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Original article

Impacts of social distancing, rapid antigen test and vaccination on the Omicron outbreak during large temperature variations in Hong Kong: A modelling study

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ABSTRACT

Background: The impacts of non-pharmaceutical interventions (NPIs) and vaccine boosters on the transmission of the largest outbreak of COVID-19 (the fifth wave) in Hong Kong have not been reported. The outbreak, dominated by the Omicron BA.2 subvariant, began to spread substantially after the Spring Festival in February, 2022, when the temperature varied greatly (e.g. a cold surge event). Tightening social distancing measures did not succeed in containing the outbreak until later with the use of rapid antigen tests (RAT) and increased vaccination rates. Temperature has been previously found to have significant impact on the transmissibility. Understanding how the public health interventions influence the number of infections in this outbreak provide important insights on prevention and control of COVID-19 during different seasons. **Methods:** We developed a transmission model incorporating stratified immunity with vaccine-induced antibody responses and the daily changes in population mobility, vaccination and weather factors (i.e. temperature and relative humidity). We fitted the model to the daily reported cases detected by either PCR or RAT between 1 February and 31 March using Bayesian statistics, and quantified the effects of individual NPIs, vaccination and weather factors on transmission dynamics.

Results: Model predicted that, with the vaccine uptake, social distancing reduced the cumulative incidence (CI) from 58.2% to 44.5% on average. The use of RAT further reduced the CI to 39.0%. Without vaccine boosters in these two months, the CI increased to 49.1%. While public health interventions are important in reducing the total infections, the outbreak was temporarily driven by the cold surge. If the coldest two days (8.5 °C and 8.8 °C) in February were replaced by the average temperature in that month (15.2 °C), the CI would reduce from 39.0% to 28.2%.

Conclusion: Preventing and preparing for the transmission of COVID-19 considering the change in temperature appears to be a cost-effective preventive strategy to lead people to return to normal life.

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Introduction

The recent Omicron variant was expected to cause a high infection rate with substantial hospitalisations and deaths in a highly

susceptible population, such as mainland China or Hong Kong (China) due to low numbers of previous infections [1]. The locations of which, as other countries around East or South East Asia, normally face rapid falls in temperature followed by a few cold days during winter or spring seasons (e.g. cold surge, referred to as a rapid decline in temperature over 1–2 days that characterised by air masses from high latitude) [2]. The outbreak in Hong Kong (known as the ‘fifth wave’), which was dominated by the Omicron BA.2 subvariant, occurred since the Chinese Spring Festival (began on 1 February 2022) [3,4]. The outbreak grew rapidly later when the temperature varied a lot (including a cold surge event), leading to the largest

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outbreak of COVID-19 about 1.1 million confirmed cases (in a total population of 7.48 million) within two months. Without lockdowns, a sharp epidemic peak, rather than a much flatter plateau that was commonly seen in many nearby tropical countries was observed (Fig. S1). What factors contributed to driving or containing the outbreak are unknown.

Despite the tightenings of social distancing since 10 February 2022 and later [5,6], the number of new cases suddenly rose from about 10,000 on 25 February to the peak of near 80,000 within just five days. Meanwhile, on 25 February, because the PCR testing capacity was overwhelmed, the government decided that Rapid Antigen Test (RAT) can be used for case confirmation [7] and began to distribute these kits [8]. Faced with a growing number of cases, the population who received vaccine boosters increased from approximately 20,000 to over 40,000 per day since February 2022 [9]. A previous study found that the neutralizing antibody titres induced by two or three doses of vaccination against the Omicron variant in Hong Kong were not particularly high for some individuals [10], likely resulting in insufficient protection. To take into account differences in serological responses, epidemic models with multiple susceptible states (called stratified immunity) have been developed [11]. Incorporating stratified immunity into modelling to capture the distribution of antibody titres after vaccination allows the epidemic dynamics to be predicted more accurately [11].

In addition, lower temperatures (within a certain range) have been found to be associated with higher transmissibility in respiratory diseases, such as COVID-19 [12–16] and influenza [17–19]. The relationship between the relative humidity and the transmissibility has also been explored but with different conclusions [13–16,20]. During the outbreak, Hong Kong experienced a cold surge event (i.e. from 15.9 °C to 8.5 °C within two days) [21] with high relative humidity in February, and the spring season brought warmer conditions in the next month. Taking into account weather conditions is critical in calibrating an epidemic model.

It is important to know how each major intervention (i.e. social distancing, rapid antigen test and vaccination) helped to suppress the outbreak. The study aimed at understanding how public health interventions shaped the incidence during the fifth wave in Hong Kong when temperature varied greatly. To improve the model forecast, we used a stratified immunity model to quantify the impacts of individual interventions (such as vaccine booster, social distancing measures and increased antigen testing) and weather conditions (i.e. temperature and relative humidity) while capturing the individual differences in serological responses after vaccination.

Material and methods

Daily numbers of reported cases detected by PCR and by RAT were collected from the Hong Kong Centre for Health Protection [3]. Daily vaccination rates of BioNTech and CoronaVac were collected from the Hong Kong Vaccination Dashboard [9]. Population mobility data were collected from Google mobility [22]. Daily mean temperature and relative humidity were collected from Hong Kong Observatory [23]. The increase of antibody titre after full immunisation (2nd dose) or booster doses from two different vaccines (BioNTech and CoronaVac) was collated from the previous serum data [10].

