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Analyzing the COVID-19 vaccination behavior based on epidemic model with awareness-information

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A R T I C L E I N F O

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A B S T R A C T

Background: The widespread use of effective COVID-19 vaccines could prevent substantial morbidity and mortality. Individual decision behavior about whether or not to be vaccinated plays an important role in achieving adequate vaccination coverage and herd immunity.

Methods: This research proposes a new susceptible–vaccinated–exposed–infected–recovered with awareness-information (SEIR/V-AI) model to study the interaction between vaccination and information dissemination. Information creation rate and information sensitivity are introduced to understand the individual decision behavior of COVID-19 vaccination. We then analyze the dynamical evolution of the system and validate the analysis by numerical simulation.

Results: The decision behavior of COVID-19 vaccination in China and the United States are analyzed. The results showed the coefficient of information creation and the information sensitivity affect vaccination behavior of individuals.

Conclusions: The information-driven vaccination is an effective way to curb the COVID-19 spreading. Besides, to solve vaccine hesitancy and free-ride, the government needs to disseminate accurate information about vaccines safety to alleviate public concerns, and provide the widespread public educational campaigns and communication to guide individuals to act in group interests rather than self-interest and reduce the temptation to free-riding, which often results from individuals who are inadequately informed about vaccines and thus blindly imitate free-riding behavior.

1. Introduction

Nowadays, the novel coronavirus disease (COVID-19) as a major health hazard is spreading around the world and has attracted extremely wide public attention. In this crisis, many diagnostic methods and therapeutic strategies have been developed based on understanding the clinic pathological features of SARS-CoV-2 infection (Chakraborty et al., 2020; Cynthia et al., 2020). The vaccines are considered to be of great importance to prevent and control COVID-19 (Velavan and Meyer, 2020; Liu et al., 2020; Randolph and Barreiro, 2020), thus many countries are developing COVID-19 immune-mediated therapeutics and vaccines based on SARS-CoV-2 mechanisms of infection and its impact on host immunity (Helena et al., 2020; Emmanuel et al., 2020). However, one of the important challenges facing COVID-19 vaccination is the uncertainty of public acceptance of the COVID-19 vaccines (Taman et al., 2021). When realizing the potential risks of vaccine, e.g. quality control, potential side effects, and associated COVID-19 illness, individuals will reduce their willingness to get vaccinated, which induces substantial obstacles to achieve coverage and herd immunity (Kadali et al., 2021; Su et al., 2021; Jiang, 2020).

It is well known that, to expand vaccination coverage, awareness-information spread through multiple channels could have a considerable effect on the acceptance of COVID-19 vaccines, for example, the reported event of disease will trigger the spread of awareness among individuals, which may influence their vaccination decisions (Xia and Liu, 2014; Gao et al., 2018; Zuo et al., 2021). It is obvious that the obtained awareness-information amount of disease will substantially affect individuals' perceptions about disease severity and, hence, increase their tendency to vaccination. On the other hand, when realizing the potential risks of vaccine, individuals who are vaccine hesitant will reduce their willingness and delay in acceptance or refusal of vaccination despite the availability of vaccines and information about disease (Dror et al., 2020; Soares et al., 2021; Chou and Budenz, 2020). Besides, the ‘free riding’ is a very general phenomenon, some Individuals do not vaccinate even

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with complete information, while implicitly relying on enough others getting vaccinated to provide herd immunity (Yong and Choy, 2021; Ibuka et al., 2014; Feng et al., 2011). It is obvious that individuals are insensitive to the availability of vaccines and information about disease, which will lead to the declined acceptance of vaccination. Conversely, individuals who are extremely sensitive to diseases information will take immediate vaccination measures to protect themselves once their neighbors are found infected.

Motivated by the above considerations, we research how the information awareness affects the effectiveness of vaccination based on the previous researches (Ruan et al., 2012; Zhao et al., 2021). Two parameters are introduced to quantitatively characterize the information-driven vaccination. One is the information creation rate λ, which describes the amount of information acquired by individual. The other is the information sensitivity η, the stronger the sensitivity, the greater the likelihood of individual vaccination. The parameters are designed to facilitate the understanding of the decision behavior of COVID-19 vaccines.

The paper is organized as follows. In Section 2, we introduce the SEIR/V-AI model. In Section 3, we present the numerical simulations. In Section 4, we analyze the decision behavior of COVID-19 vaccines. Finally, conclusions and discussions are presented in Section 5.

2. Models

This work utilizes a variant of the analytical epidemic SEIR/V model to research the effect of information on vaccination. We assume that individuals start susceptible to infection (S), and can become exposed (E) after contact with an infectious individual. After a latent period, exposed individuals become infectious (I). After an infectious period, they either recover (R) or die (D). Some susceptible could develop into vaccinated individuals (V) to be protected. There is a constant birth rate δ and a fixed death rate μ, so that the total population N remains stable, and it is assumed that all newborns are unaware and susceptible to infection. The diffusion of information evolves with the parameters λ and η, and information from several neighbors will be collected by a susceptible individual at time t and $k_j(t)$ of them are infected that will increase with λ. The rate of vaccinated individuals p is proportional to $k_j(t)$ and η and expressed as $p(t) = 1\text{-}e^{-\eta k_j(t)}$.

As the state and transition probability of nodes in each time step can be described by dynamic transition diagram, we can obtain the differential equations to characterize the dynamical process, as shown in Fig. 1. The evolution of individuals through the SEIR/V model with information-driven vaccination is modeled with the following set of ordinary differential equations:

$$\begin{cases} \dfrac{dS}{dt} = \delta N - \beta \dfrac{S}{N} I - \left(1 - e^{-\eta k_j(t)}\right) S - \mu S \\ \dfrac{dE}{dt} = \beta \dfrac{S}{N} I - \alpha E - \mu E \\ \dfrac{dI}{dt} = \alpha E - \gamma I - \mu I \\ \dfrac{dR}{dt} = \gamma I - \mu R \\ \dfrac{dV}{dt} = \left(1 - e^{-\eta k_j(t)}\right) S - \mu V \end{cases} \tag{2.1}$$

where β is the coefficient of infection rate, α is the coefficient of migration rate of latency, and γ is probability of recovery.

The next generation matrix method (Diekmann et al., 2010; Fosu et al., 2020; Yang, 2014; Van d Watmough, 1945) begins by separating the classes of the model into two vectors: the vector X of"infected"classes is a disease compartment including asymptomatic stages of infection as well as symptomatic; the vector Y of"uninfected"classes is the uninfected compartment including susceptible and recovered individuals.

