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Heterogeneous influence of individuals' behavior on mask efficacy in gathering environments

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Abstract Wearing masks is an easy way to operate and popular measure for preventing epidemics. Although masks can slow down the spread of viruses, their efficacy in gathering environments involving heterogeneous person-to-person contacts remains unknown. Therefore, we aim to investigate the epidemic prevention effect of masks in different real-life gathering environments. This study uses four real interpersonal contact datasets to construct four empirical networks to represent four gathering environments. The transmission of COVID-19 is simulated using the Monte Carlo simulation method.

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The heterogeneity of individuals can cause mask efficacy in a specific gathering environment to be different from the baseline efficacy in general society. Furthermore, the heterogeneity of gathering environments causes the epidemic prevention effect of masks to differ. Wearing masks can greatly reduce the probability of clustered epidemics and the infection scale in primary schools, high schools, and hospitals. However, the use of masks alone in primary schools and hospitals cannot control outbreaks. In high schools with social distancing between classes and in workplaces where the interpersonal contact is relatively sparse, masks can meet the need for prevention. Given the heterogeneity of individual behavior, if individuals who are more active in terms of interpersonal contact are prioritized for mask-wearing, the epidemic prevention effect of masks can be improved. Finally, asymptomatic infection has varying effects on the prevention effect of masks in different environments. The effect can be weakened or eliminated by increasing the usage rate of masks in high schools and workplaces. However, the effect on primary schools and hospitals cannot be weakened. This study contributes to the accurate evaluation of mask efficacy in various gathering environments to provide scientific guidance for epidemic prevention.

Keywords COVID-19, masks, behavioral heterogeneity, asymptomatic infection

1 Introduction

As of November 2021, global reported COVID-19 cases have exceeded 250 million, with more than 7 million deaths. Countries have adopted measures such as isolating cases (Patterson et al., 2020), isolating susceptible individuals (Cui et al., 2020), and closing public places (Sun and Wah, 2020) to suppress the spread of the virus. Although these measures can effectively control the development of an epidemic, a huge number of infections

can still occur before the epidemic is detected. Therefore, prevention measures should be adopted in daily life to reduce the burden of subsequent epidemic prevention work.

Prevention measures include maintaining social distance (Thu et al., 2020), wearing masks (Leung et al., 2020), and being vaccinated (Alvarez et al., 2021). Wearing masks is a low-cost, easy-to-operate, and easy-to-popularize epidemic prevention measure. Masks can block the transmission of droplets or aerosols from coughers and protect wearers from inhaling droplets or aerosols from nearby coughers. Thus, masks can inhibit the spread of diseases that are transmitted by droplets or aerosols (Brien et al., 2010; Lai et al., 2012; Davies et al., 2013). Chu et al. (2020)'s meta-analysis of 39 studies found that, on average across social settings, people wearing masks have a 3.1% chance of being infected, while those without masks have a 17.4% chance of being infected with SARS-CoV-2 and the betacoronavirus that cause severe acute respiratory syndrome (SARS) and Middle East respiratory syndrome (MERS).

However, mask efficacy can vary in different regimes of virus abundance, the population's average infection probability, and the virus' reproduction number (Cheng et al., 2021). In real-life gathering environments, such as schools, hospitals, and workplaces, mask efficacy and the epidemic prevention effect of masks are still unknown. In addition to virus-related changes, whether individual behavior and individual heterogeneity (Rong et al., 2019; Mao et al., 2021) can affect mask efficacy is an issue that needs to be discussed. This study aims to fill these gaps by analyzing the relationship between the epidemic prevention efficacy and adoption rate of masks in several critical social gathering settings. Specifically, we use a multi-agent modeling method to simulate the epidemic spreading in human contact networks harvested by real-time tracking devices. Four datasets are used to construct the human contact networks in schools, hospitals, and workplaces. By tuning the mask adoption rate and the personnel for whom mask-wearing is mandatory in the model, we look for the optimal mask adoption rate and strategy so that the epidemic can be suppressed.

The rest of this study is organized as follows. In Section 2, we describe real interpersonal contact datasets in primary school, hospital, high school, and workplace; introduce the infectious disease model used for the simulations; and explain the various forms of mask-wearing strategies used in the model. In Section 3, we discuss the influence of the heterogeneity of individuals within environments and environmental heterogeneity on mask efficacy and the epidemic prevention effect of masks, analyze two methods to improve the prevention effect of masks, and discuss the effect of asymptomatic infection on the prevention effect of masks. In Section 4, we conclude.

2 Data and method

2.1 High-resolution real interpersonal contact datasets

This study uses four real interpersonal contact datasets: People within primary school, high school, hospital, and workplace, respectively (Stehlé et al., 2011; Vanhems et al., 2013; Gemmetto et al., 2014; Génois et al., 2015; Mastrandrea et al., 2015). In the four environments, individuals wear customized RFID (radio frequency identification devices) sensors (Cattuto et al., 2010) to detect and record close contact between individuals at a time resolution of 20 s. The primary school dataset includes the contact information of 242 students or teachers over two days. The high school dataset includes the contact information of 329 students over five days. The hospital dataset includes the contact information of 92 patients or staff over five days. The workplace dataset includes the contact information of 92 employees over ten days.

Given that the datasets only include contact information gathered over two, five, or ten days, we need to expand the four datasets in the time dimension to ensure that the epidemic simulation can be carried out over a longer period. The extension method we use is similar to that used in previous research on disease simulation (Gemmetto et al., 2014). Given that most primary schools, high schools, and workplaces are closed on Saturdays and Sundays, individuals in these three environments are considered to have no contact with each other. Therefore, for the primary school, the two days of data are used in turn during school days. For the high school, five days of data correspond to contact activity from Monday to Friday. For the workplace, ten days of data correspond to contact activity from Monday to Friday over a two-week period. The hospital is unique in that patients' hospitalization is not restricted to weekdays, so we do not distinguish between weekdays and weekends. Therefore, five days of data are used interlaced.

Based on the expanded datasets, we use 20 minutes as a time slice to construct temporal networks (Gemmetto et al., 2014). The networks use individuals as nodes and contacts as connecting edges, reflecting the contact activities of people in gathering environments.

