Modified SEIR Model Based on Real-World Data for Epidemic Prevention and Control: A Postprint

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Abstract

Background: The Omicron variant has spread extensively worldwide. Shenzhen, as a critical transportation hub connecting domestic and international routes, has been continuously impacted since February 2022, with a rapid increase in infections.

Objective: To develop a modified Susceptible-Exposed-Infected-Recovered (SEIR) model to provide actionable policy references and recommendations for Shenzhen's COVID-19 prevention and control efforts, thereby mitigating control pressures.

Methods: Building upon the traditional SEIR infectious disease dynamics model and accounting for Omicron's epidemiological characteristics—including rapid transmission, high stealth, and universal population susceptibility—we introduced policy-specific compartments: close contacts, secondary close contacts, Shenzhen-entry quarantined individuals, and carriers. The modified SEIR model was constructed, with parameters determined by fitting Shenzhen epidemic data from February 18–28, 2022.

Results: The model's predictions aligned substantially with actual data from March 1–4, 2022, providing a reliable foundation for forecasting subsequent epidemic development. The model further projected trends for March 5–19, offering guidance on manual intervention intensity, intervention timing, and healthcare resource requirements—including bed capacity and isolation room availability—for Shenzhen's continued epidemic response.

Conclusion: The modified SEIR model demonstrates significant practical value for epidemic trend prediction, prevention and control strategy formulation and adjustment, and medical resource allocation.

Full Text

Preamble

ChinaXiv Partner Journal ・Research on Digital Healthcare and Informatization ・Application of a Modified SEIR Model Based on Real-World Data for Epidemic Prevention and Control

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Abstract

Background: The Omicron variant of Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) has spread globally. Since February 2022, Shenzhen, as a major transportation hub connecting domestic and international routes, has been continuously affected, with rapidly increasing numbers of infected cases. **Objective:** To construct a modified Susceptible-Exposed-Infected-Recovered (SEIR) model to provide policy references and practical recommendations for Shenzhen's epidemic prevention and control efforts, thereby alleviating pressure on the public health system. **Methods:** Based on the traditional SEIR infectious disease dynamics model and targeting the epidemiological characteristics of Omicron—such as rapid transmission, high concealment, and universal population susceptibility—this study introduced policy-relevant groups including close contacts, secondary contacts, inbound quarantined individuals, and carriers to build a modified SEIR model. The model parameters were determined by fitting Shenzhen's epidemic data from February 18–28, 2022. **Results:** The model's predictions were essentially consistent with actual data from March 1–4, 2022, providing a reliable basis for forecasting subsequent epidemic development. The model further predicted epidemic trends for March 5–19, 2022, offering guidance for Shenzhen's prevention and control measures regarding the intensity and timing of interventions, as well as healthcare resource requirements such as hospital beds and isolation rooms. **Conclusion:** The modified SEIR model demonstrates significant practical value in predicting epidemic development, formulating and adjusting control measures, and allocating health resources.

Keywords: COVID-19; Omicron; Modified SEIR model; Forecasting; Policy recommendations; Health resource allocation

Introduction

Since November 2021, the global spread of the Omicron variant has driven COVID-19 into its fourth pandemic wave. Characterized by high transmissibility, rapid spread, substantial concealment, and universal population susceptibility, Omicron has created unprecedented pressures and challenges for China's epidemic prevention and control efforts [1]. In February 2022, multiple regions in China experienced local outbreaks. Among them, Shenzhen, as a critical port city and international-domestic transportation hub with a complex population structure, high cross-regional mobility, and numerous ports, faced particularly severe epidemic conditions. Consequently, providing actionable policy references and recommendations for Shenzhen's epidemic response became essential for mitigating control pressures.

In recent years, classic infectious disease models such as the Susceptible-Exposed-Infected-Removed (SEIR) model have been widely applied to COVID-19 prediction and evaluation. Chen Jiali et al. [2] developed the SVEPIUHDR model by incorporating pre-symptomatic infected individuals, isolation measures, and vaccination into the SEIR framework to predict daily new cases in the UK and US under varying vaccination rates. Yu Zhenhua et al. [3] proposed the SLEIR model, which added populations adopting protective measures, and applied it to forecast India's COVID-19 epidemic from March to May 2020. Zhou Qian et al. [4] employed the SIR-MCMC method to evaluate epidemic development and control measures in Hubei Province based on basic reproduction number and vaccine intervention. However, Omicron exhibits substantially different epidemiological characteristics from earlier SARS-CoV-2 variants—its transmission capacity is twice that of the Delta variant, and Omicron BA.2 is 30% more transmissible than BA.1 [5]. Moreover, earlier transmission dynamics models broadly defined the latent period group, making it difficult to promptly identify the timing and scope of concealed transmission. Therefore, a more targeted transmission model was needed to accurately predict Shenzhen's COVID-19 epidemic trends.

