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Prediction of SARS-CoV-2 infection cases based on the meta-SEIRS model

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Abstract

Predicting epidemic trends of coronavirus disease 2019 (COVID-19) remains a key public health concern globally today. However, the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) reinfection rate in previous studies of the transmission dynamics model was mostly a fixed value. Therefore, we proposed a meta-Susceptible-Exposed-Infectious-Recovered-Susceptible (SEIRS) model by adding a time-varying SARS-CoV-2 reinfection rate to the transmission dynamics model to more accurately characterize the changes in the number of infected persons. The time-varying reinfection rate was estimated using random-effect multivariate meta-regression based on published literature reports of SARS-CoV-2 reinfection rates. The meta-SEIRS model was constructed to predict the epidemic trend of COVID-19 from February to December 2023 in Sichuan province. Finally, according to the online questionnaire survey, the SARS-CoV-2 infection rate at the end of December 2022 in Sichuan province was 82.45%. The time-varying effective reproduction number in Sichuan province had two peaks from July to December 2022, with a maximum peak value of about 15. The prediction results based on the meta-SEIRS model showed that the highest peak of the second wave of COVID-19 in Sichuan province would be in late May 2023. The number of new infections per day at the peak would be up to 2.6 million. We constructed a meta-SEIRS model to predict the epidemic trend of COVID-19 in Sichuan province, which was consistent with the trend of SARS-CoV-2 positivity in China. Therefore, a meta-SEIRS model parameterized based on evidence-based data can be more relevant to the actual situation and thus more accurately predict future trends in the number of infections.

1. Introduction

Since 2023, the number of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) infections and deaths reported by the World Health Organization (WHO) has declined [1]. The WHO declared that the outbreak no longer constituted a public health emergency of international concern on 5 May 2023 [2]. However, previous evidence [3] showed that the disease burden of coronavirus disease 2019 (COVID-19) may extend far beyond the acute infection period and that the medium- to long-term outcomes following COVID-19 (i.e., defined as long-term COVID-19). It will significantly affect the quality of life, increase the burden on health systems, and pose a serious threat to global health. Moreover, it has been shown [4] that a fourth dose of the mRNA vaccine is ineffective and short-lasting in preventing SARS-CoV-2 infections of Omicron variants, and the effectiveness of vaccination in preventing the emergence of new variants in the future is not yet clear. At the same time, the presence of SARS-CoV-2 reinfection was demonstrated. Jonathan et al. [5] showed a dramatic increase in the rate of SARS-CoV-2 reinfection following the emergence and dissemination of the Omicron variant (from December 2021 to February 2022).

Surveillance data from the Chinese Center for Disease Control and Prevention (CDC) showed that the number of positive nucleic acid tests for COVID-19 and the positivity rate of the reporting population in China presented a trend of increasing and then decreasing since the liberalization of the epidemic policy (after 9 December 2022). Specifically, the number of positives peaks on 22 December (6.94 million) and then fluctuates and declines, but then shows a gradual increase beginning in late April 2023 [6]. As a result, the current epidemiological trend of COVID-19 was fluctuating and there were still many uncertainties, and the COVID-19 outbreak is very likely to re-emerge and pose risks to the health of the population. Considering the import of exogenous strains B.7, BQ.1, and XBB, Sichuan province is highly likely to see a second wave of epidemics in the future. Therefore, in this situation, how to predict the second wave of the epidemic in Sichuan province is still important. With the current guidelines for the treatment of COVID-19 not yet perfected, the sequelae not yet clear, and the gradual loosening COVID-19 restrictions, how to accurately track COVID-19 and find out its impacts, curb future COVID-19 pandemics, minimize the number of positives, and ensure the normal functioning of the health system remains a key public health concern. By exploring the dynamics of COVID-19 transmission and predicting future trends in COVID-19 epidemics, it is possible to provide data to optimize key public health interventions and preventive strategies in Sichuan province, and thus respond more effectively to the potential threats posed by a possible 'resurgent' COVID-19 pandemic [7].

A large number of methods were conducted to predict COVID-19 propagation trends, such as regression model [8], time series model [9], Markov model [10, 11], machine learning [12, 13], and transmission dynamics [14–16] model. Compared with the other models, the transmission dynamics model emphasizes the transmission process of diseases in the population. It quantitatively reveals and describes the connection of people between different states, and it can be combined with the measures taken in the actual prevention and control work to help discover the transmission mechanism of infectious diseases and predict the epidemic trend. Some of the studies on transmission dynamics modelling had taken population reinfection into account in their modelling by increasing the probability of transfer from the recovered (R) to the susceptible (S) state. They set the parameter to a fixed value [17–19] or referenced from related studies. However, variants of COVID-19 evolve, and the risk of transmission [20–22] and clinical deterioration of the disease are not consistent, resulting in the SARS-CoV-2 reinfection rate that also does not remain at a fixed level. Considering the time-varying reinfection rate in the Susceptible-Exposed-Infectious-Recovered-Susceptible (SEIRS) model would better match the actual COVID-19 infection and make the predictions more scientific. However, it is not yet clear how reinfection rates of COVID-19 trend over time, and the parameters of COVID-19 reinfection in China are not yet known. As we know, this caused an important information asymmetry, that was, while it was uncertain for China when the second wave of the epidemic would arrive, the rest of the world has already experienced multiple waves of epidemic. From the perspective of methodology, such information asymmetry provided a special opportunity to study the joint framework of evidence- and practice-based methods. Therefore, in the context of the urgent need to predict the epidemic situation in Sichuan province and the failure to obtain relevant important parameters, we used meta-regression to estimate the time-varying reinfection rates based on published evidence of SARS-CoV-2 reinfection rates, so that the inclusion of time-varying reinfection rates in the transmission dynamics model could more accurately characterize changes of infectors.

We initially presented the time-varying reproduction number (Section 2.1), the meta-analysis (Section 2.2), and the meta-SEIRS model (Section 2.3). Then, the meta-SEIRS model was used to predict the trend of the number of infectors in Sichuan province, China, as an example.

