Research Article

Coronavirus disease 2019 epidemic prediction in Shanghai under the "dynamic zero-COVID policy" using time-dependent SEAIQR model

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ABSTRACT

It's urgently needed to assess the COVID-19 epidemic under the "dynamic zero-COVID policy" in China, which provides a scientific basis for evaluating the effectiveness of this strategy in COVID-19 control. Here, we developed a time-dependent susceptible-exposed-asymptomatic-infected-quarantined-removed (SEAIQR) model with stage-specific interventions based on recent Shanghai epidemic data, considering a large number of asymptomatic infectious, the changing parameters, and control procedures. The data collected from March 1st, 2022 to April 15th, 2022 were used to fit the model, and the data of subsequent 7 days and 14 days were used to evaluate the model performance of forecasting. We then calculated the effective regeneration number (R_t) and analyzed the sensitivity of different measures scenarios. Asymptomatic infectious accounts for the vast majority of the outbreaks in Shanghai, and Pudong is the district with the most positive cases. The peak of newly confirmed cases and newly asymptomatic infectious predicted by the SEAIQR model would appear on April 13th, 2022, with 1963 and 28,502 cases, respectively, and zero community transmission may be achieved in early to mid-May. The prediction errors for newly confirmed cases were considered to be reasonable, and newly asymptomatic infectious were considered to be good between April 16th to 22nd and reasonable between April 16th to 29th. The final ranges of cumulative confirmed cases and cumulative asymptomatic infectious predicted in this round of the epidemic were 26,477 ∼ 47,749 and 402,254 ∼ 730,176, respectively. At the beginning of the outbreak, R_t was 6.69. Since the implementation of comprehensive control, R_t showed a gradual downward trend, dropping to below 1.0 on April 15th, 2022. With the early implementation of control measures and the improvement of quarantine rate, recovery rate, and immunity threshold, the peak number of infections will continue to decrease, whereas the earlier the control is implemented, the earlier the turning point of the epidemic will arrive. The proposed time-dependent SEAIQR dynamic model fits and forecasts the epidemic well, which can provide a reference for decision making of the "dynamic zero-COVID policy".

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1. Introduction

Coronavirus disease 2019 (COVID-19) has become a significant public health challenge that poses a severe threat to human life, economic, and social development due to its rapid transmission, strong concealment, and high viral load.[1–3] According to the latest epidemiological survey by the World Health Organization, as of April 19th, 2022, 503,131,834 cases and 6,200,571 deaths have been confirmed. Currently, new coronavirus variants are emerging, but the immune barrier of the population has not been

entirely constructed, and there are still some unknowns in the global understanding of COVID-19.[4–5] Various countries and regions constantly upgrade their risk levels and intervention measures to contain the COVID-19 spread. On December 7th, 2021, China determined the general strategy of "guarding against imported cases and preventing a resurgence of the outbreak at home" and "dynamic zero-COVID policy". The "dynamic zero-COVID policy" is to take effective and comprehensive measures when a local case occurs under the premise of "one case found, one case cured". It completely cuts off the chain of epidemic transmission and quickly "zeroes out" the infected, achieving maximum results at a minimal cost. Thanks to the "dynamic zero-COVID policy" guidance and the country's effective coordination capacity, the outbreaks in Xi'an and Jilin, China, which occurred early this year, have been effectively controlled in the short term. All of these are Chinese experiences in preventing and controlling the COVID-19.

The susceptible-exposed-infected-removed (SEIR) compartmental model is a classical epidemiological model for infectious diseases with an incubation period and lifelong immunity after curing. It has been widely used to analyze various pandemics, and the ongoing COVID-19 pandemic is no exception.[6–8] The SEIR model plays an active role in studying the rate and route of transmission of infectious diseases. Since the outbreak of COVID-19, several studies have used the SEIR model or modified SEIR model to determine the development trend of COVID-19 to prospectively predict the number of confirmed, cured, and death cases.[9–12] He et al. proposed an optimized SEIR model considering quarantine and treatment, and the results showed that the SEIRHQ model was more suitable for analyzing COVID-19 prevalence.[13] A modeling study by Hou C et al. indicated that minimizing the contact rate while strengthening tracking and isolation can effectively reduce the peak of the outbreak and delay its arrival.[14] Ma et al. presented an SEIR-type epidemic model with the contacting distance between the healthy groups and the asymptomatic or symptomatic infected groups. The results figured out that the contacting distance and the immigration rate play a key role in controlling COVID-19.[15] However, the SEIR model needs to be further modified and optimized in that SARS-CoV-2 is in the process of continuous variation, and accurate predictions of the spread of COVID-19 are still challenging.

