

Assessing the impact of interventions on the major Omicron BA.2 outbreak in spring 2022 in Shanghai



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ABSTRACT

Background: Shanghai experienced a significant surge in Omicron BA.2 infections from March to June 2022. In addition to the standard interventions in place at that time, additional interventions were implemented in response to the outbreak. However, the impact of these interventions on BA.2 transmission remains unclear.

Methods: We systematically collected data on the daily number of newly reported infections during this wave and utilized a Bayesian approach to estimate the daily effective reproduction number. Data on public health responses were retrieved from the Oxford COVID-19 Government Response Tracker and served as a proxy for the interventions implemented during this outbreak. Using a log-linear regression model, we assessed the impact of these interventions on the reproduction number. Furthermore, we developed a mathematical model of BA.2 transmission. By combining the estimated effect of the interventions from the regression model and the transmission model, we estimated the number of infections and deaths averted by the implemented interventions.

Results: We found a negative association (-0.0069 , 95% CI: 0.0096 to -0.0045) between the level of interventions and the number of infections. If interventions did not ramp up during the outbreak, we estimated that the number of infections and deaths would have increased by 22.6% (95% CI: 22.4–22.8%), leading to a total of 768,576 (95% CI: 768,021–769,107) infections and 722 (95% CI: 722–723) deaths. If no interventions were deployed during the outbreak, we estimated that the number of infections and deaths would have increased by 46.0% (95% CI: 45.8–46.2%), leading to a total of 915,099 (95% CI: 914,639–915,518) infections and 860 (95% CI: 860–861) deaths.

Conclusion: Our findings suggest that the interventions adopted during the Omicron BA.2 outbreak in spring 2022 in Shanghai were effective in reducing SARS-CoV-2 transmission and disease burden. Our findings emphasize the importance of non-pharmacological interventions in controlling quick surges of cases during epidemic outbreaks.

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1. Background

China experienced multiple localized Omicron outbreaks in the first half of 2022 (National Health Commission of the People's Republic of China). Specifically, Shanghai underwent a major outbreak of the Omicron BA.2 variant in March 2022, resulting in a total of 0.62 million reported infections (~2.4% of the Shanghai population) and 588 deaths (The State Council Information Office of the People's Republic of China). In response to this outbreak, a set of additional interventions were implemented, including district-wide and city-wide mass nucleic acid screening, as well as lockdown measures (Chen et al., 2022). Moreover, Hong Kong faced its fifth wave of coronavirus disease 2019 (COVID-19) in late December 2021, leading to over 3.0 million infections (Centre for Health Protection of the Department of Health and the Hospital Authority), affecting a substantial 41.1% of the Hong Kong population. To safeguard people's health and protect the healthcare system from collapse, mitigation strategies such as rapid antigen tests (RATs) (The Government of the Hong Kong Special Administrative Region) and the “StayHomeSafe” scheme (The Government of the Hong Kong Special Administrative Region) were deployed. These measures have been demonstrated to significantly contribute to reducing the reproduction number and easing the isolation and treatment burden of hospitals (Du et al., 2022). However, the quantitative impact of these interventions on BA.2 transmission in Shanghai has yet to be quantified.

In this study, we utilized a log-linear regression model to evaluate the impact of these interventions on the reproduction number. Furthermore, we employed a stochastic susceptible-latent-infectious-recovered (SLIR) model to simulate the transmission of BA.2 in Shanghai. The objective of this study is to assess the effect of these interventions on the disease burden and estimate the number of averted infections and deaths under counterfactual scenarios on alternative interventions.

2. Methods

2.1. Data sources

For the entire duration of the Omicron BA.2 wave in Spring 2022 in Shanghai, we systematically collected data on the daily number of newly reported COVID-19 infections from March 1 to June 1, 2022 (Supplementary Table 1) (The State Council Information Office of the People's Republic of China).

