Infectious Disease Modelling 8 (2023) 562–573

Contents lists available at ScienceDirect

Infectious Disease Modelling

journal homepage: www.keaipublishing.com/idm

Forecast for peak infections in the second wave of the Omicron after the adjustment of zero-COVID policy in the mainland of China

Sheng-Tao Wang [a], Yong-Ping Wu [b, **], Li Li [c, ***], Yong Li [d], Gui-Quan Sun [a, e, *]

[a] Complex Systems Research Center, Shanxi University, Taiyuan, 030006, China
[b] College of Physical Science and Technology, Yangzhou University, Yangzhou, 225002, China
[c] School of Computer and Information Technology, Shanxi University, Shanxi, Taiyuan, 030006, China
[d] School of Information and Mathematics, Yangtze University, Jingzhou, 434023, China
[e] School of Mathematics, North University of China, Shanxi, Taiyuan, 030051, China

ARTICLE INFO

Article history:
Received 14 April 2023
Received in revised form 17 May 2023
Accepted 28 May 2023
Available online 30 May 2023
Handling Editor: Dr Yijun Lou

Keywords:
Omicron
Parameter estimation
The zero-COVID policy
The severe cases
Nelder-Mead Simplex direct search algorithm

ABSTRACT

On December 7, 2022, the Chinese government optimized the current epidemic prevention and control policy, and no longer adopted the zero-COVID policy and mandatory quarantine measures. Based on the above policy changes, this paper establishes a compartment dynamics model considering age distribution, home isolation and vaccinations. Parameter estimation was performed using improved least squares and Nelder-Mead simplex algorithms combined with modified case data. Then, using the estimated parameter values to predict a second wave of the outbreak, the peak of severe cases will reach on 8 May 2023, the number of severe cases will reach 206,000. Next, it is proposed that with the extension of the effective time of antibodies obtained after infection, the peak of severe cases in the second wave of the epidemic will be delayed, and the final scale of the disease will be reduced. When the effectiveness of antibodies is 6 months, the severe cases of the second wave will peak on July 5, 2023, the number of severe cases is 194,000. Finally, the importance of vaccination rates is demonstrated, when the vaccination rate of susceptible people under 60 years old reaches 98%, and the vaccination rate of susceptible people over 60 years old reaches 96%, the peak of severe cases in the second wave of the epidemic will be reached on 13 July 2023, when the number of severe cases is 166,000.

1. Introduction

With the outbreak of the COVID-19 at the end of 2019, it has now been four years (Sun et al., 2022a; Wang et al., 2022). During these four years, the SARS-CoV-2 has continued to evolve for better survival and spread, with 5 mutated branches causing outbreaks and epidemics around the world (Asamoah et al., 2022; Ma et al., 2022a; The State Council The People,

* Corresponding author. Complex Systems Research Center, Shanxi University, Taiyuan, 030006, China.
** Corresponding author.
*** Corresponding author.
E-mail addresses: ypwu@yzu.edu.cn (Y.-P. Wu), lili831113@sxu.edu.cn (L. Li), gquansun@126.com (G.-Q. Sun).
Peer review under responsibility of KeAi Communications Co., Ltd.

https://doi.org/10.1016/j.idm.2023.05.007

2022). On 9 December 2021, China detected two imported cases of Omicron (Tan et al., 2022), which is also the first exposure to the Omicron strain in China. Compared to previous generations of strains, Omicron has a reduced ability to replicate in cell models (Shuai et al., 2022). In addition, in one study, Omicron replication in the upper and lower respiratory tracts of K18-hACE2 mice was significantly reduced, resulting in a significant reduction in lung pathological changes, compared with previous generations of strains, Omicron infection caused by reduced animal weight loss, animal mortality, and reduced replication and pathogenicity in mouse models (Shuai et al., 2022). Not only in animals, the study found that during the spread of Omicron in the United States, the hospitalization rate, ICU utilization rate, and case fatality rate in the United States decreased, but the total number of emergency departments, hospitalizations, and deaths was still very large (Iuliano et al., 2022), which means that although the fatality rate of Omicron has been reduced to a certain extent (Menni et al., 2022), it has stronger transmission ability (Callaway & Ledford, 2021; Ma et al., 2022b; Nyberg et al., 2022) and immune escape ability (Evans et al., 2022; Kannan et al., 2021).

Since the beginning of the spread of Omicron in China, the Chinese government has adopted a zero-COVID policy (Su et al., 2022), which has made China the most successful country in the world on epidemic prevention and control, and the number of severe cases and deaths in China have been well controlled (Burki, 2022). However, with the frequent occurrence of Omicron in various regions of China, the change of public attitude towards the current epidemic prevention and control policies (Mallapaty, 2022), and the weakening of Omicron's pathogenicity, the Chinese government issued a notice on December 7, 2022 to optimize the current epidemic prevention and control measures (National Health Commission of the People' s Republic of China, 2022a). Compared with the previous zero-COVID policy, this optimization has the following changes, including that various places will no longer adopt any form of temporary lockdown; do not carry out nucleic acid testing for all people according to administrative regions; except for special places, no negative nucleic acid certificate is required, and health codes are not checked; no more cross-regional personnel will be checked for negative nucleic acid certificates and health codes, and landing inspections will no longer be carried out; confirmed patients can be isolated at home and transferred to designated hospitals for treatment after their symptoms worsen (National Health Commission of the People' s Republic of China, 2022a).

With the release of new epidemic prevention and control policies, some new problems began to emerge. The elimination of mandatory isolation of confirmed patients and the lifting of temporary lockdown measures mean that more people will move around society (including some confirmed cases), the risk of people contracting Omicron has surged, and home isolation after people infected with Omicron will also lead to further infection within family members, especially in the elderly in the family, plus most elderly people have certain underlying diseases. This has led to a surge in demand for beds in designated hospitals and an increase in coronavirus-related deaths. In addition, the elimination of cross-regional personnel to check the negative nucleic acid certificate and health code means that the infection between regions will become frequent, coupled with the arrival of the Spring Festival, the population flow between regions will become more frequent than usual, which will also lead to an increase in the number of new infections.

Before China adjusted the zero-COVID policy, some regions had already adopted a relatively liberal policy for the COVID-19. After adjusting its epidemic prevention measures in February 2022, Hong Kong ushered in the first wave of the epidemic after liberalization, and reached a single-day peak of new confirmed cases on 4 March 2022. Six months later, the second wave of the epidemic after the liberalization was ushered in, but compared with the first wave, the second wave of the epidemic after Hong Kong's liberalization had a large reduction in confirmed cases (Mathieu et al., 2020). Similarly, the peak of the second wave of infections after the liberalization of relevant policies in Germany has also been greatly reduced compared with the first wave peak (Mathieu et al., 2020).