Currently, the world is experiencing the fifth wave of the COVID-19 pandemic. Since March 2022, the epidemic has rebounded in many parts of China, with characteristics of being wider and more frequent. The current outbreak in Shanghai occurred in March 2022, and the prevalent strain is Omicron BA.2. This strain is insidious, highly infectious, and has a short incubation period, which, combined with the high population density and risk of transmission in Shanghai, has led to the rapid spread of the epidemic.[16–17] As the center of China's economy, finance, trade, and shipping, the government initially adopted the policy of "precision prevention and control" given the local and national impact of economic losses: grid-based nucleic acid screening was implemented without closing the city, but this precise lockdown of risky sites may miss the best time to control the epidemic, combined with factors such as high contagiousness of Omicron BA.2, which contributed to the subsequent large-scale spread of the virus. In April 2022, the Shanghai municipal government took decisive and thorough measures by carrying out several rounds of city-wide nucleic acid testing and strictly controlling people entering and leaving Shanghai. This study aims to propose a modified SEIR model with stage-specific prevention and control measures based on data from the current outbreak in Shanghai. We fitted the model parameters, estimated the effective regeneration number, and evaluated the effectiveness of interventions, which provides a reference basis for the government to optimize

rapid local decision-making or public health policy and respond to subsequent epidemics.

2. Methods

2.1. Data sources

The epidemic data and population data were obtained from the Shanghai Municipal Health Commission (https://wsjkw.sh.gov.cn/) and Shanghai Municipal Bureau Statistics (https://tjj.sh.gov.cn/), including newly confirmed cases, newly asymptomatic infectious, cumulative infected cases and permanent residents.

2.2. Modified SEIR model

Common infectious disease models include SI, SIR, SIRS, and SEIR, where the SEIR model further considers that a proportion of those who have been in contact with the patient is infectious, resulting in a longer period of disease transmission. The classical SEIR model divides people into four categories: Susceptible (S), Exposed (E), Infected (I), and Removed (R).[18] Considering a large number of asymptomatic infectious, the changing parameters, and control procedures in the current round of the epidemic in Shanghai, our study further added four compartments to construct the time-dependent SEAIQR model, namely Asymptomatic Infectious (A), Quarantined (Q) [Quarantined Susceptible (Sq), Quarantined Exposed (Eq), and Hospitalized (H)]. The model assumed that after exposure to an infectious source such as E, I, and A, S entered Sq if traced with probability q but not infected with probability $1 − β$, entered Eq if traced with probability q and infected with probability β, entered E if not traced with probability $1 − q$ but infected with probability β, and entered R if immunity threshold reached v. For Sq, if no abnormality was seen after the expiration of the isolation period of $1/λ$, the isolation was released and re-entered into S. For R, as the antibody levels decreased, it also re-entered into S in the ratio of h. For E, if it converted to symptomatic at a rate of $1 − p$ after the incubation period of $1/σ_I$ then it went to I, and if it converted to asymptomatic at a rate of p after the incubation period of $1/σ_A$ then it went to A. A, I, and Eq entered H for treatment at the conversion rate of $δ_I$ and $δ_q$. There are parts of A, I, and H that entered R at the recovery rate of $γ_A$, $γ_I$, and $γ_H$, and a mortality rate of $α$. Here, it was considered that H had been treated in isolation and did not have conditions for transmission. We have the constraint N = S + Sq + E + Eq + A + I + H + R (Compartment I did not include asymptomatic cases, which became confirmed cases during isolation). The relationship between the different compart-
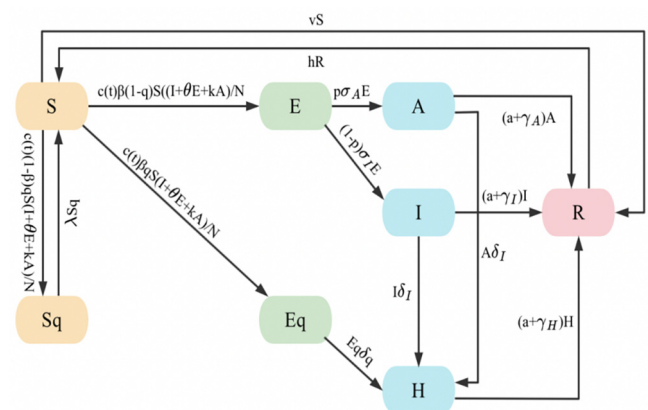

Fig. 1. Flowchart of the SEAIQR model for COVID-19.

ments is shown in Fig. 1, and the COVID-19 dynamics are given by the following eight differential equations:

$$dS/dt = -c(t)[\beta + q(1-\beta)]S(I + \theta E + kA)/N + \lambda Sq - vS + hR \quad (1)$$

$$dSq/dt = c(t)q(1-\beta)S(I + \theta E + kA)/N - \lambda Sq \quad (2)$$

$$dE/dt = c(t)\beta(1-q)S(I + \theta E + kA)/N - p\sigma_A E - (1-p)\sigma_I E \quad (3)$$

$$dEq/dt = c(t)\beta qS(I + \theta E + kA)/N - \delta_q Eq \quad (4)$$

$$dA/dt = p\sigma_A E - (\delta_I + \alpha + \gamma_A)A \quad (5)$$

$$dI/dt = (1-p)\sigma_I E - (\delta_I + \alpha + \gamma_I)I \quad (6)$$

$$dH/dt = \delta_I(I + A) + \delta_q Eq - (\alpha + \gamma_H)H \quad (7)$$

$$dR/dt = \gamma_I I + \gamma_A A + \gamma_H H + vS - hR + \alpha(I + A + H) \quad (8)$$