2.2 Interpersonal contact in four environments

The contact situations of the four environments are heterogeneous (Fig. 1). More intensive interpersonal contact is present in primary school and hospital, as shown by the relatively large proportion of red nodes in both graphs. In these two environments, most individuals have a large degree (number of contacts) and a large weight (contact duration). The average degree of individuals is 0.28

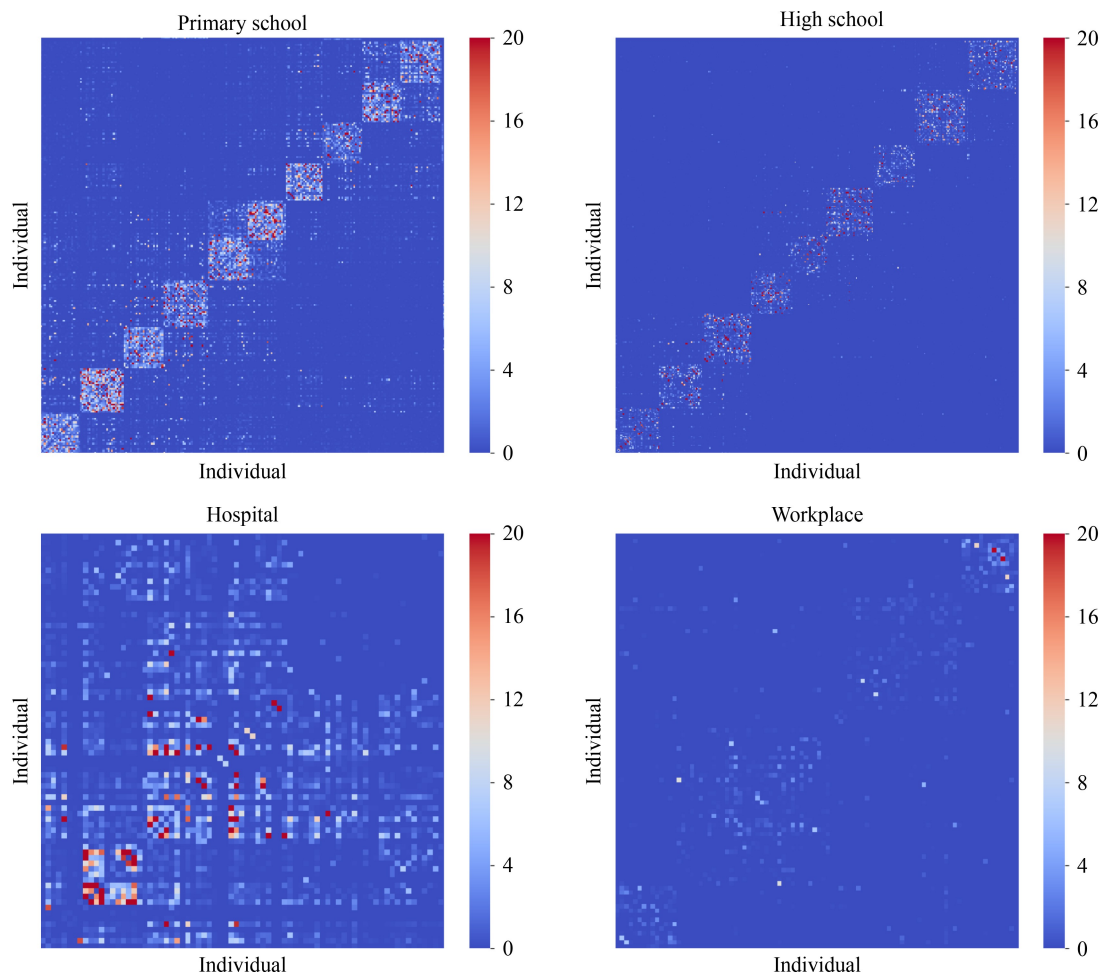


Fig. 1 Contact between individuals in the four environments (students are arranged by their classes in the primary school and high school plots; the colors represent the duration of contact between individuals each day, where red means that the contact duration exceeds 10 min, while blue means that it is less than 10 min).

(primary school) and 0.40 (hospital), respectively, of the total population, while the average contact duration for every two individuals who come into contact is 2.52 and 2.37 min a day, respectively. The contacts between students in the same class form obvious boxes in Fig. 1. Given that the high school in this study restricts contact between classes and grades, the outside of these boxes is mostly blue. The average degree of individuals is 0.09 of the total population, which is significantly lower than that in primary school. No restrictions are placed on contact between individuals in the same class, so the average contact duration for every two individuals who come into contact is 2.56 min a day, which is slightly higher than that in primary school. Figure 1 shows that the workplace environment has the fewest red nodes, and most of the contact duration is shown in blue. Therefore, the workplace has the sparsest interpersonal contact. Most individuals have a small degree and a small contact weight.

Figure 2 shows the degree and weight distributions of

individuals in the four environments. For both distributions, we divided the X -axis into 20 groups on average according to the maximum and minimum values of the X -axis. The results reveal obvious differences between the degree and weight of individuals in gathering environments. In addition to the heterogeneity among environments, individuals within a particular environment are also heterogeneous. How this heterogeneity affects mask efficacy is discussed in Section 3.

2.3 SEIR model with variable infection rate

Classical disease transmission models include the SI, SIS, SIR and SEIR models. In the SI model, individuals have only susceptible (S) state and infectious (I) state. Susceptible individuals who do not carry the virus but can be infected have a probability of transferring to the infectious state, in which they show symptoms and are infectious. Infectious individuals in the SIS model can re-transfer to susceptible state. The SIR model adds a removed (R) state based on the SI model; infectious

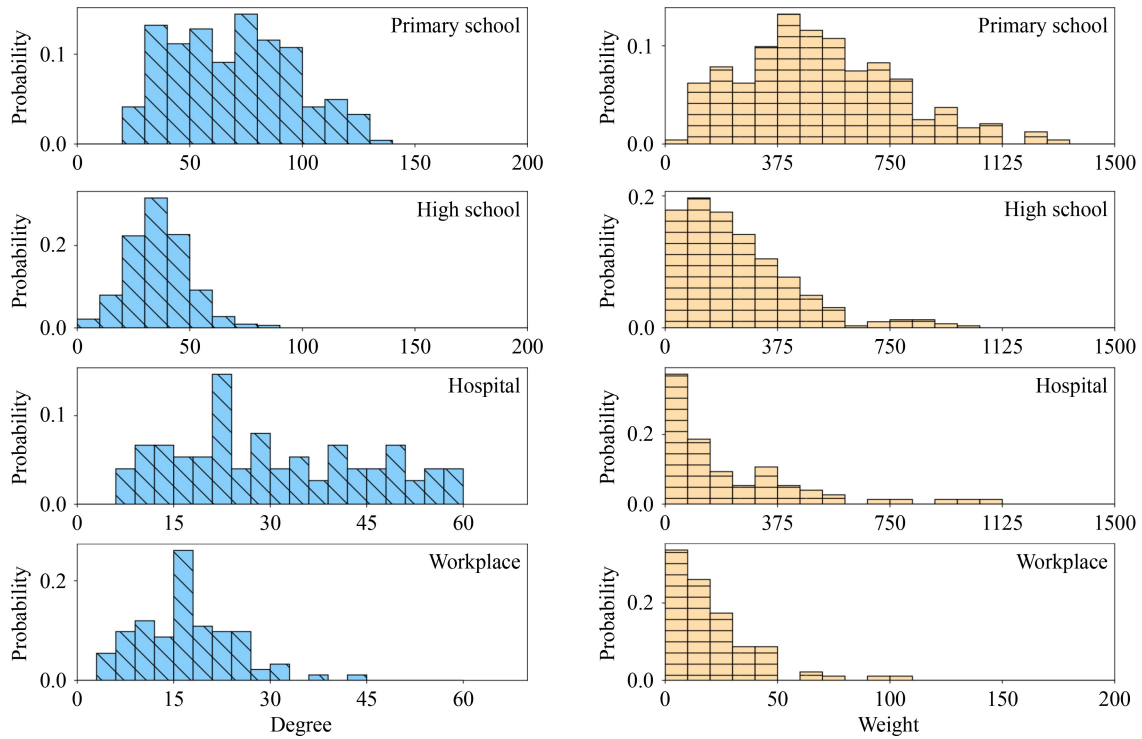


Fig. 2 Degree distribution (left) and weight distribution (right) of individuals in the four environments.