2. Materials and methods

The purpose of this study is to add the time-varying reinfection rate into the transmission dynamics model based on the results of the previous meta-analysis, and further construct a meta-SEIRS model so that the prediction results can be more in line with the actual epidemic trend. The prediction of the number of SARS-CoV-2 infections based on meta-SEIRS modelling will be divided into three parts: estimation of the time-varying reproduction number (R_t), estimation of time-varying reinfection rates based on meta-analysis, and construction of the meta-SEIRS model.

2.1. Estimation of R_t

We estimated R_t based on the onset date and reporting date of infectors [23]. This Bayesian method took uncertainty into the sequence interval distribution (i.e., the time between the symptoms of primary infectors and the symptoms of secondary infectors) and did not limit the step size of the data.

We assumed that infectors have an infectivity profile given by a probability distribution, dependent on the time since the infection of the case, but independent of the calendar time. The R_t can be estimated by the ratio of the number of new infectors generated at time step t, to the total infectiousness of infected individuals at time t, given by $\sum_{s=1}^{t} I(t-s)w_s$, the sum of infection incidence up to time step $t-1$, weighted by the infectivity function w_s. R_t is given by:

$$R_t = \frac{I(t)}{\sum_{s=1}^{t} I(t-s)w_s}. \tag{1}$$

Due to:

$$E[I(t)] = R_t \sum_{s=1}^{t} I(t-s)w_s. \tag{2}$$

Therefore, with the number of infectors generated at time t, $I(t)$ and probability distribution w_s can estimate R_t. $R_t > 1$, indicating that the epidemic will continue to grow; $R_t > 1$, indicating that the epidemic is declining.

2.2. Estimation of time-varying reinfection rates based on a meta-analysis

On 26 December 2022, the National Health Commission of the People's Republic of China issued the 'Overall Plan on the Implementation of "Measures against Class B infectious diseases" for COVID-19', which shifted the focus of prevention and control of COVID-19 from prevention to treatment, that is, from 'dynamic clearing' to 'prevention of outbreaks, serious illnesses, and deaths [24]'. However, the SARS-CoV-2 reinfection rate could not be obtained due to individual-level reasons after loosening COVID-19 restrictions in China; therefore, the time-varying reinfection rate was estimated by referring to published studies. We preliminarily searched PubMed, Web of Science, Medline (Ovid), Embase (Ovid), Cochrane Central Register of Controlled Trials, and other databases for literature reporting SARS-CoV-2 reinfections, and ultimately included 55 papers (the specific inclusion and exclusion criteria and literature extraction information were shown in Supplementary Table S1), and the random-effects multivariate meta-regression analysis was used to estimate the change in reinfection rates over time.

We used the working definition of the SARS-CoV-2 reinfection as the positive laboratory result at least 90 days after laboratory confirmation of primary infection (laboratory testing methods include reverse transcription-polymerase chain reaction or rapid antigen test, also called lateral flow devices and so on) [25, 26]. Meta-analysis is a method to obtain weighted average results from various studies. In addition to pooling effect sizes, meta-

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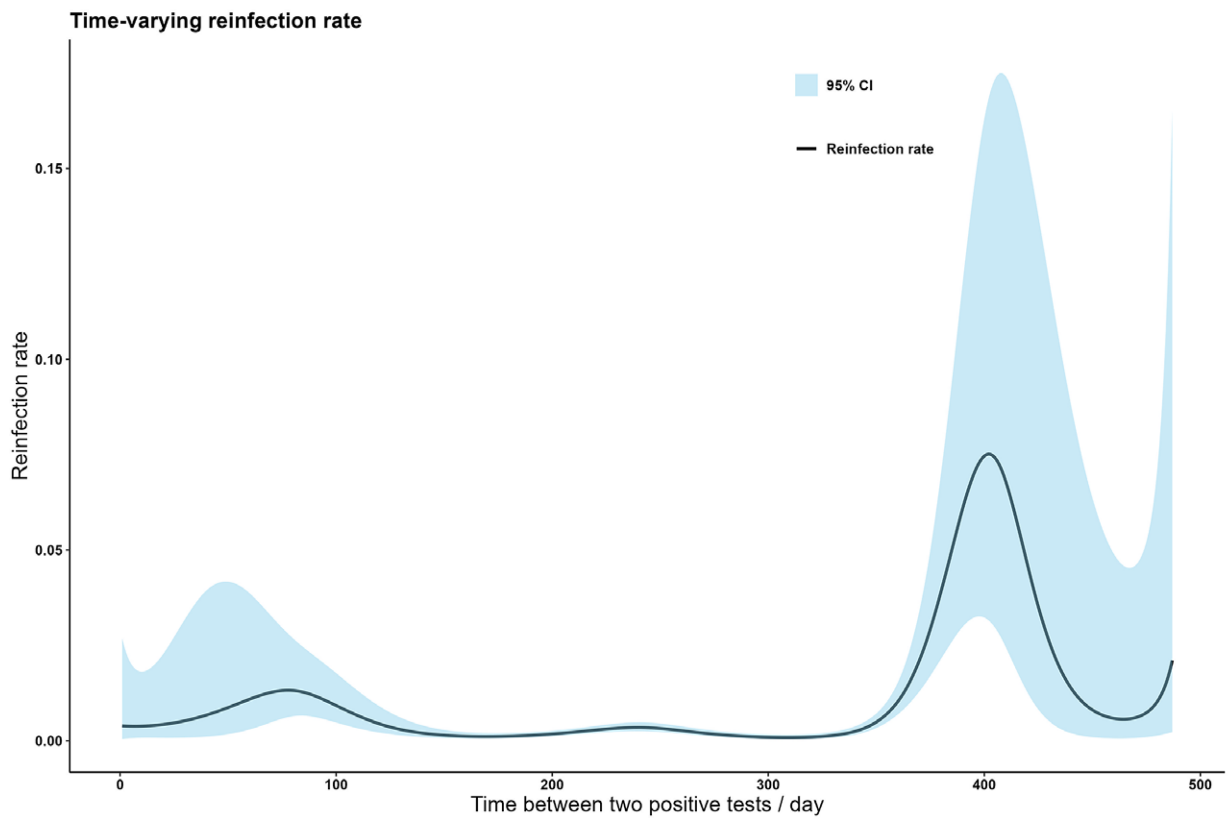