2.3. Model parameters

Markov Chain Monte Carlo (MCMC) is a statistical method for dynamic simulation within the framework of Bayesian theory. The MCMC method first constructs a Markov Chain so that its stable distribution is the posterior distribution of the parameter to be estimated. Subsequently, a Monte Carlo simulation is performed according to the sample of the stable distribution, which enables approximate numerical calculations of the estimates of the random variables.[19] Metropolis-Hastings (MH) sampling is an improvement to the MCMC sampling algorithm pair that can compensate for the possible deficiencies of MCMC with low acceptance probability. The 10 parameters, including infectious rate, index decline rate ($t_1 \leq t < t_2$), index decline rate ($t \geq t_2$), infectivity coef-

ficient (exposed), infectivity coefficient (asymptomatic infectious), recovery rate (infected), recovery rate (asymptomatic infectious), recovery rate (hospitalized), conversion rate of quarantine (infected/asymptomatic infectious to hospitalized) and conversion rate of quarantine (quarantined exposed to hospitalized), were estimated using the MH algorithm with 90,000 simulations and 75,000 annealings, and the remaining parameters were obtained from the actual epidemic, literature reports, and expert opinions[20] (Table 1).

2.4. Segmented time-dependent contact number

In the SEAIQR model, $c(t)$ denotes the time-dependent contact number, which is a segmented function of time.[21] Stage 1 – in the early phase of the outbreak, Shanghai did not implement any community or traffic closure policies for the rest of the city outside the medium-risk sites, and the massive flow of people caused the rapid spread of the virus. During this period, the contact number was constant: $c(t) = c_0$. Stage 2 – on April 4th, 2022, Shanghai carried out the first round of city-wide nucleic acid testing and adopted region-wide static management, which made $c(t)$ decrease exponentially at the rate of w. Stage 3 – on April 13th, 2022, Shanghai took more resolute and decisive measures to effectively build a closed-loop defense line, requiring residents to stay at home, cutting off the route of transmission completely, which caused $c(t)$ to decline at a faster rate of r. The contact number in the entire epidemic period can then be expressed by the following segmented function:

$$c(t) = \begin{cases} c_0 & 0 \leq t < t_1 \\ (c_0 - c_1)e^{-w(t-t_1)} + c_1 & t_1 \leq t < t_2 \\ (c_0 - c_1)e^{-w(t_2-t_1)}e^{-r(t-t_2)} + c_1 & t \geq t_2 \end{cases}$$

Table 1
Model parameters and their values.

Compartments& parameters	Interpretations	Value	Source
S(0)	Initial susceptible	24,870,838	Actual epidemic
Sq(0)	Initial quarantined susceptible	0	Actual epidemic
E(0)	Initial exposed	53	Actual epidemic
Eq(0)	Initial quarantined exposed	0	Actual epidemic
A(0)	Initial asymptomatic infectious	1	Actual epidemic
I(0)	Initial infected	1	Actual epidemic
H(0)	Initial hospitalized	2	Actual epidemic
R(0)	Initial removed	0	Actual epidemic
β	Infectious rate	0.041	MCMC
c_0	Number of early contacts	20	Actual epidemic
c_1	Number of minimum contacts	2	Actual epidemic
w	Index decline rate ($t_1 \leq t < t_2$)	0.096	MCMC
r	Index decline rate ($t \geq t_2$)	3.060	MCMC
θ	Infectivity coefficient (exposed)	0.887	MCMC
k	Infectivity coefficient (asymptomatic infectious)	0.917	MCMC
q	Quarantine rate	0.150	Actual epidemic
σ_I	Incubation rate (exposed to infected)	1/7	Actual epidemic
σ_A	Incubation rate (exposed to asymptomatic infectious)	1/10	Actual epidemic
p	Proportion of asymptomatic infectious to infected	0.912	Actual epidemic
α	Mortality rate of the virus	0.002	Actual epidemic
λ	Quarantine release rate	1/14	Literature reports
γ_I	Recovery rate (infected)	0.086	MCMC
γ_A	Recovery rate (asymptomatic infectious)	0.104	MCMC
γ_H	Recovery rate (hospitalized)	0.114	MCMC
h	Decrease in antibody levels	0.700	Actual epidemic
v	Immunity threshold (vaccination rate × vaccine protection rate)	0.700	Actual epidemic
δ_I	Conversion rate of quarantine (infected/asymptomatic infectious to hospitalized)	0.775	MCMC
δ_q	Conversion rate of quarantine (quarantined exposed to hospitalized)	0.812	MCMC

2.5. Effective regeneration number

The basic regeneration number (R_0) is a key critical threshold parameter in epidemiology that determines the ability of an outbreak to spread. Generally, R_0 is constant in the early stages of infectious disease development and changes dynamically with the implementation of control measures, which is called the effective regeneration number (R_t). It can judge the trend of infectious diseases, reflect the effectiveness of external interventions, and can be used as a reference for disease risk management policies. If $R_t > 1$, the number of cases increases exponentially, suggesting that prevention and control measures should be optimized and strengthened. When $R_t < 1$, the infectious disease gradually disappears, and current measures will gradually contain the epidemic.[22] The next-generation matrix method[23] is used to calculate the effective regeneration number of the model in our study, expressed as:

$$F = \begin{bmatrix} \frac{c(t)\beta(1-q)S(I+\theta E+kA)}{N} \\ \frac{c(t)\beta qS(I+\theta E+kA)}{N} \\ 0 \\ 0 \end{bmatrix} \quad V = \begin{bmatrix} p\sigma_A E + (1-p)\sigma_I E \\ \delta_q Eq \\ -p\sigma_A E + (\delta_I + \alpha + \gamma_A)A \\ -(1-p)\sigma_I E + (\delta_I + \alpha + \gamma_I)I \end{bmatrix}$$