Additionally, researchers have begun using SEIR models to investigate the impact of interventions on curbing transmission. Xiao Yanni et al. [6] constructed new evolution equations based on the SEIR model to explore relationships between intervention implementation, public behavior changes, vaccination coverage and timeliness, external triggers, and viral transmission intensity. Tang Sanyi et al. [7] combined dynamics models with limited real-time data to analyze epidemic risks and evaluate the effectiveness and timeliness of prevention strategies. However, most studies have been retrospective, overlooking the SEIR model's crucial role in early warning, policy support, and guiding real-time control adjustments and resource allocation.

Building upon previous research, this study constructed a modified SEIR model with three key innovations: (1) introducing a carrier group based on in-depth analysis of Omicron's epidemiological features; (2) subdividing quarantined individuals into three policy-relevant categories—close contacts (Q1), secondary contacts (Q3), and inbound quarantined individuals (Q2)—according to Shenzhen's intervention intensity and timing; and (3) conducting simulation using Python based on real-world data. The resulting predictions not only enabled early warning but also provided decision-making support for subsequent policy adjustments and medical resource allocation in Shenzhen.

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1. Methods

1.1 Data Sources and Assumptions

Real-world epidemic data were obtained from the Shenzhen Municipal Health Commission official website (http://wjw.sz.gov.cn/), the National Health Commission (http://www.nhc.gov.cn/) epidemic bulletins, industry reports [8], news sources [9-11], Baidu real-time data [12], and other publicly available sources. These data were validated by relevant experts and frontline personnel.

The modified SEIR model in this study is based on the following assumptions:

1. Population remains constant, excluding births, deaths, and migration. The region is treated as a closed environment where the total population is fixed:

$$S(t) + A(t) + R(t) + D(t) + Q_1(t) + Q_2(t) + Q_3(t) = 17,560,100$$

2. During the epidemic, inbound migrants to Shenzhen must undergo centralized quarantine according to local policies. These individuals are designated as "inbound quarantined persons," primarily comprising travelers from domestic medium/high-risk areas, overseas arrivals, and arrivals from Hong Kong. Based on available data, the daily number of inbound quarantined individuals remains approximately 900, so we set $L_1 = 900$.
3. Universal screening will eventually identify all local positive cases (not necessarily immediately, but under China's strict measures, no positive cases will be missed).
4. No specific cure for COVID-19 exists.
5. For model simplification, recovered individuals who test positive again are not considered.

1.2 Modified SEIR Model

The SEIR model is a classic dynamics model in infectious disease research, first proposed by Kermack et al. [13] in 1927. It is concise with few parameters and has been widely studied and applied. The SEIR model assumes that all individuals in a complex network can be divided into a limited number of states, which researchers can combine according to epidemic development and research needs to represent transition sequences and epidemic stages. The classic SEIR model categorizes populations into Susceptible (S), Exposed (E), Infected (I), and Recovered (R).

This study introduces two key modifications to the traditional SEIR model based on Shenzhen's current prevention and control policies by adding policy-relevant groups: close contacts (Q1), secondary contacts (Q3), inbound quarantined individuals (Q2), and carriers (A):

1. In the traditional SEIR model, E represents individuals who have been exposed to infected persons but are not yet infectious. However, Omicron has an incubation period of 1–3 days with strong transmissibility, making the traditional SEIR model inadequate for Omicron transmission. Therefore, this study introduces the carrier group A to replace the exposed group E, defining this group as individuals who have contracted Omicron but remain concealed in the local transmission chain until testing positive.

2. Shenzhen's COVID-19 prevention strategies include: closed-loop management of individuals arriving from medium/high-risk areas, overseas, and Hong Kong; universal nucleic acid screening; centralized quarantine of close and secondary contacts; and designated hospital treatment for infected individuals. Accordingly, our model incorporates inbound quarantined individuals (Q2) and closed-loop management strategies. The carrier group A influences the duration and frequency of universal screening, while the new groups Q1 and Q3 affect the implementation of centralized quarantine policies. Both symptomatic and asymptomatic infected individuals are immediately sent to designated hospitals for isolation and treatment, so our modified SEIR model categorizes both as infected individuals. The population transition relationships are illustrated in Figure 1 [Figure 1: see original paper], where black arrows represent state transitions between groups.