individuals can transfer to removed state, in which they cannot be re-infected and are not infectious. This paper only considers removed individuals to be cured rather than dead. The SEIR model builds upon the SIR model but adds an exposed (E) state to incorporate the incubation period. In this model, individuals have a total of four states: Susceptible (S), exposed (E), infectious (I), and removed (R). Whenever a susceptible individual is in contact with an infectious individual, the probability p of being infected continually increases with the exposure time Δt at a constant rate β_{const} , i.e., $p = \beta_{\text{const}} \Delta t$ as shown in Fig. 3. If $\beta_{\text{const}} \Delta t > 1$, the susceptible individual is infected and transfers to exposed state, at which point the individual enters the incubation period and does not demonstrate any symptom. After the incubation period, the exposed individual will enter the infectious state. If the infectivity of patients during the incubation period is not considered, the infection rates are shown by the green line in Fig. 3. Given that COVID-19 patients in the incubation period are infectious, some studies use SEIR with infectivity during the incubation period. The resulting infection rates are shown by the blue line in Fig. 3. A constant infection rate assumes that the virus shedding volume is constant during the infectious period.

However, constant virus shedding volume does not apply to SARS-CoV-2. Experiments on cynomolgus macaques inoculated with SARS-CoV-2 have shown that the virus shedding volume from macaques gradually increases from the first day after infection, peaks on the fifth day, and then gradually decreases until recovery or

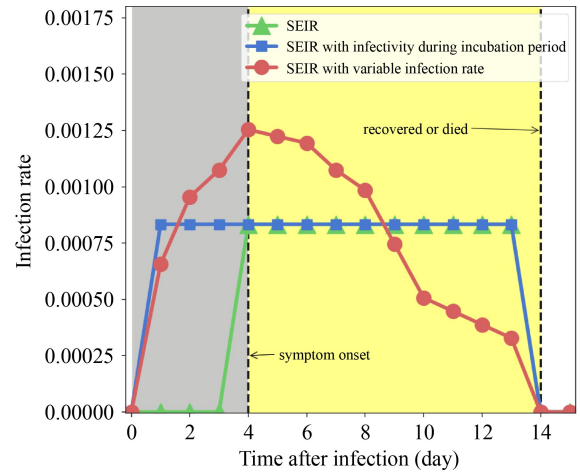


Fig. 3 Constant and variable infection rate models (the gray and yellow areas are the infection rate of the exposed and symptomatic state, respectively).

death (Rockx et al., 2020). Based on the empirical virus shedding volumes, researchers characterize the transmissibility of COVID-19 patients with a variable infection rate (the red line in Fig. 3). This is introduced into the SEIR model to propose a variable infection rate model. This model considers the infectivity during the incubation period and more closely matches the virus excretion of COVID-19 patients (Sun et al., 2021). Four assumptions are made in this model. First, a patient's infection rate is proportional to the logged virus shedding volume, i.e., $\beta(t) \sim \log E(t)$ (Du et al., 2020). Second, the incubation

period is four days (Guan et al., 2020) and the recovery period is ten days (Wang et al., 2020). Third, the cumulative infection rates of the variable infection model and the traditional SEIR model are the same. Fourth, most SARS-CoV-2 outbreaks are caused by the Delta variant at present. The R_0 value of this virus is 5–10 (R_0 is the basic reproductive number of an infectious disease, which is defined as the average number of people that each infectious individual can infect during the infectious period) (Liu and Rocklöv, 2021). To ensure that the average R_0 value of the four environments remains in this range, this study sets β_{const} as $8.3 \times 10^{-4} \text{ s}^{-1}$. In other words, a 20 min accumulated contact can cause an infection. Based on β_{const} and virus shedding (Rockx et al., 2020), we can set the variable infection rate of COVID-19 patients (Sun et al., 2021), as shown in Fig. 3.

This study used the Monte Carlo simulation method. To eliminate the randomness of the results, each experiment was simulated 5000 times.

2.4 Mask strategy

We select a certain proportion of people to wear masks before each simulation to introduce masks into the simulation model. Researchers found that those who wear masks have a 3.1% chance of being infected, whereas those who do not have an infection chance of 17.4% (Chu et al., 2020). Therefore, the risk of infection of individuals without masks is 5.6 (17.4/3.1) times higher than that of individuals wearing masks. To show the difference between wearing masks and not doing so during the simulation, we set the virus transmission between individuals as follows.

1) When both infected and susceptible individuals do not wear masks as shown in Fig. 4(a), susceptible individuals can be transformed into exposed individuals with the probability of β .

2) When either infected or susceptible individuals wear masks as shown in Figs. 4(b) and 4(c), susceptible individuals can be transformed into exposed individuals with probability of $\beta \times (1/5.6)$.

3) When both infected and susceptible individuals wear masks as shown in Fig. 4(d), susceptible individuals can be transformed into exposed individuals with probability of $\beta \times (1/5.6^2)$.

3 Experimental results

3.1 Influence of the heterogeneity of individuals on mask efficacy

Mask efficacy is defined as

$$\text{mask efficacy} = (P_{\text{inf, pop}} - P_{\text{inf, pop, mask}}) / P_{\text{inf, pop}}, \quad (1)$$

where $P_{\text{inf, pop}}$ is the probability that an individual without a mask is infected (i.e., the infected proportion in all people without a mask), and $P_{\text{inf, pop, mask}}$ is the probability that an individual wearing a mask is infected (i.e., the infected proportion in all people wearing a mask) (Cheng et al., 2021). We use Chu et al. (2020)'s data and consider $P_{\text{inf, pop}} = 17.4\%$, $P_{\text{inf, pop, mask}} = 3.1\%$, and hence $\text{mask efficacy} = 82.2\%$ is considered as the baseline mask protection efficacy across social settings. Chu et al. (2020)'s $P_{\text{inf, pop}}$ and $P_{\text{inf, pop, mask}}$ were gathered from studies that only consider virus spreading for at least ten days. To compare the masks efficacy in gathering environments with the baseline efficacy, this study also set the same virus transmission time, i.e., the simulation time to 10 days.

In an environment where individuals are heterogeneous, such as in the four environments used in this study, mask efficacy can significantly differ from the baseline efficacy.