Further, the partial derivatives of F and V with respect to E, Eq, A and I at the disease-free equilibrium point are obtained as follows:

$$F(t) = \begin{bmatrix} \frac{c(t)\beta(1-q)S\theta N-c(t)(1-q)S(I+\theta E+kA)}{N^2} & 0 & \frac{c(t)\beta(1-q)SkN-c(t)\beta(1-q)S(I+\theta E+kA)}{N^2} & \frac{c(t)\beta(1-q)SN-c(t)(1-q)S(I+\theta E+kA)}{N^2} \\ \frac{c(t)\beta qS\theta N-c(t)\beta qS(I+\theta E+kA)}{N^2} & 0 & \frac{c(t)\beta qSkN-c(t)\beta qS(I+\theta E+kA)}{N^2} & \frac{c(t)\beta qSN-c(t)\beta qS(I+\theta E+kA)}{N^2} \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$V(t) = \begin{bmatrix} p\sigma_A + (1-p)\sigma_I & 0 & 0 & 0 \\ 0 & \delta_q & 0 & 0 \\ -p\sigma_A & 0 & \delta_I + \alpha + \gamma_A & 0 \\ -(1-p)\sigma_I & 0 & 0 & \delta_I + \alpha + \gamma_I \end{bmatrix}$$

The next-generation regeneration matrix is written as:

$$FV^{-1} = \begin{bmatrix} \frac{c(t)\beta(1-q)\theta}{p\sigma_A+(1-p)\sigma_I} + \frac{c(t)\beta(1-q)pk\sigma_A}{(\delta_I+\alpha+\gamma_A)[p\sigma_A+(1-p)\sigma_I]} + \frac{c(t)\beta(1-q)(1-p)\sigma_I}{(\delta_I+\alpha+\gamma_I)[p\sigma_A+(1-p)\sigma_I]} & 0 & \frac{c(t)\beta(1-q)k}{\delta_I+\alpha+\gamma_A} & \frac{c(t)\beta(1-q)}{\delta_I+\alpha+\gamma_I} \\ \frac{c(t)\beta q\theta}{p\sigma_A+(1-p)\sigma_I} + \frac{c(t)\beta qpk\sigma_A}{(\delta_I+\alpha+\gamma_A)[p\sigma_A+(1-p)\sigma_I]} + \frac{c(t)\beta q(1-p)\sigma_I}{(\delta_I+\alpha+\gamma_I)[p\sigma_A+(1-p)\sigma_I]} & 0 & \frac{c(t)\beta qk}{\delta_I+\alpha+\gamma_A} & \frac{c(t)\beta q}{\delta_I+\alpha+\gamma_I} \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Therefore, R_t of the model is defined as follows:

$$R_t = \rho(FV^{-1})$$

$$= c(t)\beta(1-q)\left[\frac{\theta}{p\sigma_A+(1-p)\sigma_I} + \frac{pk\sigma_A}{(\delta_I+\alpha+\gamma_A)[p\sigma_A+(1-p)\sigma_I]}\right.$$

$$\left. + \frac{(1-p)\sigma_I}{(\delta_I+\alpha+\gamma_I)[p\sigma_A+(1-p)\sigma_I]}\right]$$

2.6. Error estimation

We limited the data analysis from March 1st, 2022 to April 15th, 2022, to develop a prediction model and used the following 7 days and 14 days for validate. The mean absolute percentage error (MAPE) and root mean squared percentage error (RMSPE) were used to evaluate the prediction performance or accuracy of the established model: error $\geq$ 50% is poor, 20% $\leq$ error <50% is reason-

able, 10% $\leq$ error < 20% is good, and error < 10% is accurate. MAPE and RMSPE are defined as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|\frac{y_i* - y_i}{y_{i*}}| \times 100\%$$

$$RMSPE = \sqrt{\frac{\sum_{i=1}^{n}(\frac{y_{i*}-y_i}{y_{i*}})^2}{n}} \times 100\%$$

y_{i*} and y_i are the actual and predicted values, and n is the number of data.

2.7. Statistical analysis

Parameter estimation, model construction, and sensitivity analysis were performed using Python (version 3.0). R^2, MAPE and RMSPE were used to determine the fitting and prediction effects of the model.

3. Results

3.1. Epidemic characteristics in Shanghai

As of April 29th, 2022, the cumulative number of COVID-19 cases reported in Shanghai has exceeded 500,000. Unlike in the past, the proportion of asymptomatic infectious in this epidemic round was extremely high, accounting for about 90% (Fig. 2). Since some asymptomatic infectious may occur during the incubation period of confirmed cases, the rapid growth of asymptomatic infectious was approximately a week earlier than that of confirmed cases.

Fig. 3 shows the geographical distribution of cumulative infected cases in Shanghai as of April 29th, 2022. Districts with a large number of cases were mainly concentrated in the eastern part of Shanghai, such as Pudong (215,981). In contrast, the southern districts, such as Jinshan (1,553) and Fengxian (2,665), had a relatively low number of cases.