For the Chinese government's epidemic prevention and control measures, scholars at home and abroad have studied and predicted the development of the epidemic in China on this basis. Yu et al. (Cai et al., 2022) found that if the Chinese government lifted the zero-COVID policy in March 2022, it will not be enough to prevent the Omicron wave, which will cause a large number of critically ill patients and further collapse the medical system, in this case, intensive care units expected to peak at 15.6 times the current demand, and eventually about 1.55 million deaths. As Hong Kong lifted the zero-COVID policy two years before the outbreak, Mallapaty (Mallapaty, 2022) used the cumulative peak cases and deaths of the BA.1 wave in Hong Kong to predict the development of the epidemic after the Chinese government canceled the zero-COVID policy, and the forecast showed that there would be 167 million to 279 million cases of infection, which could lead to 1.3 million to 2.1 million deaths. Ioannidis et al. (Ioannidis et al., 2023) predicted the development of the epidemic in China based on data from Hong Kong and South Korea in 2022, they assume that if all Chinese people were infected with the virus, the Chinese mainland would have at most 987,000 and 619,000 deaths from the COVID-19, respectively. Chen et al. (Chen et al., 2023) built a dynamic model taking into account vaccination and loss of immune protection, fitted deaths in six Asian and Oceanian countries, in addition to estimates of *IFR* and $\mathcal{R}_0(t)$. However, there are relatively few articles on the timing and peak prediction of the second wave of the epidemic after China's adjustment of the zero-COVID policy, and here we will make parameter estimates based on the data of the first wave after the adjustment policy, as well as, predicate the peak and time of severe cases in the second wave of the epidemic.

This paper will start from the following parts: In the Method part, we establish a compartment dynamics model (Chang et al., 2022; Sun et al., 2022b) based on the current transmission characteristics of Omicron and the isolation measures taken in China; secondly, the improved least squares method and Nelder-Mead simplex algorithm are used to estimate the parameters, and the epidemic data released by the Chinese Center for Disease Control and Prevention (CDC) are selected to verify the accuracy of the model. In the Results section, the results of parameter estimation are first demonstrated. Then we

estimate the peak number of severe cases and deaths in the second wave. Next, the decay time of antibodies obtained after infection is discussed, and the development trend of the second wave of the epidemic under different attenuation times is considered. Finally, we analyse the important role of strengthening the vaccination rate in the second wave of the epidemic. The Conclusion section summarizes all the conclusions reached in this paper.

2. Method

2.1. Data

We collected severe cases and deaths from December 7, 2022 to February 6, 2023 from the National Health Commission and CDC. Starting from December 25, 2022, the National Health Commission no longer released daily epidemic information, and the CDC began to release relevant epidemic information (National Health Commission of the, 2022). Since the epidemic data released by CDC is relatively discrete, we interpolate the discrete case data on this basis, and obtain the severe cases and cumulative deaths from December 7, 2022 to February 6, 2023 through cubic spline interpolations, and the interpolation results are detailed in Fig. 1.

In addition, Wu Z., chief expert in epidemiology of the CDC, attending the "Annual Meeting of Finance and Economics 2023: Forecast and Strategy", which announced that the national epidemic infection rate will reach 30%, and the proportion of severe and critical diseases in hospitals as of December 5, 2022 will be reduced to 0.18% (Cai Lian News, 2022), with the adjustment of China's zero-COVID policy. Combined with the above data, it is calculated that the number of severe cases in China will reach 763,000, so we revise the interpolated case data on this basis, and the correction result is also shown in Fig. 1.

2.2. Model

Taking into account the changes in isolation measures and the surge in the number of infected people after adjusting the zero-COVID policy, we classify susceptible people according to age (Bajiya et al., 2021) and construct a compartment dynamic model to estimate the peak of severe patients under the epidemic. Combined with the current transmission characteristics of Omicron in China, the total population is divided into nine epidemiological subgroups, including susceptible population (under 60 years old) S_1, susceptible population (over 60 years old) S_2, latent population (under 60 years old) E_1, latent population (over 60 years old) E_2, asymptomatic and mildly symptomatic patients I, patients in home isolation and non-severe patients in designated hospitals (under 60 years old) A_1, patients in home isolation and non-severe patients in designated hospitals (over 60 years old) A_2, severe patients in designated hospitals H, recovered population R, see Table 1 for a detailed description. Before constructing the model, in order to better characterize the actual situation of Omicron spreading in China after adjusting the zero-COVID policy, we make the following assumptions:

1. Because the study was short-lived, the model do not consider the natural birth rate and natural death rate of the population between December 7, 2022 and February 6, 2023.
2. We assume that the infected susceptible people are not contagious during the latent period, that is, the latent person $E_i(i = 1, 2)$ does not infect the susceptible population.
3. We divide the latent population into two subgroups (E_1, E_2) according to different ages, for E_1, when they are contagious, assuming that some people will not be directly in a state of home isolation due to factors such as work and school, these people will continue to flow in society, and wait until the symptoms begin to be worsen before transferring to

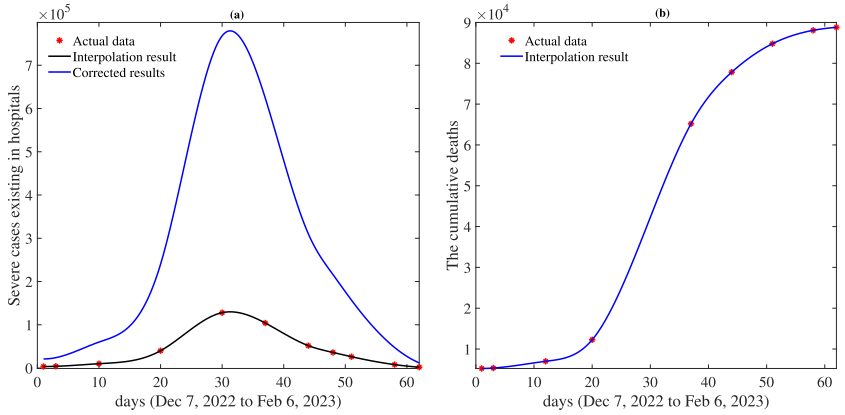

Fig. 1. The chart of the interpolation results and data corrections. **(a)**Interpolation results and data correction for severe cases. **(b)**Interpolation results for cumulative deaths.

Table 1
The definition of each compartment in the model.

Variables	Description (at initial moment t_0)	Value	Source
$S_1(t_0)$	Susceptible population (under 60 years old)	1145053560	Compiled by National Bureau of Statistics of China (2022)
$S_2(t_0)$	Susceptible population (over 60 years old)	267546440	Compiled by National Bureau of Statistics of China (2022)
$E_1(t_0)$	Latent population (under 60 years old)	100000	Fixed
$E_2(t_0)$	Latent population (over 60 years old)	25000	Fixed
$I(t_0)$	Asymptomatic and mildly symptomatic patients	50000	Fixed
$A_1(t_0)$	Patients in home and non-severe patients in hospitals (under 60 years old)	35000	Fixed
$A_2(t_0)$	Patients in home and non-severe patients in hospitals (over 60 years old)	15000	Fixed
$H(t_0)$	Severe patients in designated hospitals	21000	Fixed
$R(t_0)$	Recovered population	0	Fixed

compartment A_1. Correspondingly, for E_2, we assume that it will be directly in home isolation A_2 or directly transfer to a designated hospital to become a severe patients H, depending on the severity of symptoms.

4. When we build the model, we only consider the attenuation of antibodies obtained after recovering from infection with the COVID-19 with time, and do not consider the attenuation of antibodies obtained through vaccines. Assume that the antibodies obtained through vaccination are effective for a long time.
5. This model is a stage structure model, so we do not consider the transition between people over 60 years old and people under 60 years old.
6. We assume that medical resources are always plentiful.

