The impact of neighbor-reliant immunity on vaccination for COVID-19

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Abstract Recently, people have been being vaccinated the vaccine against covid-19 for some time, but the vaccine is new, while people want to obtain immunity through vaccination, they are also worried about the efficacy and side effects after vaccination. Not everyone is absolutely willing to get vaccinated. A typical idea resistant to vaccination is that if the people around the individual itself are vaccinated, the individual itself will not be infected without being vaccinated and will not have to bear the risk of vaccination. We call this neighbor-reliant immunity (NRI). In this article, we mainly studies how the trust in vaccines against COVID-19 and the reliance on neighbors affect individuals' attitude toward vaccination and the process of vaccination based on network. Every time how the willingness to get vaccinated of the individual itself changes is affected by the vaccination performance of its neighbors. What we can find is that when people's trust in vaccines increases or their reliance on neighbors increases, it will lead to an increase in the rate of vaccination and speed up the process of vaccination.

Keywords COVID-19 · Vaccination dynamics · Neighbor-reliant immunity

1 Introduction

Since the coronavirus disease 2019 (COVID-19) broke out at the end of 2019 in Wuhan, China, it has deprived countless lives and done great harm on thousands of families in past two years. COVID-19 has imposed tremendous pressures onto the healthcare system in all regions and countries. Without any exaggeration, some public medical systems have almost been paralyzed during the severe epidemic. This ongoing epidemic is destined to be a heart-wrenching disaster [1,2].

Epidemic dynamics has always been a topic of great concern to scholars. They have always been trying to establish various models to explore the internal mechanism in the transmission of different kinds of diseases, analyzing various factors affecting epidemic dynamics, and hoping to find effective methods to inhibit its spread [3,4,5]. Before the outbreak of COVID-19, a large number of scholars have accumulated much experiences on the spread of the disease. They have researched transmission mechanisms of epidemics with different models based on different networks [7,8,9,10]. After the COVID-19 broke out, as a kind of unknown, highly contagious and extremely harmful disease, it quickly attracted the attention of scholars all over the world [11,12]. They try to build proper models based on past experiences and existing data to understand its transmission mechanism and predict its future development, so as to propose favorable methods to slow down the spread and reduce the loss [13,14,15,16]. At the same time, before a qualified vaccine has been produced, as an epidemic that can be transmitted from person to person, experts are actively proposing various methods to reduce contact between people and try to suppress the increase in the number of infected individuals [17,18,19,20].

When the vaccine against COVID-19 came out, governments were encouraging residents to get vaccinated to reduce the possibility of being infected. The immunity established by vaccination has an absolute advantage in preventing from being infected [22,23]. However,
the vaccine is new, which means it has not undergone long-term and stable clinical test. On one hand, people are well aware of the advantages of vaccination, on the other hand, they always have certain doubt about the efficacy and side effects of the new vaccine. Therefore, although the vaccine against COVID-19 is qualified have, and the government is encouraging people to get vaccinated, not everyone is absolutely willing to get vaccinated where the epidemic is relatively stable, especially in areas that it has been basically controlled and eliminated due to the above considerations. Based on these analysis, In this paper we mainly studies a typical resistant thought, that is, one wants to gain immunity from the vaccine, but does not want to bear the side effects the vaccine may cause. A reliable prerequisite to the realize this scenario is that all members around the individual are vaccinated. More specifically, if all neighbors are vaccinated, then a individual will be in a safe encirclement, and thus it can choose not to get vaccinated. We call this kind of psychology as neighbor-reliant immunity (NRI). This is why many people were paying attention on whether their neighbors were going to get vaccinated in the early days, holding the idea that if they did, then I do not do it.

In the paper, we attempted to investigate two questions. The first one is how does trust in vaccines affect the process of vaccination? The second is how does reliance on neighbors affect individuals’ willingness to get vaccinated? The greater the dependence on neighbors means that every time when the neighbor’s performance on vaccination changes, it will cause greater fluctuations in the vaccination willingness for the individual itself. The results show that the more trust people have in the vaccine, then more people will get vaccinated eventually, and the vaccination process will speed up. What is more impressive is that when people become more reliant on the performance of their neighbors, more people will get vaccinated eventually, and the vaccination process will also slightly speed up. Making a comparison between the two, increasing trust in vaccines will cause a more significant improvement.

The remaining part of the paper is organized as follows. In the Sec. 2, we describe the process of vaccination reliant on neighbors. The main conclusion is in Sec. 3. Finally, the main work in the paper is summarized and its practical significance is discussed.

\section{Model}

In this paper, we construct a model to describe how the vaccination process evolves with the idea of neighbor-reliant immunity. It include two key factors, the trust in vaccines and the reliance on neighbors. The model is based on a network. The relationship in a community can be described by an adjacency matrix \( A_{N \times N} \), where \( N \) denotes the size of the network which means how many people in the community and each node represents an individual. If \( A_{ij} = 1 \), then node \( i \) is connected to node \( j \), which means that the individual \( i \) and the individual \( j \) are neighbors. Their attitude towards vaccination has a direct influence on each other; otherwise, \( A_{ij} = 0 \), then node \( i \) is not connected to node \( j \), which means that the individual \( i \) and the individual \( j \) are not neighbors. Their willingness of vaccination has an indirect impact on each other at most. \( N_i = \sum_{j=1}^{N} A_{ij} \) represents the number of neighbors for individual \( i \).