Figure 1. Meta-regression of time-varying reinfection rates (black line indicates the true value and blue shading indicates 95% *CI*).

analysis can also be used to estimate disease frequencies, such as incidence and prevalence. Considering the change in the reinfection rate over time, we constructed a multiple meta-regression using the time interval between two positive tests as the independent variable, to estimate the time-varying reinfection rate. Subgroup analyses were performed by meta-regression to fit stratified rates of reinfection based on the variables such as variant and country. The meta-regression model for selecting non-stratified time-varying reinfection rates based on AIC was presented in the form of splines with eight degrees of freedom between the reinfection interval and product terms of country and variant, and the calculation results of AIC are shown in Supplementary Table S2.

The pooled SARS-CoV-2 reinfection rate was 0.94% (95% *CI*: 0.65%–1.35%). Based on the meta-regression results, we plotted the change curve of the reinfection rate concerning the reinfection interval, as shown in Figure 1. Overall reinfection rose first and then fell, with a period of plateauing and then a trend of rising and then falling. The first inflection point was on day 78, with a predicted reinfection rate of 0.0133 (95% *CI*: 0.0063–0.0280). The second inflection point was at the 402nd day, with a predicted reinfection rate of 0.0752 (95% *CI*: 0.0316–0.1684), with the second wave of reinfection rates peaking higher than the first. More information can be found in our previous work, estimating time-varying reinfection rates based on global evidence [27].

2.3. Construction of the meta-SEIRS model

The possibility of reinfections of recovered people was considered based on the SEIR model, that is, recovering for a period of time and then re-exposing to diseases with the same or similar pathogens/variant viruses. Therefore, the model was modified to the SEIRS model, as shown in Figure 2, and the mathematical model is shown in Equation (3).

$$\begin{cases} \dfrac{dS}{dt} = -\dfrac{r\beta SI}{N} + \theta R \\ \dfrac{dE}{dt} = \dfrac{r\beta SI}{N} - \alpha E \\ \dfrac{dI}{dt} = \alpha E - \gamma I \\ \dfrac{dR}{dt} = \gamma I - \theta R \end{cases}, \tag{3}$$

Here are the definitions for the variables. N denotes the total number of people in the region; r denotes the average number of infectors contact with susceptible; β denotes the probability of infection per unit of time after contact with other people; α denotes the rate at which an exposed person is converted to an infector; γ denotes the rate at which infectors are recovered; and θ denotes the rate at which recovered go to susceptible as a result of loss of immunity.

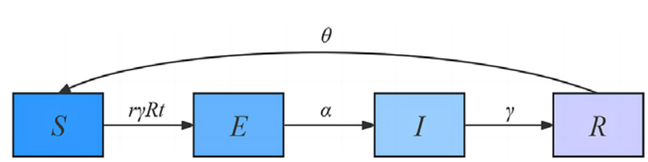

Figure 2. SEIRS model (*S*: Susceptible, *E*: Exposed, *I*: Infectious, *R*: Recovered).

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Table 1. Definitions and settings of model parameters

Parameter	Definition	Setting	Setting basis
N	Total number of people in the region	83,740,000	Population of Sichuan province
I (0)	Initial number of infectors	1,000	Sichuan province Rapid Assessment Survey data
R (0)	Initial number of recovered persons	71,162,000	The cumulative infection rate in Sichuan province was about 85%
r	Average number of infectors exposed to susceptible persons	1–20	Zhang J, Iuliano AD, et al. [20,21]
α	Transition rate of conversion of exposed persons to infectors	0.29	Lyngse FP, et al. [22]
γ	Transition rate of removal of infectors	1/5.5	Iuliano AD, et al. [23]
r_{re}	Reinfection rate	–	See 2.2 Meta-analysis
θ	Transition rate of recovered to susceptible	–	$\theta = r_{re}/(r \cdot \gamma \cdot R_t \cdot \alpha)$

To utilize the number of daily infections to a greater extent, we improved the SEIRS model by using the time-varying [23] effective reproduction number, as shown in Equation (4).

$$\begin{cases} \dfrac{dS}{dt} = -\dfrac{rR_t\gamma}{N}SI + \theta R \\ \dfrac{dE}{dt} = \dfrac{rR_t\gamma}{N}SI - \alpha E \\ \dfrac{dI}{dt} = \alpha E - \gamma I \\ \dfrac{dR}{dt} = \gamma I - \theta R \end{cases} . \quad (4)$$

Most of the parameter settings were derived from actual data or literature in the context of global mass vaccination with the COVID-19 vaccine with the Omicron strain epidemic, as shown in Table 1. However, since the study was conducted on the example of Sichuan province, it was adjusted to take into account the actual situation. The total population in the region was derived from the data of the '2022 Sichuan National Economic and Social Development Statistics Bulletin [28]'. The number of permanent residents of Sichuan province was 83.74 million at the end of 2022. SARS-CoV-2 infection was no longer included in the management of quarantine infectious diseases under the Law of the People's Republic of China on State Border Hygiene and Quarantine as of 8 January 2023 [24], so there was a lack of data on the number of daily infections. However, Sichuan CDC released three rounds of questionnaires via the Internet to quickly assess SARS-CoV-2 infections in Sichuan province. Analysis of the 'Findings of the Third Round of Rapid Assessment of SARS-CoV-2 Infections in Sichuan province [29]' showed that when the daily average number of new infections was below 1,000, the incidence rate had levelled off and the trend was trailing. This was more in line with January, so the initial number of infections was set to 1,000. Based on the report of