Based on the above assumptions, a schematic diagram used to illustrate the propagation dynamics of Omicron infection in China is shown in Fig. 2. The model (1) is described by the following system of ordinary differential equations, and the actual meaning of the parameters in the model is shown in Table 2. For model (1), we let $N = S_1 + S_2 + E_1 + E_2 + A_1 + A_2 + I + H + R$ and $A = A_1 + A_2$.

$$
\begin{cases}
\dfrac{dS_1}{dt} = \varphi qR - \beta_1(t)S_1\rho_1\epsilon\dfrac{(I+kA)}{N} - \beta_1(t)S_1(1-\rho_1)\dfrac{(I+kA)}{N},\\
\dfrac{dE_1}{dt} = \beta_1(t)S_1\rho_1\epsilon\dfrac{(I+kA)}{N} + \beta_1(t)S_1(1-\rho_1)\dfrac{(I+kA)}{N} - \alpha E_1,\\
\dfrac{dI}{dt} = \alpha\rho E_1 - \gamma I,\\
\dfrac{dS_2}{dt} = \varphi(1-q)R - \beta_2(t)S_2\rho_2\epsilon\dfrac{(I+kA)}{N} - \beta_2(t)S_2(1-\rho_2)\dfrac{(I+kA)}{N},\\
\dfrac{dE_2}{dt} = \beta_2(t)S_2\rho_2\epsilon\dfrac{(I+kA)}{N} + \beta_2(t)S_2(1-\rho_2)\dfrac{(I+kA)}{N} - \alpha E_2,\\
\dfrac{dA_1}{dt} = \alpha(1-\rho)E_1 + \gamma I - \delta_1 A_1,\\
\dfrac{dA_2}{dt} = \alpha E_2 - \delta_2 A_2\\
\dfrac{dH}{dt} = \delta_1\theta_1 A_1 + \delta_2\theta_2 A_2 - (\omega+\mu)H,\\
\dfrac{dR}{dt} = \delta_1(1-\theta_1)A_1 + \delta_2(1-\theta_2)A_2 + \omega H - \varphi R.
\end{cases}
\tag{1}
$$

2.3. Parameter estimation

In this part, we use 62 days of severe cases and cumulative deaths from December 7, 2022 to February 6, 2023 to fit model parameters using the improved least squares method (Tuncer et al., 2022) and the Nelder-Mead simplex algorithm (Lagarias et al., 1998), which can be achieved by using the fminsearchbnd function in Matlab (the Mathworks, Inc.). The fminsearchbnd function is improved on the basis of the fminsearch function, and the derivative-free method is used to calculate the minimum value of the unconstrained multivariate function when the upper and lower bounds of the model parameters are controlled, that is, the minimum value of the improved least squares method is solved through continuous iteration. In this

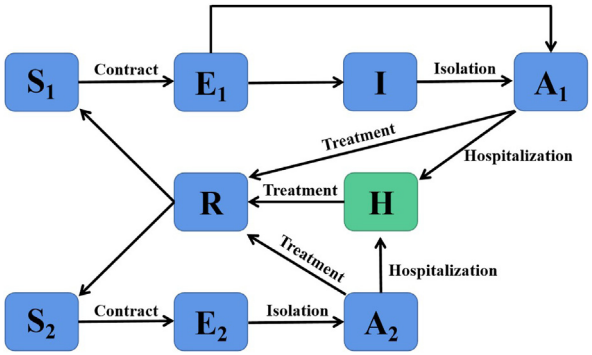

Fig. 2. Flow chart of compartments of the model.

paper, we solve the following optimization constraint problem by using the fminsearchbnd function, so as to realize the estimation of parameters in the model:

$$\begin{cases} J = \min\left(\frac{1}{n}\sum_{i=1}^{n}\frac{\left|y_1(t_i) - Y_1^i\right|^2}{\hat{Y}_1{}^2} + \frac{1}{n}\sum_{i=1}^{n}\frac{\left|y_2(t_i) - Y_2^i\right|^2}{\hat{Y}_2{}^2}\right), n = 62, \\ \hat{Y}_1 = \frac{1}{n}\sum_{i=1}^{n} Y_1^i, \hat{Y}_2 = \frac{1}{n}\sum_{i=1}^{n} Y_2^i \end{cases} \tag{2}$$

where $Y_1^i, i = 1, 2, \ldots, 62$ represents the actual number of severe patients per day, $Y_2^i, i = 1, 2, \ldots, 62$ represents the actual number of cumulative deaths per day, $y_1(t_i)$, $i = 1, 2, \ldots, 62$ represents the fitted value of severe patients per day, $y_2(t_i)$, $i = 1, 2, \ldots, 62$ represents the fitted value of cumulative deaths per day, $\hat{Y}_1$ is the average number of daily cases of severe cases and $\hat{Y}_2$ is the average number of daily cases of cumulative deaths between December 7, 2022 and February 6, 2023.

Among the 17 parameters of the model, we selected 11 parameters for estimation, including β_1, β_2, k, ρ, ϵ, ω, μ, θ_1, θ_2, δ_1, δ_2, and the remaining six parameters were fixed. For the transmission rate of different populations, here we consider a time-varying transmission rate, by referring to the results of Linka et al. (Linka et al., 2020), assuming that the transmission rate $\beta_i(t)$, $i = 1, 2$ is a hyperbolic tangent function:

$$\begin{cases} \beta_1(t) = \beta_0 - \frac{1}{2}\left[1 + \tanh\left(\frac{t - t^*}{T}\right)\right]\left(\beta_0 - \beta^*\right), \\ \beta_2(t) = 1.5\beta_1(t), \end{cases} \tag{3}$$

where β_0 represents the initial transmission rate at the beginning of the epidemic, β^* represents the minimum value to which the transmission rate decreases over time, t^* is the adaptation time and T is the transition time. From the results of Yu et al.

Table 2
The interpretation of the parameters in the model.

Parameters	Description
$\beta_1(t)$	Transmission rate of susceptible population(under 60 years old)
$\beta_2(t)$	Transmission rate of susceptible population(over 60 years old)
q	Proportion of the population under 60 years old
φ	Rate of loss of immunity protection
ρ	The proportion of asymptomatic and mild patiens
ρ_1	The vaccine coverage rate for people under 60 years old
ρ_2	The vaccine coverage rate for people over 60 years old
k	Infectivity reduction factor
$1/\alpha$	Average duration of latent period
ϵ	Relative susceptibility of vaccinated vs. unvaccinated
γ	The rate of transition to compartment A_1 in asymptomatic and mild patients
δ_1	The Transfer rate of compartment A_1(under 60 years old)
δ_2	The Transfer rate of compartment A_2(over 60 years old)
θ_1	The proportion of people under 60 years old with severe disease
θ_2	The proportion of people over 60 years old with severe disease
ω	The recover rate of severe cases in designated hospitals
μ	The fatality rate among severe cases in designated hospitals

(Cai et al., 2022), we set the average duration ($1/\alpha$) of Omicron to 1.52 days; according to the reference of Chen et al. (Chen et al., 2023), the attenuation rate of antibodies acquired by infection (φ) is set to 0.0083; the proportion of the population under 60 years old (q) is calculated by the Chinese Statistical Yearbook (Compiled by National Bureau of Statistics of China, 2022); the vaccination rate of people over 60 years old (ρ_1) and people under 60 years old (ρ_2) can be calculated by the data released by the Health Commission at the press conference (National Health Commission of the People' s Republic of China, 2022b) and the rate (γ) of asymptomatic or mild patients transferred to compartment A_1 is fixed at 0.5. For detailed parameter values, see Table 3.