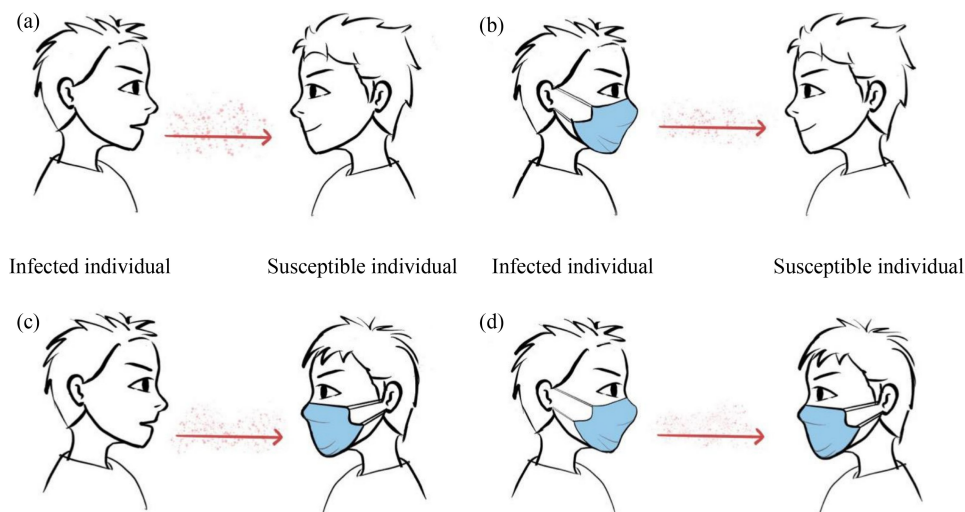


Fig. 4 Diagram of virus transmission.

As shown in Fig. 5, the intensity of interpersonal contact and the usage rate of masks are two factors that affect mask efficacy in a specific environment. In environments with relatively sparse interpersonal contact, such as at workplace and high school, when the usages of masks are 10.0% and 60.0%, respectively, mask efficacy can be greater than the baseline. In environments with relatively intensive interpersonal contact, such as at hospital and primary school, surpassing the baseline requires almost 90.0% and 100% usages of masks, respectively.

Mask efficacy improves as the usage rate of masks increases in the same environments. In the workplace, sparse contact between individuals results in mask efficacy greater than 90.0% at 10.0% usage rate of masks.

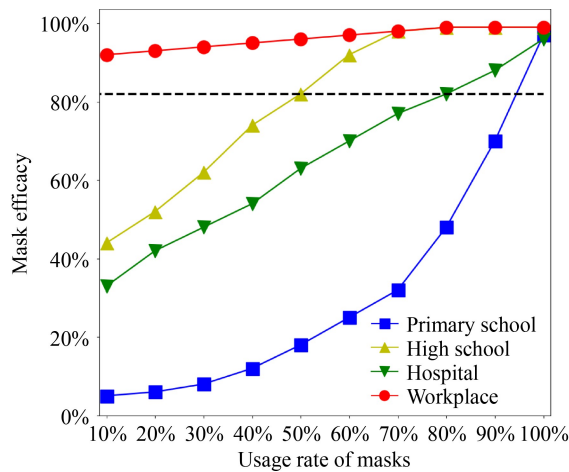


Fig. 5 Comparison of mask efficacy in the four environments and the impact of usage rate of masks on mask efficacy (the dotted line shows the baseline of mask efficacy in social situations).

Increasing usage does not improve mask efficacy significantly. For the other three environments, with the increase in mask usage rate, mask efficacy significantly improves, especially in primary school and hospital. When all the people wear masks, mask efficacies in hospital and primary school are 96.0% and 97.0%, respectively, increased by 63.0% and 92.0%, respectively, compared with that when the usage rate of masks is 10.0%.

3.2 Differences in the epidemic prevention effect of masks among gathering environments caused by environmental heterogeneity

Mask efficacy can reflect the possibility of reducing the chance of infection but cannot reflect the epidemic prevention effect of masks in specific environments. To evaluate the epidemic prevention effect of masks more carefully in the four environments, we set two indicators. (1) The probability of a clustered epidemic. In gathering environments, the occurrence of five or more cases can indicate that a clustered epidemic has occurred. Therefore, we define it as the number of simulations with more than five cases divided by the total number of simulations. (2) Infection scale. If one only considers simulations in which clustered epidemics can occur, the average number of cumulative infections in these simulations indicates the infection scale. These two indicators reflect the overall prevention effect of masks in the four environments, as shown in Fig. 6.

First, the probability of clustered epidemics and the infection scale can be reduced with increased usage rate of masks. Given obvious heterogeneity in terms of the contact situation in the four environments, the overall

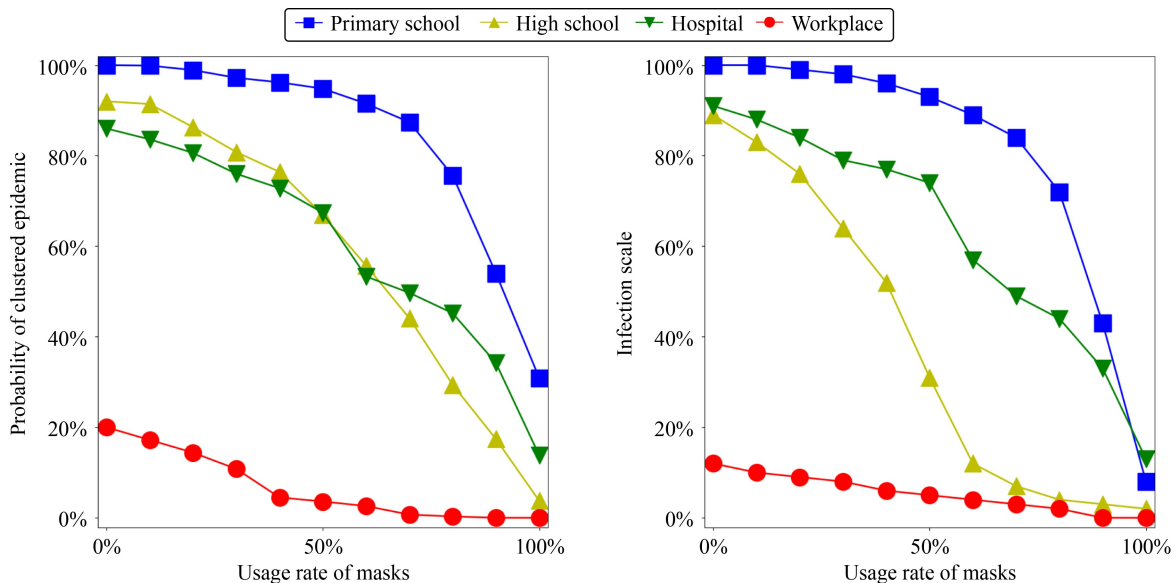


Fig. 6 Overall epidemic prevention effect of masks in the four environments.

prevention effect of masks also differs among them. In primary school, hospital, and high school, the decreasing trend is more obvious. The probability decreased by 70.0%, 73.0%, and 91.0%, respectively, and the infected cases decreased by 222, 58, and 286, respectively, when all the people wear masks. By contrast, in the workplace, increasing the usage rate of masks cannot significantly reduce the probability of a clustered epidemic and the infection scale. This finding shows that wearing masks and increasing the usage rate of masks is more important for primary school, high school, and hospital. Second, owing to the close interpersonal contact in the hospital and primary school, a high probability of clustered epidemics (13.8% and 31.0%, respectively) and a large infection scale (9 and 19 cases, respectively) still exist when all individuals wear masks. Compared with the primary school, the high school limits contact between classes and grades. Although the contact duration between individuals is longer in the high school, each individual has fewer close contacts. Therefore, when all the people wear masks, the probability of clustered epidemics (2.0%) and the infection scale (9 cases) are lower. In the workplace, which has the sparsest density of interpersonal contact, when more than 70.0% of individuals wear masks, clustered epidemics will hardly occur. When mask usage is greater than 90.0%, there will be almost no infection incidents.