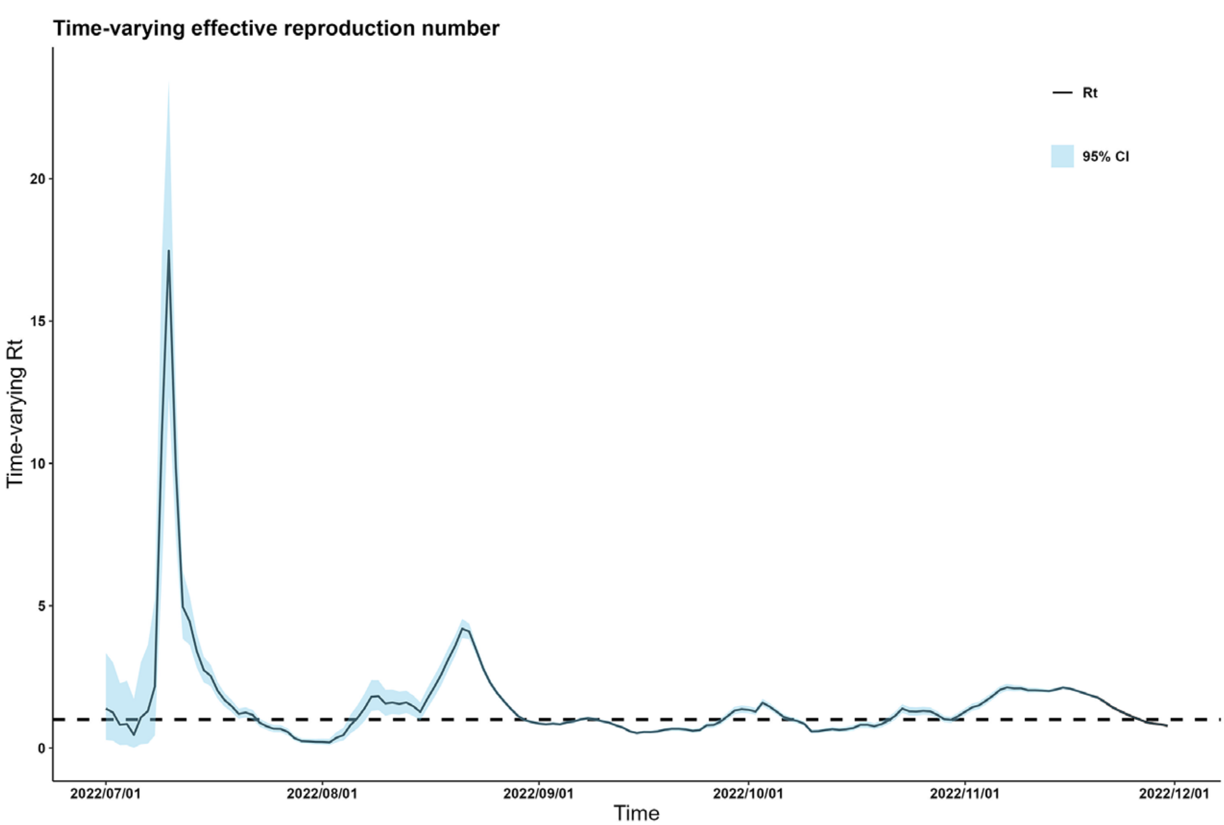

Figure 3. Time-varying effective reproduction number.

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Table 2. Reporting of infections by city (state)

Region	Confirmed cases (cases)	Asymptomatic infections (cases)	Total number of infections (cases)
Sichuan province	58,036	3,477	61,513
Chengdu	13,925	543	14,468
Luzhou	5,281	322	5,603
Yibin	4,198	185	4,383
Deyang	3,479	200	3,679
Nanchong	3,395	203	3,598
Liangshan	2,806	346	3,152
Bazhong	2,799	283	3,082
Neijiang	2,707	168	2,875
Mianyang	2,629	54	2,683
Guangyuan	2,375	158	2,533
Zigong	2,372	129	2,501
Ya'an	2,268	38	2,306
Guang'an	1,673	218	1,891
Ziyang	1,351	264	1,615
Leshan	1,558	33	1,591
Panzhihua	1,521	20	1,541
Suining	1,206	137	1,343
Meishan	932	112	1,044
Aba	805	13	818
Dazhou	430	26	456
Ganzi	326	25	351

'Sichuan province Emergency Response Command for SARS-CoV-2 Infections Held a Video Dispatch Meeting on Epidemic Prevention and Control' on January 16th, the authors of the Yang participated in it, the cumulative infection rate in Sichuan province exceeded 85%. However, considering the fact that some infectors passed away due to complications, a conservative estimate of 85% was adopted, setting the number of initially recovered persons at 85% of the total population. Because of the consideration that the reinfection rate of SARS-CoV-2 infections varies with the prevalent strains and the immunity of the population, the reinfection rate in our model was constantly changing over time; that is, the time-varying reinfection rate was estimated by random-effects meta-regression (see Section 2.2).

The following assumptions were proposed about the SEIRS model:

(1) The effect of factors such as births and deaths in the population was not considered, that is, the total population N was assumed to be constant over the study period.
(2) Assuming that no strain with significantly enhanced immune escape over the currently globally detected variants will emerge in Sichuan province within 1 year and that the Omicron strain will remain predominantly endemic.
(3) Since morbidity and mortality rates of the Omicron strain were already equal to or slightly lower than influenza [30–32], the population impact of factors such as morbidity and mortality was not considered, and the state of R was all assumed to be recovered.

2.4. Data

Due to the publication of 'Notice on Further Optimizing the Implementation of Preventive and Control Measures for the COVID-19 Epidemic' on 7 December 2022 [33], we utilized data on the daily infections of SARS-CoV-2 from 1 July to 7 December 7 2022, in Sichuan province, obtained from the National Health Commission of the People's Republic of China [34]. The positive rate of SARS-CoV-2 in China, utilized in this study, was sourced from the open data provided by the Chinese CDC [35]. In addition, the number of reported cases of SARS-CoV-2 in Sichuan province from 1 January to 5 June 2023 was obtained from Sichuan CDC. The original reinfection rate was derived from publicly published literature, as detailed in Section 2.2. The data of the meta-analysis were introduced in Supplementary Material and in our previous work [27]. Other parameters used in the meta-SEIRS model and their sources are listed in Table 1.