2.4. The basic reproduction number

The basic reproduction number ($\mathcal{R}_0$) indicates the number of second-generation cases in which a case enters a susceptible population and can be infected without external intervention (Diekmann et al., 1990). Usually, we use $\mathcal{R}_0 = 1$ as the threshold to determine whether the disease is prevalent (Wang & Zhao, 2008), when $\mathcal{R}_0 > 1$, the final disease will spread and turn into endemic, and when $\mathcal{R}_0 < 1$, the final disease will be controlled and eventually extinct (Wang et al., 2023). From the results of Driessche and Watmough (Van den Driessche & Watmough, 2002), we can calculate the basic reproduction number as follows:

$$\begin{aligned} \mathcal{R}_0 &= \mathcal{R}_0^{(1)} + \mathcal{R}_0^{(2)}, \\ \mathcal{R}_0^{(1)} &= \frac{81\beta_1 k(1-\rho_1+\epsilon\rho_1)}{100\delta_1} + \frac{81\beta_1\rho(1-\rho_1+\epsilon\rho_1)}{100\gamma}, \\ \mathcal{R}_0^{(2)} &= \frac{19\beta_2 k(1-\rho_2+\epsilon\rho_2)}{100\delta_2}, \end{aligned} \tag{4}$$

where $\mathcal{R}_0^{(1)}$ represents the basic reproduction number of susceptible people under 60 years old, and $\mathcal{R}_0^{(2)}$ represents the basic reproduction number of susceptible people over 60 years old.

3. Result

3.1. Fitting results and prediction

In the model, we fitted both severe cases and cumulative deaths, and the fitting results are shown in Fig. 3.

From Fig. 3, it can be seen that the basic trends of the two sets of data have been well matched, and then the parameter values obtained by the fitting are used to predict the peak of the second wave of the epidemic after China's adjustment of the zero-COVID policy, and the prediction results are also shown in Fig. 3, the model predicts that the second wave of the epidemic after the release will break out on May 8, 2023, and the number of severe cases is expected to reach 206,000, compared with the outbreak of the first wave, the peak of severe cases has been greatly reduced. From 8 February 2023 to 8 May 2023, the cumulative number of deaths will be controlled at 29,000, decreased by 67.4% compared to the cumulative number of deaths in the first wave of the epidemic.

From the results of parameter estimation, it can be seen that most susceptible people under the age of 60 will not be in self-isolation at home for the first two days after the latent period, and only about 30% will take home isolation immediately after the latent period. In addition, the average recovery time of severe cases in hospital is 6.25 days, and the proportion of people over 60 years old with severe disease in hospital is also higher than that of people under 60 years old.

Table 3
The fitting values of the parameters in the model.

Parameters	Values	Source	Parameters	Values	Source
q	0.8106	Compiled by National Bureau of Statistics of China (2022)	β_0	5.38	Estimated
φ	0.0083	Chen et al. (2023)	t^*	5.30	Estimated
ρ_1	0.9123	National Health Commission of the People' s Republic of China (2022b)	T	10.02	Estimated
ρ_2	0.8642	National Health Commission of the People' s Republic of China (2022b)	δ_1	0.29	Estimated
α	0.6579	Cai et al. (2022)	δ_2	0.50	Estimated
β^*	3.5	Fixed	θ_1	0.0016	Estimated
γ	0.5	Fixed	θ_2	0.0038	Estimated
ρ	0.69	Estimated	ω	0.16	Estimated
k	0.48	Estimated	μ	0.0051	Estimated
ϵ	0.25	Estimated			

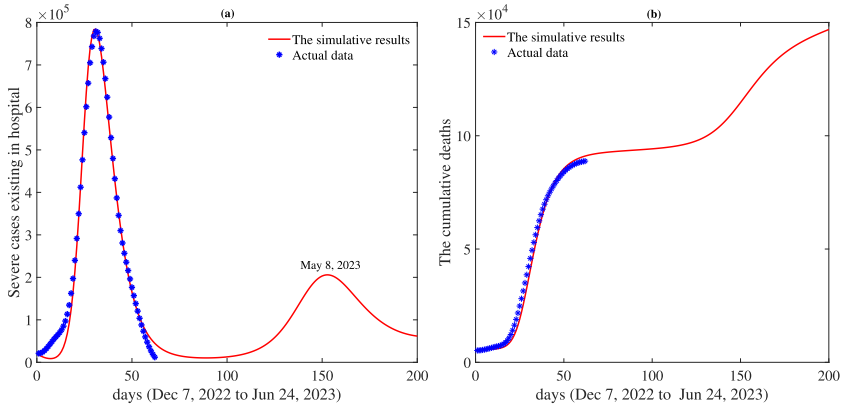

Fig. 3. The chart of the fitted result and prediction curve. **(a)** Fitting results and prediction for severe cases. **(b)** Fitting results and prediction for cumulative deaths.

3.2. The results of basic reproduction number

In this part, we calculate the basic reproduction number using the estimated parameter values. The basic reproduction number of susceptible people of different ages between December 7, 2022 and February 6, 2023 was calculated, and the results of $\mathcal{R}_0$ are shown in Fig. 4.

3.3. Sensitivity analysis of $\mathcal{R}_0$

Sensitivity analysis is used to determine the sensitivity of predictor parameters to inputs (Samsuzzoha et al., 2013). The sensitivity analysis of $\mathcal{R}_0$ can obtain the parameters that are more sensitive to $\mathcal{R}_0$, so as to change the parameter values of the model by taking corresponding measures, and finally achieve the effect of controlling the epidemic. In this paper, referring to the research results of Chitnis et al. (Chitnis et al., 2008), the basic reproduction number is analyzed by using the model parameters based on fixed point estimation.

As can be seen from Table 4, β_1, ϵ, k has a positive effect on $\mathcal{R}_0^{(1)}$ and ρ_1, δ_1, γ has a negative effect on $\mathcal{R}_0^{(1)}$; β_2, ϵ, k has a positive effect on $\mathcal{R}_0^{(2)}$ and ρ_2, δ_2 has a negative effect on $\mathcal{R}_0^{(2)}$. If the sensitivity index is positive, it indicates that $\mathcal{R}_0$ increases with the increase of parameters. A negative sensitivity index indicates that $\mathcal{R}_0$ decreases with the increase of the parameter. If we want to decrease $\mathcal{R}_0^{(1)}$ by 1%, we can reduce k by 2.0084% or increase γ by 1.9916%.

3.4. The final size relation

Whenever an infectious disease emerges or re-emerges in a population, people are more concerned about the possible scale of the infectious disease, which is often called the final scale of the infectious disease (Ma & Earn, 2006). In this section, we discuss the relationship between the basic reproduction number $\mathcal{R}_0$ and the final size of the outbreak.

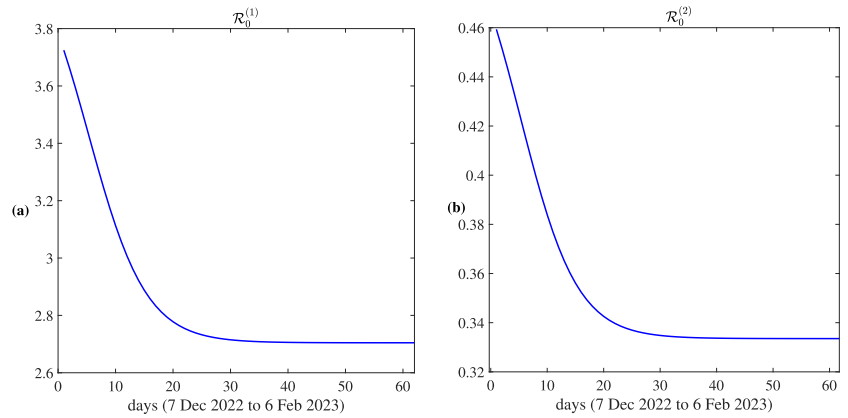

Fig. 4. The change chart of the $\mathcal{R}_0$. **(a)** Change curve of $\mathcal{R}_0$ in susceptible people under 60 years old. **(b)** Change curve of $\mathcal{R}_0$ in susceptible people over 60 years old.