The modified SEIR dynamics equations for Omicron prevention and control are constructed as follows:

$$\frac{dS}{dt} = -(p_1 + p_3 + \beta)S(\theta_1 A + \theta_1 \times \theta_2 I) + \lambda_1 Q_1 + \lambda_3 Q_3 + q_s Q_2 - L_1 \tag{1}$$

$$\frac{dA}{dt} = \beta S(\theta_1 A + \theta_1 \times \theta_2 I) - \varepsilon A \tag{2}$$

$$\frac{dI}{dt} = \varepsilon A + \delta_1 Q_1 + \delta_3 Q_3 + q_i Q_2 - (r_i + d_i)I \tag{3}$$

$$\frac{dR}{dt} = r_i I \tag{4}$$

$$\frac{dD}{dt} = d_i I \tag{5}$$

$$\frac{dQ_1}{dt} = p_1 S(\theta_1 A + \theta_1 \times \theta_2 I) - [\lambda_1 + \delta_1]Q_1 \tag{6}$$

$$\frac{dQ_2}{dt} = L_1 - (q_i + q_s)Q_2 \tag{7}$$

$$\frac{dQ_3}{dt} = p_3 S(\theta_1 A + \theta_1 \times \theta_2 I) - [\lambda_3 + \delta_3]Q_3 \qquad (1) \tag{8}$$

Based on literature [14], this study assumes that carriers and infected individuals have equivalent transmission capacity, hence the parameter θ_1 (Figure 1). Inbound quarantined individuals under closed-loop management have minimal impact on local outbreaks, so θ_2 represents the ratio of infected individuals triggering local transmission to all identified infected individuals (Figure 1). Omicron's incubation period is generally 2–3 days [15]; this study sets the mean time to positive detection at 3 days, thus $\varepsilon = 1/3$ according to literature [15].

Similarly, based on literature [16], Shenzhen implements 14-day centralized quarantine for close contacts, so $\lambda_1 = 1/14$, and 7-day centralized quarantine for secondary contacts, so $\lambda_3 = 1/7$. Literature [17] examined the Wuhan epidemic from January 23 to February 12, 2020. Due to longer incubation periods, weaker early interventions, and limited vaccine coverage during the Wuhan outbreak, the contact infection probability β was overestimated. Therefore, this study uses Shenzhen data from February 18–28, 2022 as a training set to adjust β from 2.05×10^{-9} to 1×10^{-9}. Additionally, parameters q_s, δ_1, and δ_3 were fitted and optimized based on more recent raw data to improve prediction accuracy.

For parameter estimation of q_s, δ_1, and δ_3, this study employs a heuristic algorithm [18]. Since q_s represents the probability of identifying infected individuals among inbound quarantined persons per unit time, δ_1 represents the probability of close contacts becoming infected through exposure per unit time, and δ_3 represents the probability of secondary contacts becoming infected through exposure per unit time, all three parameters $\in [0, 1]$. Random sampling was conducted within this range, with q_s at magnitude 1×10^{-3} and δ_1 and δ_3 at granularity 1×10^{-5}. The sampling process was iterated 10,000 times, with different parameter samples input into the modified SEIR equations. Optimization followed the principle of minimizing root mean squared error (RMSE) when comparing with real data.

$$\text{RMSE} = w_1 \times \text{RMSE}_1 + w_2 \times \text{RMSE}_2 \qquad (2)$$

where RMSE_1 and RMSE_2 represent the RMSE of existing infected individuals and existing close contacts, respectively. w_1 and w_2 are weights that accelerate the search for optimal solutions and can be adjusted during fitting; in this study, both were set to 1.

Other relevant parameters p_1, p_3, and q_i were calculated from real data. For brevity, we illustrate the calculation using the conversion rate q_i from susceptible to close contacts (see equation (3)):

$$p_1 = \frac{\text{Average daily new close contacts}}{S(t) \times (\theta_1 \times A(t) + \theta_1 \times \theta_2 \times I(t))} \qquad (3)$$

where θ_1 indicates that each Omicron carrier infects an average of 1.5 people under interventions [19]. Additionally, the infected group in this study includes both community-detected cases and cases identified among inbound quarantined individuals. Data analysis [20] reveals that nearly two-thirds of new infections in our infected group originated from inbound quarantine, with these cases under closed-loop management having minimal spillover risk, thus we set the local outbreak association parameter $\theta_2 = 0.316$.