3. Results

3.1. Prevalence in Sichuan province

We estimated the time-varying effective reproduction number based on the monitoring data of the number of infected persons with COVID-19 from 1 July to 7 December 2022, in Sichuan, as shown in Figure 3. The maximum peak value of R_t was approximately 15.

A total of 61,513 cases of SARS-CoV-2 infection were reported in Sichuan in January 2023 (92–6,040 cases reported per day), an increase of 432.03% compared with the number of cases reported in the previous month (11,562 cases). The top three cities in Sichuan with the highest number of reported cases were Chengdu (14,468 cases), Luzhou (5,603 cases), and Yibin (4,383 cases), accounting for 39.75% of the total cases, as shown in Table 2.

Sichuan CDC carried out the first round of the SARS-CoV-2 infection network survey on 17–19 December 2022, with 487,567 people from 190 counties in 21 cities participating in the survey, covering 2,243,348 people of all family members. Among them, 413,261 families lived in urban areas (accounting for 84.76%), and 74,306 families lived in rural areas (accounting for 15.24%). In the first round of the survey, 228,809 people were positive for the SARS-CoV-2, with an infection rate of 46.93%. Areas with infection rates exceeding 50% included Mianyang (54.05%), Chengdu (53.01%), and Ziyang (50.46%). There are 32 counties with infection rates exceeding 50%.

The second round of the online questionnaire survey was conducted on 24–28 December 2022. Then, 233,192 people from 190 counties in 21 cities participated in the survey, of which 62,999 people participated in the first survey, with a repeat rate of 27.02%. Among them, the population in urban areas was 191,901 (82.29%) and the population in rural areas was 41,291 (17.71%). Of the 233,192 people surveyed in the second round, there were 148,492 confirmed cases and 43,774 clinically diagnosed cases, with a morbidity rate of 82.45%. The morbidity rate exceeded 80% in 13 cities. The lowest incidence rate was 63.70% in Aba Prefecture. The morbidity situation in each city is shown in Figure 4.

3.2. Predicted results

Based on the assumptions of the transmission dynamics model described above, the development trend of the SARS-CoV-2 infection in Sichuan in 2023 was predicted, as shown in Figure 5. The black curve represents the prediction of the number of daily new

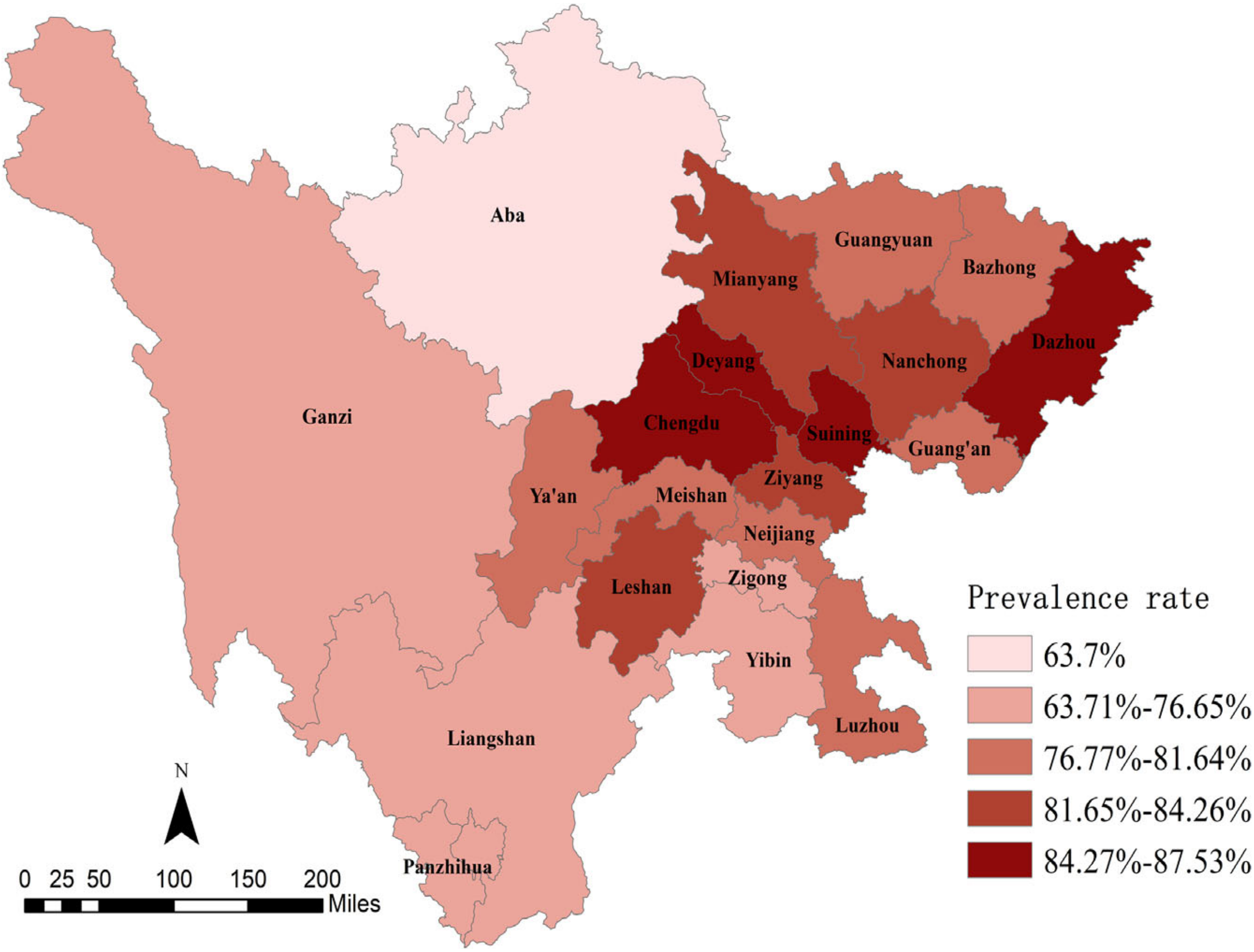

Figure 4. Regional distribution of SARS-CoV-2 infection in Sichuan province.