Table 4
Sensitivity index of different parameters to $\mathcal{R}_0$.

The parameter	Sensitivity index to $\mathcal{R}_0^{(1)}$	The corresponding percentage change (%)
β_1	1	−1
ϵ	0.7192	−1.3904
k	0.4979	−2.0084
ρ_1	−2.2014	0.4543
γ	−0.5021	1.9916
δ_1	−0.4979	2.0084
The parameter	Sensitivity index to $\mathcal{R}_0^{(2)}$	The corresponding percentage change (%)
β_2	1	−1
k	1	−1
ϵ	0.6103	−1.6385
ρ_2	−1.8679	0.5354
δ_2	−1	1

First, the model (1) is normalized,
where

$$s_i = \frac{S_i}{N}, e_i = \frac{E_i}{N}, a_i = \frac{A_i}{N}, i = \frac{I}{N}, h = \frac{H}{N}, r = \frac{R}{N}, i = 1, 2. \tag{5}$$

We considered normalized models at mortality rate for severe disease in hospital $\mu = 0$ and the rate of antibody loss after recovery $\varphi = 0$:

$$\begin{cases} \dfrac{ds_1}{dt} = -\beta_1 s_1 \rho_1 \epsilon (i + ka) - \beta_1 s_1 (1 - \rho_1)(i + ka), \\ \dfrac{de_1}{dt} = \beta_1 s_1 \rho_1 \epsilon (i + ka) + \beta_1 s_1 (1 - \rho_1)(i + ka) - \alpha e_1, \\ \dfrac{di}{dt} = \alpha \rho e_1 - \gamma i, \\ \dfrac{ds_2}{dt} = -\beta_2 s_2 \rho_2 \epsilon (i + ka) - \beta_2 s_2 (1 - \rho_2)(i + ka), \\ \dfrac{de_2}{dt} = \beta_2 s_2 \rho_2 \epsilon (i + ka) + \beta_2 s_2 (1 - \rho_2)(i + ka) - \alpha e_2, \\ \dfrac{da_1}{dt} = \alpha (1 - \rho) e_1 + \gamma i - \delta_1 a_1, \\ \dfrac{da_2}{dt} = \alpha e_2 - \delta_2 a_2, \\ \dfrac{dh}{dt} = \delta_1 \theta_1 a_1 + \delta_2 \theta_2 a_2 - (\omega + \mu) h, \\ \dfrac{dr}{dt} = \delta_1 (1 - \theta_1) a_1 + \delta_2 (1 - \theta_2) a_2 + \omega h. \end{cases} \tag{6}$$

We can conclude from model (6) that no recruitment ensures that the disease will eventually burn out, i.e., $e_i(\infty) = 0$, $a_i(\infty) = 0$ and $i(\infty) = 0$, note that the positive orthant is invariant so all solutions of Eq. (6) lie in the non-negative, bounded set defined by s_i,Se_i, a_i, i, h, $r \geq 0$, $(i = 1, 2)$ and $s_1 + s_2 + e_1 + e_2 + a_1 + a_2 + i + h + r = 1$. Observing that

$$\frac{d}{dt}(s_i(t) + e_i(t)) = -\alpha e_i(t), \tag{7}$$

we see that $s_i(t) + e_i(t)$ is decreasing whenever $e_i(t) > 0$. However, $s_i + e_i$ is bounded below by 0; hence it has a limit. Moreover, model (6) implies that $\frac{d}{dt}(s_i(t) + e_i(t))$ is bounded because $e_i(t)$ is bounded. Hence $\lim_{t\to\infty} \frac{d}{dt}(s_i(t) + e_i(t)) = 0$, so $e_i(\infty) = 0$. Similarly, we can get $a_i(\infty) = 0$ and $i(\infty) = 0$. We adopt the convention that, for an arbitrary continuous function $w(t)$ with non-negative components, $w_\infty = \lim_{t\to\infty} w(t)$ and $\bar{w} = \int_0^\infty w(t)dt$ (Jin et al., 2011). We integrate equation (7) from $t = 0$ to ∞,

$$e_i(0) - e_i(\infty) + s_i(0) - s_i(\infty) = \alpha \bar{e}_i. \tag{8}$$

The left-hand side of (8) is finite because the components of $s_i(0)$, $s_i(\infty)$, $e_i(0)$ and $e_i(\infty)$ are bounded by the initial total population size. Therefore, the right-hand side of (8) is also finite and α is positive. Since $e_i(\infty) = 0$, we have

$$\bar{e}_i = \frac{1}{\alpha}[s_i(0) - s_i(\infty) + e_i(0)]. \tag{9}$$

Similarly, we can obtain

$$\bar{i} = \frac{\alpha\rho\bar{e}_1 + i(0)}{\gamma}, \bar{a}_1 = \frac{\alpha\bar{e}_1 + a_1(0) + i(0)}{\delta_1}, \bar{a}_2 = \frac{\alpha\bar{e}_2 + a_2(0)}{\delta_2}. \tag{10}$$

We get the integral of the first equation of Eq. (6) from 0 to t

$$\ln\frac{s_i(0)}{s_i(t)} = \beta_i\rho_i\epsilon\left[\int_0^t i(t)dt + k\int_0^t a(t)dt\right] + \beta_i(1-\rho_i)\left[\int_0^t i(t)dt + k\int_0^t a(t)dt\right]. \tag{11}$$

Letting $t \to \infty$ and $\lambda_i = s_i(0) - s_i(\infty) + e_i(0)$, $i = 1, 2$, we have