Masks can inhibit the occurrence of clustered epidemics and protect individuals from being infected. We use the proportion of uninfected individuals with masks among all individuals with masks to represent the individual protective effect. The result is shown in Fig. 7. First, increasing the usage rate of masks can limit the spread of the virus, reducing the chance of individuals being infected. The individual protective effect of masks is therefore improved. Second, the heterogeneity of the four environments leads to differences in the individual protective effect. In the hospital and primary school, 4–5 and 2–3 of people wearing masks are still infected when all individuals wear masks, respectively. In the high school, when the usage rate of masks is more than 90.0%, the probability of mask-wearing individuals being infected is less than 1.0%. In the workplace, individuals wearing masks are hardly infected.

Based on the above results, we conclude that the heterogeneity of environments causes the overall prevention effect and individual protective effect of masks to differ significantly among the four environments. Wearing masks is an important preventive measure for people within primary school, high school, and hospital. Wearing masks can meet prevention needs in high school and workplace, but the high school needs to ensure that all individuals wear masks. However, masks only cannot meet prevention needs in primary school and hospital, given the high probability of clustered epidemics, and individuals wearing masks are still at risk of infection.

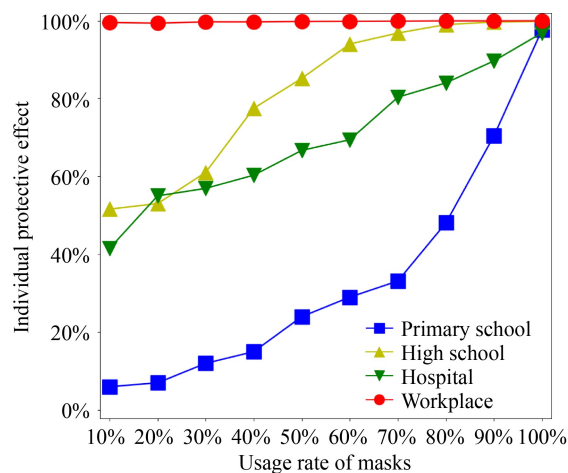


Fig. 7 Individual protective effect of masks in the four environments.

3.3 Individual mask-wearing selection strategies based on the heterogeneity of behavior

In the four environments, individual behavior is heterogeneous, as shown in Fig. 2. Individuals with a large degree or weight have a higher infection risk. On this basis, we propose three selection strategies for people wearing masks: (1) degree strategy, in which individuals with a large degree are given priority to wear masks, (2) weight strategy, in which individuals with a large weight are given priority to wear masks, and (3) random strategy, in which individuals are randomly selected to wear masks.

The relationship of probability of clustered epidemics and different mask usage rates under three strategies in the four environments is shown in Fig. 8. First, the degree strategy and the weight strategy can similarly optimize the prevention effect of masks under the same mask usage, resulting in a lower probability of a clustered epidemic. The optimization effect of the two strategies is similar due to the strong correlation between the degree and weight of individuals. Second, the optimization effect of these two strategies (degree strategy and weight strategy) differs among the four environments. In the primary school, given that most individuals have a large degree and weight, the two strategies can be optimized only when the usage rate of masks is greater than 50.0%. The optimization effect is more obvious in the hospital and high school. The hospital environment shows greater heterogeneity in individual behavior. Therefore, the optimization effect is obvious when the usage rate of masks is greater than 10.0%. In the high school, the two strategies can be optimized when the usage rate of masks is greater than 20.0%. In the workplace, individuals have a lower risk of infection than in the other environments, so the optimization effect is not obvious.

Figure 9 shows the individual protective effect of three

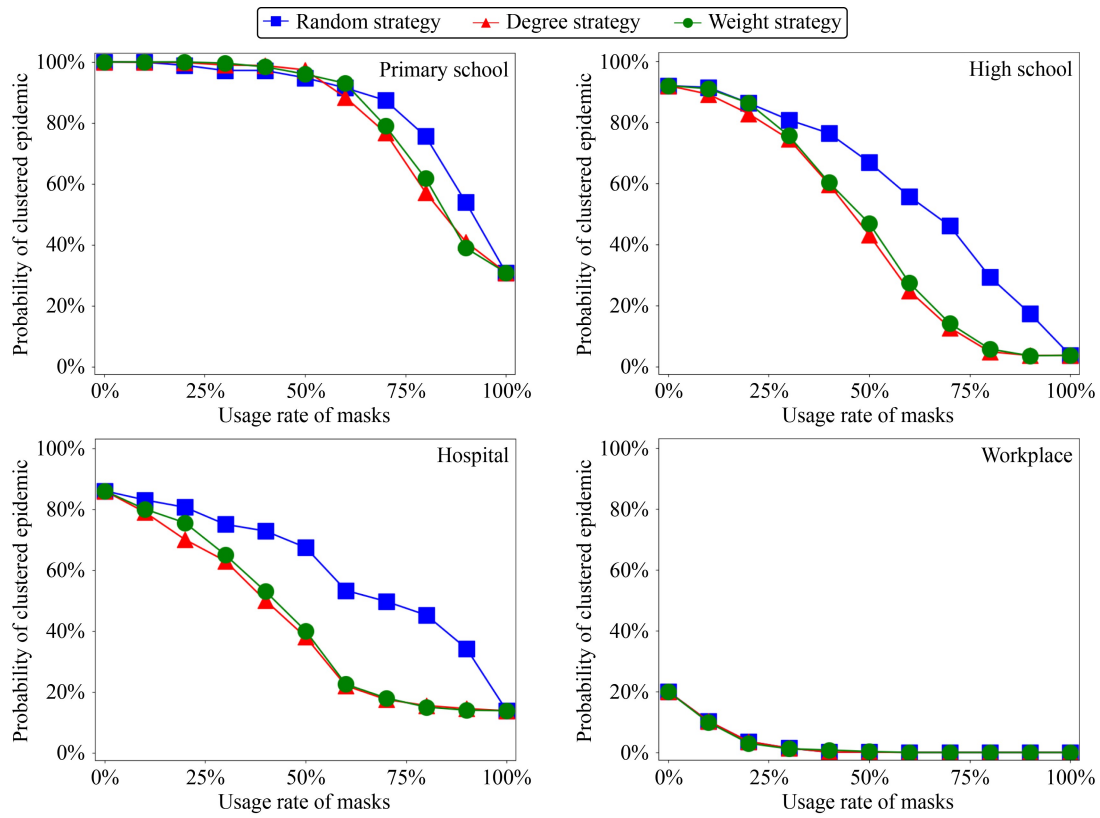


Fig. 8 The probability of clustered epidemic of three mask-wearing selection strategies under different mask usage rates.