The period of the outbreak in our study was defined as beginning on 1 February 2022 when the daily case number was consistently above 100, and as ending on 31 March 2022 when the daily number was constantly less than 10% of the epidemic peak since then. In order to capture the impacts of NPIs and seasonal factors in a population with increasing immunity from vaccination, we integrated our previous stratified immunity [11] and NPI models [24] and incorporated daily changes in vaccination, mobility and weather conditions (Fig. 1 and Fig. S2).

The force of infection λ_i , the rate at which susceptible individuals having antibody titre level i are infected by infectious individuals (i.e. cases after their latent period but not under isolation) is proportional to their susceptibility, social mixing, and temperature and relative humidity they were exposed to at each day:

$$\lambda_i = \text{susc}_i \cdot (1 + \beta_m \text{mob}) \cdot e^{\beta_T(T-T_0)} e^{\beta_{RH}(RH-RH_0)} \cdot X \quad (1)$$

where susc_i is the susceptibility of infection (i.e. the probability of being infected given a contact by infected people) for susceptible individuals having antibody titre level i . β_m is the coefficient for the percent reduction of population mobility (mob), compared to the pre-pandemic period. T is the daily temperature and T_0 is the baseline temperature (i.e. the average temperature in February). β_T is the coefficient for temperature. Similarly, RH is the daily relative humidity and RH_0 is the baseline relative humidity. β_{RH} is the coefficient for relative humidity. Note that X here represents the effects from the infectious individuals, who are not isolated. On the other hand, the force of infection for susceptible individuals to be infected by home-isolated cases was calculated separately. See [Supplementary Materials](#) for detailed descriptions.

Vaccine-induced protection

There are seven titre levels (from 1 to 7). Each of them indicates a different dilution, such as < 1:10, 1:10, 1:20, ..., 1:160, or $\geq 1:320$. Antibody boosting, represented as the increase in antibody titre from the original to a boosted level, was parameterised by a log-normal distribution (see Fig. S3). The relationship of antibody titre and its susceptibility (susc_i), described by a sigmoid function, was determined simultaneously with other model parameters after fitting the model to the daily numbers of reported cases (see Fig. 1B).

We assumed that antibody levels in people who received vaccination more than three months ago had waned already and the amount of antibodies increased 7 days after having the second or third dose [25,26]. Hence, pre-existing immunity was defined as the proportion of individuals who had been vaccinated either with two or three doses between 25th October 2021 and 25th January 2022 (a week before the study period) (see Fig. 3 A).

Modelling testing, tracing and isolation

We modelled two types of diagnostic tests: the PCR test and the RAT. Since the RAT kits were widely distributed, a certain amount of infected cases used these kits to perform self-testing. After the latent period, once they were detected, they self-reported positive outcomes (e.g. through an online self-reporting website in Hong Kong), and self-isolated at home. Home-isolated cases were still able to transmit the virus but with a lower rate at 10.9% (95% Credible Interval (CI): 7.1–14.7%) [24] of that among infectious cases.

Since the testing capacity had nearly reached its limit in February (see Table 1's footnote) [27], the proportion of infectious cases that were detected by PCR was assumed to be inversely associated with the 'true' number of cases (including both detected and undetected cases) (see section *Time-varying detection rate* in [Supplementary Materials](#)). Additional delays in reporting PCR-confirmed cases were also dependent on the true case number. Hence, the ratio of detected to undetected cases, affected by different diagnostic methods and delays, varied throughout the outbreak (Fig. S4). We also modelled contact tracing following our previous approach [24]. Cases that were traced were assumed to be either quarantined (during their latent period) or isolated at home. Their samples were sent for PCR testing. For the full description of testing, tracing and isolation, see [Supplementary Materials](#).