Infected individuals I in our model represent the number of existing cases up to day t, defined as:

$$I(t) = \text{Daily new infections on day } t - \text{Daily new recoveries on day } (t-1) + \text{Existing infections on day } (t-1)$$

Similar definitions apply to variables Q_1, Q_2, and Q_3.

The parameter values and meanings of the modified SEIR model are shown in Table 1 , with sources indicated. To validate model fit, we used Shenzhen data from February 18–28, 2022 for existing infected individuals and close contacts to fit model parameters, obtaining initial estimates and 95% confidence intervals. Comparing model predictions for March 1–4 with reported data showed all values within confidence intervals (Figure 2 [Figure 2: see original paper] and Figure 3 [Figure 3: see original paper]), demonstrating the model's reliability for assessing epidemic trends.

However, as shown in Table 2 , Shenzhen timely revised and preemptively implemented new interventions on March 4 and March 12. The modified SEIR model's comparison with pre-March 4 data thus maintains accuracy and timeliness. Subsequent tightened control policies clearly resulted in actual values falling below predicted values for March 5–19, indicating significant prevention effectiveness. Therefore, actual data after March 4 are not presented.

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2. Results and Discussion

As Omicron spread globally, Shenzhen faced substantial epidemic prevention pressure as a crucial transportation hub. This study constructed a modified SEIR model based on Shenzhen's real epidemic data, using Python to simulate COVID-19 trends. The analysis provides decision support for local policy adjustment and medical resource allocation, with methods applicable to other regions and countries for COVID-19 or similar infectious disease control.

Using real-time data published by Shenzhen Municipal Health Commission from February 18–28, 2022, we conducted simulation calibration based on the Omicron-modified SEIR dynamics model, predicting trends through March 19 for infected individuals, close contacts, local new infections, secondary contacts, and inbound quarantined individuals to facilitate early warning. Our findings are presented in three areas: early warning of epidemic trends, guidance for control measure adjustment, and optimization of medical resource allocation.

2.1 Early Warning for Shenzhen's COVID-19 Epidemic

Model predictions indicated that continuing pre-March 3 control measures would result in linear growth of infected individuals in Shenzhen before March 19, reaching approximately 1,800 cases by March 19 (Figure 4 [Figure 4: see original paper]), with close contacts increasing to 30,000 (Figure 5 [Figure 5: see original paper]). These stark predictions served as clear warnings: (1) infected individuals would severely strain hospital beds, increasing risk of medical resource depletion; (2) isolation rooms would rapidly become insufficient.

Based on this early warning, Shenzhen could timely adjust allocations of backup beds, isolation rooms, and other resources (detailed analysis in section 3.3) while simultaneously tailoring epidemic control measures. We compiled Shenzhen's evolving prevention measures along the timeline (Table 2), showing how policy adjustments prevented the adverse scenarios predicted in the early warning.

2.2 SEIR Dynamics Model for Shenzhen's Control Measure Adjustment

By introducing the carrier group, this study generated predictions for local daily new infections (Figure 6 [Figure 6: see original paper]). Based on screening experience, carriers are typically identified as positive within 3 days through nucleic acid testing. Therefore, we converted predicted carrier data from day $(n-3)$ to predicted local new infection data for day n, comparing these with officially reported data to guide universal screening intensity.

Figure 6 shows that during February 18–March 3, Shenzhen's reported daily local new infections significantly exceeded model predictions. This analysis yields the following conclusion: when screened local new infections exceed predicted values, it indicates effective screening in the previous stage. Maintaining current screening intensity would identify more infections and prevent further spread, leading to a gradual decline in daily local new infections. However, Shenzhen adjusted intervention measures and screening intensity for close and secondary contacts during March 4–11. Official data showed a significant decrease in screened local new infections during this period, contradicting model predictions and indicating that the epidemic 拐点 had not yet arrived. Concealed community transmission persisted with diffusion risk, making increased screening intensity urgent. Official data later validated this conclusion. The epidemic first rebounded on March 12 with 66 local new infections—demonstrating that previous "optimistic" data (e.g., only 6 new cases on March 8) resulted from missed cases rather than effective control. Consequently, after the March 12 early morning announcement upgrading controls in all "10+1" districts, Shenzhen's COVID-19 Prevention and Control Command issued another notice on March 13 evening, pressing the "pause button" for March 14–20 while conducting three rounds of citywide screening. Official data showed that after this one-week "slow living" period, epidemic transmission was comprehensively contained with clear improvement.