3.2. Prediction of newly infected cases and effective regeneration number

Newly confirmed cases and newly asymptomatic infectious in Shanghai from March 1st, 2022 to April 15th, 2022 were selected for predictive analysis. The number of predicted results is shown in Fig. 4, and the results based on the SEAIQR model were highly consistent with the actual situation, especially for newly asymptomatic infectious (R^2 = 0.954). The number of newly confirmed cases and newly asymptomatic infectious is expected to peak on April 13th, 2022, with 1963 and 28,502 cases, respectively. As most patients are found in isolation control sites, zero community transmission may be achieved in early to mid-May. For the data of the

subsequent 7 days and 14 days, which were not included in the model fitting, the prediction errors for newly confirmed cases were considered to be reasonable, and newly asymptomatic infectious were considered to be good between April 16th to 22nd and reasonable between April 16th to 29th (Table 2). The final ranges of cumulative confirmed cases and cumulative asymptomatic infec-

tious predicted in this round of the epidemic were 26,477 ∼ 47,749 and 402,254 ∼ 730,176, respectively (Fig. 5).

At the beginning of the outbreak, R_t was constant at 6.69. To control the spread of the epidemic as soon as possible, Shanghai conducted the first round of city-wide nucleic acid testing on April 4th, 2022 (day 34), after which R_t showed a gradual downward trend until it dropped below 1.0 on April 15th, 2022 (day 45) (Fig. 6).

3.3. Sensitivity analysis of different measures evaluation

Based on the SEAIQR model, the sensitivity of four types of prevention and treatment measures scenarios – time to implement control (t), quarantine rate (q), recovery rate (γ), and immunity threshold (v) – was evaluated by changing the corresponding parameters of one measurement while fixing the others. Had interventions been implemented 10 days or 20 days earlier, the newly confirmed cases and newly asymptomatic infectious would have peaked by April 3rd, 2022 or March 24th, 2022, with a decrease of about 86% or 98%. Approximately 77% increase if performed 10 days later, peaking on April 22nd, 2022 (Fig. 7a, b). The peak of newly confirmed cases and newly asymptomatic infectious was approximately 52% higher if the quarantine rate q decreased to 0.1 and approximately 53% and 78% lower if q increased to 0.2 and 0.25, respectively, while the time of peak occurrence remained constant (Fig. 7c, d). When the recovery rate γ was 0.1, 0.15, and 0.2, and the immunity threshold v was 0.7, 0.75, and 0.8, the number of newly confirmed cases and newly asymptomatic infectious decreased with increasing γ and v, while the time of peak occurrence also remained constant. (Fig. 7e, f, g, h) (Table 3). It is worth noting that with the early implementation of control measures and the improvement of quarantine rate, recovery rate, and immunity threshold, the peak number of infections will continue to decrease, with smaller and smaller increases before reaching the peak and decreases after reaching the peak.

4. Discussion

Since China entered the normalized prevention and control phase of COVID-19, there have been several outbreaks, with a cumulative total of more than 1,000 confirmed cases. After the outbreak in Wuhan in December 2019, Shanghai has seen the widest spread of the virus and the most significant number of infected people, posing great difficulties for local prevention. The epidemic is still at a high level, with newly asymptomatic infectious accounting for many cases. The "precise prevention and control" proposed by the Shanghai Municipal Government does not apply
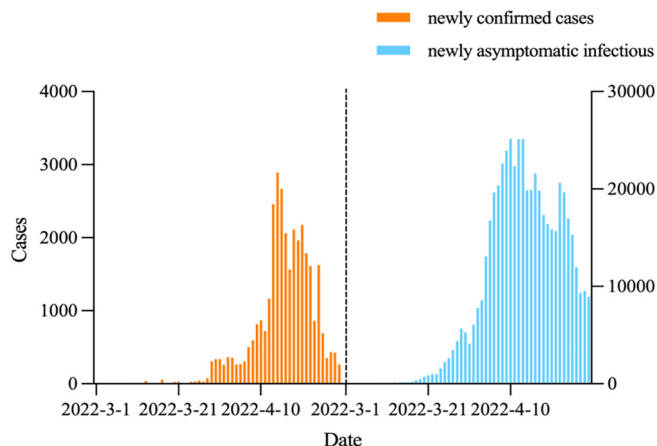