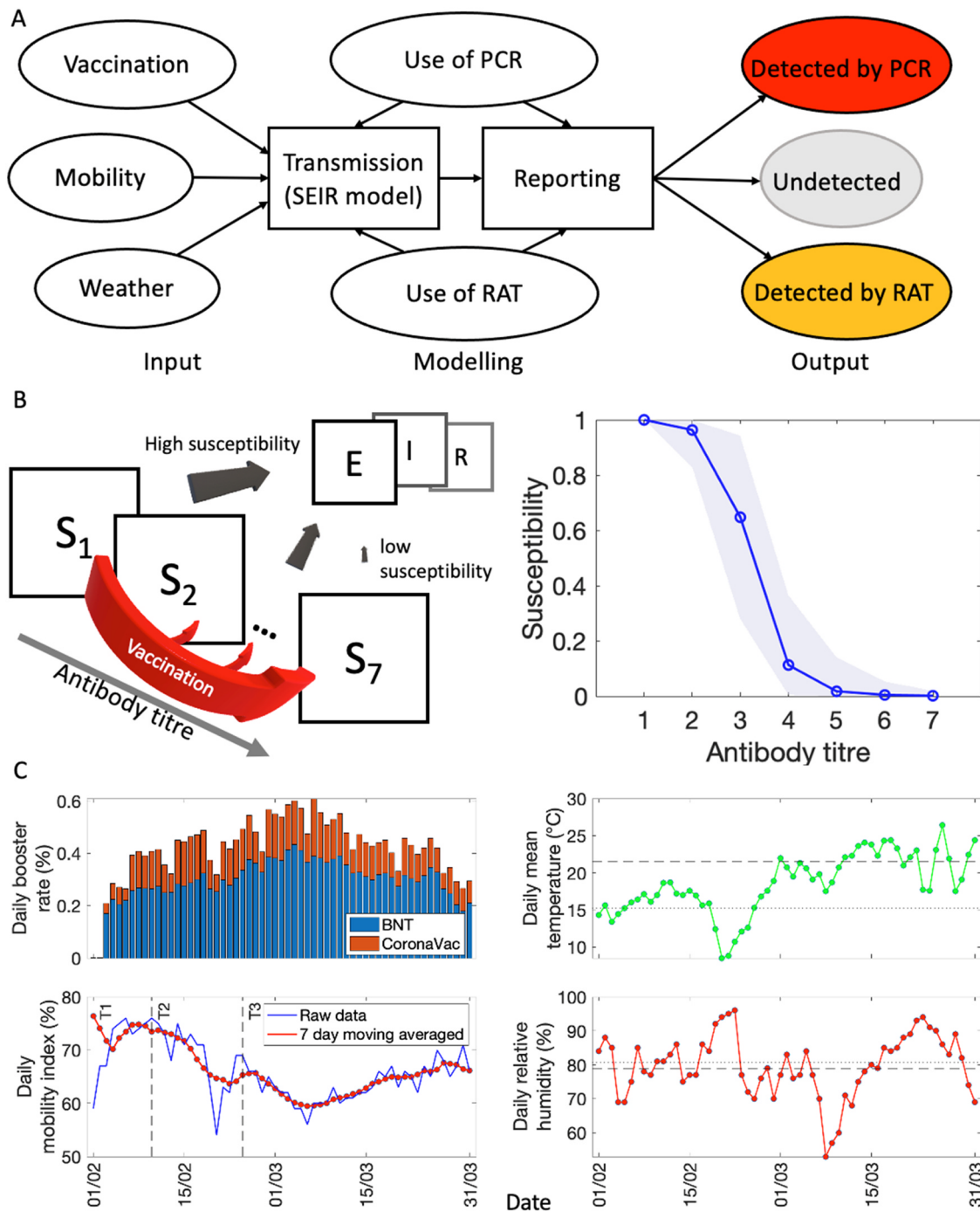


Fig. 1. Critical factors that influence the transmission of the outbreak. (A) The relationships between the factors (i.e. vaccination, population mobility, weather conditions and the uses of PCR and RAT) and the transmission and/or reporting in modelling. The reported cases are detected by PCR (red) and RAT (yellow). (B) *Left*, simplified schematic of a Susceptible (S), Exposed (E), Infectious (I), Recovered (R) model incorporating stratified immunity with antibody response from vaccination. The subscript in S_i denotes the i th antibody titre level. *Right*, the relationship between antibody titre and susceptibility. Shaded area represents 95% credible interval. (C) Daily booster vaccine rates, mobility, and weather conditions (such as daily mean temperature and relative humidity) throughout the outbreak. *Bottom left*, T1–3 represent individual social distancing tightenings. *Bottom right*, dotted lines represent average weather conditions in February and dashed lines represents average conditions in March.

Parameter estimation and model comparison

The posterior distributions of the parameters of the model for Hong Kong were obtained after fitting the model simultaneously to the daily number of reported cases detected by PCR and the daily number detected by RAT. The posterior distributions were estimated using a Markov chain Monte Carlo (MCMC) algorithm with 10^6 steps to guarantee an effective sample size (ESS) of greater than 1000 for all parameters (see Fig. S5, Table S1). We compared the full model to

the ‘reduced’ model, in which the weather effects were not included. The performance was measured by deviance information criterion (DIC).

The time-dependent effective reproduction number, R_e , was calculated using the next-generation matrix approach after the posterior distributions of the model parameters were obtained. For the full description of the parameter estimation, see [Supplementary Materials](#).

Table 1

Description of significant non-pharmaceutical interventions and their impacts on the transmission of the outbreak during the study period. Note that, cumulative incidence resulting from T1 only or T1&T2 was calculated assuming that after the end of each tightening, the mobility maintained at the average level during its implemented period. For example, for T1 only, the mobility maintained at –26.4% after 09 February.