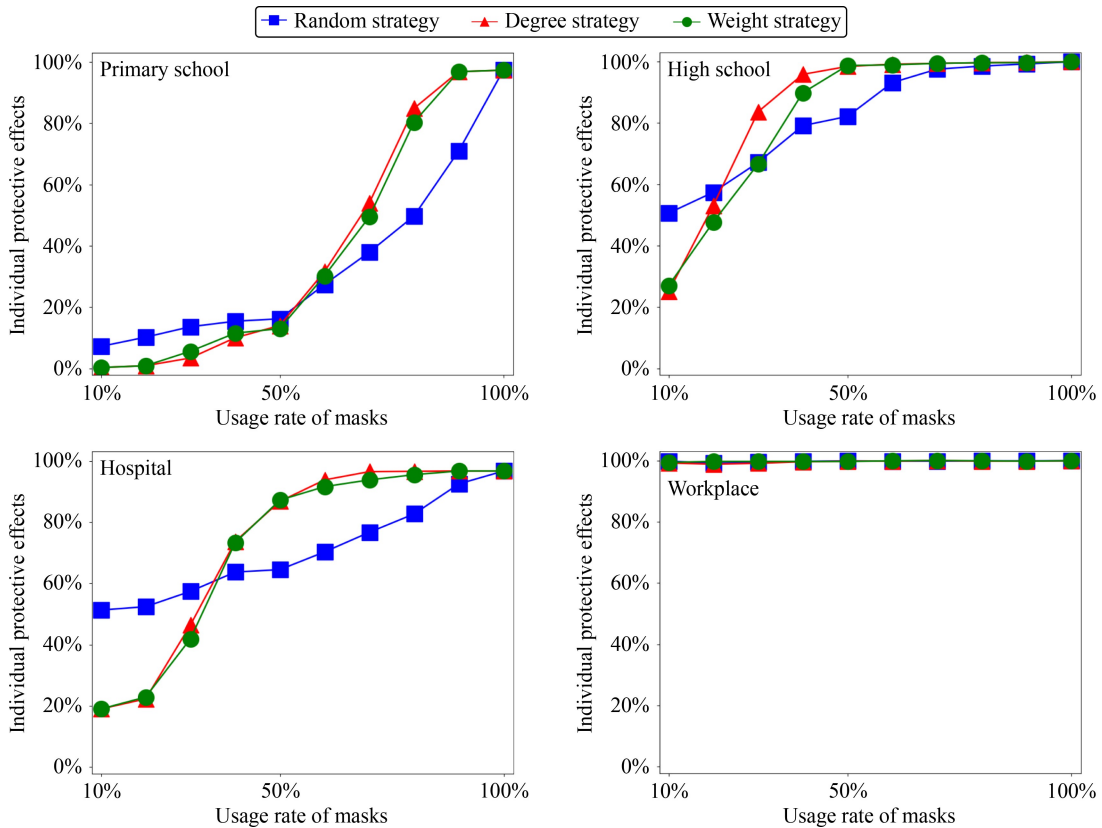


Fig. 9 Individual protective effect of three mask-wearing selection strategies under different mask usage rates.

mask-wearing selection strategies under different mask usage rates. When the usage rate of masks is lower, masks cannot inhibit the spread of the virus. Mask-wearing individuals who are very active in terms of interpersonal contact still have a high risk of infection, so the effects of the degree strategy and weight strategy are worse than that of a random strategy. The heterogeneity of the environments leads to different usage thresholds under which the degree and weight strategies could produce better effects. The superior effects of the degree strategy and weight strategy are achieved when the usage rate of masks is greater than 30.0% in hospital and high school and 50.0% in primary school. In the workplace, the effects of all three strategies are similar.

On the basis of the above results, we conclude that due to the heterogeneity of individual behavior within particular environments, when individuals with a high level of contact activity wear masks, the prevention effect of masks can be significantly improved. The heterogeneity of environments leads to different usage thresholds for producing superior effects, so appropriate

usage rate of masks should be set for different environments to ensure that the prevention effect of masks can be improved.

3.4 Influence of asymptomatic infection on the epidemic prevention effect of masks

In this study, asymptomatic patients are those who still do not show symptoms after the incubation period; these infections cannot be detected without nucleic acid testing (Day, 2020). Therefore, they have always been a problem for epidemic prevention. In this study, we experiment with different proportions of asymptomatic patients in the model and analyze the impact of asymptomatic infection on the prevention effect of masks.

Figure 10 shows the impact of asymptomatic infection on mask efficacy. Asymptomatic probability indicates the probability that patients will not show symptoms after the incubation period. In primary school and hospital, mask efficacy decreases as asymptomatic probability increases at any usage rate of masks. In the high school, this

