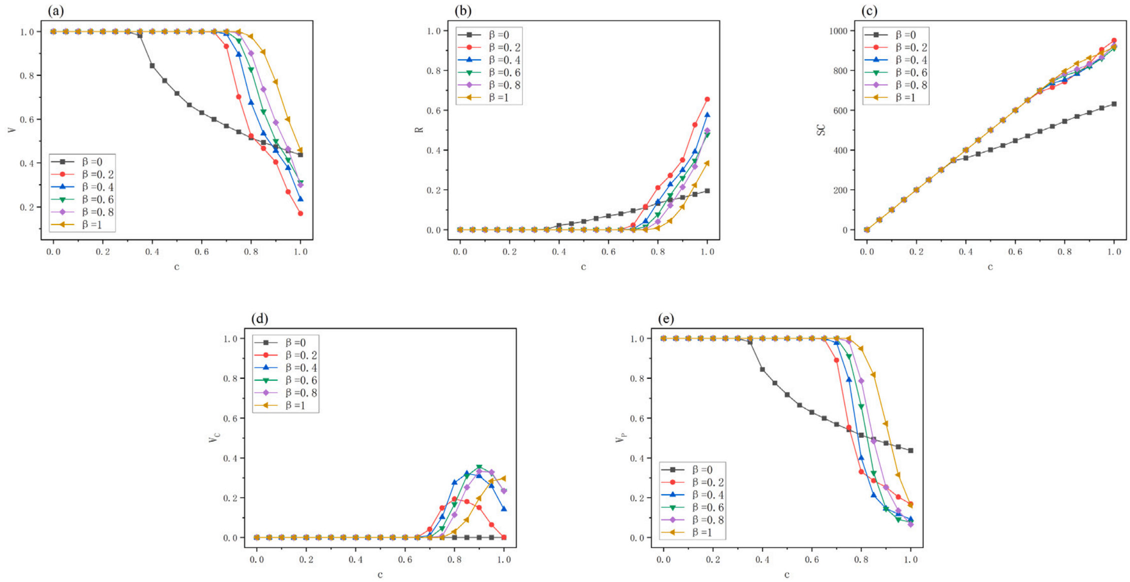

Fig. 2. (a) the vaccination fraction V, (b) the final epidemic size R, (c) the social cost SC, (d) the proportion of pure vaccinators V_C, and (e) the proportion of punishers V_P as functions of the relative cost of vaccination c with several typical values of the fines β. Parameters: $N = 1000$, $\langle k \rangle = 4$, $\lambda = 0.55$, $\mu = 1/3$, $K = 1$, $\gamma = 1$, $p = 0.04$.