The infectious subsystem is deduced from Eq. (2.1) as:

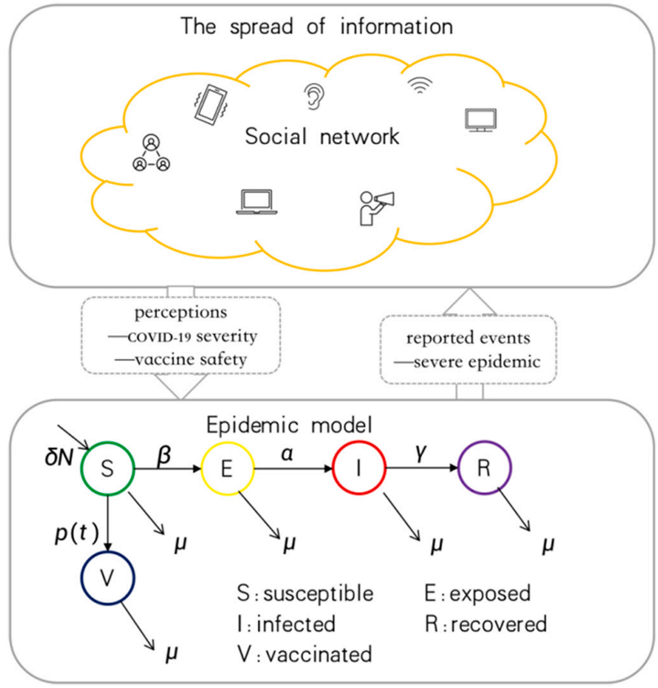

Fig. 1. Diagram of the SEIR model with vaccination.

$$X = \begin{pmatrix} E_{(t)} \\ I_{(t)} \end{pmatrix} = \begin{pmatrix} \beta \dfrac{S}{N} I - \alpha E - \mu E \\ \alpha E - \gamma I - \mu I \end{pmatrix} \tag{2.2}$$

The next step is to divide the X equation for discouraged classes into two separate rate vectors: F describes the rates of all transfers from Y to X, and V describes rates of all other transfers. We also adapt signs so that

$$X = F - V \tag{2.3}$$

The separation is

$$X = \begin{pmatrix} \beta \dfrac{S}{N} I \\ 0 \end{pmatrix} - \begin{pmatrix} \alpha E + \mu E \\ \gamma I + \mu I - \alpha E \end{pmatrix} \tag{2.4}$$

so

$$F = \begin{pmatrix} \beta \dfrac{S}{N} I \\ 0 \end{pmatrix} \quad V = \begin{pmatrix} \alpha E + \mu E \\ \gamma I + \mu I - \alpha E \end{pmatrix} \tag{2.5}$$

Then the Jacobian matrix from the system (2.5) is computed as

$$F = \text{Jaconbian}\left(F_{1,2}(E, I)\right) = \begin{pmatrix} 0 & \beta \dfrac{S}{N} \\ 0 & 0 \end{pmatrix}$$

$$V = \text{Jaconbian}\left(F_{1,2}(E, I)\right) = \begin{pmatrix} \alpha + \mu & 0 \\ -\alpha & \gamma + \mu \end{pmatrix} \tag{2.6}$$

The maximum eigenvalue of the inverse of the transition matrix is also computed as

$$\rho\left(FV^{-1}\right) = \frac{\alpha\beta S}{N(\mu + \gamma)(\mu + \alpha)} \tag{2.7}$$

The disease-free equilibrium in the following system (2.1) is $\left(\frac{\delta N}{\mu + 1 - e^{-\eta k_j(t)}} \ 0\ 0\ 0\ \frac{\delta N\left(1 - e^{-\eta k_j(t)}\right)}{\mu^2 + \mu\left(1 - e^{-\eta k_j(t)}\right)}\right)$, and the basic reproductive number is

$$R_0 = \frac{\alpha\beta\delta}{(\mu+\gamma)(\mu+\alpha)(\mu+1-e^{-\eta k_j(t)})} \tag{2.8}$$

In this case, we do not consider the effect of total population N, natural birth rate δ and death rate μ on the basic reproductive number R_0. Fig. 2 shows the evolution of the basic reproduction number R_0 for various parameters. In each subgraph, for those values of parameters at which the graph is under the line which indicates where R_0 crosses the unity, the disease can be extinct. However, when it is over the line, the disease can persist. It is evident that R_0 declines for parameters α and β while rises for parameters γ and η. Thus, the disease can be retarded or even removed by controlling the parameters such that R_0 to lie beneath unity.

3. Numerical simulations

Considering that epidemics can be more favorably and easily controlled on scale-free networks than on random networks under voluntary vaccination (Zhang et al., 2010), we perform simulation on a scale-free network with size $N = 2000$ and average degree k=4, and run the proposed model with the above-mentioned parametrizations under various scenarios to reveal the impact of information on individual's vaccination.

Firstly, 1% of the total nodes to be infected is randomly chosen, parameters α = 0.4, β = 0.6, γ = 0.2 are fixed and the effect of information creation rate λ on the disease spreading is analyzed through setting the information sensitivity η = 0.4. Fig. 3 shows the evolution of ρ^I and $\rho^R$for λ = 0.2, 0.4, and 0.6, respectively. As information rate λ increases, the proportion of infected individuals decreases from a holistic view in Fig. 3(a). As shown in Fig. 3(b), the density of recovered individuals shows a downward trend. In other words, the larger λ is, the smaller the number of individuals is infected. Aware of disease infections, individuals may choose to be vaccinated to protect themselves from disease infections.

Secondly, information generation rate λ = 0.4 is set to explore the effect information sensitivity η has on epidemic propagating. Fig. 4 shows the evolution of ρ^I and $\rho^R$for η = 0.5, 1, and 2, respectively. Fig. 4 (a) shows that the number of infected individuals decreases as η value decreases. Fig. 4(b) demonstrates the decreasing density trend of recovered individuals as η value grows. Thus, the larger η is, the node is more likely to get vaccinated to reduce the spread of epidemic once it finds infected neighbors. While for a smaller η, individuals are reluctant to vaccinate because of vaccine hesitancy and free-riding behavior. To depict the effect λ and η have on disease spreading, the final refractory density ρ^R is calculated. As shown in Fig. 5, ρ^R becomes large when either λ or η is small. When λ and η become large, ρ^R gradually declines to a small value.

Thirdly, we explore the impact of information creation rate λ (information sensitivity η) on the density $\mu=\rho^V$of the final vaccination by setting information sensitivity η = 0.4 (information creation rate λ = 0.8). Fig. 6 illustrates the density $\mu=\rho^V$of the final vaccination for three typical parameters λ = 0.2, 0.4, and 0.6 (η = 0.5, 1, and 2), respectively. From Fig. 6(a), we see that the number of individuals vaccinated rise with the increase of information dissemination coefficient λ. As illustrated in Fig. 6(b), as individuals become more sensitive to information, more and more individuals get vaccinated. Fig. 7 illustrates how the