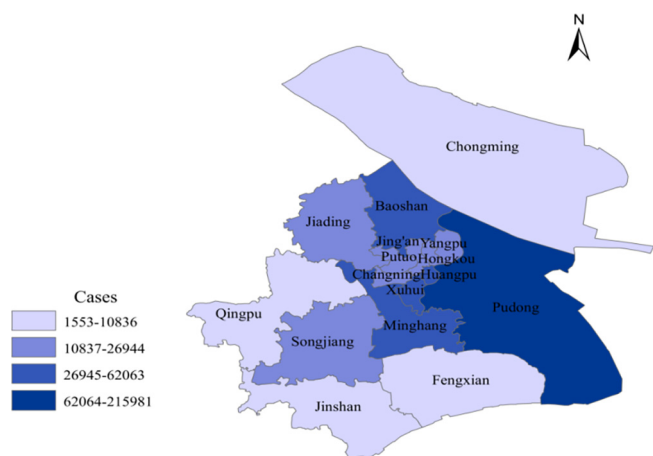**Fig. 2.** COVID-19 cases curve in Shanghai.
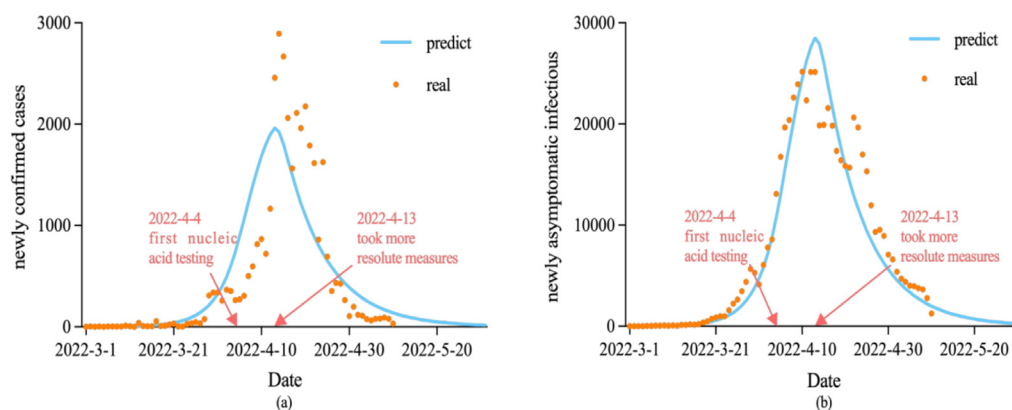

Fig. 3. Infected regions in Shanghai.

Fig. 4. The SEAIQR model predicted COVID-19 cases in Shanghai: (a) newly confirmed cases; (b) newly asymptomatic infectious.

Table 2
Performance evaluation results of MAPE and RMSPE.

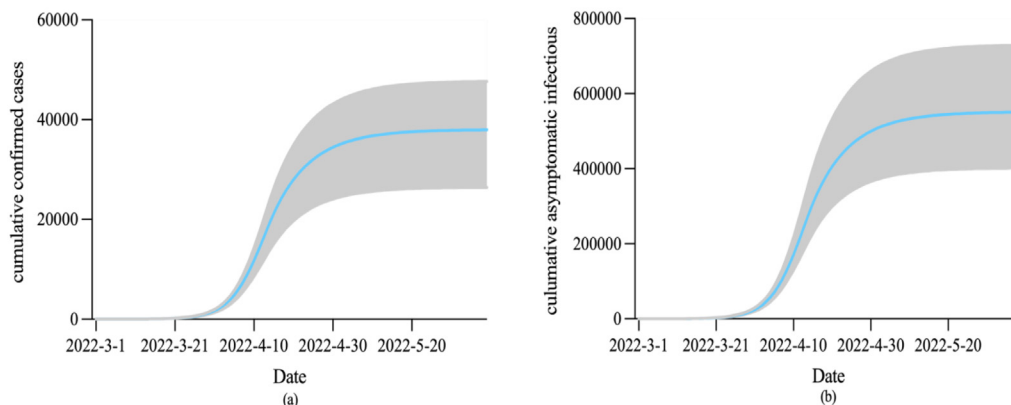| Variable	MAPE (RMSPE) (%)		Predicting result	
	7 days	14 days	7 days	14 days
Newly confirmed cases	33.86(37.01)	33.54(39.51)	Reasonable	Reasonable
Newly asymptomatic infectious	12.34(16.45)	22.01(25.79)	Good	Reasonable

Fig. 5. Predicted final range of COVID-19 cases in Shanghai: (a) cumulative confirmed cases; (b) cumulative asymptomatic infectious.
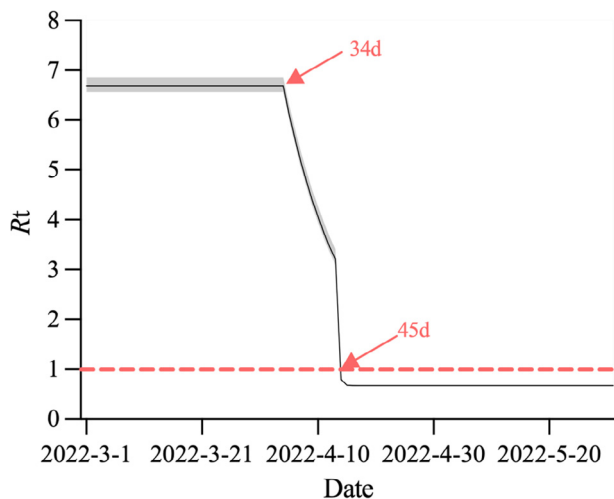

Fig. 6. Trend of R_t in Shanghai.

to the current complex and challenging situation. Our study showed that it is still necessary to adhere to the "dynamic zero-COVID policy".

According to the epidemic curve of COVID-19 in Shanghai, the cumulative number of infected cases has exceeded 500,000 as of April 29th, 2022, and the epidemic is still evolving. Unlike in the past, the majority of asymptomatic infectious in this outbreak were related, we believe, to the reduced pathogenicity of Omicron BA.2 and the high vaccination rate of the COVID-19 vaccine in Shanghai. We also found that the areas with more cases were mainly concentrated in the eastern part of Shanghai, such as Pudong. This suggests that the government should tilt more health resources to Pudong, including increasing nucleic acid testing and establishing module hospitals, to allocate limited resources more reasonably and effectively.