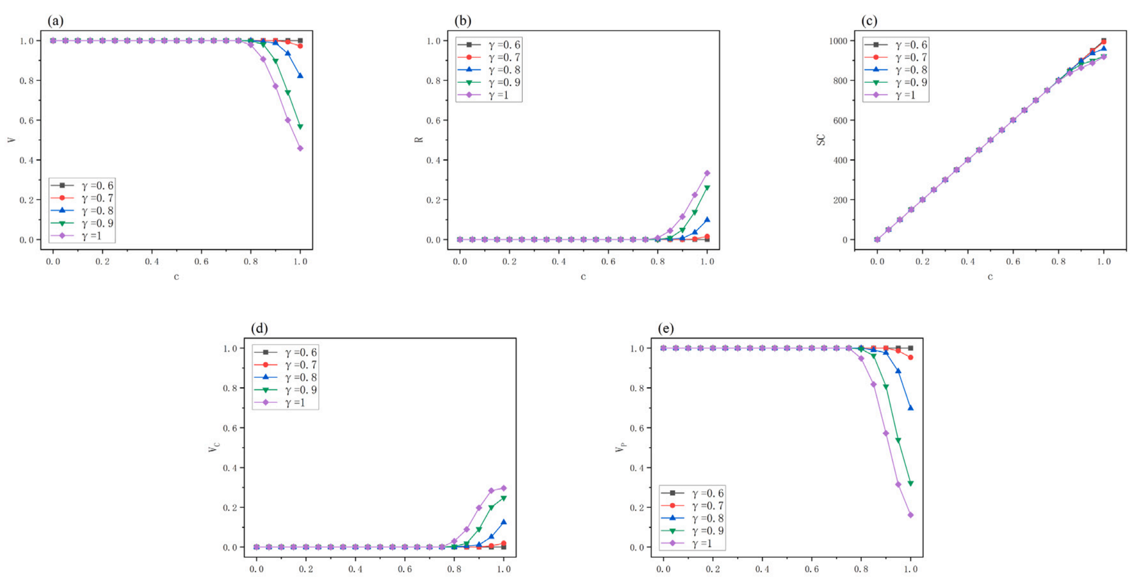

Fig. 3. (a) the vaccination fraction V, (b) the final epidemic size R, (c) the social cost SC, (d) the proportion of pure vaccinators V_C, and (e) the proportion of punishers V_P as functions of the relative cost of vaccination c with several typical values of the punishment cost-related multiplication factors γ. Parameters: $N = 1000$, $\langle k \rangle = 4$, $\lambda = 0.55$, $\mu = 1/3$, $K = 1$, $\beta = 1$, $p = 0.04$.

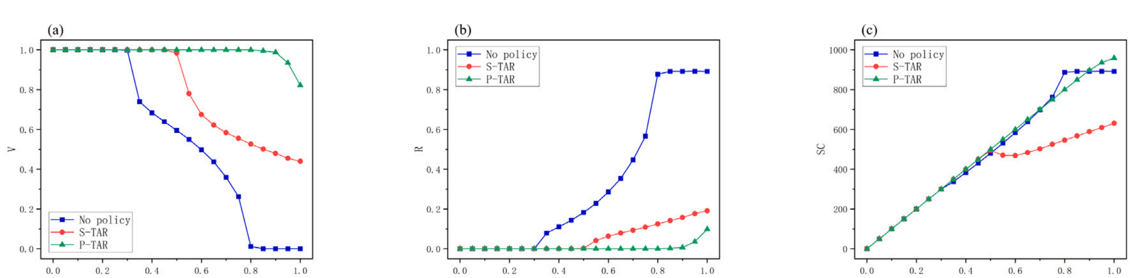

Fig. 4. Comparison of different policies in the BA network. (a) the vaccination fraction V, (b) the final epidemic size R, (c) the social cost SC, (d) the proportion of pure vaccinators V_C, and (e) the proportion of punishers V_P as functions of the vaccination relative cost c. Parameters: $N = 1000$, $\langle k \rangle = 4$, $\lambda = 0.55$, $\mu = 1/3$, $K = 1$, $\beta = 1$, $\gamma = 0.8$, $p = 0.04$.