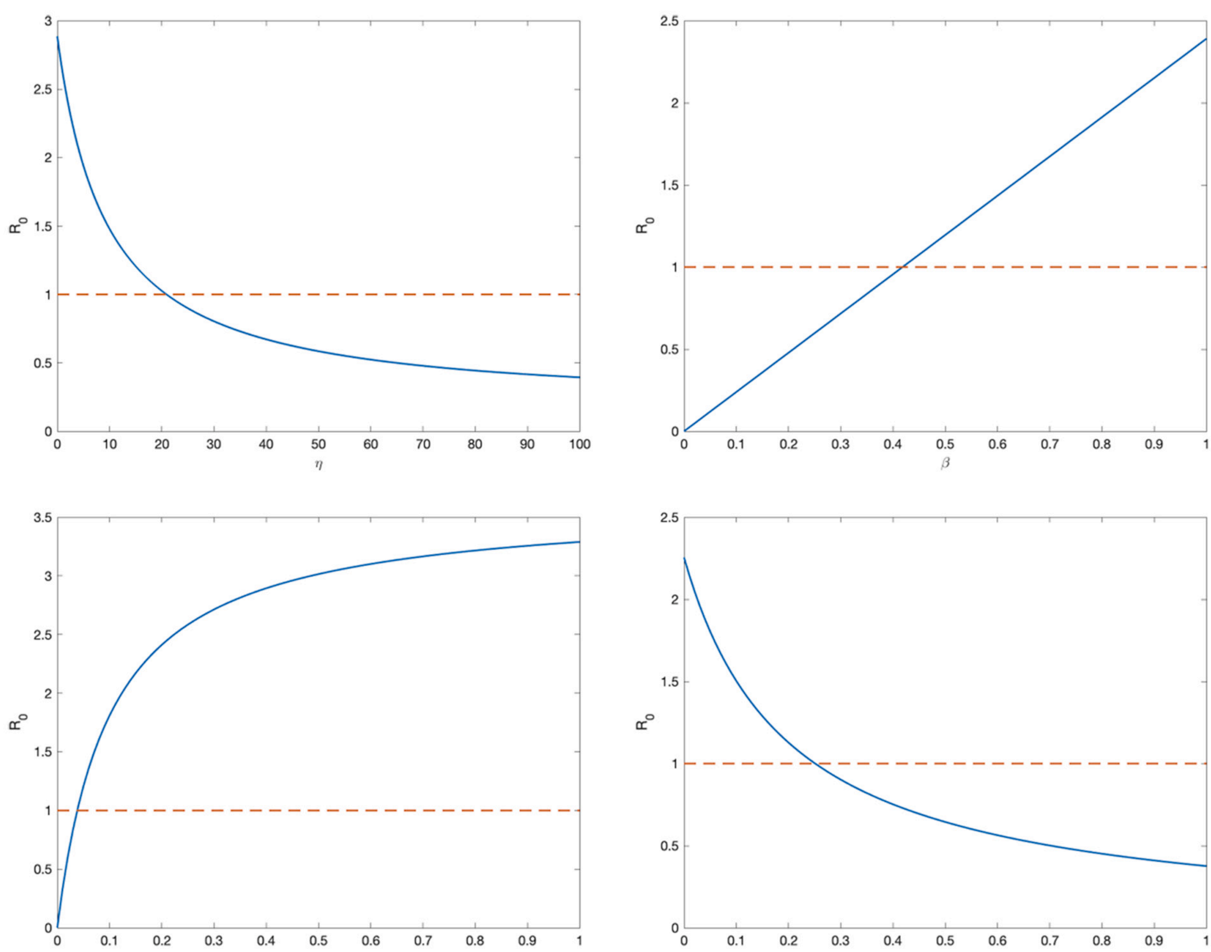

Fig. 2. The basic reproduction number R_0 for model (solid lines) for the corresponding model without vaccination in terms of parameters η,β, α, and γ, respectively.

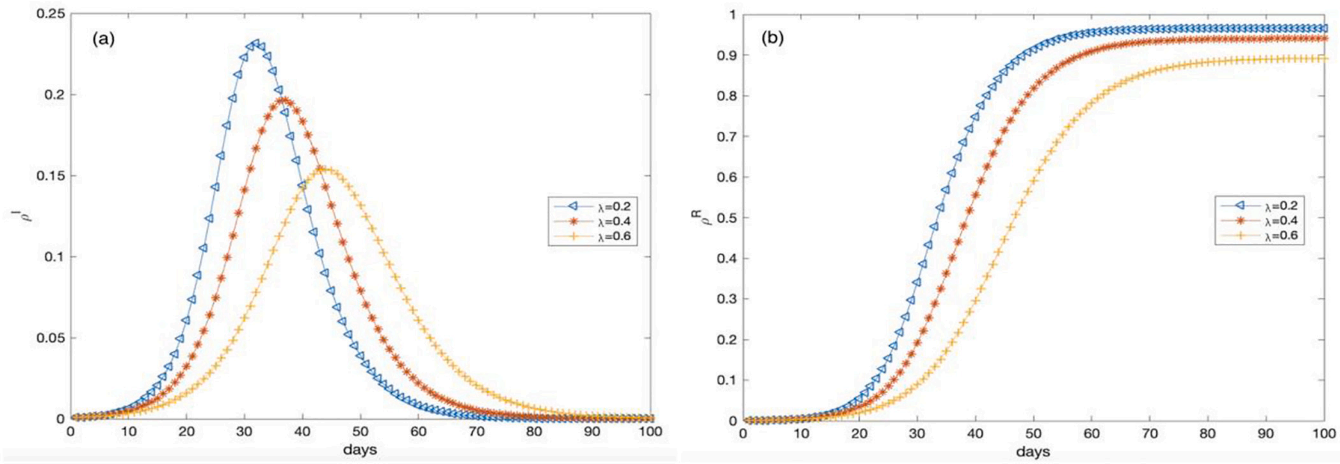

Fig. 3. ρ^I and ρ^R as functions for fixed parameter $\eta = 0.4$, where three lines represent the cases of λ =0.2,0.4, and 0.6, respectively.

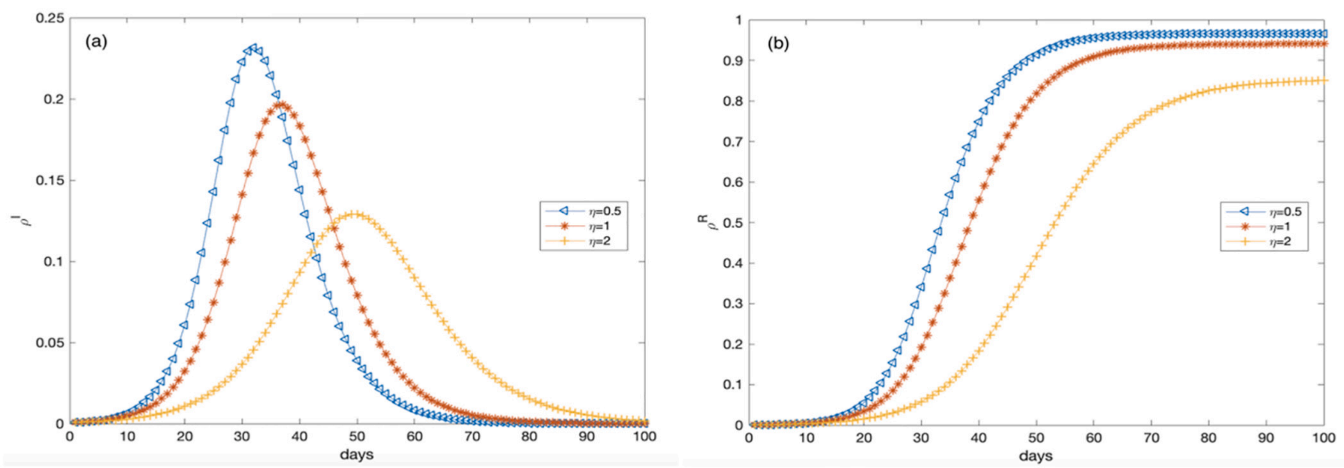

Fig. 4. $\rho^I$and ρ^R as functions for fixed parameter $\lambda = 0.4$, where three lines represent the cases of η =0.2,0.4, and 0.6, respectively.