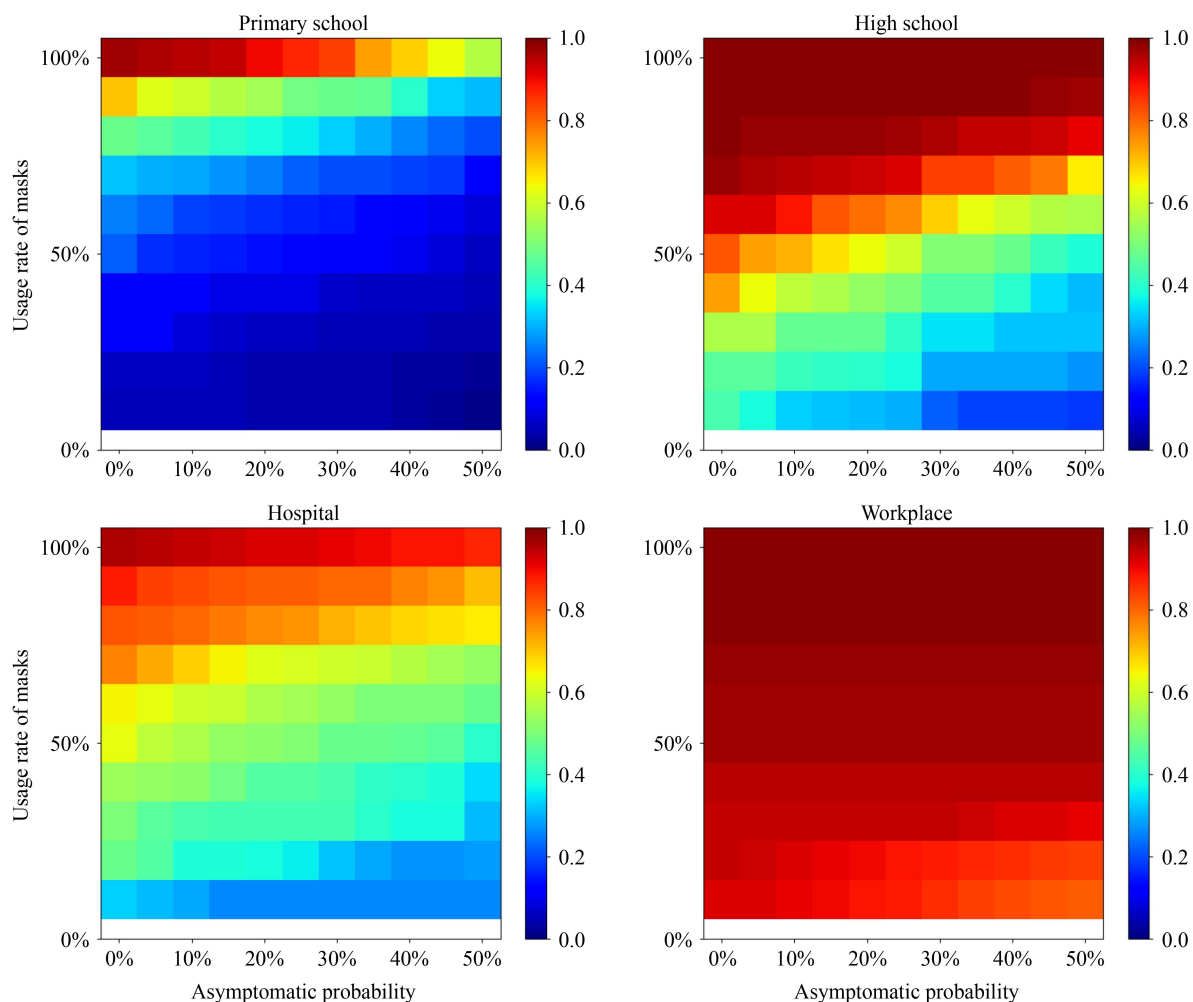


Fig. 10 Impact of asymptomatic infection and usage rate of masks on mask efficacy.

weakening trend can be prevented if all the people wear masks. In the workplace, when usage rate of masks is greater than 40.0%, mask efficacy cannot be reduced by asymptomatic infections.

Figure 11 shows the overall epidemic prevention effect of masks under different asymptomatic probabilities and different mask usage rates. In primary school, hospital, and high school, the probability of a clustered epidemic increases as the asymptomatic probability increases. Wearing masks cannot stop this trend. The impact of asymptomatic infection in workplace can be reduced or even eliminated by increasing the usage rate of masks. The result with an asymptomatic probability of zero is similar to the result with an asymptomatic probability of 50.0% when all individuals wear masks.

The impact of asymptomatic infection on the individual protective effect is shown in Fig. 12. The primary school and hospital are heavily affected. The protective effect decreases as the asymptomatic probability increases. In the high school, the impact of asymptomatic infection on the individual protective effect decreases as mask usage

increases. When all individuals wear masks, the protective effect under an asymptomatic probability of 0 is similar to that under an asymptomatic probability greater than 0. In the workplace, when the mask usage is greater than 80.0%, the impact of asymptomatic infection on the protective effect is almost eliminated.

In summary, asymptomatic infection can affect the prevention effect of masks. The heterogeneity of the environments results in the different degrees of impact among the environments. In primary school and hospital, even if all the people wear masks, asymptomatic infection still weakens the mask efficacy and prevention effect. In the high school, increasing the usage rate of masks can reduce the impact of asymptomatic infection on the mask efficacy and individual protective effect, while asymptomatic infection still has a large impact on the overall epidemic prevention effect of masks. In the workplace, as the number of individuals wearing masks increases, the impact of asymptomatic infection can be weakened or even eliminated.

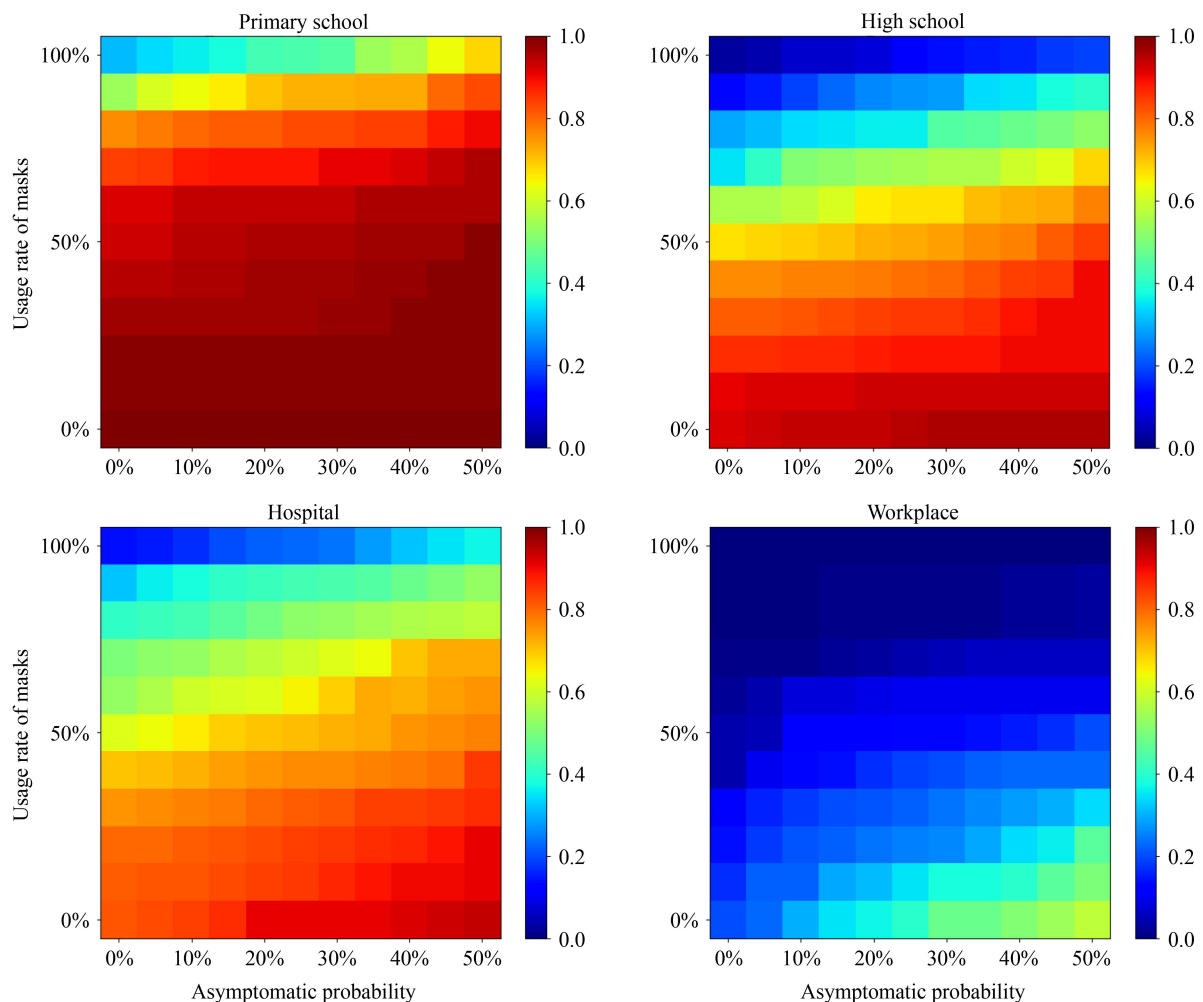


Fig. 11 Impact of asymptomatic infection and usage rate of masks on the overall epidemic prevention effect of masks.