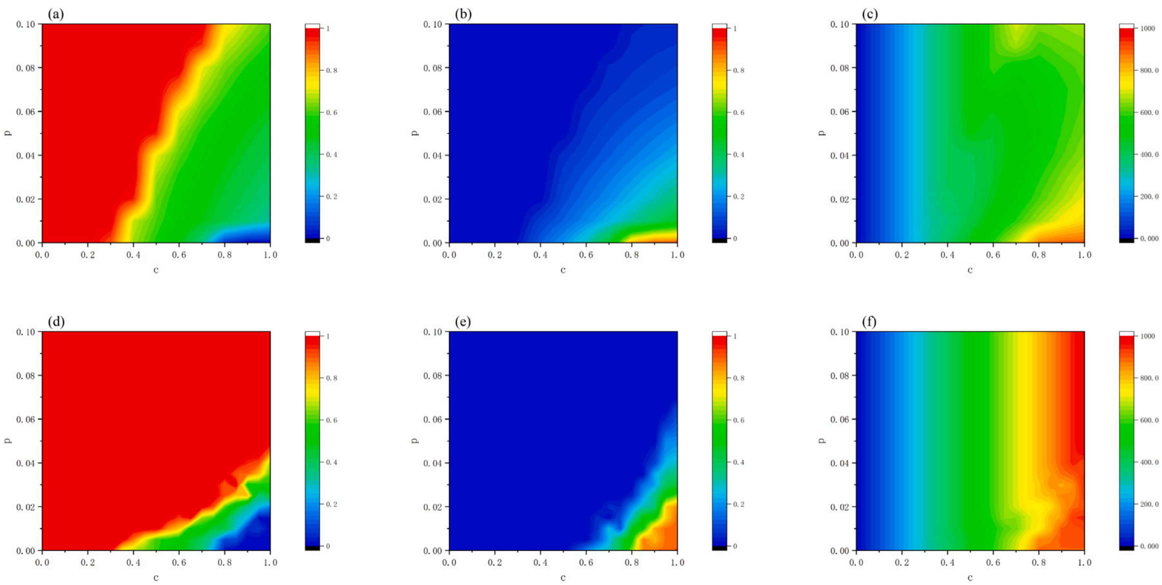

Fig. 5. The heat maps of S-TAR (top panel) and P-TAR (bottom panel) rely on vaccination cost c and the fraction of subsidized individuals p on the vaccination coverage V, the final epidemic size R, and the social cost SC, respectively. Parameters: $N = 1000$, $\langle k \rangle = 4$, $\lambda = 0.55$, $\mu = 1/3$, $K = 1$, $\beta = 1$, $\gamma = 0.8$.

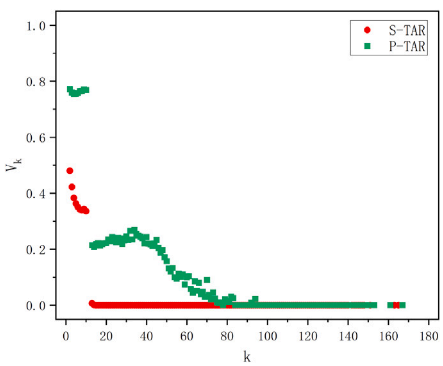

Fig. 6. The voluntary vaccination probability V_k as functions of degree k for S-TAR and P-TAR policy. Parameters: $N = 1000$, $\langle k \rangle = 4$, $\lambda = 0.55$, $\mu = 1/3$, $K = 1$, $\beta = 1$, $\gamma = 0.8$, $c = 0.95$, $p = 0.04$.

and p is low, the areas with lower vaccination coverage and larger epidemic sizes are more widespread. This is because the vaccination cost and the punishment cost for the punishers need to be subsidized under the P-TAR policy, the proportion of individuals being subsidized is smaller and subsidized punishers are not necessarily individuals with the highest degrees. However, when p is large enough, vaccination coverage is high even when $c = 1$.

We will explain deeply how the P-TAR and S-TAR policies affect vaccination coverage in the BA network. To investigate the voluntary vaccination behavior of each node in the BA network, we define the voluntary vaccination probability (excluding subsidized individuals) V_k as a proportion of the number of nodes with the same degree k (N_k^v) that voluntarily vaccinated to the total number of nodes with degree k (N_k), given as $V_k = N_k^v / N_k$. Fig. 6 compares the voluntary vaccination probability of the P-TAR and S-TAR policies. Hub nodes (nodes with higher degrees) are subsidized in both policies, thus, $V_k = 0$. Unsubsidized nodes are small nodes (nodes with lower degrees) in the BA network that are less likely to get vaccinated because of minimized infection risks. For the P-TAR policy, the probability of voluntary vaccination is higher for small nodes because there are more punishers around. As a result, the P-TAR policy effectively increases the vaccination coverage of all nodes compared to the S-TAR policy.

To show how the last evolutionary stable state gets reached for typical parameter values as time passes, Fig. 7 plots a detailed evolution process of vaccine coverage and epidemic size as functions of time steps with the implementation of P-TAR and S-TAR policies. Under the same conditions, for the S-TAR policy in Fig. 7(a), vaccination coverage quickly stabilized at around 0.66, and the final epidemic size is around 0.07. This result is consistent with the findings in Fig. 7(c). For the P-TAR policy, the vaccination coverage rapidly rises to 1 within just 50 MC steps and the epidemic size falls to 0 in Fig. 7(b). More specifically, the number of pure vaccinators increases in the short term, then declines, while punishers increase until the system reaches an equilibrium state. This is because highly connected nodes are more likely to become subsidized punishers and are less likely to change their vaccination decisions during the strategy update period. With the epidemic spreading, several susceptible individuals are aware of the risk of illness and are quickly becoming vaccinators or punishers. Therefore, the P-TAR policy can make sure that hub nodes are vaccinated and dynamically impact the strategies of unvaccinated individuals. Due to the influence of the subsidy policy, the number of punishers gradually increases over time and eventually reaches the entire network at 100 MC steps, as shown in Fig. 7(d).