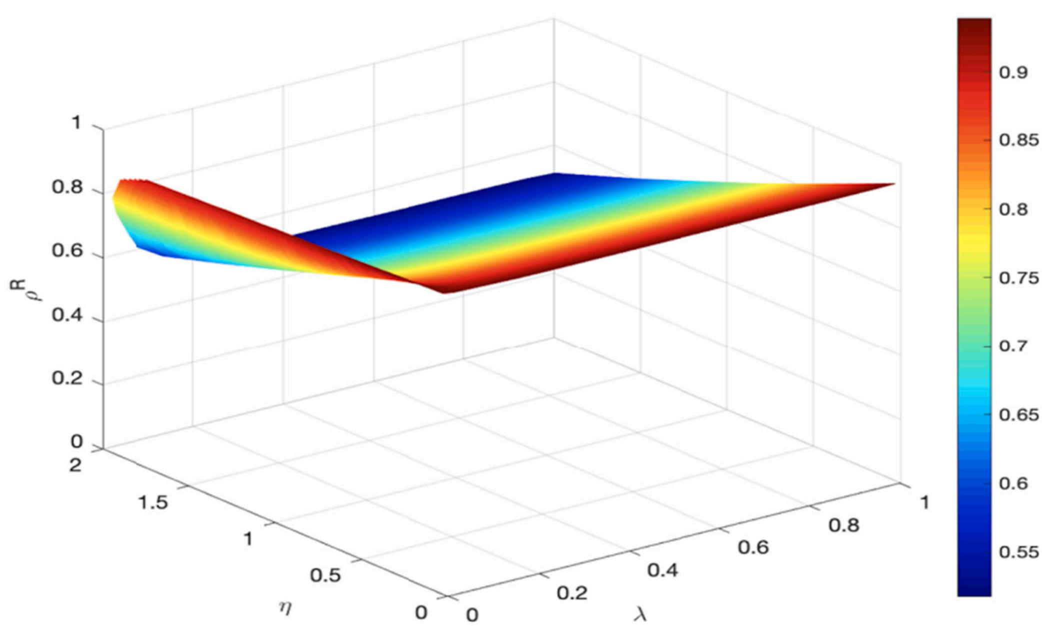

Fig. 5. The final refractory density ρ^R versus the parameters λ and η.

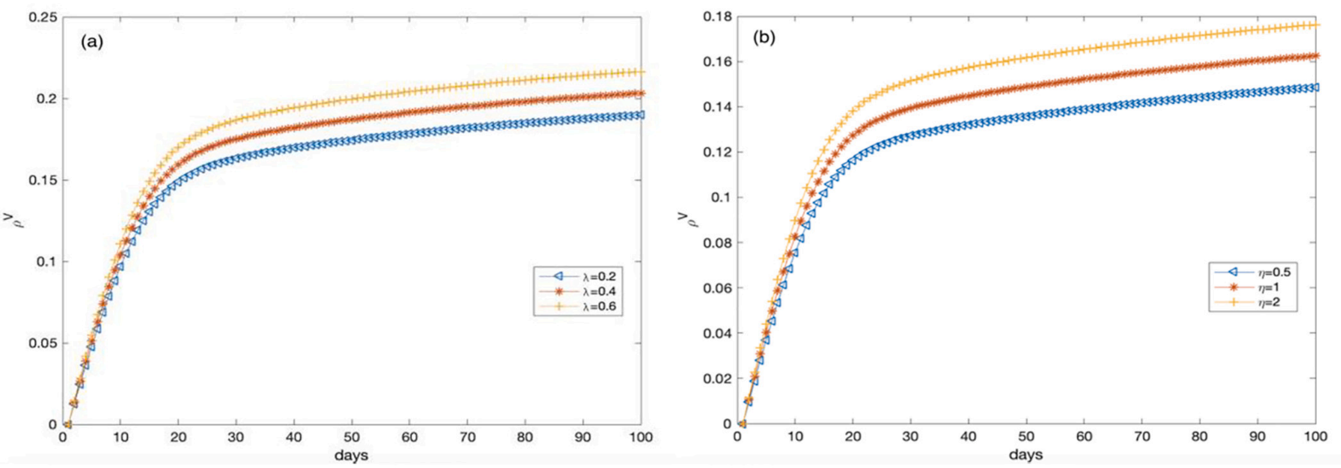

Fig. 6. (a).ρ^Vas functions for fixed parameter η = 0.4, where three lines represent the cases of λ = 0.2,0.4, and 0.6, respectively. (b).ρ^Vas functions for fixed parameter λ = 0.4, where three lines represent the cases of η = 0.2, 0.4, and 0.6, respectively.

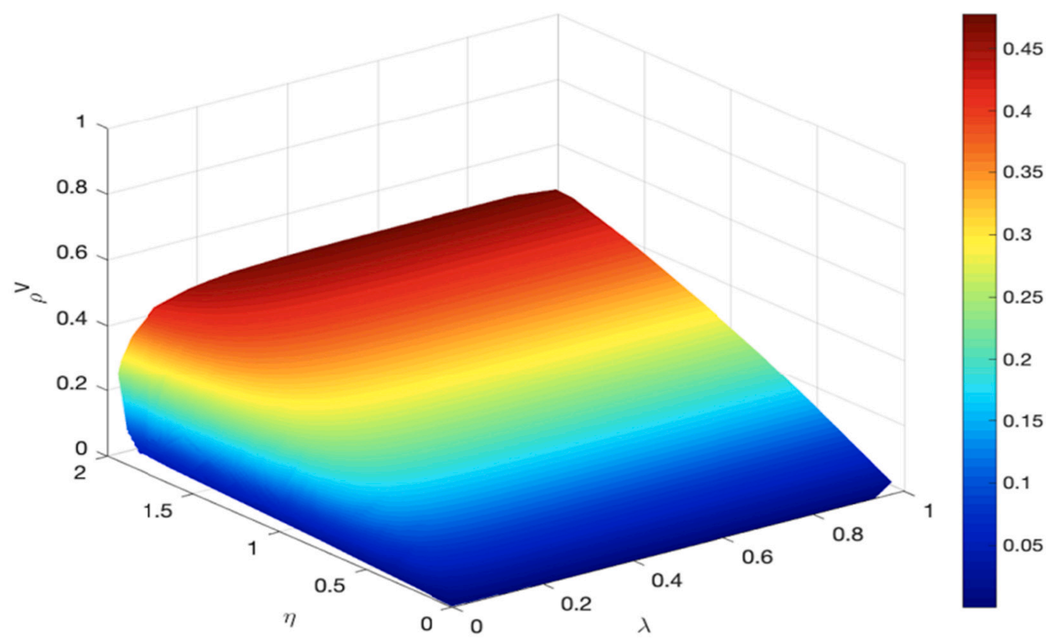

Fig. 7. The final vaccinated density ρ^V versus the parameters λ and η.

final ρ^V relies on parameters λ and η. It is clear that ρ^V has smaller values when λ and η are beyond the optimal region and increases much faster at the onset of evolution when λ and η are large. This phenomenon illustrates that the higher information creation rate λ and information sensitivity η is, the more willingness individuals will have to get vaccinated.

4. Case analysis of the decision behavior of COVID-19 vaccines in the United States and China

As of 30 June 2021, it was reported that 3.09 billion doses of COVID-19 vaccines had been administered worldwide, including 326.52 million and 1.24 billion doses in the United States and China, respectively.

As shown in Fig. 8, the United States has already struggled with reaching high rates of vaccine coverage. This phenomenon can be explained as: in the early stages of the COVID-19 outbreak, the utilities of vaccines to prevent future infections and deaths have been strongly advocated by public health authorities in the process of vaccine development. More importantly, health communication have reached all communities to educate individuals about the safety of vaccines. Thus, when individuals receive more global information announced by public health authorities and local information from social neighbors, the information creation rate λ increases constantly, making individuals prefer to getting vaccinated. As shown in Fig. 9, from mid-January 2021 to early March, daily confirmed cases of COVID-19 have dropped dramatically, the case fatality rate has dropped from 10% to 2%. Meanwhile, successful vaccinations strengthen public trust in government, public health and vaccine science, which further induces the increase of information sensitivity η, thus improving the willingness to vaccinate.