2.2. Public health response

We downloaded public health response data from the Oxford COVID-19 Government Response Tracker (Hale et al., 2021). Changes in policy indicators related to containment and closure policies (C1–C8) and health system policies (H1–H8) in Shanghai from February to July 2022 are illustrated in Supplementary Fig. 1. The containment and health index (denoted as C_t) served as an index grouping these two families of policy indicators. Before the start of the Omicron BA.2 wave, Shanghai maintained a baseline level of non-pharmacological interventions to prevent potential outbreak of COVID-19. Between March and June 2022, additional interventions, including district-wide and city-wide mass nucleic acid screening and lockdown, were implemented in response to the outbreak. The majority of the containment measures (such as lockdowns) were lifted at the end of the outbreak (Fig. 1 and Supplementary Table 2).

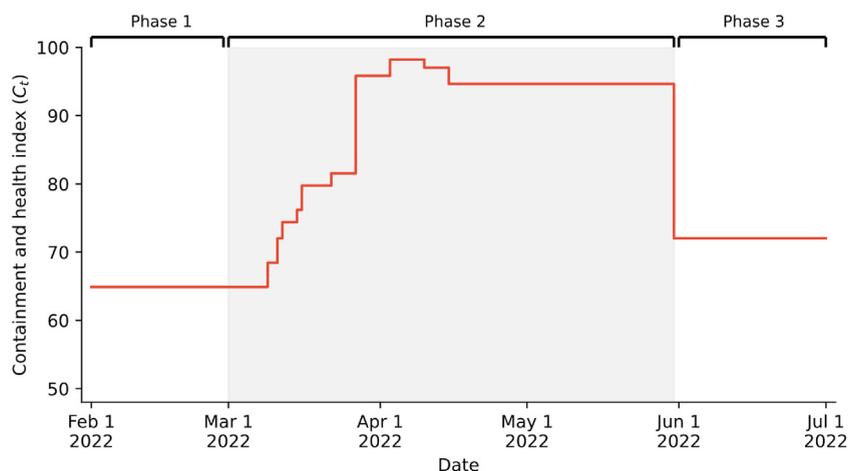


Fig. 1. Containment and health index (C_t) over time during the Omicron BA.2 outbreak in Shanghai. Phase 1 (Pre-March 2022): Implementation of baseline interventions to prevent potential COVID-19 outbreaks. Phase 2 (March to June 2022, shaded grey area): Implementation of baseline and additional interventions in response to the Omicron BA.2 outbreak. Phase 3 (Post-June 2022): Easing of containment and closure policies.

2.3. Effective reproduction number

We applied a Bayesian approach to estimate the real-time daily effective reproduction number (denoted as R_t^d) (Liu et al., 2018). This method relies on the time series of the daily number of new infections and knowledge of the distribution of the generation time. Since our dataset provided only the official reporting date, we generated the date of sample collection for each infection using a Poisson distribution with the mean equal to the delay between the date of sample collection and the reporting date. In our main analysis, we considered delays of 2 days, 3 days, and 2 days between the date of sample collection and reporting for periods before March 15, between March 16 and May 14, and after May 15, respectively, based on previous findings (Chen et al., 2022). Additionally, a 4-day delay for the period between March 16 and May 14 was considered as a sensitivity analysis. This estimated sampling date was assumed to approximate the date of symptom onset. The generation time was assumed to follow a gamma distribution of mean 2.7 days (shape: 3.25, scale: 0.84), in agreement with the mean serial interval estimated in reference (Mefsin et al., 2022). As a sensitivity analysis, we considered a gamma distribution of mean 3.3 days (shape: 1.89, scale: 1.75), in agreement with the mean serial interval estimated in reference (Backer et al., 2022). The weekly effective reproduction number (denoted as R_t^w) was derived as the weekly geometric mean of R_t^d .