3.3. Sensitivity analysis

In this section, we first discuss the results of the model for the larger network size $N = 2000$ and the average degree $\langle k \rangle = 4$, as illustrated in Fig. 8. $\gamma = 1$ is still set in this experiment. Our results show that vaccination coverage at larger network sizes begins to decline at $c = 0.6$ while the epidemic size rises. It demonstrates the faster spread of disease at larger network sizes. Obviously, the social cost SC increases proportionally with the network size. In addition, we study the impact of vaccination cost c and the fraction of subsidized individuals p on vaccination behavior, as depicted in Fig. 9. Notably, the results for the two network sizes are nearly consistent (Figs. 4(d)(e)(f) and 9).

In actually, the punished individual is usually punished only once rather than multiple times in a season. For example, when a person is proven guilty of a crime and determined to be guilty, they usually face a single punishment in the form of imprisonment, probation, or fines. As shown in Fig. 10, we compare two different punishment types: unvaccinated individuals are being punished by the surrounding punishers sequentially (punish-full) and only once (punish-one). In the above-mentioned results, punish-full is used as the punishment method.

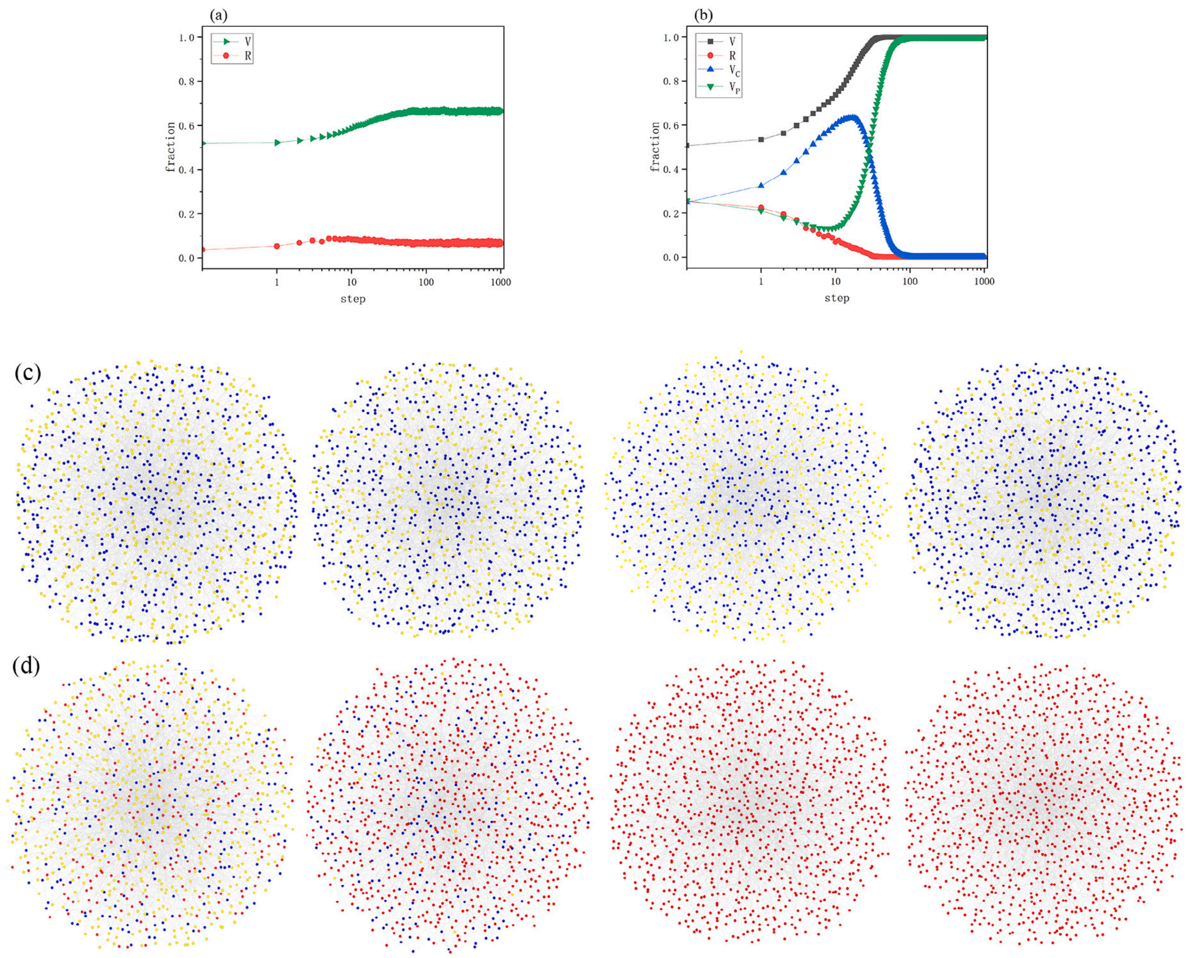

Fig. 7. The vaccination coverage and final epidemic size over time under S-TAR and P-TAR are shown in (a) and (b). Snapshots of individual simulations in the BA network for the S-TAR and P-TAR policies are shown in (c) and (d). The time steps are 0, 50, 100, and 2900 from left to right. Red nodes denote the punishers, blue nodes represent the pure vaccinators, and yellow nodes signify the unvaccinated individuals. Parameters: $N = 1000$, $\langle k\rangle = 4$, $\lambda = 0.55$, $\mu = 1/3$, $K = 1$, $\beta = 1$, $\gamma = 0.8$, $c = 0.6$, $p = 0.04$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

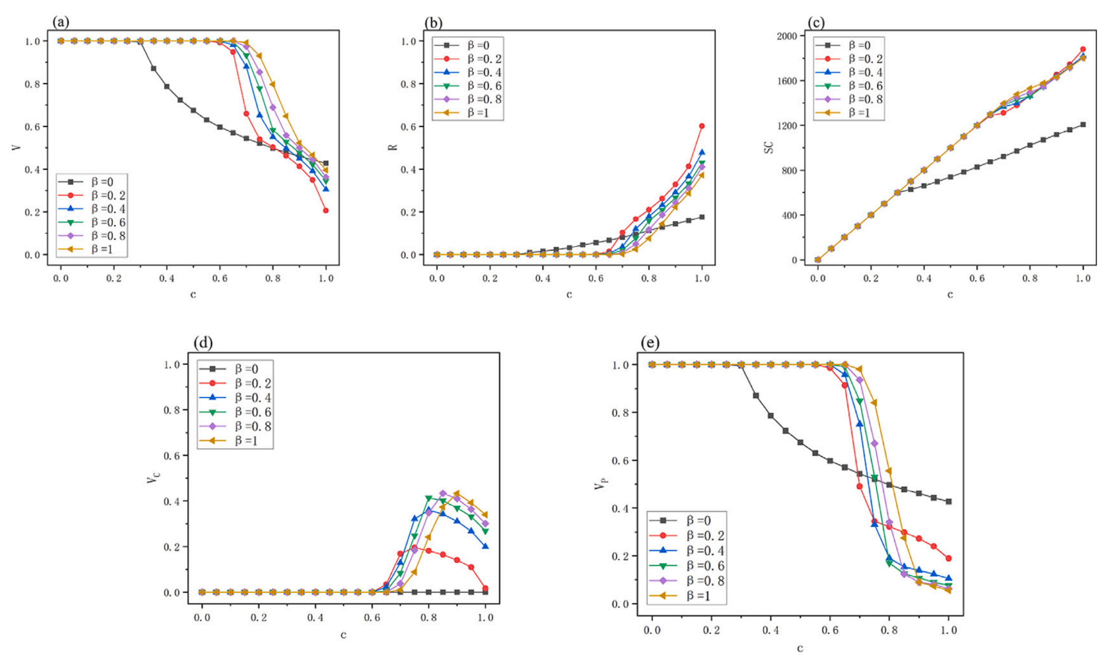

Fig. 8. (a) the vaccination fraction V, (b) the final epidemic size R, (c) the social cost SC, (d) the proportion of pure vaccinators V_C, and (e) the proportion of punishers V_P as functions of the relative cost of vaccination c with several typical values of the fines β. Parameters: $N = 2000$, $\langle k\rangle = 4$, $\lambda = 0.55$, $\mu = 1/3$, $K = 1$, $\gamma = 1$, $p = 0.04$.