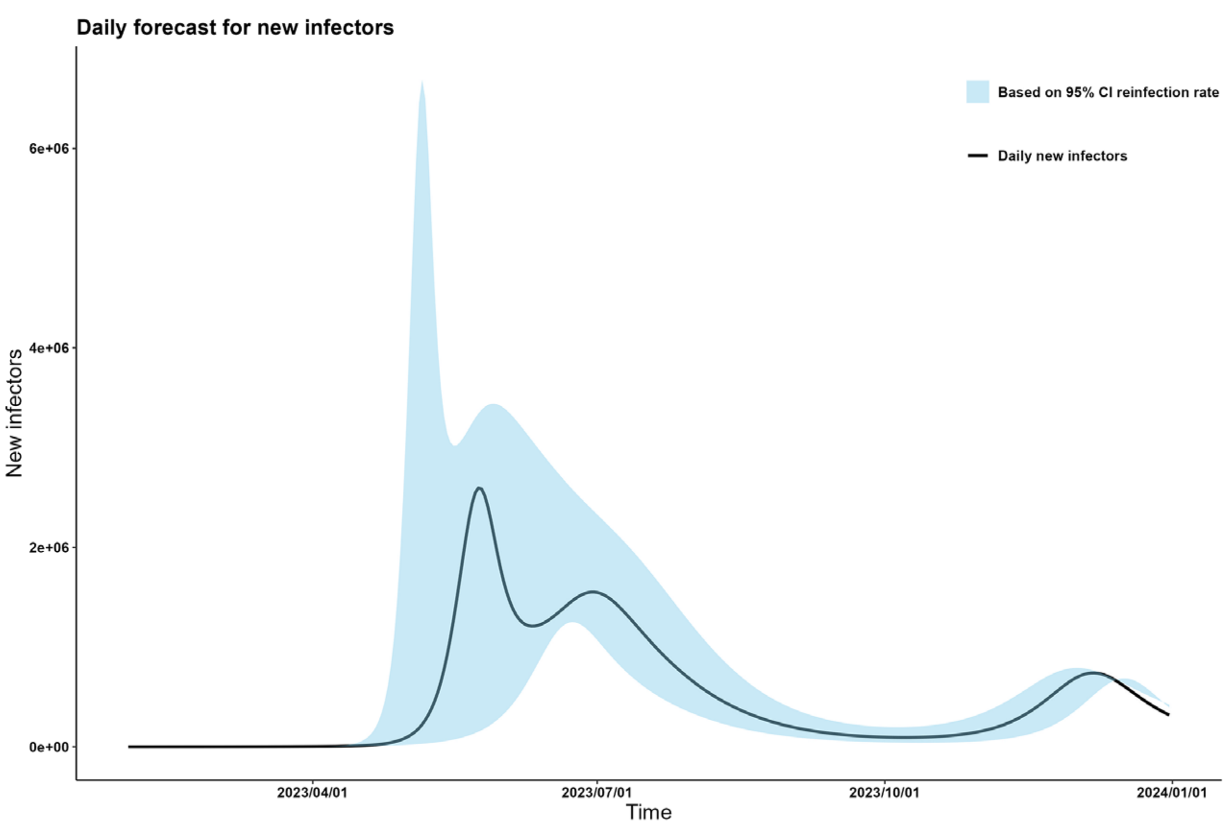

Figure 5. Predicted new infectors.

Table 3. Inflection points in the predicted change of new infections

Date	Time elapsed since the last infection (day)	Number of new infections (range)
24 May 2023	113	2,596,925.00 (151,792.40–3,342,301.65)
30 June 2023	150	1,551,125.28 (1,105,917.25–2,359,137.60)
12 July 2023	310	740,432.70 (524,082.70–763,702.90)

infections when the reinfection rate is the mean, and the blue shadow represents the 95% *CI*. The peak occurred in late May, with the daily increase of new infections predicted to be 2,596,925 (24 May 2023). The second and third peaks of new infections occurred at the end of June and the beginning of December, respectively, with specific time points and numbers shown in Table 3. The number of new infections corresponding to the second and third peaks was smaller than that of the first peak and decreased progressively.

According to the results of our meta-analysis, most studies had reinfection rates between 1% and 7% (see in the Supplementary Table S1), and only a few studies had reinfection rates greater than 10% [36–39]. Therefore, we compared the prediction results of the meta-SEIRS model, the results of SEIRS models with fixed reinfection rates (1%, 7%, and 15%), and the actual surveillance data in Sichuan province (see Figure 6). Our results showed that the number of new infections predicted by SEIRS with fixed parameters was much smaller than that predicted by the meta-SEIRS model, and the maximum number of new infections per day was about 270,000, which was much smaller than that predicted by Professor Zhong. In addition, the number of new infections predicted by fixed-parameter SEIRS models would only begin to rise in June,