NPIs	Description	Predicted cumulative incidence (%)	Relative effects (percent reduction in cumulative incidence)
Baseline social distancing tightening (T1)	<ul style="list-style-type: none"> From 7 January, the government tightened social distancing measures. Group gatherings of more than four persons in public places are prohibited. A person must wear a mask all the time while on public transportation or in a specified public place. Mobility reduced to –26.4% on average between 01 and 09 February. 	58.2 (54.2 – 61.5)	–
Second tightening (T2; from 10 February to 23 February)	<ul style="list-style-type: none"> From 10 February, the maximum number of people permitted for gatherings in public places was reduced from 4 to 2. The maximum number of persons per table in catering premises was 2 except for people presenting their vaccination records in certain premises[5]. Mobility reduced to –31.1% on average between 01 and 23 February. 	49.1 (45.2 – 52.7)	15.6 (14.1 – 17.1)
Third social distancing tightening (T3; from 24 February)	<ul style="list-style-type: none"> Starting on 24 February 2022, all persons shall wear a mask in any public places. The maximum number of persons per table in catering premises was reduced to 2[6]. Mobility further reduced to –36.4% on average between 24 February and 31 March. 	44.5 (40.5–48.1)	9.5 (8.7 – 10.5)
Adopting rapid antigen test	<ul style="list-style-type: none"> Starting on 26 February, members of the public tested positive by RAT, whether distributed by the government or on their own purchase, should be considered positive cases and they should take all necessary steps to avoid further spreading of the virus, including staying at home[7]. Because the PCR capacity had reached its limit^a, RAT kits were distributed by the government[8]. 	39.0 (36.7–41.1)	13.2 (11.4 – 15.5)

^a Total number of PCR tests conducted in February was 6,762,550, about 1.5-fold higher than January (4,304,653). The number further reduced to 3,820,839 in March.

Results

We incorporated the changes in vaccination, NPIs and weather into modelling in order to understand how these factors influence the growth and decline of the fifth wave in Hong Kong.

Characterising the fifth wave

We first compared two models: the full model, in which the force of infection was determined by vaccine-induced protectiveness, the implementation of social distancing and rapid antigen test, and weather conditions (temperature and relative humidity); and the 'reduced' model, in which the weather effects were not included. The reduced model could only capture the reported case number before reaching its peak (Fig. 2AE).

The full model successfully reproduced the observed pattern (Fig. 2AC), i.e. a rapidly increasing trend, followed by a sudden reduction in case number. The model was significantly improved when weather conditions were included (1995.1 versus 2650.9 in DIC). Hence, the full model was used to characterise the fifth wave.

The maximum daily number of reported cases about 77,000 was successfully predicted on 3 March (Fig. 2AC). Furthermore, the model predicted that the true daily infection rate (i.e. all newly infected people including unreported cases) reached its peak on 23 February of 231,381 (95% Credible Interval (CI): 210,705–256,860). Around this time, the cumulative incidence (i.e. cumulative infections in the percentage of total population) was about 0.78 million cases, only 10.5% of the population (Fig. 2D), appearing to be lower than the expected population immunity to suppress this outbreak [1]. However, the predicted infection rate reduced rapidly from the peak by about two-thirds to around 80 thousand per day five days later. The rate continued to reduce to around 25 thousand until the middle of March (Fig. 2C). The model estimated that up to the end of March, the cumulative incidence was 39.0% (95%CI: 36.7–41.1%), while only 38% of these infections were reported (about 1.1 million cases) and nearly 35% of these reported cases were detected by RAT (Fig. 2D).

R_e gradually decreased from about 5 to 3 in the first three weeks of February but increased sharply to 10.6 (95%CI: 9.9–11.4) on 20 February, despite a large mobility reduction (Fig. 1C). The number then reduced quickly to 1.0 (95%CI: 0.9–1.1) within 8 days (until 28 February) (Fig. 2B).

Changes in vaccine-induced population immunity

We first assessed whether vaccination was able to explain the rapid reduction in R_e during the late February. After incorporating antibody responses of second and third doses of BioNTech and CoronaVac, the pre-existing immunity before the study period only produced very limited protection (Fig. 3A). About 99% of individuals whose antibody titre levels were correlated with susceptibility greater than 50% (i.e. titre < 1:40) (see Fig. 1B).

With the rapid spreading of the Omicron virus, many individuals who obtained two doses have continued to take the vaccine booster. According to the daily booster rate (Fig. 1C), about 6.9% of the population have taken the booster doses (361,289 for BioNTech and 156,923 for CoronaVac) after one week before 1 February until one week before the predicted incidence peak date (23 February), and only 4.3% were estimated to have antibody titre \geq 1:40, defined as seroprevalence (Fig. 3B). The immunological dynamics show that the predicted seroprevalence in susceptible individuals resulting from vaccination is relatively low (Figure 3CD). Hence, the reduction of R_e in the late February appears not to be explained by vaccine booster.

Impacts of social distancing, rapid antigen test and vaccination

Next, we assessed the impact of each significant NPI (see Table 1). Social distancing regulations were further tightened twice during the study period. The baseline tightening (denoted as T1) was maintained from 7 January until 9 February. The population mobility reduced by 26.4% on average between 1 and 9 February (mobility data in January was not considered because they were before the study period) compared to the mobility before the pandemic began in 2020. The second tightening (T2) was introduced from 10 February until 23 February with the mobility reduced by 31.1% on