It is clear that the constantly increasing information creation rate λ and information sensitivity η have led to the higher vaccination rates in the United States. However, Chinese attitude toward vaccines contrast with those in the United States in the following four stages.

(1) The first stage (between the 15 February and 15 March, 2021)

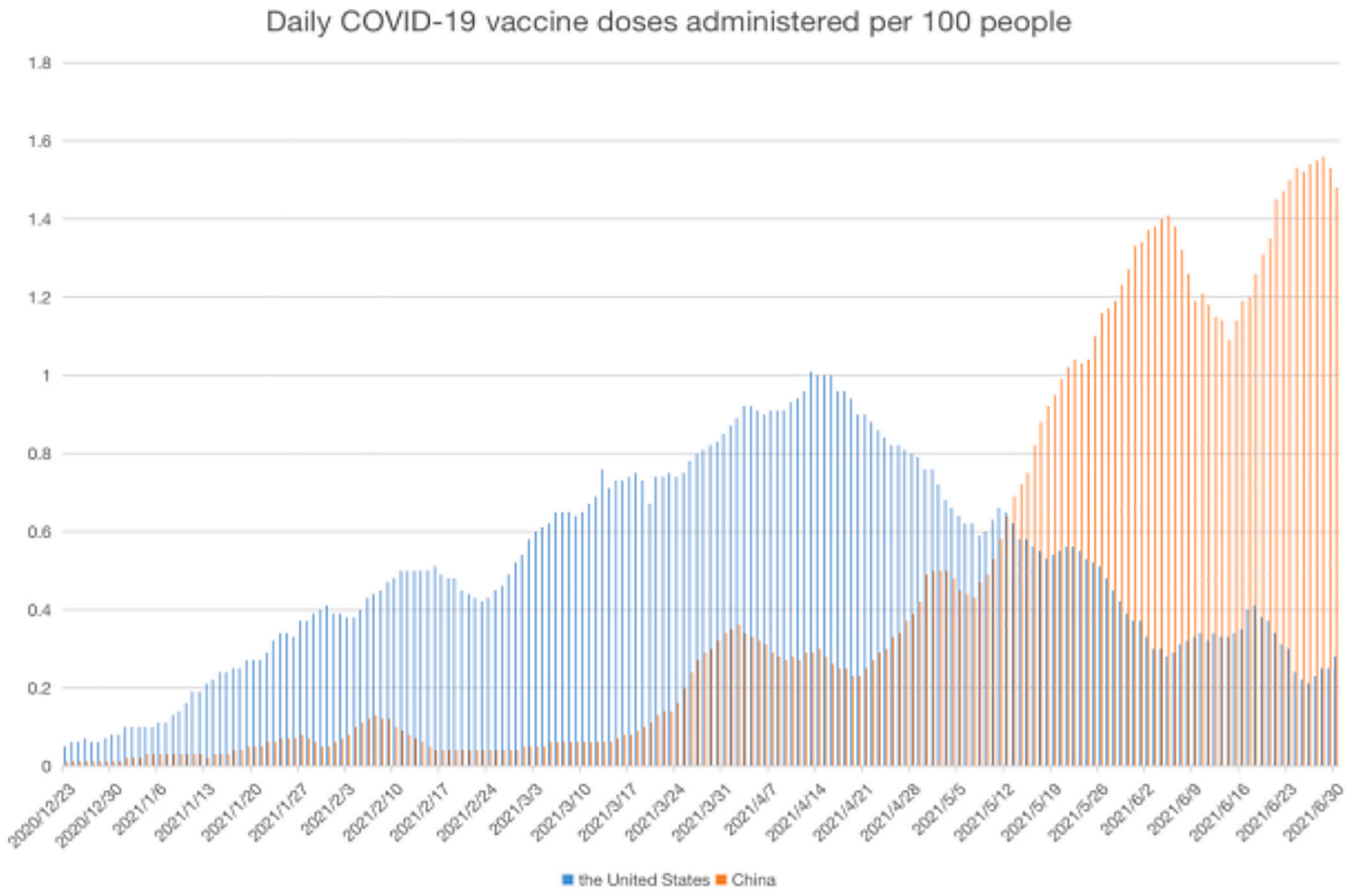

Fig. 8. Daily COVID-19 vaccine doses administered per 100 people in China and the United States.

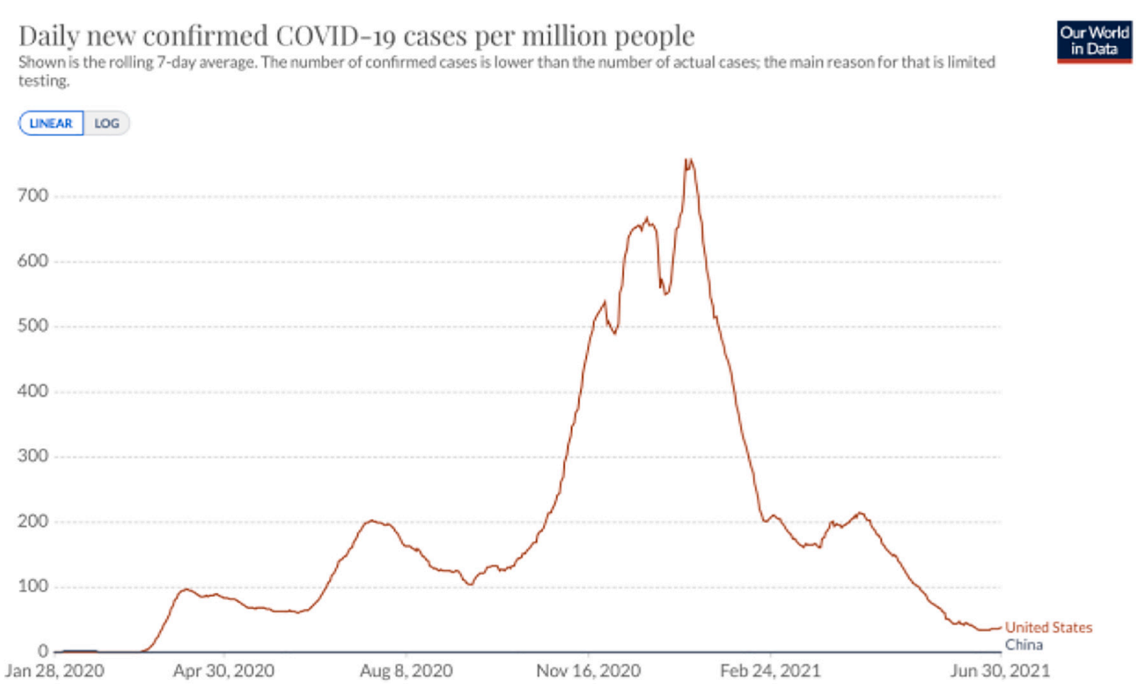

Fig. 9. Daily new confirmed COVID-19 cases per million people in China and the United States.