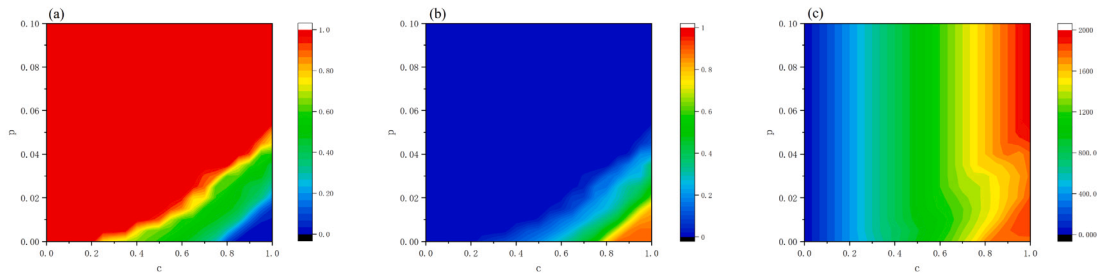

Fig. 9. The heat maps of P-TAR rely on vaccination cost c and the fraction of subsidized individuals p on the vaccination coverage V, the final epidemic size R, and the social cost SC, respectively. Parameters: $N = 2000$, $\langle k \rangle = 4$, $\lambda = 0.55$, $\mu = 1/3$, $K = 1$, $\beta = 1$, $\gamma = 0.8$.

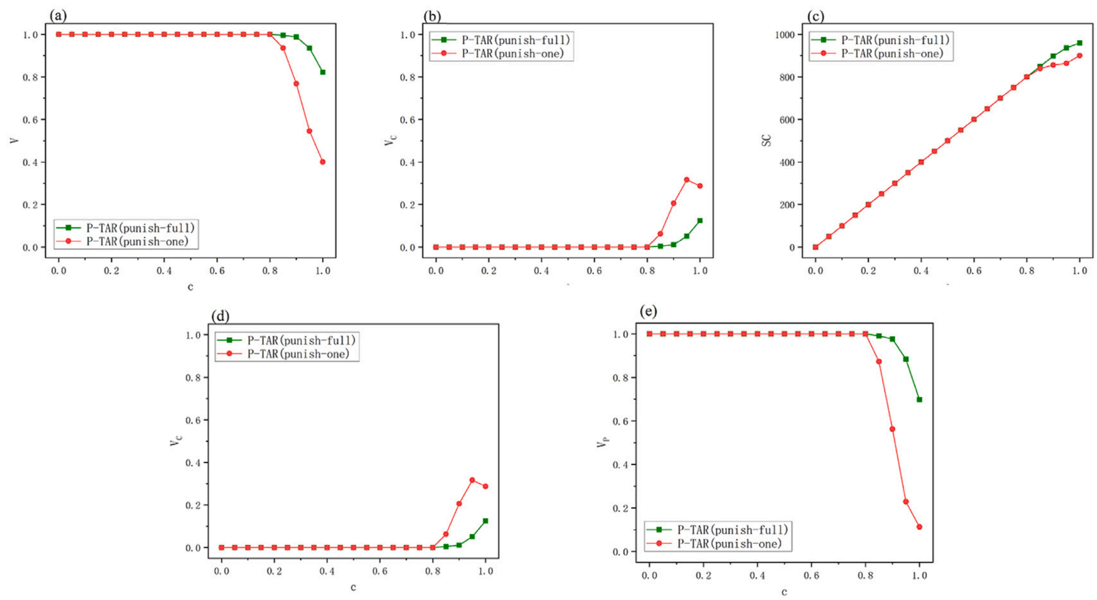

Fig. 10. Comparison of two punishment types. (a) the vaccination fraction V, (b) the final epidemic size R, (c) the social cost SC, (d) the proportion of pure vaccinators V_C, and (e) the proportion of punishers V_P as functions of the relative cost of vaccination c. Parameters: $N = 1000$, $\langle k \rangle = 4$, $\lambda = 0.55$, $\mu = 1/3$, $K = 1$, $\beta = 1$, $\gamma = 0.8$, $p = 0.04$.