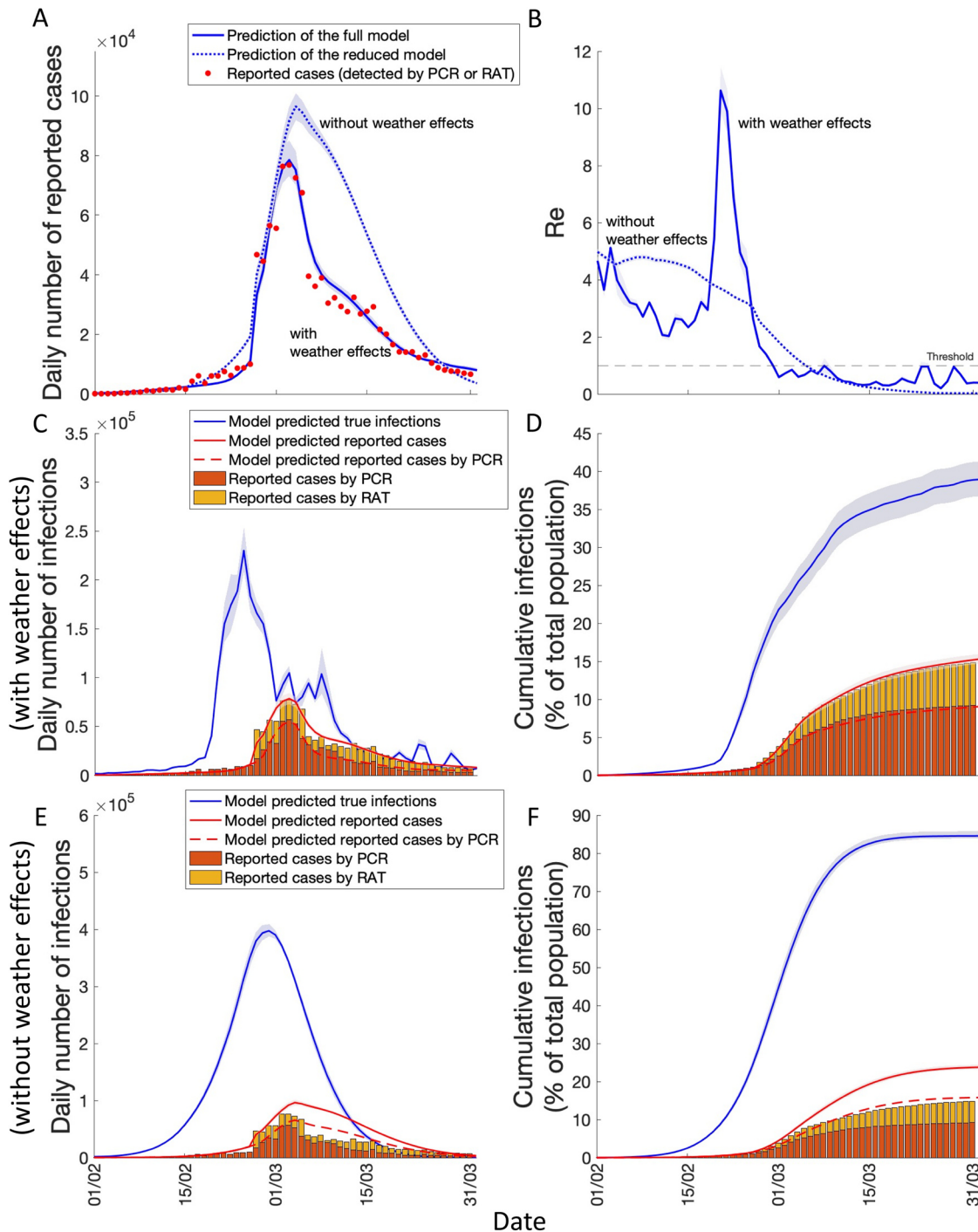


Fig. 2. Transmission dynamics and reproduction numbers derived from the full model (CD) and the reduced model (without incorporating weather effects) (EF). (A) Predicted numbers of daily reported cases from the full model (solid blue line) and the reduced model (dotted blue line). (B) Corresponding R_e of the two models over time. (C) Predicted numbers of true daily infections (solid blue line), daily reported cases (red solid line), and daily reported cases detected by PCR (red dashed line). Bars represent the observed daily numbers of reported cases detected by PCR (red) and RAT (yellow). (D) Cumulative incidence (i.e. cumulative infections in the percentage of total population) over time. Types of individual lines and bars represent the as in (C). (E), same as (CD) but the numbers are predicted from the reduced model. Shaded areas represent 95% credible intervals.

average. The third tightening (T3) was introduced on 24 February, which allowed the mobility reduced by 36.4% on average until 31 March. In addition to PCR test, since 26 February, RAT kits were widely distributed and were used for confirming infection with the virus.

Model predicted that, among all major interventions, if only T1 was used, the cumulative incidence increased from 39.0% to 58.2% (95%CI: 54.2–61.5%) (Fig. 4A). The subsequent implementation of T2 and T3 further reduced the cumulative incidence to 49.1% (95%CI:

45.2–52.7%) and 44.5% (95%CI: 40.5–48.1%), respectively. With the use of RAT, the cumulative incidence further decreased to our estimated proportion (39.0%). Without the booster in these two months, the cumulative incidence increased from 39.0% to 49.1% (95%CI: 53.6–45.7%) (Fig. S6).