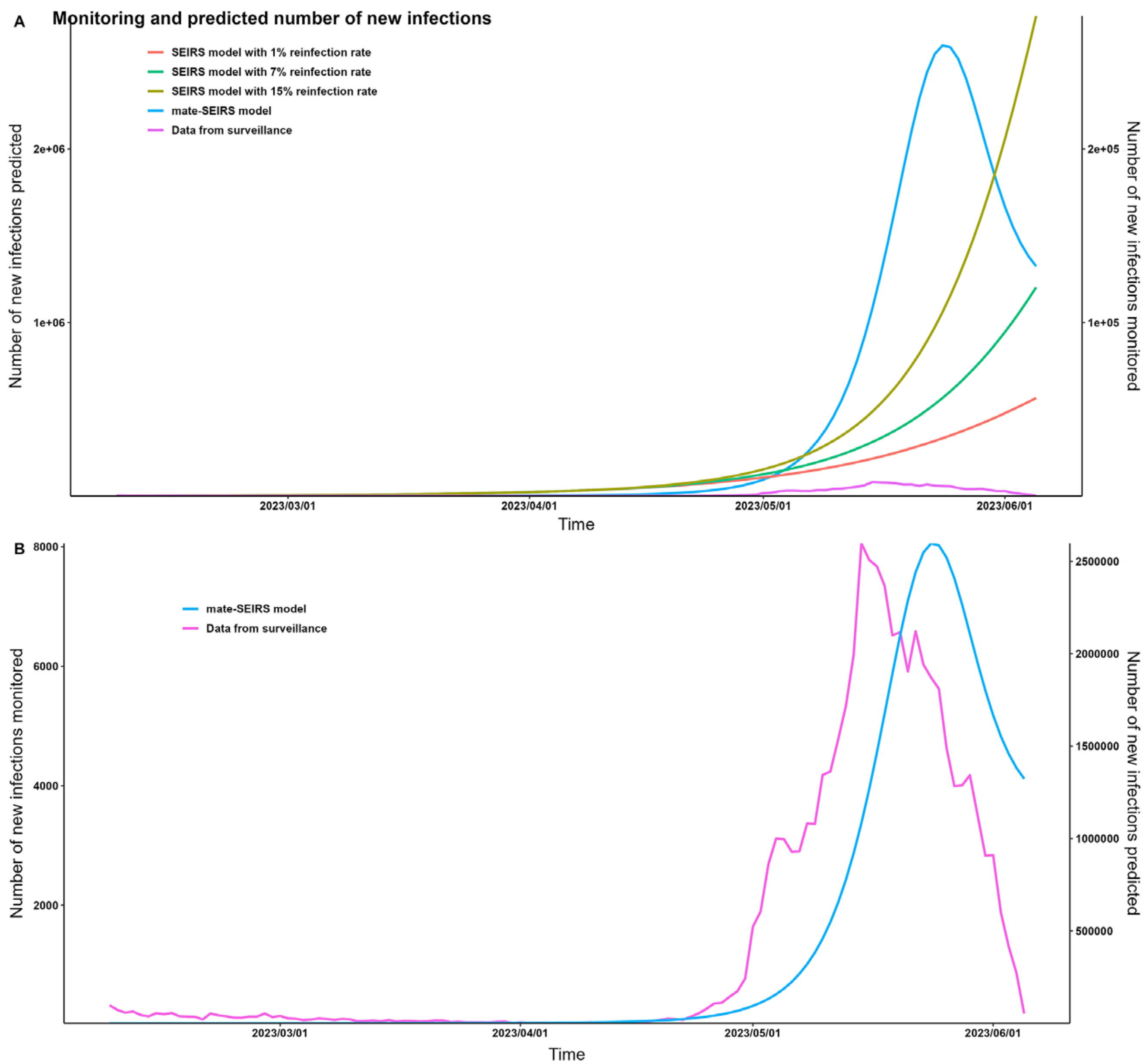

Figure 6. Monitoring and predicted number of new infections in Sichuan province.

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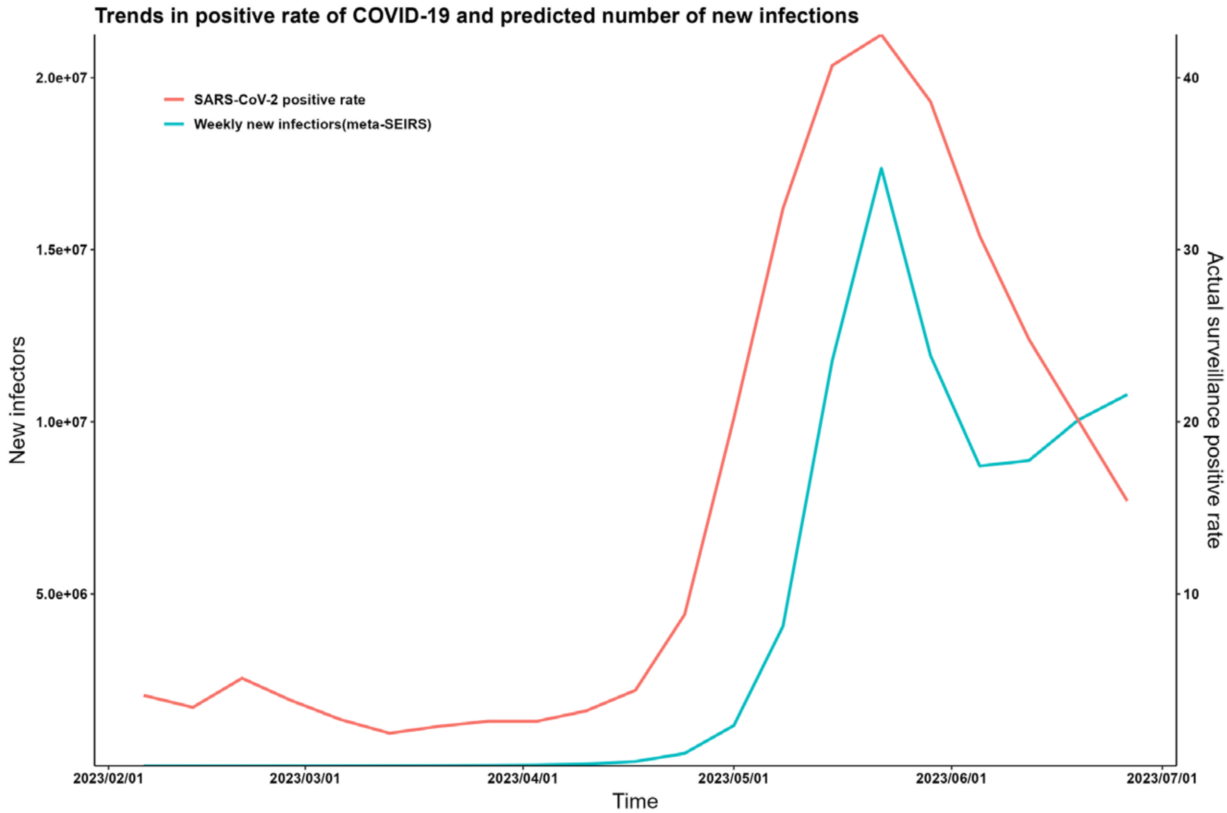

Figure 7. Trends in the positive rates of COVID-19 and the predicted number of new infections in influenza-like cases in sentinel hospitals in China.

which was significantly later than the actual surveillance results in the Sichuan province. However, the trend of new infections estimated by the meta-SEIRS model was consistent with the actual surveillance results in Sichuan. We found that the monitoring data are consistent with the trend of our forecast data that COVID-19 infections in Sichuan province will continue to rise in May 2023 and gradually decrease by June. However, the monitoring data are incomplete, and it is impossible to compare the difference between our predicted results and the absolute values of the monitoring data.