For punish-one, the fine for unvaccinated individual i at time t is defined as $W_i(t) = \beta \cdot f(N_{pv,i}(t-1))$, where the step-like function $f(Z)$ is 1 if $Z > 0$ and 0 otherwise. unvaccinated individuals be punished by a randomly selected punisher in the neighborhood. Fig. 10 shows the results of the two punishment approaches in terms of the vaccination coverage, the final epidemic size, and the social cost. It is clear that the social cost is lower for punish-one (Fig. 10(c)). Further analysis of the results indicates that both types of punishment yield similar results at lower vaccination costs ($c \leq 0.8$). Nevertheless, punish-full leads to higher vaccination coverages and smaller epidemic sizes than punish-one at higher vaccination costs ($c > 0.8$). Therefore, it can be concluded that unvaccinated individuals are being punished sequentially by the surrounding punishers are more likely to promote vaccination.

In the previous part, we assume that vaccination provide perfect immunity each season. Actually, the failure of vaccines due to improper storage, transportation, or usage can increase the risk of infection for vaccinated individuals. Here, we introduce a parameter θ to describe the vaccine failure rate [51], which describes the probability that susceptible individuals will not achieve immunity even after vaccination. As depicted in Fig. 11, we analyze the common effects of vaccination cost c and the fraction of subsidized individuals p on vaccination behavior for different vaccine failure rates θ. It is obvious that subsidy policy with punishment mechanism is still a positive impact on promoting individual vaccination and preventing epidemic transmission at the lower vaccine failure rates ($\theta = 0.02$). As θ increases, fewer healthy individuals opt for vaccination, which increases the risk of epidemic outbreaks. In scenarios where the vaccine failure rate is high ($\theta = 0.8$), on the one hand, vaccination coverage remains relatively high when the cost of vaccination is relatively low. On the other hand, the fraction of subsidized individuals p is ineffective in terms of promoting vaccination behavior. Therefore, after introducing vaccine failure rates in our model, it can be found that θ greatly influences the evolution of vaccination behavior.

4. Conclusion and discussion

In this study, we explore how individual vaccination behavior is influenced by the combination of subsidy policy and punishment mechanism. More specifically, we introduce the punisher, who can monitor the group and then decide whether it will be subsidized according to the degree of the punisher. First, by simulating based on the SIR epidemic dynamics to analyze the effects of fines and punishment costs on vaccination behavior under the P-TAR policy. The results show that with fines are high and punishment costs are low, this strategy can be effective in preventing the spread of epidemics despite the vaccination cost is high. In these situations, unvaccinated individuals face more constraints because there are more punishers. Then, We compare the P-TAR policy with the S-TAR policy, and the results show that the P-TAR policy is more effective in improving vaccination coverage than the S-TAR policy. We also analyze the co-effect of subsidized population proportion and vaccination cost on vaccination behavior, showing that individuals are more inclined to be vaccinated at larger subsidized population proportions and smaller vaccination costs, and the P-TAR have larger areas with high vaccination coverage and smaller areas with