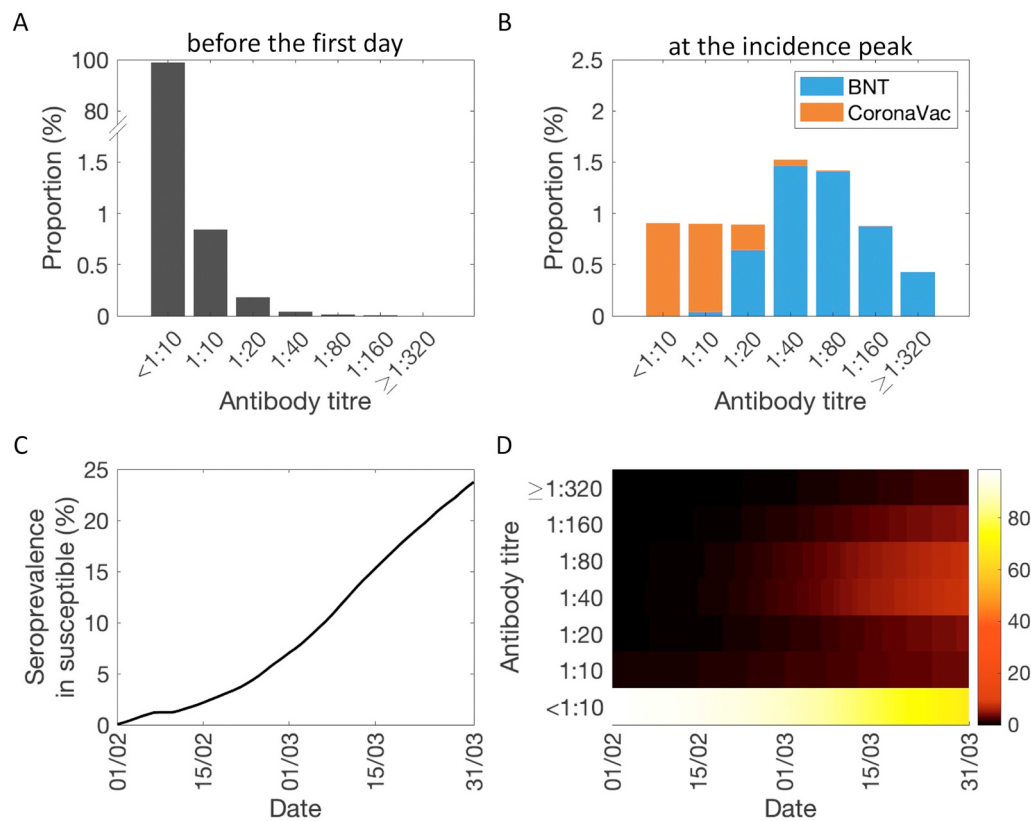


Fig. 3. Immunological dynamics induced by vaccination throughout the outbreak. (A) The estimated pre-existing immunity (i.e. the distribution of antibody titers among the population) on 1 February, 2022. (B) Vaccine-induced population immunity at the predicted peak time (23 February) of the daily infection rate. (C) Predicted seroprevalence (i.e. the percentage of people whose antibody titre $\geq 1:40$) induced by vaccination in susceptible individuals. (D) Changes in the proportion of susceptible individuals with each antibody titre level over time.

Impacts of weather factors

Moreover, temperature was found to be associated with the force of infection substantially. The average monthly temperature (the average of daily mean value for a given month) increased from 15.2 °C (February) to 21.5 °C (March) while the average monthly relative humidity reduced slightly from 80.8% to 76.8%. The model estimated that an increase of 1 °C was associated with a relative reduction of 16.0% (95%CI 14.9–17.1%) in the force of infection and therefore in R_e (see Fig. S7A). A rapid reduction of temperature, from 15.9 °C to 8.5 °C within two days since 18 February was associated with a 3.6-fold (95%CI 3.3–4.0) increase in R_e , driving it from 2.9 to a maximum value of 10.6. Since then, an increasing temperature from 8.5 °C to 18.9 °C observed within 8 days until the end of February was associated with a 83.6% (95%CI 81.3–85.7%) reduction in R_e (from 10.6 to 1.7). Together with NPIs and population immunity, the number was actually reduced to 1. On the other hand, we found that one percent increase in relative humidity was associated with only a 0.3% relative increase in R_e (Fig. S7B).

We further projected the total number of infections under different scenarios of weather conditions. Assuming that the relationship between weather conditions and force of infection held, if the two coldest days (20 and 21 February 2022 with 8.5–8.8 °C and 94–95% relative humidity) were replaced by the average February's weather condition, the cumulative incidence reduced significantly to 28.2% (95%CI 25.0–31.5) (Fig. 4B). If the warmer weather in March were still maintained as the average February's level, the cumulative incidence increased to 77.5% (95%CI 75.1–81.1) up to the end of March (Fig. 4B).

In order to verify whether the sharp pattern of R_e was affected by NPIs or vaccination, we further simulated R_e after removing T2&T3,

T3, RAT or vaccine boosters, respectively. We found that the pattern of R_e was generally similar with a moderate level of upward shift (Fig. S6). Using the reduced model without weather effects, R_e gradually decreased without the sharp peak (Fig. 2B). These suggest that the large and rapid variation in R_e was not resulting from NPIs or vaccinations.