The spread of COVID-19 had been effectively controlled and reduced to sporadic local outbreaks in China due to the strict measures implemented by Chinese government (Fang et al., 2020; He et al., 2020; Xu et al., 2020). Most individuals took it for granted that the chance of infection was low and they didn't need vaccinations to protect themselves in China. Thus, Individuals lacked sufficient information creation rate λ, and had low information sensitivity η, resulting in their reluctance to get vaccinated and subsequently the low vaccination rates, as shown in Fig. 10. Chinese government thus faced an uphill battle in convincing people to get vaccinated since there's less urgency than United States, where COVID-19 epidemic had run rampant.

(2) The second stage (between 15 March and 15 April, 2021)

During this period, China only administered enough doses for just under 2% of its population, while it aimed to vaccinate 40% of its population (or 560 million people) by June. Facing this dilemma, Chinese government became more active to encourage people to get vaccinated. Thus, with growing information awareness obtained from government's publicity (information creation rate λ increases), individuals changed their vaccination behaviors and became more willing to get vaccinated. But surprisingly, the positive effect of global information awareness on vaccination rates was limited because of the lack of local information contributions from the reported number of infected cases, which promoted the ongoing act of vaccine hesitancy and free-riding behavior. Thus, the insufficient information creation rate λ and relatively low information sensitivity η resulted in the slow growth rate of vaccination, as shown in Fig. 11.

(3) The third stage (between 15 April and 15 May, 2021)

China continued to implement the harshest lockdown measures to combat local outbreaks caused by imported cases even though COVID-19 had been largely contained. Such measures, along with a renewed fear of catching the virus, triggered strong incentives for getting vaccinated. At the same time, clear and consistent communication from authoritative sources is crucial to setting up public confidence in vaccine program (Harrison and Wu, 2020). For example, the infectious diseases expert, Dr. Zhang Wenhong and Zhong Nanshan, explained the development process and efficiency level of vaccine, as well as the significance of population-wide coverage to achieve community immunity. It was obvious that these measures implemented, together with advocacy from experts, alleviated public concerns about vaccine safety and encouraged vaccine-hesitant people to get vaccinated, which prompted the increase of the sensitivity of information η and the global information creation rate λ, as shown in Fig. 12.

(4) The fourth stage (between 15 May and 30 June, 2021)

In mid-May, a small outbreak in provinces Anhui and Liaoning prompted authorities to institute local lockdowns, prevent people and vehicles from leaving their local areas, close schools, and require residents to get tested for COVID-19. Days later, Anhui reported that a record of 1.1 million people had signed up for vaccines with residents waiting in long lines outside vaccine centers to get injected. The daily dose reached its peak on June 28 (daily COVID-19 vaccine doses administered per 100 people was 1.56). The number of vaccinations had increased dramatically. This phenomenon can be explained as: the repeated local outbreaks seemed to be an effective way to enhance individual's information sensitivity η and thus urge the public to get vaccinated. On the other hand, the fact that Chinese vaccines were internationally recognized may also convert vaccine skeptics. For example, on June 1, the World Health Organization (WHO) announced that the COVID-19 vaccine developed by China Sinovac had officially passed the emergency use certification, raising public trust in vaccines. Thus, individual's information sensitivity η and global information creation rate λ were further improved, promoting the high vaccination coverage, as shown in Fig. 13.

5. Conclusion

In this paper, we propose a SEIR/V-AI model to study the influence of

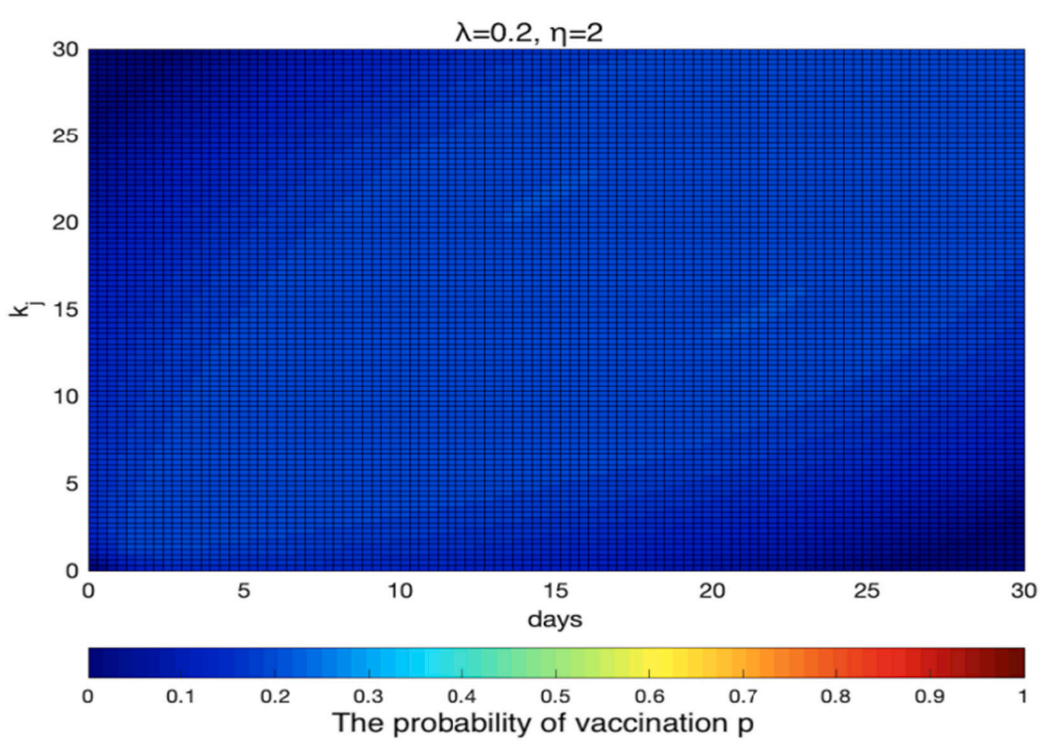

Fig. 10. The probability of vaccination p corresponds to the information creation rate $\lambda = 0.2$ and the information sensitivity $\eta = 2$ in China.