The evolution model is described as follows. The basic idea is that at each time, whether a individual’s willingness to vaccinate changes is decided by the trust in vaccines \( T \in [0, 1] \) and neighbors’ average willingness to get vaccinated. The bigger \( T \) is, the more people trust in the vaccine. And how to change is decided by the reliance on neighbors \( r \in [0, 100] \). When \( r \) is greater, people are more reliant on their neighbors. The willingness of vaccination is denoted by the probability \( P_i(t) \) \( (i = 1, 2, \ldots, N, t = 0, 1, 2, \ldots) \), which represents the possibility to get vaccinated for individual \( i \) at time \( t \).

The initial value

\[ P_i(0) = \frac{N_i}{N_{\text{max}}} + \delta_i, \]  

where \( N_{\text{max}} \) represents the most neighbors a individual has. And \( \delta_i \in [0, 1] \) is the disturbance, representing other factors that influence the individual’s willingness to get vaccinated at first. From formula (1), we can see that when the vaccine comes out, the more neighbors a individual has, the more likely it is to get vaccinated for the individual. The reason is that more neighbors means more risk to be infected so people will have stronger willingness to get vaccinated and avoid the risk.

At each time \( t \), every individual can choose to increase the probability to get vaccinated or decrease the probability to get vaccinated or keep the same as last time. Take individual \( i \) as an example. That is,

\[ P_i(t) = \begin{cases} P_i(t-1)(1+r\%) & \text{if } AP_i(t-1) < T \\ P_i(t-1) & \text{if } AP_i(t-1) = T \\ P_i(t-1)(1-r\%) & \text{if } AP_i(t-1) > T \end{cases} \]  

t = 1, 2, 3, \ldots, where \( AP_i(t) = \left( \sum_{j=1}^{N} P_j(t-1) \right) / N_i \) represents the average probability of neighbors to get vaccinated. A larger \( d \) means the neighbors’ choice has a greater influence on the individual. Here, it is worth noting that \( P_i(t) \in [0, 1] \) \( (i = 1, 2, \ldots, N, t = 0, 1, 2, \ldots) \), if \( P_i(t) \geq 1 \) at any time \( t \), then \( P_i(t) \triangleq 1, \forall t^* \geq t \). That means that once \( P_i(t) \) reaches 1, then the
individual $i$ will go to get vaccinated. So the individual has been vaccinated and its status will not change from then on.

### 3 Results

In this section, we perform a mass of stochastic simulations to show the impact of neighbor-reliant immunity on the process of vaccination. Before that, we need to make some statements about the network. We build a BA network as an approximate representation of relationship between individuals in a community. Initially, we introduce $m_0 = 200$ nodes. The new nodes continue to be linked the existing network with each $m = 5$ until the size of the network reaches $N = 5000$. Then all the simulations are based on this network.

First, we focus on the impact of trust in vaccines on vaccination. It can be seen from Fig. 1 that, as $T$ increases, nodes clustering in low vaccination probability become less and gradually approach to higher vaccination probability. The distribution of nodes tends to stabilize at a faster speed when $T$ increases. That is to say, as people trust vaccines more, people’s willingness to vaccinate will be stronger, and the entire vaccination process will speed up. In addition, how the average vaccination probability of the whole network $AP = \sum_{i=1}^{N} P_i(t)/N$ changes over time presents three different trends as shown in Fig. 3(a). When $T$ is relatively small, the average vaccination probability to get vaccinated of all individuals will rapidly rise to a peak at first, and then slowly rises until it stabilizes at a relatively small level. When $T$ is moderate, the average willingness will first rapidly increases to a higher peak and then gradually decreases until it stabilizes at a relatively higher level. When $T$ is great, the average vaccination probability will first rapidly increases to a much higher peak, then go through a short period of decline, and then slowly increases until it stabilizes at a much higher level. Also, from Fig. 3(b) it can be seen that the final fraction of vaccinated individuals $VP = \sum_{i=1}^{N} P_i(t)/N, P_i(t) = 1$ is increasing and stabilizes more rapidly as $T$ is increases. And the time
Fig. 2 The time evolution of the proportion of nodes in different vaccination probability under several different values of $r$ with $T = 0.7$. There are 50 stochastic simulations performed. $r = 0.05, 0.1, 0.15, 0.2, 0.25$ and 0.3.

evolutions of it keeps similar under different $T$, which rises fast at first and then gradually stabilizes. It is worth noting that even a period of decline in the middle will occurs when $T$ is great, but the initial peak of the average vaccination probability and the final vaccination rate will increase with the increase of $T$, and the process of vaccination will also speed up under a higher $T$. It shows that enhancing the trust in vaccines is an effective way to promote the rate of vaccination even through during the process people will experience a short time of willingness decreasing.