2.4. Log-linear regression model

Following the approach presented in reference (te Beest et al., 2013), we used a regression model to establish the relationship among R_t^w , the depletion of susceptible individuals, and implemented interventions C_t . The log-linear regression model is expressed as:

$$\ln(R_t^w) \approx \ln(R_0 S_0) + \alpha h_t + \varepsilon C_t$$

where:

- R_0 represents the basic reproduction number,
- S_0 represents the initial fraction of susceptible individuals in the population,
- h_t represents the observed cumulative incidence of infections up to week $t-1$,
- α represents the rate at which susceptible individuals are depleted,
- ε represents the coefficient measuring the effect of the implemented interventions.

R-squared was calculated to measure the goodness of fit of the regression model. In the main analysis, we analyzed an 11-week dataset of R_t^w , centered on the peak incidence of reported COVID-19 infections (April 9, 2022). This dataset covered the period from March 2 to May 17, 2022. Additionally, we performed a sensitivity analysis by adjusting the duration of the dataset to 10 or 12 weeks.

2.5. SARS-CoV-2 transmission model

We utilized the standard SLIR model to simulate the transmission of BA.2 in Shanghai (Supplementary Method). This model classified the population into four epidemiological categories: susceptible, latent, infectious, and recovered. Upon infection, susceptible individuals enter a latent compartment and become infectious after a latent period of 1.0 days (Leung et al., 2023). Infectious individuals could transmit the virus to susceptible individuals during an infectious period of 1.7 days, after which they naturally recover. Since latent and infectious periods are both exponentially distributed, their sum corresponds to the generation time of average 2.7 days (Wallinga et al., 2007). We modeled the transitions between compartments using a stochastic chain binomial process (Cai et al., 2022a; Liu et al., 2024). Given the limited protection against infection provided by the inactivated vaccine and the rapid decline in immunity (Huang et al., 2022), we assumed that the population was fully susceptible to infection during the analyzed outbreak.

Using the estimated coefficients in the regression model, we determined the initial net reproduction number (denoted as R_e) as $R_e = e^{\ln(R_0 S_0)}$. The transmission rate in absence of interventions (denoted as β_0) was estimated following its relationship with R_e : $\beta_0 = e^{\ln(R_0 S_0)} \gamma$, where γ represents the recovery rate. The number of reported infections was assumed to be proportional to the number of infected individuals, and the seeding date was set at March 1, 2022. To calibrate the model, we fitted it to the time series of cumulative infections, identifying the number of initial infectious seeds that best matched the observed data.

The baseline scenario (denoted as S0) corresponds to the real-world situation, and simulations were carried out using the observed time series of interventions (C_t) and the estimated real-time transmission rate $\beta_t = \beta_0 e^{\varepsilon C_t}$. Then, we reconstructed the transmission rate β_t by varying C_t values to simulate the transmission of BA.2 under two counterfactual scenarios. Counterfactual scenario 1 (denoted as S1) assumes that the level of interventions remained constant at the level observed before the start of the outbreak, namely $\beta_t = \beta_0 e^{\varepsilon C_0}$. In counterfactual scenario 2 (denoted as S2), no interventions were implemented, namely the values of C_t were set to zero throughout the entire outbreak and $\beta_t = \beta_0$. Given the number of

infections projected by the transmission model, the overall crude infection-fatality ratio (0.094% [The State Council Information Office of the People's Republic of China](#)) was used to estimate the number of deaths.

3. Results

A total of 626,806 infections were officially reported in Shanghai between March and June 2022 ([Fig. 2A](#) and [Supplementary Fig. 2](#)). In response to this outbreak, additional interventions were implemented. R_t^d initially fluctuated around 2 and gradually decreased due to district-wide mass nucleic acid screening and lockdown. Subsequently, there was a rapid drop below the epidemic threshold following the implementation of city-wide mass nucleic acid screening and lockdown ([Fig. 2B](#)). Consistent findings were observed when considering a 4-day delay between the sampling date and reporting date in the period from March 16 to May 14, 2022, and using a gamma-distributed generation time with a mean of 3.3 days ([Supplementary Fig. 3](#)).