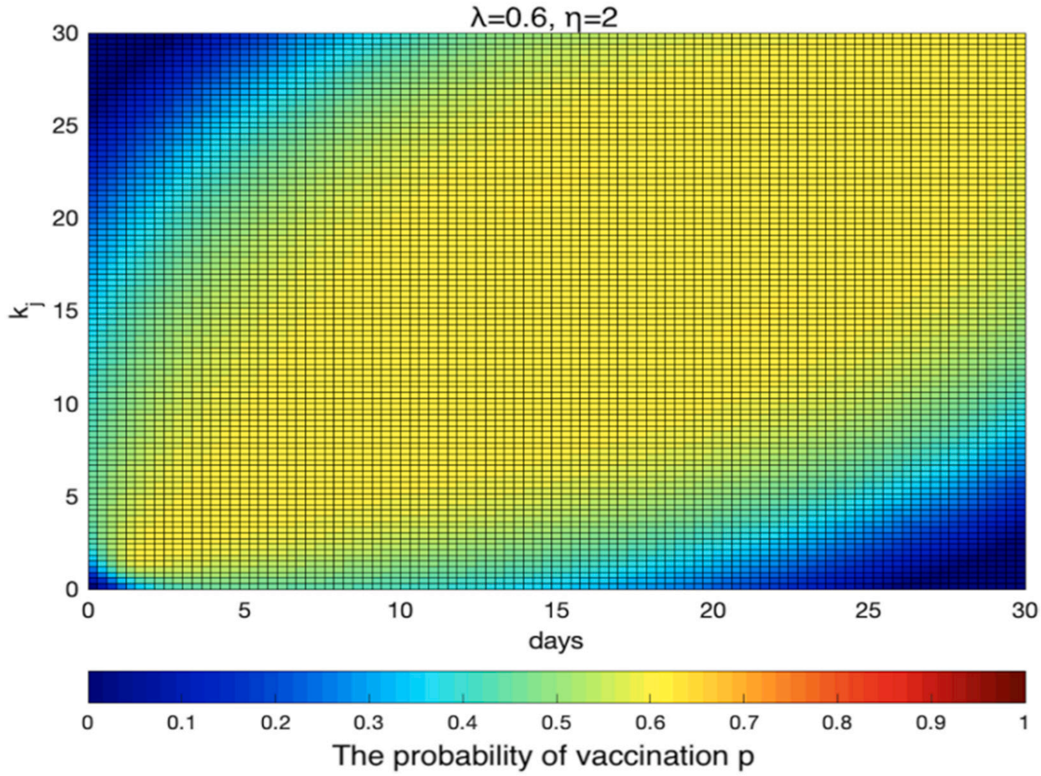

Fig. 11. The probability of vaccination p corresponds to the information creation rate $\lambda = 0.6$ and the information sensitivity $\eta = 2$ in China.

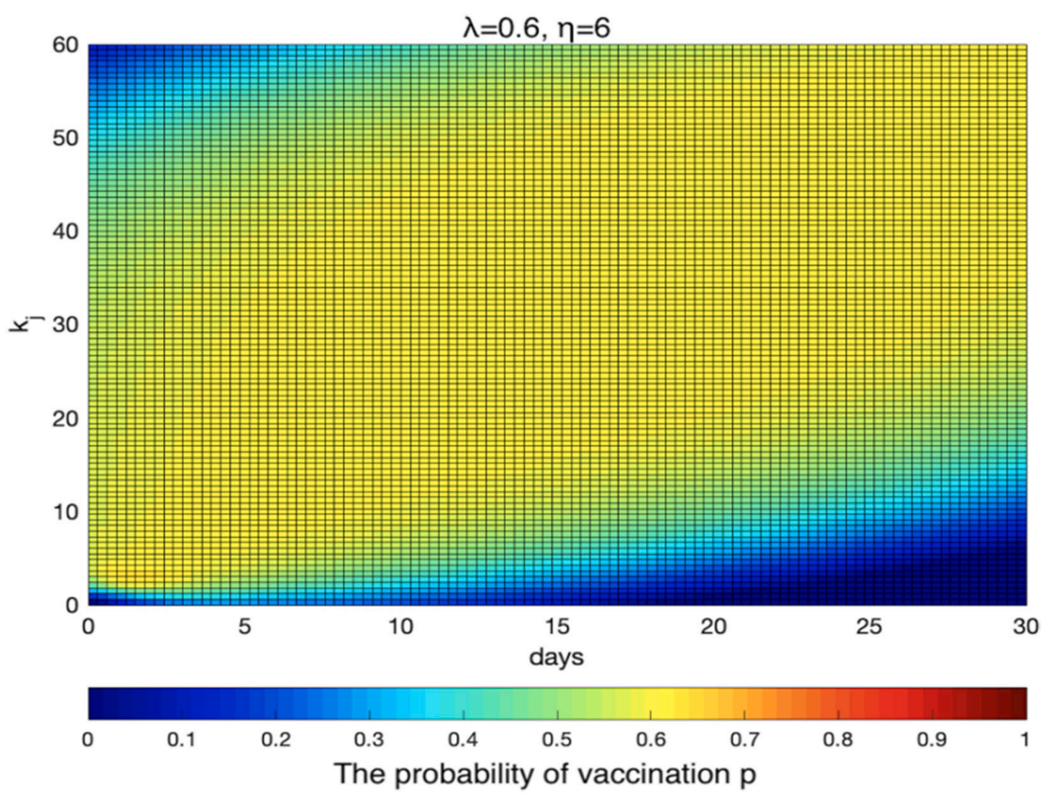

Fig. 12. The probability of vaccination p corresponds to the information creation rate $\lambda = 0.6$ and the information sensitivity $\eta = 6$ in China.

awareness-information on individual vaccination behavior. The model introduces the information creation rate λ and the information sensitivity η to offers insights on the decision behavior of COVID-19 vaccination. Through carrying out a series of simulations, and analyzing the decision behavior of COVID-19 vaccination in China and the United States, we reveal that the coefficient of information creation λ and the

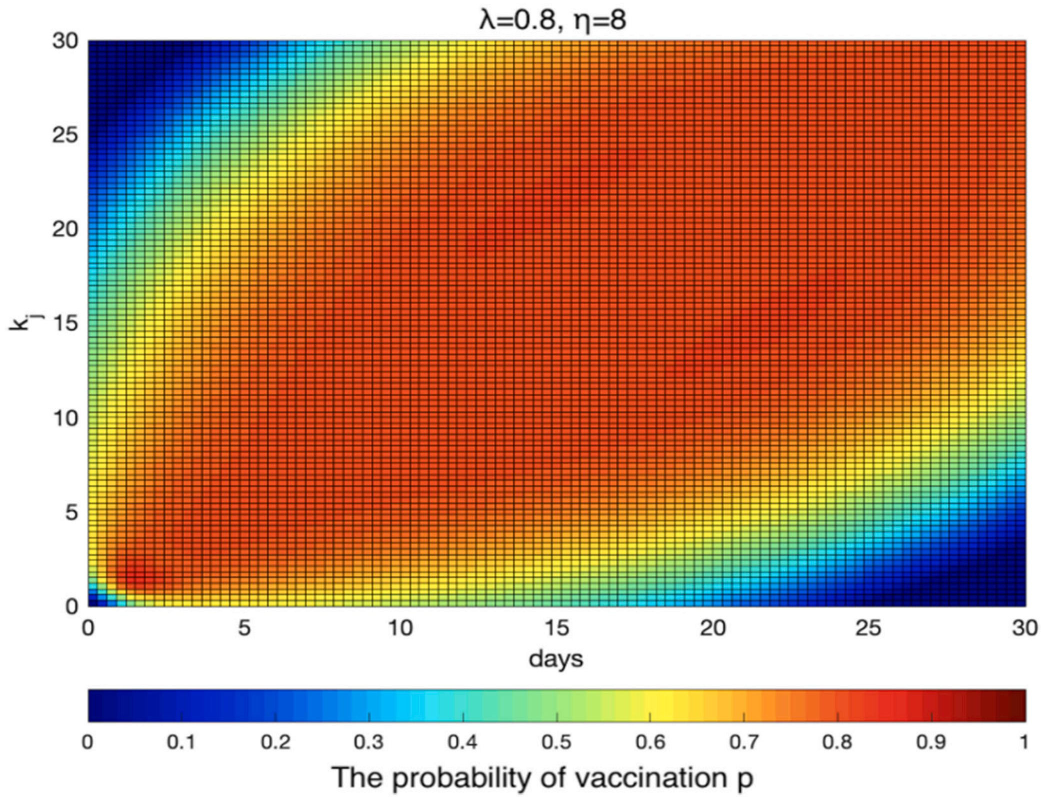

Fig. 13. The probability of vaccination p corresponds to the information creation rate $\lambda = 0.8$ and the information sensitivity $\eta = 8$ in China.

information sensitivity η can affect vaccination behavior of individuals. Thus, the information-driven vaccination is a good way to control the epidemic spreading. Besides, to solve vaccine hesitancy and the free-riding behavior, the government needs to disseminate accurate information about vaccines safety and efficacy to alleviate public concerns, and provide the widespread public educational campaigns and communication to guide individuals to act in group interests rather than self-interest and reduce the temptation to free-riding, which often results from individuals who are inadequately informed about vaccines and thus blindly imitate free-riding behavior.