China's national COVID-19 epidemic data from the Chinese CDC also shows that the positive rate of COVID-19 infection in China peaked in mid-to-late May and gradually declined in June, as shown in Figure 7. It can be seen that the trend of our forecast results is consistent with the trend of COVID-19 infection surveillance in China and Sichuan province.

4. Discussion

Estimation of the time-varying effective reproduction number in Sichuan province, based on the surveillance data, indicated that there were two peaks of SARS-CoV-2 infection in Sichuan province from July to September 2022, stabilizing around 1 thereafter. It showed that the COVID-19 outbreak was still spreading among the population of Sichuan from July to September 2022. Based on 55 articles, our meta-analysis found that the pooled SARS-CoV-2 reinfection rate globally was 0.94% (95% *CI*: 0.65%–1.35%). Subsequently, using the meta-SEIRS model, we predicted the development trend of SARS-CoV-2 infection in Sichuan province in 2023, which was largely consistent with the monitoring trend.

Sichuan CDC conducted a second round of online questionnaire surveys from 24 December to 28 December 2022. The infection rate was 82.45%, and the number of infected persons was much higher than the number of reported cases in Sichuan in January 2023 [29]. However, the population covered by the online survey was mostly urban people who used mobile phone more and were concerned about their health. For the rest of the population who did not complete the questionnaire, there may be inconsistencies with the profile of those who completed this part of the survey. In addition, because people with asymptomatic or mild symptoms of the SARS-CoV-2 infection may not actively seek medical attention, the Sichuan CDC cannot monitor this part of the population. For the above reasons, the infection rate in Sichuan from December 2022 to January 2023 may be much higher than the results of the December online survey in Sichuan and the January report from the Sichuan CDC. The survey results suggested that the first wave of infections in Sichuan might have been concentrated between 12 and 20 December 2022, after which the number of new infections gradually declined. Therefore, after the first peak of the epidemic in Sichuan has passed, due to the decline of vaccine and natural immunities over time as well as the possible emergence of new variants of COVID-19 in the future, we need to take into account the rebound of the epidemic caused by repeated infections of COVID-19. For the 31st Summer Universiade that would be held in Chengdu from July to August 2023, and considering Chengdu's status as an international city frequently hosting various international events, it was crucial to predict the trend of the COVID-19 epidemic to control its rapid spread and ensure the normal functioning of the healthcare system amidst the high flow of people. Our research can also serve as a reference for risk assessment before other cities host international events.

We proposed the meta-SEIRS model, which combined meta-analysis with the transmission dynamics model and set model parameters based on evidence-based medicine, thus making the model more relevant. And we estimated time-varying reinfection rates, which allows dynamic prediction of infection trends in conjunction with population immunization levels. We assumed that the total population *N* remained unchanged during the study period. Besides, there will not be strains with significantly enhanced immune escape than the current globally detected variants in Sichuan within 1 year, implying that the epidemic will still be dominated by the Omicron strain, as shown in Figure 5. Zhong based on the SEIRS model predicted the trend of the second wave of the COVID-19 epidemic in China [40]. The peak number of infected individuals reached 40 million per week by the end of May 2023. The COVID-19 epidemic report from the Chinese CDC also showed that the number of fever clinic visits in China began to rise gradually from May 2023, reaching a peak in mid-to-late May. Moreover, the proportion of influenza-like illnesses to outpatient (emergency) visits at sentinel hospitals nationwide as well as the rate of SARS-CoV-2 positivity in influenza-like illnesses also peaked in mid-to-late May [35]. These trends were consistent with the predicted trends of this study. Comparing our results with the actual monitoring data (Figure 6, Figure 7), we found that the predicted trend based on the meta-SEIRS model was basically consistent with the actual surveillance trend in Sichuan province and the trend of SARS-CoV-2 positive rate monitored by sentinel hospitals in China. In addition, compared with the SEIRS models with fixed parameters (the re-infection rate was set at 1%, 7%, and 15%, respectively), the peak time of infection predicted by the meta-SEIRS model was more consistent with the actual situation. This indicates that our meta-SEIRS model may be more in line with the actual epidemic trend of COVID-19 than the SEIRS model with fixed parameters, and can realize the prediction of early detection of COVID-19 infection, which is helpful for relevant medical and health institutions to take early intervention measures.

The strength of this study is that it combines meta-regression with the transmission dynamics model to predict transmission trends based on the most recent evidence and to provide ideas for parameterization of the transmission dynamics model. The limitation is that there is no individual-level data on changes in antibody concentrations, and only population-based calculation of proportions as reinfection rates. However, the propagation dynamics model does not require individual-level data either. In the future, as research progresses, if antibody concentration data are available, predictions can be made by using individual-level network models [41, 42] and so on. The transmission dynamics model constructed in this study did not consider the effect of population vaccination status on the transmission of SARS-CoV-2 infection because the study showed that the effectiveness of previous vaccinations in preventing infections with the Omicron variant or the new variant was low and that the effect of vaccinations on reducing the transmission was likely to be small [4, 43]. Coupled with our inability to accurately capture vaccine efficacy for Omicron variants or new variants, population vaccination was not considered in the modelling of this study.

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Data availability statement. The data will be made available upon request from the corresponding authors.

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Competing interest. The authors declare there is no conflict of interest.

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