We applied a log-linear regression model to assess the impact of interventions on the reproduction number ([Fig. 3A](#)). The parameter ε was estimated to be -0.0069 (95% CI: 0.0096, -0.0045). This negative value indicates that the implementation of interventions effectively reduced the reproduction number. The estimated parameters of the regression model are reported in [Supplementary Table 3](#). Shortening or lengthening the duration of dataset to 10 or 12 weeks had little effect on model outcomes ([Supplementary Figs. 4–5](#)).

We then fit the transmission model to the time series of cumulative infections. The best fit was obtained by setting initial infectious seeds to 230, which projected 626,858 (95% CI: 625,959–627,674) infections and 589 (95% CI: 588–590) deaths ([Fig. 3B](#)). Using the calibrated model, we assessed the impact of interventions on the disease burden ([Fig. 4](#)). In counterfactual scenario 1, the estimated cumulative number of infections and deaths were 768,576 (95% CI: 768,021–769,107) infections and 722 (95% CI: 722–723), respectively. Compared to the baseline scenario, the absence of additional interventions would have resulted in a 22.6% (95% CI: 22.4–22.8%) increase in disease both in the number of infections and deaths. Counterfactual scenario 2 projected a total of 915,099 (95% CI: 914,639–915,518) infections and 860 (95% CI: 860–861) deaths. This suggests that if no interventions were deployed the disease burden would have increased by 46.0% (95% CI: 45.8–46.2%) as compared to the baseline scenario.

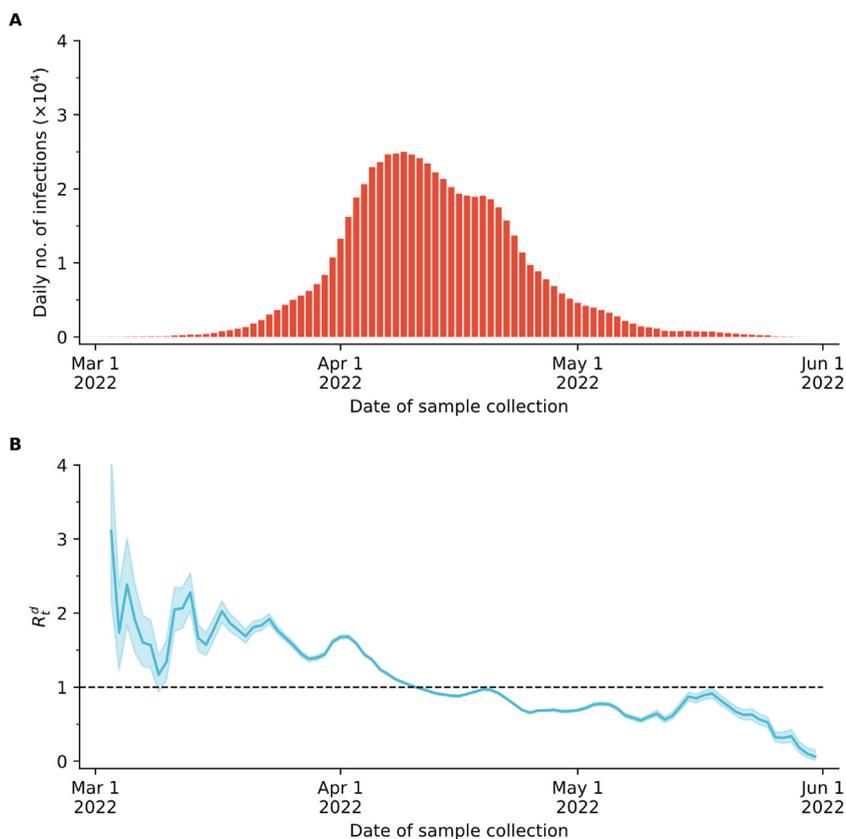


Fig. 2. Epidemic curve and estimated R_t^d during the Omicron BA.2 outbreak in Shanghai. **A** Daily number of newly reported infections by date of sample collection. **B** Daily effective reproduction number R_t^d as estimated from our Bayesian approach. Lines and shaded areas: mean and 95% CI of 100 simulations. The horizontal line represents the epidemic threshold.