Required Interventions for outbreak prevention

Our simulation results showed that the Omicron outbreak was not easily preventable by NPIs and pre-existing immunity in a cooler condition. For example, assuming February's average weather conditions (i.e. 15.2 °C), even with a booster coverage of 80%, population mobility still needs to be reduced at least 65% to suppress the outbreak (Fig. 4C). This intensity is far exceeding than the average reduction in mobility observed during a more tightened period (i.e. when T3 was implemented). Otherwise, during a more relaxed period (i.e. when only T1 was implemented) with the high booster coverage, the detection rate (i.e. the proportion of infectious cases that were detected per day) by RAT has to be greater than 60%, which is far higher than the estimated level (Fig. 4E). Without social distancing (i.e. 0% reduction in mobility) or RAT, high booster coverage such as 80% is still not useful.

In comparison, if the average weather conditions in March were assumed (i.e. 21.5 °C), R_e of below 1 can be achieved when more than one-third of people had taken booster doses during the tightened period (Fig. 4D). Meanwhile, a detection rate by RAT of at least 10% allowed social distancing measures to relax as the mobility level of T1 (Fig. 4F). Without social distancing or RAT, 70% booster coverage can prevent the outbreak.

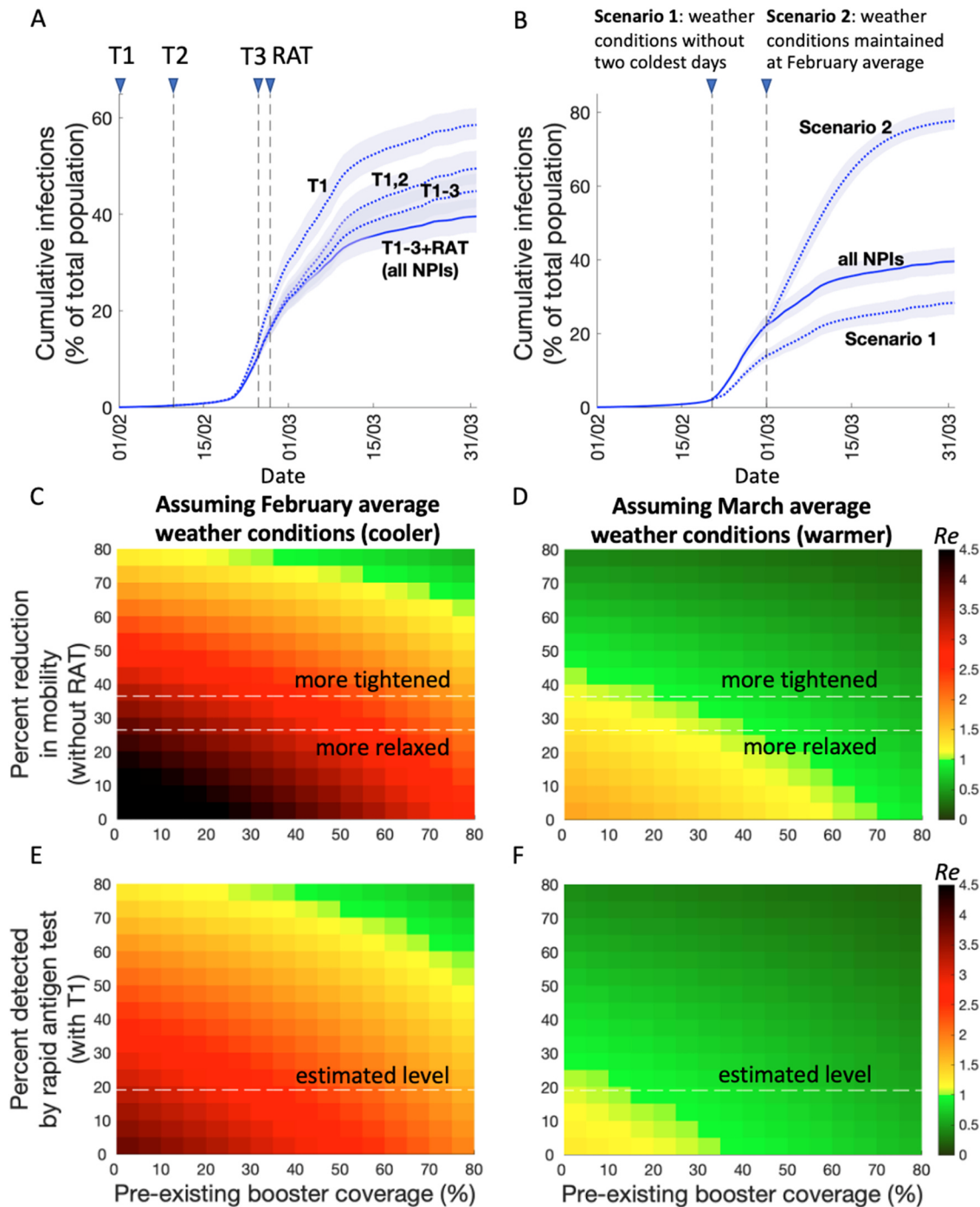


Fig. 4. Impacts of individual non-pharmaceutical interventions (NPIs) and weather conditions on cumulative infections and R_e . (A) Projected cumulative infections are plotted in the solid line (with all NPIs) and in the dotted lines (with different combinations of interventions). The triangles represent different start date of the interventions. (B) Projected cumulative infections of all NPIs under two different scenarios of weather change. Scenario 1: the coldest two days are replaced by the average February's weather condition. Scenario 2: the weather in March are replaced by the average weather condition in February, which is cooler. Shaded areas represent 95% credible intervals. (CD) Comparisons between cooler (February) and warmer (March) weather conditions for interventions needed for outbreak prevention. More tightened: average mobility reduction in T3, and more relaxed: average mobility reduction in T1. Dashed lines in (EF) indicate the estimated detection rate by RAT.