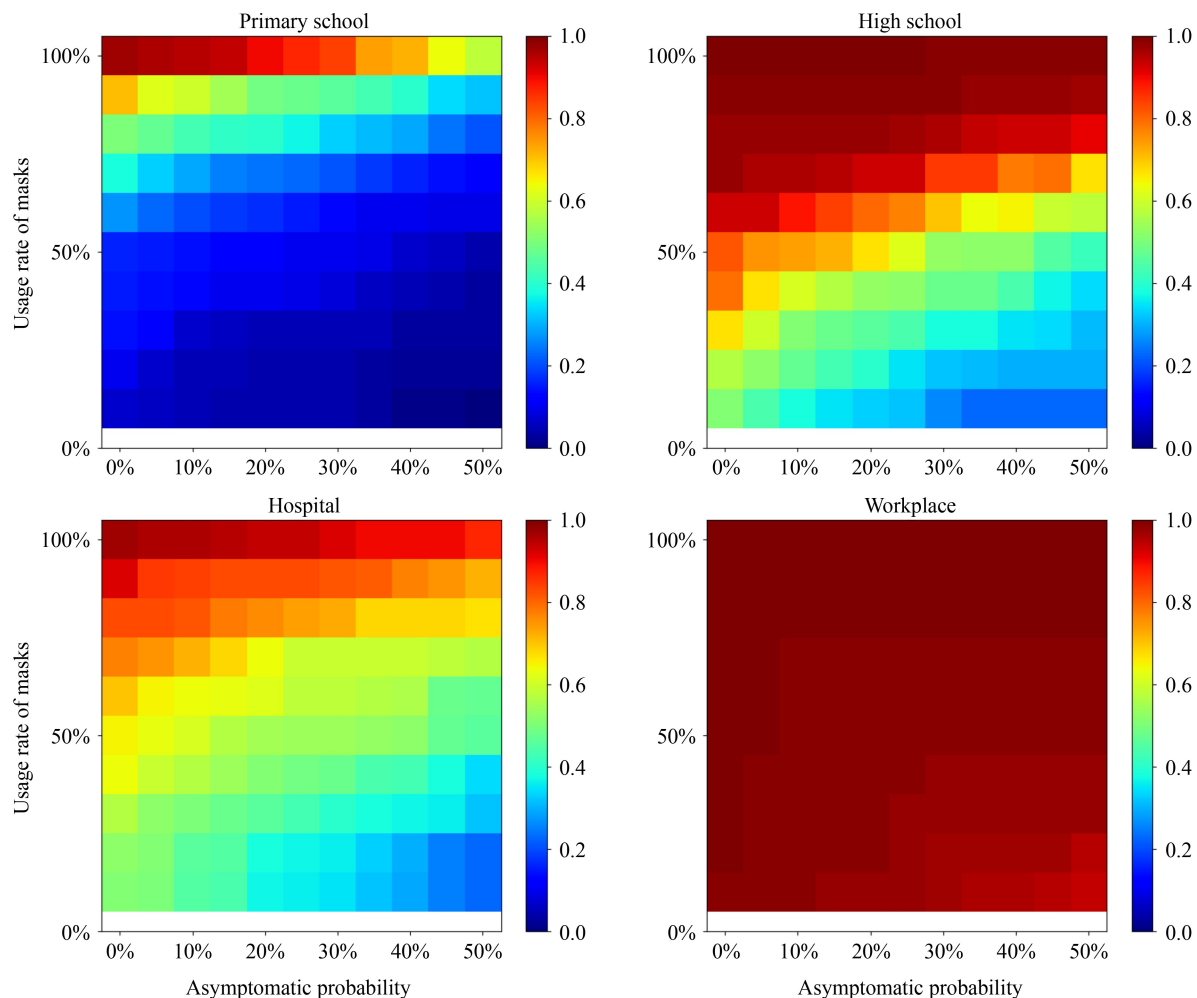


Fig. 12 Impact of asymptomatic infection and usage rate of masks on the individual protective effect of masks.

4 Conclusions

This study focuses on the epidemic prevention effect of masks in gathering environments. It uses real interpersonal contact datasets from primary school, high school, hospital, and workplace, and a variable infection model that fits the virus excretion of patients with COVID-19. Based on the Monte Carlo simulation method, the prevention effects of masks in the above gathering environments are simulated and analyzed. We found that increased usage rate of masks can suppress the occurrence of cluster outbreaks, reduce the scale of infection when outbreaks occur, and improve the protective effect of masks on individuals. Therefore, wearing masks is an effective prevention measure in gathering environments.

The heterogeneity of individuals in gathering environments causes mask efficacy in these environments to differ from the baseline efficacy of general society. Whether efficacy in these environments is greater or less than the baseline is affected by the usage rate of masks

and interpersonal contact density. The efficacies in high school, hospital, and primary school are higher than the baseline when the usage rate of masks achieves 60.0%, 90.0%, and 100%, respectively. In the workplace, the efficacy is greater than the baseline at any usage. The situation of high efficacy with high mask usage rate in primary school, high school, and hospital indicates the greater importance of improving the usage rate of masks in these three environments.

Environmental heterogeneity results in different overall prevention effects and individual protective effects of masks among the four environments. Wearing masks can greatly reduce the probability of clustered epidemics and infection scales in primary school, high school, and hospital. However, in primary school and hospital, the probability of clustered epidemics remains high when all the people wear masks. Therefore, we suggest that prevention strategies other than wearing masks, such as social distancing, should be combined in these two environments. If all the people wear masks in a high school with limited contact between classes and grades,

the occurrence of clustered epidemics is curbed. This illustrates the effect of combining mask-wearing and social distancing. Masks only can meet the prevention needs in workplaces.

Owing to the heterogeneity of individual behavior, when people with a large number of contacts or long contact duration wear masks, the epidemic prevention effect of masks is better than that when people are randomly selected to wear masks.

Asymptomatic infection can reduce the prevention effect of masks. Environmental heterogeneity results in varying degrees of reduction. By increasing the usage rate of masks, the impact of asymptomatic infection can be eliminated in workplaces and weakened in high schools, but it cannot be decreased in primary schools and hospitals.

Given the above results, we make the following recommendations regarding the use of masks in gathering environments. First, the mask efficacy baseline of general society does not necessarily reflect the efficacy of masks in specific gathering environments. Mask efficacy should be re-evaluated in combination with interpersonal contact and mask usage rate in gathering environments. Second, for gathering environments with a high likelihood of intensive contact, such as primary schools and hospitals, wearing masks alone is not enough to prevent clustered epidemics. Mask-wearing should be accompanied by measures such as social distancing and strict control of personnel entry and exit. If school administrators imitate the limited contact allowed by the high school in this study, wearing masks is an effective measure. Masks can meet the prevention needs in workplaces, so in the post-epidemic era, work activities can be resumed safely with the support of masks. Third, individuals with frequent activities that involve interpersonal contact should be required to wear masks. Fourth, in the event of a high probability of asymptomatic infection, more than 80.0% of or even all workers in workplaces should be required to wear masks. For schools and hospitals, if only masks are used as a prevention measure, we do not recommend opening these places during the epidemic outbreak.

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