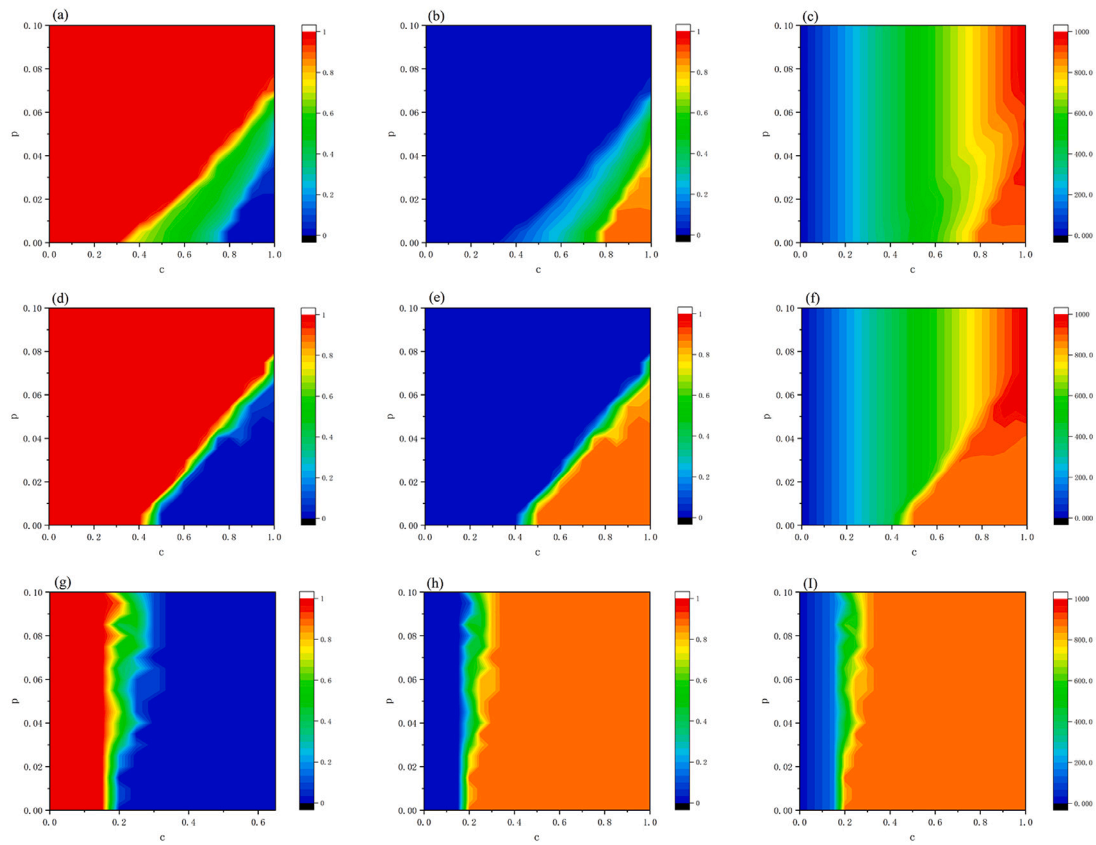

Fig. 11. The heat maps of vaccination cost c and the fraction of subsidized individuals p on the vaccination coverage V (left), the final epidemic size R (middle), and the social cost SC (right) for different vaccine failure rate θ: $\theta = 0.02$ (top panel), $\theta = 0.4$ (middle panel), $\theta = 0.8$ (bottom panel), respectively. Parameters: $N = 1000$, $\langle k \rangle = 4$, $\lambda = 0.55$, $\mu = 1/3$, $K = 1$, $\beta = 0.4$, $\gamma = 1$.

low epidemic sizes. We discover P-TAR is more effective in preventing epidemic spreading through micro-analysis because it improves vaccination coverage in all nodes. However, the social cost is significantly higher because the punishment cost is included in the social cost. The results demonstrate the implementation of a strict policy can effectively control the outbreak of epidemics. However, the social cost of the strict policy is significant high. Therefore, a reasonable balance between costs and benefits must be considered when implementing a strict policy to promote vaccination coverage.

In the section on sensitivity analysis, we initially verify the results on larger network sizes, despite the faster spread of the epidemic on larger network sizes. We find that the results for the two network sizes are nearly consistent. And the social cost increase proportionally with the network size. Next, we introduce an alternative punishment approach where unvaccinated individuals are punished only once (punish-one), regardless of the number of punishers surrounding them. This method of punishment proves to be less effective than punish-full. Lastly, we examine the impact of imperfect vaccines on individuals vaccination behavior within the model. There is still higher vaccination coverage at lower vaccine failure rates. As the vaccine failure rate increases, fewer susceptible individuals chose to vaccinate, but the vaccination coverage remains high when the vaccination cost is lower. Meanwhile, the fraction of subsidized individuals p is ineffective in terms of promoting vaccination behavior. This finding indicates that the vaccine failure rate has a greater influence on individual vaccination behavior. We hope that our study will serve as an inspiration for the formulation of vaccination policies.

CRediT authorship contribution statement

Jingrui Wang: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Huizhen Zhang:** Software, Writing – review & editing. **Xing Jin:** Investigation, Validation. **Leyu Ma:** Software, Visualization. **Yueren Chen:** Investigation, Data curation. **Chao Wang:** Funding acquisition, Validation. **Jian Zhao:** Funding acquisition, Project administration. **Tianbo An:** Conceptualization, Project administration.

Declaration of competing interest

This manuscript has not been published before and is not being considered for publication elsewhere. All authors have contributed to the creation of this manuscript for important intellectual content and read and approved the final manuscript. We declare there is no conflict of interest.

Data availability

Data will be made available on request

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