$$\begin{aligned}
&\ln\frac{s_1(0)}{s_1(\infty)} \\
&= \beta_1\rho_1\epsilon(\bar{i} + k\bar{a}) + \beta_1(1-\rho_1)(\bar{i} + k\bar{a}) \\
&= (\beta_1\rho_1\epsilon + \beta_1(1-\rho_1))\left[\frac{\alpha\rho\bar{e}_1 + i(0)}{\gamma} + k\left(\frac{\alpha\bar{e}_1 + a_1(0) + i(0)}{\delta_1} + \frac{\alpha\bar{e}_2 + a_2(0)}{\delta_2}\right)\right] \\
&= \beta_1\rho_1\epsilon\left[\frac{\rho\lambda_1}{\gamma} + \frac{i(0)}{\gamma} + \frac{k\lambda_1}{\delta_1} + \frac{ka_1(0)}{\delta_1} + \frac{ki(0)}{\delta_1} + \frac{k\lambda_2}{\delta_2} + \frac{ka_2(0)}{\delta_2}\right] + \beta_1(1-\rho_1)\left[\frac{\rho\lambda_2}{\gamma} + \frac{i(0)}{\gamma} + \frac{k\lambda_1}{\delta_1} + \frac{ka_1(0)}{\delta_1} + \frac{ki(0)}{\delta_1} + \frac{k\lambda_2}{\delta_2} + \frac{ka_2(0)}{\delta_2}\right] \\
&= \frac{\beta_1\rho_1\epsilon\rho\lambda_1}{\gamma} + \frac{\beta_1\rho_1\epsilon i(0)}{\gamma} + \frac{\beta_1\rho_1\epsilon k}{\delta_1}[\lambda_1 + a_1(0) + i(0)] + \frac{\beta_1\rho_1\epsilon k}{\delta_2}[\lambda_2 + a_2(0)] + \frac{\beta_1\rho(1-\rho_1)\lambda_2}{\gamma} + \frac{\beta_1(1-\rho_1)i(0)}{\gamma} \\
&\quad + \frac{\beta_1(1-\rho_1)k}{\delta_1}[\lambda_1 + a_1(0) + i(0)] + \frac{\beta_1(1-\rho_1)k}{\delta_2}[\lambda_2 + a_2(0)] \\
&= \frac{\beta_1\rho}{\gamma}[\rho_1\epsilon\lambda_1 + (1-\rho_1)\lambda_2] + \frac{\beta_1(\rho_1\epsilon + 1 - \rho_1)i(0)}{\gamma} + \frac{\beta_1k(\rho_1\epsilon + 1 - \rho_1)}{\delta_1}[\lambda_1 + a_1(0) + i(0)] + \frac{\beta_1k(\rho_1\epsilon + 1 - \rho_1)}{\delta_2}[\lambda_2 + a_2(0)] \\
&= \frac{100}{81}R_0^{(1)}[\lambda_1 + a_1(0) + i(0)] + \frac{\beta_1(1-\rho)(\rho_1\epsilon + 1 - \rho_1)i(0)}{\gamma} + \frac{\beta_1\rho(1-\rho_1)\lambda_2}{\gamma} + \frac{\beta_1k(\rho_1\epsilon + 1 - \rho_1)}{\delta_2}[\lambda_2 + a_2(0)] - \frac{\beta_1\rho(1-\rho_1)\lambda_1}{\gamma} \\
&\quad - a_1(0)\frac{\beta_1\rho(\rho_1\epsilon + 1 - \rho_1)}{\gamma}.
\end{aligned}$$

Similarly, we can obtain

$$\begin{aligned}
\ln\frac{s_2(0)}{s_2(\infty)} &= \frac{\beta_2\rho[\rho_2\epsilon\lambda_1 + (1-\rho_2)\lambda_2]}{\gamma} + \frac{\beta_2(\rho_2\epsilon + 1 - \rho_2)i(0)}{\gamma} + \frac{\beta_2k(\rho_2\epsilon + 1 - \rho_2)}{\delta_1}[\lambda_1 + a_1(0) + i(0)] \\
&\quad + \frac{\beta_2k(\rho_2\epsilon + 1 - \rho_2)}{\delta_2}[\lambda_2 + a_2(0)] = \frac{100}{19}R_0^{(2)}\left[[\lambda_2 + a_2(0)] + \frac{\delta_2}{\delta_1}[\lambda_1 + a_1(0) + i(0)]\right] + \frac{\beta_2(\rho_2\epsilon + 1 - \rho_2)i(0)}{\gamma} \\
&\quad + \frac{\beta_2\rho[\rho_2\epsilon\lambda_1 + (1-\rho_2)\lambda_2]}{\gamma}.
\end{aligned}$$

If $s_i(0) = s_{i0}$, $i(0) = i_0$, $e_i(0) = a_i(0) = 0$, $i = 1, 2$, then the final size relation becomes

$$\ln\frac{s_1(0)}{s_1(\infty)} = \frac{100}{81}R_0^{(1)}[[s_1(0) - s_1(\infty)] + i_0] + \frac{\beta_1(1-\rho)(\rho_1\epsilon + 1 - \rho_1)i_0}{\gamma} + \frac{\beta_1\rho(1-\rho_1)[s_2(0) - s_2(\infty)]}{\gamma}$$

$$+\frac{\beta_1 k(\rho_1\epsilon+1-\rho_1)}{\delta_2}[s_2(0)-s_2(\infty)]-\frac{\beta_1\rho(1-\rho_1)[s_1(0)-s_1(\infty)]}{\gamma},\ln\frac{s_2(0)}{s_2(\infty)}$$
$$=\frac{100}{19}R_0^{(2)}\left[[s_2(0)-s_2(\infty)]+\frac{\delta_2}{\delta_1}[s_1(0)-s_1(\infty)+i_0]\right]+\frac{\beta_2(\rho_2\epsilon+1-\rho_2)i_0}{\gamma}$$
$$+\frac{\beta_2\rho[\rho_2\epsilon[s_1(0)-s_1(\infty)]+(1-\rho_2)[s_2(0)-s_2(\infty)]]}{\gamma}.$$

Here we are not considering the prevalence of new strains in susceptible people, and if a new strain (”XBB.1.5″ strain) enters the population, there will never really be a “final” size, so we only derive the final scale under a single strain. From the derivation results, we can see that the final scale of the epidemic is closely related to $\mathcal{R}_0$, and combined with the sensitivity analysis of $\mathcal{R}_0$, we can take corresponding measures to control the parameters and further control the final scale of the epidemic through $\mathcal{R}_0$.

3.5. Prediction of epidemic peaks at different antibody decay times

The antibody decay we consider here is only the antibodies obtained after infection with the COVID-19. When people recover from the disease, the effectiveness of antibodies produced in the body generally lasts for 4–6 months. In the parameter estimation section, we assume that the effectiveness of the antibody is 4 months to get the results in Fig. 3, and then we consider the additional case of 5 months and 6 months of effectiveness, and the simulation results are shown in Fig. 5.

As can be seen from Fig. 5, with the extension of antibody decay time, the peak of severe cases in the second wave of the epidemic has also been postponed accordingly. When the time of antibody decay is five months, the second wave of severe cases will peak on June 13, 2023, the number of severe cases will reach 197,000, and when the time of antibody decay is six months, the second wave of severe cases will peak on July 5, 2023, the number of severe cases will reach 194,000. From the data point of view, with the increase of antibody validity, whether it is severe cases at peak or cumulative deaths, there will be a certain degree of reduction.

3.6. Impact of vaccination rates on the second wave of the pandemic

We summarized the vaccination rates of different age groups from the press conference of the National Health Commission on November 29, 2022, with the vaccination rate reaching 91.23% for people under 60 years old and 86.42% for people over 60 years old. Since the adjustment of the zero-COVID policy, China's vaccination work has also been continuously promoted, especially the vaccination rate of the elderly is also gradually increasing. Here we discuss the changes in the second wave of the epidemic on the basis of increasing vaccination rates, and the simulation results are shown in Fig. 6.

Fig. 6 shows that as vaccination rates increase, the time to reach the peak of severe cases under the second wave will gradually be delayed, and the number of severe cases and cumulative deaths at the peak will gradually decrease. When the vaccination rate of people under 60 years old reaches 98% and the vaccination rate of people over 60 years old reaches 96%, the peak of severe cases in the second wave will arrive on 13 July 2023, the number of severe cases is 166,000.

4. Conclusion

Since the Chinese mainland adjusted the zero-COVID policy on December 7, 2022, the transmission pattern of Omicron in China has changed. In this paper, a compartment dynamics model was constructed considering the age distribution, the changes of isolation mode, and the actual spread of Omicron epidemic in China was simulated.