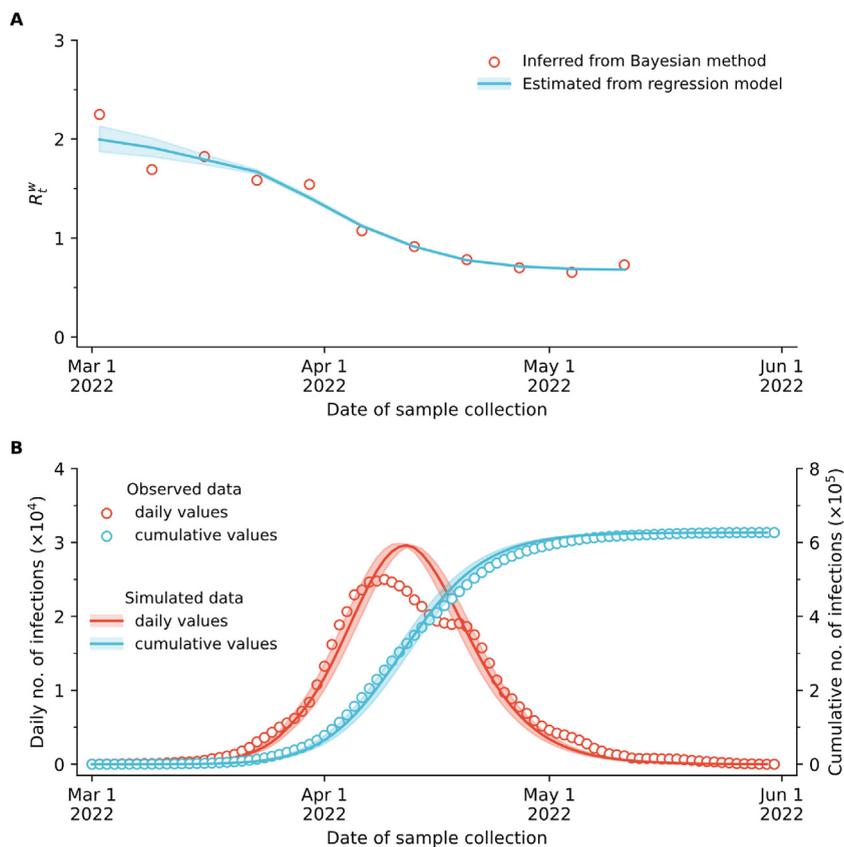


Fig. 3. Fit of the weekly effective reproduction number and epidemic curves. **A** Weekly effective reproduction number as estimated from our Bayesian approach (red circles) and as estimated from our regression model (blue line). Blue line and shaded areas: mean and 95% CI of 100 simulations. **B** Daily number of new and cumulative infections as observed in the data (red or blue circles) and as simulated by the SLIR model (red or blue lines). Lines and shaded areas: mean and 95% CI of 100 simulations.

4. Discussion

In this study, we used a combination of log-linear regression and mechanistic modeling to evaluate the impact of interventions on the Omicron BA.2 outbreak in spring 2022 in Shanghai, China. We estimated that escalation of non-pharmacological interventions in response to the outbreak decreased the disease burden by 22.6% (95% CI: 22.4–22.8%). Moreover, we estimated that in the absence of any intervention, the disease burden would have increased by 46.0% (95% CI: 45.8–46.2%).

Throughout the Shanghai Omicron BA.2 wave, most of the infectious individuals were identified through multiple rounds of mass nucleic acid screening characterized by high test sensitivity (pool size of 5–20 samples were commonly tested in the outbreak, which would lead to a detection sensitivity of 84.7–95.3% [Yelin et al., 2020](#)). Subsequently, these individuals were either isolated in the designated hospitals or dedicated isolation facilities, or they were quarantined at home. This approach contributed to the interruption of the transmission process of infectious individuals, contributing to explain the high effectiveness of the interventions estimated in this study.