To make it clear that how reliance on neighbors affects the evolution of vaccination, we respectively explored similar characters under different $s$ with $T$ fixed. From Fig. 2 we can kown that as $r$ increases, Similarly, the individuals clustering in low willingness to get vaccinated become less and approaches to area in which the probability is higher and stabilize much faster. But different from the discussion about $T$, the increasing of $s$ does not change the trend of time evolution of average vaccination probability $AP$. From Fig. 4(a) whatever $s$ is, $AP$ will first rapidly increases to a peak, then go through a short period of decline, and then slowly increases until it stabilizes to a higher level. Also a bigger $s$ means a higher peak and that the final level of average vaccination probability $VP$ will increase. Besides, 4(b) can tell us that if individuals are more reliant on neighbors, there will be more individuals willing to get vaccinated and the process of vaccination will speed up.

Finally, we simply investigate the influence of degree on the vaccination. At first step, we analyze the final proportion of individuals whose degrees are higher than the average degree or lower than the average degree in the vaccinated nodes and in the non-vaccinated nodes under different $T$ and $r$ respectively. It can be observed from Fig. 5(a) and Fig. 6(a) that compared with non-vaccinated individuals, the proportion of individuals with a degree higher than the average degree is higher in vaccinated ones. At second step, we analyze The average degree of vaccinated nodes and non-vaccinated nodes under different $T$ and $r$. It can be seen from Fig. 5(b) and Fig. 6(b) that the average degree of non-vaccinated nodes is significantly lower than the average degree, but the average degree of vacci-
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Fig. 3 (a) The time evolution of average vaccination probability of all nodes under several different values of $T$ with $r = 0.1$. There are 150 stochastic simulations performed and lines with different color represents different value of $T$ as shown. $T = 0.3, 0.4, 0.5, 0.6, 0.7$ and 0.8. (b) The time evolution of vaccinated nodes under several different values of $T$ with $r = 0.1$. There are 150 stochastic simulations performed and lines with different color represents different value of $T$ as shown. 

Fig. 4 (a) The time evolution of average vaccination probability of all nodes under several different values of $r$ with $T = 0.7$. There are 150 stochastic simulations performed and lines with different color represents different value of $r$ as shown. $r = 0.05, 0.1, 0.15, 0.2, 0.25$ and 0.3. (b) The time evolution of vaccinated nodes under several different values of $r$ with $T = 0.7$. There are 150 stochastic simulations performed and lines with different color represents different value of $r$ as shown. $r = 0.05, 0.1, 0.15, 0.2, 0.25$ and 0.3.

nated nodes is obviously higher than the average degree of. The above results means that the more neighbors, people are more willing to get vaccinated, because the more people they come into contact with each day, the greater the probability of being infected by their neighbors is. Also more neighbors means it harder to realize neighbor-reliant immunity (NRI) for it means more neighbors need to get vaccinated if the individual itself wants to be safe. So people have stronger willing to get vaccinated with more neighbors.

4 Conclusion

In this article, we simulate the vaccination process of COVID-19 mainly under the influence of a thought called NRI (neighbor-reliant immunity) in the BA network. Every time, How a individual’s willingness to get vaccinated changes is influenced by the trust in vaccines and the reliance on neighbors. When the neighbor’s average vaccination probability is lower than the individual’s confidence in the vaccine, taking the vaccine resistant to COVID-19 into account, the individual will increase their willingness to get vaccinated based on their reliance on the neighbor. When the neighbor’s vaccination probability is higher than the individual’s confidence in the vaccine, considering the risk of vaccination, individuals will decrease their willingness to get vaccinated based on their reliance on neighbors. Numerical simulations show that when people increase their trust in vaccines or increase their reliance on neighbors, both of them will lead to an increase in the final vaccination rate and speed up the vaccination process while increasing the trust in vaccines has a much more obvious help. What’s more, individuals with more neighbors
tend to have stronger willingness to be vaccinated so the percentage of individuals with a degree higher than the average degree of the network in the vaccinated ones is higher.

The significance of these conclusions is that it tells us that we can improve the vaccination rate and vaccination speed of the whole network by adopting some methods to improve people’s trust in vaccines and reliance on neighbors. But it is more effective to increase people’s trust in vaccines than to increase people’s reliance on neighbors.

In this paper a individual’s decision of vaccination is mainly determined by the average vaccination willingness of its neighbors. In fact, the process is more complicated, and the change of vaccination willingness will be affected by other important factors. For example, the number of vaccines. If the number of vaccines is limited which not everyone can get vaccinated when they want [23][24], it may increase the willingness to get vaccinated. For another example, the government may require residents to get vaccinated, if not, their travel may be restricted, and so on. Besides, the research based on multiplex network is worthy of in-depth consideration [25].

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Conflict of interest

The authors declare that they have no conflict of interest.
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