First, we collected severe cases and cumulative deaths from December 7, 2022 to February 6, 2023 from the National Health Commission of the People's Republic of China and CDC. Secondly, through the actual situation since China adjusted the zero-COVID policy, the cases collected above were corrected, and then the modified data were used to fit the model parameters and predict the actual situation of the second wave of the epidemic. Next, $\mathcal{R}_0$ for the period from December 7, 2022 to February 6, 2023 was calculated and the final size of the outbreak was derived. In addition, different antibody attenuation rates were fixed, and the peak time and peak of severe cases in the second wave of the epidemic under different attenuation rates were discussed. Finally, by assuming vaccination rates among different populations, the important role of vaccination in the second wave of the epidemic is demonstrated.

This paper combines the actual situation of the spread of Omicron in China and the relevant policy measures introduced for modelling research, although age factors, isolation measures and vaccination are considered, but there are still some shortcomings in this paper. First, our model did not consider the decay of antibodies acquired through vaccination over time, only the effectiveness of antibodies acquired after infection. In addition, although this paper takes into account the time-varying transmission rate when predicting the second wave of the epidemic, there are still many aspects that can be expanded, for example, select the optimal number of nodes for exponential cubic splines to interpolate the transmission rate (Chen et al., 2023; Song et al., 2021) or consider the influence of human behavior on the transmission rate to optimize the

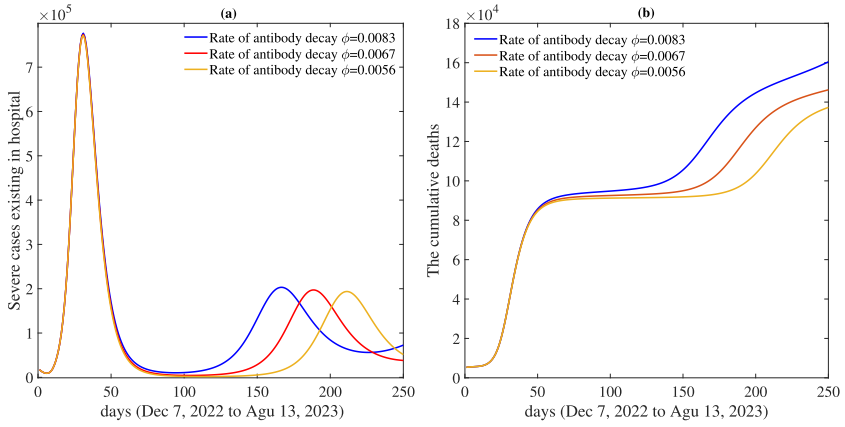

Fig. 5. Simulation result plots of different antibody decay times. **(a)** Simulation results for severe cases. **(b)** Simulation results for cumulative deaths.

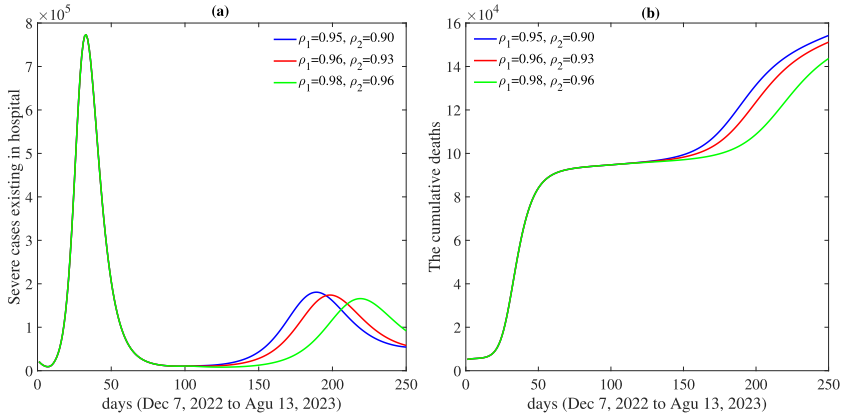

Fig. 6. Simulation result plots of different vaccination rate. **(a)** Simulation results for severe cases. **(b)** Simulation results for cumulative deaths.

model. Finally, epidemic prediction taking into account limited medical resources is also an aspect worth studying in the future.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was partially supported by the National Natural Science Foundation of China (12022113 and 12271314), Henry Fok Foundation for Young Teachers (171002), and Outstanding Young Talents Support Plan of Shanxi Province.

References

Asamoah, J. K. K., Okyere, E., Abidemi, A., Moore, S. E., Sun, G.-Q., Jin, Z., Acheampong, E., & Gordon, J. F. (2022). Optimal control and comprehensive cost-effectiveness analysis for COVID-19. *Results in Physics, 33*, Article 105177.

Bajiya, V. P., Tripathi, J. P., Kakkar, V., Wang, J., & Sun, G. (2021). Global dynamics of a multi-group SEIR epidemic model with infection age. *Chinese Annals of Mathematics B, 42*(6), 833–860.

Burki, T. (2022). Dynamic zero COVID policy in the fight against COVID. *Lancet Respiratory Medicine, 10*(6), 58–59.

Cai Lian News. (2022). In *Annual conference 2023: Forecasts and strategies*. http://news.hexun.com/2022-12-17/207501534.html. (Accessed 7 December 2022).

Cai, J., Deng, X., Yang, J., Sun, K., Liu, H., Chen, Z., Peng, C., Chen, X., Wu, Q., & Zou, J. (2022). Modeling transmission of SARS-CoV-2 Omicron in China. *Nature Medicine, 28*(7), 1468–1475.

Callaway, E., & Ledford, H. (2021). How bad is Omicron? What scientists know so far. *Nature, 600*(7888), 197–199.