Infectious disease dynamics models can be used to study the epidemiological patterns and development trends of diseases, provide evidence-based support for quantifying the risk of virus transmission, seek optimal strategies for prevention and treatment, and determine resource allocation for detection.[24–26] Our purpose of adding four compartments (Sq, Eq, A, and H) and important parameters such as contact number and immunity threshold in the classical SEIR framework is to make predictions more consistent with the actual situation. Previously, Lanzhou University, Nankai University, and Xi'an Jiaotong University all made predictions about the current epidemic in Shanghai, and the results are constantly updated and improved. The predicted results of the SEAIQR model with stage-specific prevention and control measures constructed in this study were in good agreement with practical conditions, verifying that the model is reliable in assessing the epidemic trend. Our prediction of the turning point of the epidemic in Shanghai on April 13th, 2022, coincided with the conclusions of the three universities mentioned above. It is worth noting that, although the peak of the epidemic has passed, the risk alert has not been lifted. We have to adhere to the "dynamic zero-COVID policy", continue to strengthen monitoring, and prevent the rebound of the outbreak. Furthermore, most cases were found during the control period, and the transmission route was broken; thus, we predicted that the goal of zero community transmission in Shanghai would be achieved in early to mid-May. The basic regeneration number of the COVID-19 in Shanghai was 6.69, which was much higher than that of SARS and MERS.[27–28] Since implementing comprehensive interventions, R_t showed a gradual downward trend, dropping to below 1.0 on April 15th, 2022, after which the epidemic was effectively controlled. In this study, R_t was calculated from 12 parameters using the next-generation regeneration matrix. Of which, 8 parameters were estimated using the MH algorithm with 90,000 simulations and 75,000 annealings; thus the value of R_t may have a certain deviation.

We also evaluated the sensitivity of four different non-pharmaceutical interventions to the development of the epidemic.
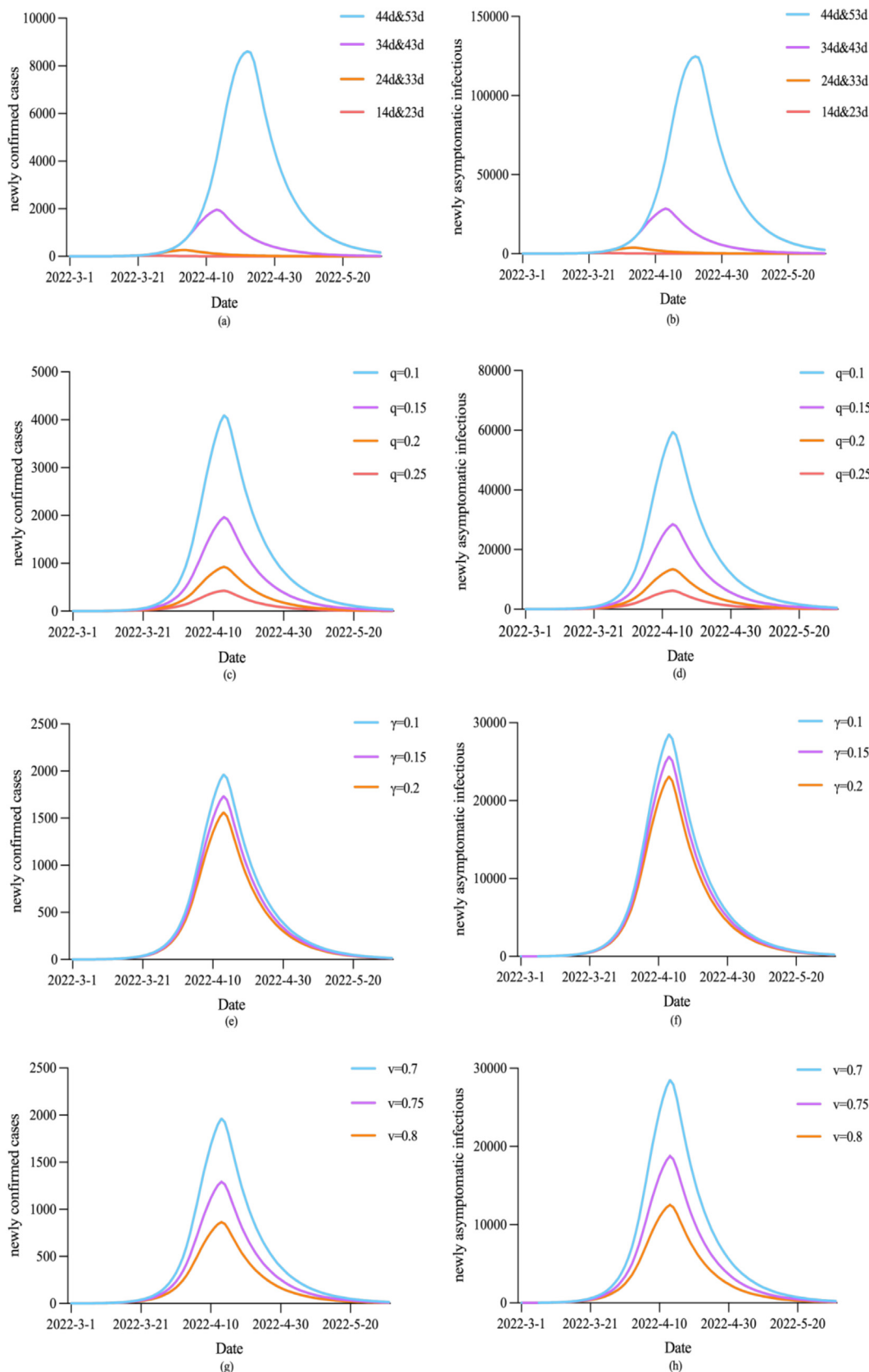
Fig. 7. Effects of different measures scenarios on COVID-19 cases in Shanghai: (a) different time to implement control on newly confirmed cases; (b) different time to implement control on newly asymptomatic infectious; (c) different quarantine rates on newly confirmed cases; (d) different quarantine rates on newly asymptomatic infectious; (e) different recovery rates on newly confirmed cases; (f) different recovery rates on newly asymptomatic infectious; (g) different immunity thresholds on newly confirmed cases; (h) different immunity thresholds on newly asymptomatic infectious.