Our study has several limitations that should be considered. First, the estimation of the effective reproduction number over time is based on the date of sample collections inferred from the date of reporting. Although this is not ideal, previous studies have used a similar approach ([Abbott et al., 2020](#); [Chen et al., 2022](#)). Moreover, it is important to stress that multiple rounds of mass screenings were implemented during the analyzed outbreak, greatly reducing the delay between infection and reporting dates. Finally, we also conducted a sensitivity analysis with different reporting delays and found consistent results. Second, the adopted interventions have likely contributed to the shortening of the duration of the generation time as compared to the intrinsic generation time of Omicron ([Manica et al., 2022](#)). Since no estimates of the realized generation time during the Omicron BA.2 outbreak in Shanghai are available in the literature, we relied on estimates of the serial interval available for an outbreak in Hong Kong that was treated with strict interventions ([Mefsin et al., 2022](#)). To assess the robustness of our findings, we conducted a sensitivity analysis assuming a longer generation time and found similar results. Third, we estimated the overall effect of the interventions adopted during the Shanghai outbreak. This analysis utilized the

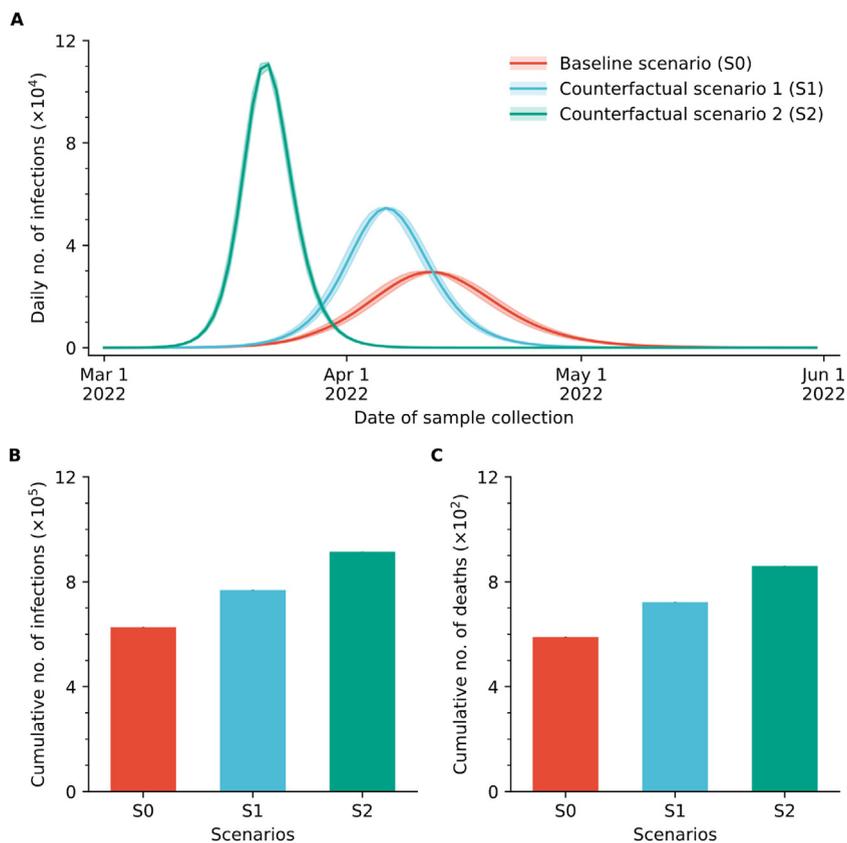


Fig. 4. Projected disease burden under baseline and counterfactual scenarios. **A** Daily number of new infections over time under different scenarios. Baseline scenario (S0): simulations are carried out using the observed time series of interventions. Counterfactual scenario 1 (S1): simulations are carried out maintaining constant pre-outbreak interventions. Counterfactual scenario 2 (S2): no interventions. Lines and shaded areas: mean and 95% CI of 100 simulations. **B** Cumulative number of infections under the three scenarios used in panel A. **C** Cumulative number of deaths under the three scenarios used in panel A.