Chang, L., Gong, W., Jin, Z., & Sun, G. Q. (2022). Sparse optimal control of pattern formations for an SIR reaction-diffusion epidemic model. *SIAM Journal on Applied Mathematics, 82*(5), 1764–1790.
Chen, B., Zhao, Y., Jin, Z., He, D., & Li, H. (2023). Twice evasions of Omicron variants explain the temporal patterns in six Asian and Oceanic countries. *BMC Infectious Diseases, 23*(1), 1–12.
Chitnis, N., Hyman, J. M., & Cushing, J. M. (2008). Determining important parameters in the spread of malaria through the sensitivity analysis of a mathematical model. *Bulletin of Mathematical Biology, 70*(5), 1272–1296.
Compiled by National Bureau of Statistics of China. (2022). China statistical Yearbook 2021. http://www.stats.gov.cn/tjsj/ndsj/2022/indexch.htm [Accessed 2022].
Diekmann, O., Heesterbeek, J. A. P., & Metz, J. A. (1990). On the definition and the computation of the basic reproduction ratio R_0 in models for infectious diseases in heterogeneous populations. *Journal of Mathematical Biology, 28*(4), 365–382.
Evans, J. P., Qu, P., Zeng, C., Zheng, Y. M., Carlin, C., Bednash, J. S., Lozanski, G., Mallampalli, R. K., Saif, L. J., & Oltz, E. M. (2022). Neutralization of the SARS-CoV-2 deltacron and BA. 3 variants. *New England Journal of Medicine, 386*(24), 2340–2342.
Ioannidis, J. P., Zonta, F., & Levitt, M. (2023). Estimates of COVID-19 deaths in Mainland China after abandoning zero COVID policy. *European Journal of Clinical Investigation*, Article e13956.
Iuliano, A. D., Brunkard, J. M., Boehmer, T. K., Peterson, E., Adjei, S., Binder, A. M., Cobb, S., Graff, P., Hidalgo, P., & Panaggio, M. J. (2022). Trends in disease severity and health care utilization during the early Omicron variant period compared with previous SARS-CoV-2 high transmission periods—United States, December 2020–January 2022. *MMWR Morb Mortal Wkly Rep, 71*(4), 146–152.
Jin, Z., Zhang, J., Song, L. P., Sun, G. Q., Kan, J., & Zhu, H. (2011). Modelling and analysis of influenza A (H1N1) on networks. *BMC Public Health, 11*(1), 1–9.
Kannan, S., Shaik Syed Ali, P., & Sheeza, A. (2021). Omicron (B. 1.1. 529)—variant of concern—molecular profile and epidemiology: A mini review. *European Review for Medical and Pharmacological Sciences, 25*(24), 8019–8022.
Lagarias, J. C., Reeds, J. A., Wright, M. H., & Wright, P. E. (1998). Convergence properties of the Nelder–Mead simplex method in low dimensions. *SIAM Journal on Optimization, 9*(1), 112–147.
Linka, K., Peirlinck, M., & Kuhl, E. (2020). The reproduction number of COVID-19 and its correlation with public health interventions. *Computational Mechanics, 66*, 1035–1050.
Ma, J., & Earn, D. J. (2006). Generality of the final size formula for an epidemic of a newly invading infectious disease. *Bulletin of Mathematical Biology, 68*, 679–702.
Mallapaty, S. (2022). Can China avoid a wave of deaths if it lifts strict zero COVID policy?, 203–203 *Nature, 612*(7939).
Ma, X., Luo, X.-F., Li, L., Li, Y., & Sun, G.-Q. (2022a). The influence of mask use on the spread of COVID-19 during pandemic in New York City, Results. *Physical, 34*, Article 105224.
Ma, X., Sun, G. Q., Wang, Z. H., Chu, Y. M., Jin, Z., & Li, B. L. (2022b). Transmission dynamics of brucellosis in Jilin province, China: Effects of different control measures. *Communications in Nonlinear Science and Numerical Simulation, 114*, Article 106702.
Mathieu, E., Ritchie, H., Guirao, L. R., Appel, C., Giattino, C., Hasell, J., Macdonald, B., Dattani, S., Beltekian, D., Ospina, E. O., & Roser, M. (2020). *Coronavirus pandemic (COVID-19), our world in data*.
Menni, C., Valdes, A. M., Polidori, L., Antonelli, M., Penamakuri, S., Nogal, A., Louca, P., May, A., Figueiredo, J. C., & Hu, C. (2022). Symptom prevalence, duration, and risk of hospital admission in individuals infected with SARS-CoV-2 during periods of Omicron and delta variant dominance: A prospective observational study from the ZOE COVID study. *Lancet, 399*(10335), 1618–1624.
National Health Commission of the People's Republic of China. (2022). Notice on further optimizing the implementation of the prevention and control measures of the COVID-19 epidemic. http://www.nhc.gov.cn/xcs/gzzcwj/202212/8278e7a7aee34e5bb378f0e0fc94e0f0.shtml, 12-07-2022.
National Health Commission of the People's Republic of China. (2022). In *Press conference of the joint prevention and control mechanism*. http://www.nhc.gov.cn/xwzb/webcontroller.do?titleSeq=11490&gecstype=1. (Accessed 29 November 2022).
National health commission of the People's Republic of China. (2022). Illustrate. http://www.nhc.gov.cn/xcs/yqtb/202212/7272431ee60c4f4d953b0c16257c230e.shtml. (Accessed 25 December 2022).
Nyberg, T., Ferguson, N. M., Nash, S. G., Webster, H. H., Flaxman, S., Andrews, N., Hinsley, W., Bernal, J. L., Kall, M., & Bhatt, S. (2022). Comparative analysis of the risks of hospitalisation and death associated with SARS-CoV-2 Omicron (B. 1.1. 529) and delta (B. 1.617. 2) variants in england: A cohort study. *Lancet, 399*(10332), 1303–1312.
Samsuzzoha, M., Singh, M., & Lucy, D. (2013). Uncertainty and sensitivity analysis of the basic reproduction number of a vaccinated epidemic model of influenza. *Applied Mathematical Modelling, 37*(3), 903–915.
Shuai, H., Chan, J. F. W., Hu, B., Chai, Y., Yuen, T. T. T., Yin, F., Huang, X., Yoon, C., Hu, J. C., & Liu, H. (2022). Attenuated replication and pathogenicity of SARS-CoV-2 B. 1.1. 529 Omicron. *Nature, 603*(7902), 693–699.
Song, H., Fan, G., Zhao, S., Li, H., Huang, Q., & He, D. (2021). Forecast of the COVID-19 trend in India: A simple modelling approach. *Mathematical Biosciences and Engineering, 18*(6), 9775–9786.
The state Council the People's Republic of China, novel coronavirus pneumonia diagnosis and treatment plan (ninth trial version). http://www.gov.cn/zhengce/zhengceku/2022-03/15/5679257/files/49854a49c7004f4ea9e622f3f2c568d8.pdf, (2022)–. (Accessed 15 March 2022).
Su, Z., Cheshmehzangi, A., McDonnell, D., Ahmad, J., Šegalo, S., Xiang, Y. T., & da Veiga, C. P. (2022). The advantages of the zero-COVID-19 strategy. *International Journal of Environment and Health, 19*(14), 8767.
Sun, G.-Q., Wang, S.-F., Li, M.-T., Zhang, J., Zhang, W., Jin, Z., & Feng, G.-L. (2022a). Transmission dynamics of COVID-19 in wuhan, China: Effects of lockdown and medical resources. *Nonlinear Dynamics, 101*, 1981–1993.
Sun, G. Q., Zhang, H. T., Chang, L. L., Jin, Z., Wang, H., & Ruan, S. (2022b). On the dynamics of a diffusive foot-and-mouth disease model with nonlocal infections. *SIAM Journal on Applied Mathematics, 82*(4), 1587–1610.
Tan, Z., Chen, Z., Yu, A., Li, X., Feng, Y., Zhao, X., Xu, W., & Su, X. (2022). The first two imported cases of SARS-CoV-2 Omicron variant—tianjin municipality, China, December 13, 2021. *CCDC Weekly, 4*(4), 76.
Tuncer, N., Timsina, A., Nuno, M., Chowell, G., & Martcheva, M. (2022). Parameter identifiability and optimal control of an SARS-CoV-2 model early in the pandemic. *Journal of Biological Dynamics, 16*(1), 412–438.
Van den Driessche, P., & Watmough, J. (2002). Reproduction numbers and sub-threshold endemic equilibria for compartmental models of disease transmission. *Mathematical Biosciences and Engineering, 180*(1–2), 29–48.
Wang, S., Li, Y., Wang, X., Zhang, Y., Yuan, Y., & Li, Y. (2022). The impact of lockdown, patient classification, and the large-scale case screening on the spread of the coronavirus disease 2019 (COVID-19) in hubei. *BioMed Research International, 2022*, Article 8920117.
Wang, S. T., Li, L., Zhang, J., Li, Y., Luo, X. F., & Sun, G. Q. (2023). Quantitative evaluation of the role of fangcang shelter hospitals in the control of Omicron transmission: A case study of the outbreak in shanghai, China in 2022. *One Health, 16*, Article 100475.
Wang, W., & Zhao, X. Q. (2008). Threshold dynamics for compartmental epidemic models in periodic environments. *Journal of Dynamics and Differential Equations, 20*(3), 699–717.