2.3 Analysis of Medical Resource Requirements: Hospital Beds and Isolation Rooms

The Diagnosis and Treatment Protocol for COVID-19 (Trial Version 8) recommends hospitalized, centralized treatment for infected individuals. According to the 1991 Implementation Regulations of the People's Republic of China Law on the Prevention and Treatment of Infectious Diseases and the 2020 Guidelines for Critical Care Medicine Construction and Management (Trial) issued by the National Health Commission, infected patients require one-bed-per-patient management. Therefore, horizontal analysis of Figure 7 [Figure 7: see original paper] shows that predicted bed requirements slightly exceed actual needs, reasonably ensuring one-bed-per-patient capacity. Around March 3, 2022, actual bed requirements began exceeding predictions, with daily growth reaching 7.8%. By March 19, bed demand would increase to 125% of capacity. Authorities should prepare in advance by constructing Fangcang hospitals, mobilizing medical staff, and stockpiling protective equipment, ventilators, and masks.

Based on Shenzhen's isolation strategies, we predicted isolation room usage from March 1–19, 2022. Compared to beds, isolation room shortages are more urgent. Figure 8 [Figure 8: see original paper]A predicts daily isolation room requirements for secondary contacts, while Figure 8B predicts total isolation rooms needed for inbound individuals, close contacts, and secondary contacts. Under existing measures, isolation room demand would rapidly exceed the 30,000-room threshold (by March 10), reaching 42,000 rooms by March 19. Decision-makers must proactively adjust isolation policies—such as reducing quarantine duration for close contacts or shifting secondary contacts from centralized to home isolation—to free up rooms. If secondary contact policies were changed starting March 9, the model predicts a maximum release of 5.9% of isolation rooms for emergency use by close contacts and inbound individuals, though shortening secondary contact quarantine poses rebound risks. Without such adjustments, insufficient rooms would directly impact centralized quarantine for close contacts and inbound individuals, creating greater difficulties for "preventing external importation." Model projections indicate authorities should tighten inbound strategies, reduce inbound numbers, and prepare backup isolation facilities.

2.4 Limitations of the SEIR Dynamics Model

First, the SEIR model has inherent limitations. Dynamics models rely on strict mathematical assumptions, while the real world is always more complex than abstract models. Models can only capture major epidemic patterns and cannot fully account for various control measures, their dynamic changes, and implementation effects, limiting predictive capability. As shown in Table 2 , Shenzhen timely revised and preemptively implemented new interventions on March 4 and March 12. Observing subsequent epidemic development, these revised interventions achieved remarkable results, demonstrating the modified SEIR model's strong theoretical guidance for early warning, policy adjustment, and resource allocation. However, the model also revealed shortcomings in short timeliness and declining subsequent accuracy, making dynamic, real-time model revision an important future research direction.

Conclusion

This study constructed a modified SEIR model based on Omicron transmission characteristics, epidemic context, and intervention policies to simulate Shenzhen's epidemic from February 18–28, 2022, and predict trends through March 19. By monitoring changes in S, A, I, R, Q_1, Q_2, and Q_3, we assessed the need for policy adjustments and rational resource allocation. Our findings demonstrate that interventions alter epidemic trajectories, with more intensive measures reducing impact. Therefore, governments should mobilize society and the public to implement preventive measures swiftly. The study also reveals that intervention timing affects epidemic outcomes, enabling advance preparation through predictive data to buy time for implementing interventions, slow epidemic progression, and reduce impacts.

Author Contributions: Yang Lichao was responsible for conceptualization, model construction, algorithm implementation, and original draft writing. Yang Lichao and Hu Mengzhi contributed to model construction, data cleaning, and manuscript revision. Tian Qiannan and Wei Liangzhou conducted investigations and data collection. Zeng Huatang and Wu Liqun provided research data and validated results. Zhu Jiming and Liang Wannian supervised the study, reviewed and revised the arguments and rationale. All authors approved the final manuscript.

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