containment and health index from the Oxford COVID-19 Government Response Tracker as a proxy of the intensity of the interventions implemented during the outbreak, which has been widely adopted in previous studies (García-García et al., 2022; Ge et al., 2022; Zhang et al., 2023). Further analyses are warranted to investigate the impact of single interventions separately. Additionally, vaccination was excluded from the transmission model due to the limited and temporarily effectiveness against infection provided by the inactivated vaccine (Huang et al., 2022). Future work would be warranted in evaluating the effectiveness of inactivated vaccine against different clinical endpoints and assess the impact of vaccination and interventions together. Moreover, the interventions deployed during the outbreak were highly heterogeneous between districts before April 2022 – after that, the entire Shanghai went to a lockdown (Chen et al., 2022). Modeling the transmission of Omicron BA.2 at the district level and assessing the impact of interventions at a higher spatial resolution could deepen our understanding of their impact. Finally, most studies, including ours, aim at evaluating the impact of interventions on epidemiological/clinical endpoints (Cai et al., 2022a, 2022b; Han et al., 2021; Liu et al., 2022, 2024; Wang et al., 2022; Yang et al., 2021), neglecting the economic costs associated with the deployed strategies. A future analysis that includes an economic evaluation of the intervention strategies implemented during the Shanghai Omicron BA.2 outbreak would be warranted as it could provide new evidence to policymakers for the design of more balanced control strategies.

In conclusion, our study estimated the effect of the interventions adopted during the Omicron BA.2 outbreak in spring 2022 in Shanghai in reducing SARS-C-V-2 transmission, measured as effective reproduction number, and disease burdens, measured as number of infections and deaths. Our findings emphasize the importance of non-pharmacological interventions in controlling quick surges of cases during epidemic outbreaks.

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Availability of data and materials

The code and data used to conduct these analyses are available through a request.

Ethics approval and consent to participate

Not applicable.

CRediT authorship contribution statement

Hengcong Liu: Writing – original draft, Software, Methodology. **Jun Cai:** Methodology. **Jiaxin Zhou:** Methodology, Formal analysis. **Xiangyan Xu:** Visualization, Data curation. **Marco Ajelli:** Methodology. **Hongjie Yu:** Funding acquisition.

Declaration of competing interest

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.idm.2024.02.013>.