As of revised paper submission (30 November 2021), it was reported that 7.96 billion doses of COVID-19 vaccines had been administered worldwide. The Omicron variant will cause significant fluctuation of vaccination rate in the near future. Some individuals may choose to take a COVID-19 vaccine booster shot immediately to combat the Omicron variant, while some individuals who consider vaccines available unable to prevent the COVID-19 variants may reduce their vaccinated willingness. Besides, many countries enter epidemic “controlled normalization process”, awareness individuals may lose competency (self-protection) over time due to the decreasing quality of the information and fading of awareness, resulting in the low vaccination rates. Motivated by the above phenomenon, we need more empirical data and propose a new model to study the influence of awareness programs on individual vaccination behavior in the future.

Contributions

Chao Zuo, Yuting Ling and Xueke Zhao contributed to model building, data analysis, and writing the paper. Fenping Zhu, Zeyang Meng and Yuzhi Zheng contributed to data collection and editing the paper.

Ethical approval

Approval was not required.

Credit author statement

Chao Zuo, Yuting Ling and Xueke Zhao contributed to model building, data analysis, and writing the paper. Fenping Zhu, Zeyang Meng and Yuzhi Zheng contributed to data collection and editing the paper.

Declaration of competing interest

The authors declare that there are no conflict of interests.

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References

Chakraborty, C., Sharma, A.R., Sharma, G., et al., 2020. SARS-CoV-2 causing pneumonia-associated respiratory disorder (COVID-19): diagnostic and proposed therapeutic options. Eur. Rev. Med. Pharmacol. Sci. 24, 4016–4026.
Chou, W.Y.S., Budenz, A., 2020. Considering emotion in COVID-19 vaccine communication: addressing vaccine hesitancy and fostering vaccine confidence. Health Commun. 35, 1718–1722.
Cynthia, L., Qiongqiong, Z., Li, Yingzhu, et al., 2020. Research and development on therapeutic agents and vaccines for COVID-19 and related human coronavirus diseases. ACS Central Sci. 6, 315–331.
Diekmann, O., Heesterbeek, J.A.P., Roberts, M.G., 2010. The construction of next-generation matrices for compartmental epidemic models. J. R. Soc. Interface 47, 873–885.
Dror, A.A., Eisenbach, N., Taiber, S., et al., 2020. Vaccine hesitancy: the next challenge in the fight against COVID-19. Eur. J. Epidemiol. 35, 775–779.
Emmanuel, M., Wendy, A.B., Edward, D.S., et al., 2020. Prospects for SARS-CoV-2 diagnostics, therapeutics and vaccines in Africa. Nat. Rev. Microbiol. 18, 690–704.

Fang, Y., Nie, Y., Penny, M., 2020. Transmission dynamics of the COVID-19 outbreak and effectiveness of government interventions: a data-driven analysis. J. Med. Virol. 92, 645–659.
Feng, F., Daniel, I.R., Wang, L., et al., 2011. Imitation dynamics of vaccination behavior on social networks. Proc. R. Soc. B 278, 42–49.
Fosu, G.O., Akweittey, E., Adu-Sackey, A., 2020. Next-generation matrices and basic reproductive numbers for all phases of the coronavirus disease. Open J. Math. Sci. 4, 261–272.
Gao, C., Tang, S., Li, W., et al., 2018. Dynamical processes and epidemic threshold on nonlinear coupled multiplex networks. Phys. A: Stat. Mech. Appl. 496, 330–338.
Harrison, E.A., Wu, J.W., 2020. Vaccine confidence in the time of COVID-19. Eur. J. Epidemiol. 35, 325–330.
He, G., Pan, Y., Tanaka, T., 2020. The short-term impacts of COVID-19 lockdown on urban air pollution in China. Nat. Sustain. 3, 1005–1011.
Helena, F.F., Ron, K., Daniella, V.K., et al., 2020. Immune-mediated approaches against COVID-19. Nat. Nanotechnol. 15, 630–645.
Ibuka, Y., Li, M., Vietri, J., et al., 2014. Free-riding behavior in vaccination decisions: an experimental study. PLoS One 9, 1–9.
Jiang, S., 2020. Don't rush to deploy COVID-19 vaccines and drugs without sufficient safety guarantees. Nature 579, 321–322.
Kadali, R.A.K., Janagama, R., Peruru, S., et al., 2021. Side effects of BNT162b2 mRNA COVID-19 vaccine: a randomized, cross-sectional study with detailed self-reported symptoms from healthcare workers. Int. J. Infect. Dis. 106, 376–381.
Liu, Z., Magal, P., Seydi, O., et al., 2020. A COVID-19 epidemic model with latency period. Infect. Dis. Model. 5, 323–337.
Randolph, H.E., Barreiro, L.B., 2020. Herd immunity: understanding COVID-19. Immunity 52, 737–741.
Ruan, Z.Y., Tang, M., Liu, Z.H., 2012. Epidemic spreading with information-driven vaccination. Phys. Rev. E 86, 1–7.
Soares, P., Rocha, J.V., Moniz, M., et al., 2021. Factors associated with COVID-19 vaccine hesitancy. Vaccines 9, 1–14.
Su, S., Du, L., Jiang, S., 2021. Learning from the past: development of safe and effective COVID-19 vaccines. Nat. Rev. Microbiol. 19, 211–219.
Taman, E., Mahmoud, M.A., Basima, A.A., et al., 2021. Acceptance and attitudes toward COVID-19 vaccines: a cross-sectional study from Jordan. PLoS One 16 (4), 1–15.
Van d Watmough, J., 1945. Further notes on the basic reproduction number. Math. Epidemiol. 2008, 159–178.
Velavan, T.P., Meyer, C.G., 2020. The COVID-19 epidemic. Tropical Med. Int. Health 25, 278–280.
Xia, S., Liu, J., 2014. A belief-based model for characterizing the spread of awareness and its impacts on individuals' vaccination decisions. J. R. Soc. Interface 11, 1–10.
Xu, T.L., Ao, M.Y., Zhou, X., et al., 2020. China's practice to prevent and control COVID-19 in the context of large population movement. Infect. Dis. Pov. 9, 1–14.
Yang, H.M., 2014. The basic reproduction number obtained from Jacobian and next generation matrices–a case study of dengue transmission modelling. Biosystems 126, 52–75.
Yong, J.C., Choy, B.K.C., 2021. Noncompliance with safety guidelines as a free-riding strategy: an evolutionary game-theoretic approach to cooperation during the COVID-19 pandemic. Front. Psychol. 12, 1–8.
Zhang, H., Zhang, J., Zhou, C., et al., 2010. Hub nodes inhibit the outbreak of epidemic under voluntary vaccination. New J. Phys. 12 (2), 1–12.
Zhao, X., Zhou, Q., Wang, A., et al., 2021. The impact of awareness diffusion on the spread of COVID-19 based on a two-layer SEIR/V–UA epidemic model. J. Med. Virol. 93, 4342–4350.
Zuo, C., Wang, A., Zhu, F., et al., 2021. A new coupled awareness-epidemic spreading model with neighbor behavior on multiplex networks. Complexity 4, 1–14.