Table 3
Epidemic peak time and peak number of cases under different measures scenarios.

Parameter	Value	Epidemic peak			
		Newly confirmed cases		Newly asymptomatic infectious	
		Time	Number	Time	Number
t_1&t_2	44&53d	4-22-2022	8,606	4-22-2022	124,861
	34&43d*	4-13-2022	1,963	4-13-2022	28,502
	24&33d	4-3-2022	266	4-3-2022	3,858
	14&23d	3-24-2022	33	3-24-2022	473
q	0.10	4-13-2022	4,096	4-13-2022	59,461
	0.15*	4-13-2022	1,963	4-13-2022	28,502
	0.20	4-13-2022	925	4-13-2022	13,432
	0.25	4-13-2022	428	4-13-2022	6,216
γ	0.10*	4-13-2022	1,963	4-13-2022	28,502
	0.15	4-13-2022	1,294	4-13-2022	18,778
	0.20	4-13-2022	864	4-13-2022	12,540
v	0.70*	4-13-2022	1,963	4-13-2022	28,502
	0.75	4-13-2022	1,734	4-13-2022	25,672
	0.80	4-13-2022	1,560	4-13-2022	23,103

*: Parameters observed or specified in the model as a reference.

With the early implementation of control measures and the improvement of quarantine rate, recovery rate, and immunity threshold, the peak number of infections will continue to decrease, whereas the earlier the control is implemented, the earlier the turning point of the epidemic will arrive.[29–31] It is suggested that early and multi-pronged interventions have considerable positive effects on controlling the outbreak.[32–33] According to the Department of Health (Hong Kong), the third dose of heterologous vaccine can significantly reduce the risk of death after infection with Omicron BA.2 and raise the immunity threshold; therefore, sequential booster immunization should be promoted in an orderly manner as soon as possible.[34–35] These results have great value when considering tactics of continuing surveillance and interventions to control COVID-19 outbreaks eventually.[36]

The limitations of this study should be acknowledged. First, the spread of the epidemic in Shanghai is still ongoing and has not yet been completely contained. Considering that many measures, such as tracing close contacts, expanding environmental decontamination, and promoting social consensus on self-protection (e.g., wearing masks and hygiene measures) are believed to have affected the epidemic, the end of the outbreak, in reality, is highly likely to come earlier than our prediction. Second, the parameters in this study were only applicable to epidemic prediction under the prevalence of Omicron strain BA.2, and the possibility of new variants is outside the scope of the model. Third, there were differences in the trends between asymptomatic infectious and confirmed cases. Since some asymptomatic infectious may occur during the incubation period of confirmed cases, the rapid growth of asymptomatic infectious was approximately a week earlier than that of confirmed cases; thus the fitting result for confirmed cases was not very good (R^2 = 0.697). However, the overall fit of this model was still very high (R^2 = 0.969). Finally, this study assumed that all individuals have the same immunity level. We would extend the model by accounting for changing effectiveness at different stages of vaccination in the future.

5. Conclusion

In conclusion, the time-dependent SEAIQR model with stage-specific prevention and control measures constructed in this study fitted the epidemic well and can be used to evaluate the effectiveness of COVID-19 interventions comprehensively. Currently, the cases in Shanghai have spilled over to many provinces, causing sporadic and localized outbreaks across the country. Therefore,

we should continue to insist on the "dynamic zero-COVID policy" and further strengthen community-wide nucleic acid testing and virus sampling in critical areas to completely interrupt the spread of the virus.

CRediT authorship contribution statement

Yifei Ma: Writing-original draft. **Shujun Xu:** Formal analysis. **Qi An:** Methodology. **Mengxia Qin:** Software. **Sitian Li:** Visualization. **Kangkang Lu:** Validation. **Jiantao Li:** Project administration. **Lijian Lei:** Data curation. Lu He: Conceptualization; Hongmei Yu: Writing-review&editing; Jun Xie: Funding acquisition.

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.

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