References

- Abbott, S., et al. (2020). Estimating the time-varying reproduction number of SARS-CoV-2 using national and subnational case counts [version 2; peer review: 1 approved, 1 approved with reservations]. *Wellcome Open Research*, 5(112).
- Backer, J. A., et al. (2022). Shorter serial intervals in SARS-CoV-2 cases with Omicron BA.1 variant compared with Delta variant, The Netherlands, 13 to 26 December 2021. *Euro Surveillance*, 27(6), Article 2200042.
- Cai, J., et al. (2022a). Modeling transmission of SARS-CoV-2 Omicron in China. *Natura Med*, 28(7), 1468–1475.
- Cai, J., et al. (2022b). Assessing the transition of COVID-19 burden towards the young population while vaccines are rolled out in China. *Emerging Microbes & Infections*, 11(1), 1205–1214.
- Chen, Z., et al. (2022). Epidemiological characteristics and transmission dynamics of the outbreak caused by the SARS-CoV-2 Omicron variant in Shanghai, China: A descriptive study. *Lancet Reg Health West Pac*, 29, Article 100592.
- Du, Z., Tian, L., & Jin, D.-Y. (2022). Understanding the impact of rapid antigen tests on SARS-CoV-2 transmission in the fifth wave of COVID-19 in Hong Kong in early 2022. *Emerging Microbes & Infections*, 11(1), 1394–1401.
- García-García, D., et al. (2022). Assessing the effect of non-pharmaceutical interventions on COVID-19 transmission in Spain. *Euro Surveillance*, 27(19), Article 2100869.
- Ge, Y., et al. (2022). Untangling the changing impact of non-pharmaceutical interventions and vaccination on European COVID-19 trajectories. *Nature Communications*, 13(1), 3106.
- Centre for Health Protection of the Department of Health and the Hospital Authority. Statistics on the fifth wave of COVID-19. [cited 2023 October 30]; Available from: https://www.coronavirus.gov.hk/pdf/5th_wave_statistics/5th_wave_statistics_20230727.pdf.
- The Government of the Hong Kong Special Administrative Region. StayHomeSafe" Scheme launched. [cited 2023 October 30]; Available from: <https://www.info.gov.hk/gia/general/2022/08/P20220800726.htm>.
- Hale, T., et al. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour*, 5(4), 529–538.
- Han, S., et al. (2021). Time-varying optimization of COVID-19 vaccine prioritization in the context of limited vaccination capacity. *Nature Communications*, 12(1), 4673.
- Huang, Z., et al. (2022). Effectiveness of inactivated and Ad5-nCoV COVID-19 vaccines against SARS-CoV-2 Omicron BA. 2 variant infection, severe illness, and death. *BMC Medicine*, 20(1).
- Leung, K., et al. (2023). Estimating the transmission dynamics of SARS-CoV-2 Omicron BF.7 in Beijing after the adjustment of zero-COVID policy in November - December 2022. *Natura Med*.
- Liu, Q. H., et al. (2018). Measurability of the epidemic reproduction number in data-driven contact networks. *Proceedings of the National Academy of Sciences of the U S A*, 115(50), 12680–12685.
- Liu, H., et al. (2022). Investigating vaccine-induced immunity and its effect in mitigating SARS-CoV-2 epidemics in China. *BMC Medicine*, 20(1), 37.
- Liu, H., et al. (2024). Counterfactual analysis of the 2023 Omicron XBB wave in China. *Infectious Disease Modelling*, 9(1), 195–203.
- Manica, M., et al. (2022). Intrinsic generation time of the SARS-CoV-2 Omicron variant: An observational study of household transmission. *Lancet Reg Health Eur*, 19, Article 100446.
- Mefsin, Y. M., et al. (2022). Epidemiology of infections with SARS-CoV-2 Omicron BA.2 variant, Hong Kong, January–March 2022. *Emerging Infectious Diseases*, 28(9), 1856–1858.
- te Beest, D. E., et al. (2013). Driving factors of influenza transmission in The Netherlands. *American Journal of Epidemiology*, 178(9), 1469–1477.
- National Health Commission of the People's Republic of China. Update on COVID-19. [cited 2023 October 30]; Available from: http://www.nhc.gov.cn/xcs/yqtb/list_gzbd.shtml.
- The State Council Information Office of the People's Republic of China. The press conference of COVID-19 in Shanghai. [cited 2023 October 30]; Available from: http://www.scio.gov.cn/xwfb/dfxwfb/gssfbh/sh_13834/.
- The Government of the Hong Kong Special Administrative Region. Government continues adopting risk-based testing strategy. [cited 2023 October 30]; Available from: <https://www.info.gov.hk/gia/general/2022/02/25/P2022022500816.htm>.

- Wallinga, J., & Lipsitch, M. (2007). How generation intervals shape the relationship between growth rates and reproductive numbers. *Proceedings of the Royal Society B: Biological Sciences*, 274(1609), 599–604.
- Wang, Y., et al. (2022). Assessing the feasibility of sustaining SARS-CoV-2 local containment in China in the era of highly transmissible variants. *BMC Medicine*, 20(1).
- Yang, J., et al. (2021). Despite vaccination, China needs non-pharmaceutical interventions to prevent widespread outbreaks of COVID-19 in 2021. *Nature Human Behaviour*, 5(8), 1009–1020.
- Yelin, I., et al. (2020). Evaluation of COVID-19 RT-qPCR test in multi sample pools. *Clinical Infectious Diseases*, 71(16), 2073–2078.
- Zhang, X., et al. (2023). Assessing the impact of COVID-19 interventions on influenza-like illness in Beijing and Hong Kong: An observational and modeling study. *Infectious Diseases of Poverty*, 12(1), 11.