Discussion

If outbreaks are much harder to prevent during colder conditions for zero-COVID countries, as predicted by our model (Figure 4CE), the public health focus may need to be switched from strict containment to avoiding an excessive number of severe cases or deaths by maintaining healthcare capacity and/or managing a sudden surge of hospitalised cases.

Compared to previous studies based on cross comparison or cross-sectional analysis [12,15], for the first time, we found that a few days' cold surge appeared to drive the transmission substantially (Figure 2 BCE and Fig. 4B) even in the presence of social distancing measures. There are some factors that may explain the large influence of temperature. First, the astonishingly large impact was obtained after studying the Omicron outbreak in Hong Kong, a densely populated subtropical city. During the cold days, the virus can be more stable [28,29] and people may spend more time indoors.

Hence, cold surge may worsen the outbreak situation in such environments [30] by increasing indoor airborne transmission risk [31]. Second, temperature may modulate the host defense mechanisms including innate immune responses [32]. People in South East Asia generally live in warm weather throughout the year. Whether a large reduction in temperature poses a substantial impact on individuals' immunity in an environment that is generally warm remains unclear. A study has found that cold conditions and influenza activities were significantly associated with asthma hospitalisations in adults in a subtropical setting [33]. In addition, as many factors were difficult to be well controlled (e.g. differences in policies, environments, and the behaviours, etc.), the estimates in the previous studies might differ from the estimates made in a single city using a modelling approach. On the other hand, our model integrated a wide variety of data sources, including the change in population immunity, differences in serological responses and detection methods (PCR and RAT), and population mobility in a Bayesian framework to allow a more accurate parameter estimation and model forecast (Fig. 1).

Policy implications

Although the NPIs were still important in reducing the number of infections during the fifth wave (Table 1), without preparing for the potential surges resulting from large temperature drops, these interventions may not be sufficient enough to reduce the disease burden (Fig. S6). Hence, our results highlight the importance of the following works:

- i) **Having additional doses or boosters before winter arrives.** Our results are consistent with the hypothesis that the current pandemic is likely to become a seasonally reoccurring epidemic [34]. Given that the immunity is likely to wane after several months, additional boosters at right timing become important.
- ii) **Determining the impacts of critical incidents that drive local transmission.** Cold surges may likely occur as rare events but can nonetheless pose substantial impacts on COVID-19 and healthcare system. If relaxing social distancing is inevitable, knowing the consequence of such critical incidents is essential in order to reduce the associated health burden.
- iii) **Preventing and preparing for a surge in transmission resulting from such incidents.** An early warning of such events can be issued according to weather forecast. Temporarily increasing the use of RAT or strengthening other NPIs within a short period following these incidents is likely to reduce the total number of infections significantly (Fig. 4), which appears to be a cost-effective solution.

Limitations

Some limitations may exist in our study. First, the study focused on the disease transmissibility but not disease mortality. Second, the number of total infections was likely to be underestimated since the proportion of cases that were underreported was largely unknown when the testing capacity was limited. Hence, we incorporated the changes in underreporting and reporting delay into modelling. Third, the accuracy of the model may be sensitive to the assumption of the protectiveness of vaccine or natural infections. Here the data used in our study were based on a published empirical study without age stratification [10]. Fourth, we did not study the impact of wearing face masks. However, because most people in Hong Kong were wearing masks during the study period, this behaviour was likely not able to influence the estimation of other interventions. Fifth, whether more people stayed at home during very cold days is unknown. In places like Hong Kong where many people live in tiny flats in high-rise buildings, whether more people at home can lead to

more indoor transmissions remains to be studied. In addition, certainly, correlations may exist between temperature and some other environmental factors, such as UV levels. As discussed in a previous study, modelling was likely unable to discern the effects of each of the correlated environmental factors, and therefore temperature was proposed as a reliable environmental predictor [12].

Conclusions

In summary, our findings suggest that avoiding an outbreak during cold conditions after reopening is challenging; therefore, preventing and preparing for a possible surge in the COVID-19 transmission resulting from rapid temperature drops is of importance in avoiding a substantial disease burden. Compared to repeated strict interventions or no any limits on socialising, this preventive strategy appears to be a more cost-effective way to lead people to return to normal life.

Ethics approval and consent to participate

Not applicable.

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CRediT authorship contribution statement

Hsiang-Yu Yuan: Conceptualization; Data curation; Formal analysis; Methodology; Writing – original draft; Writing – review & editing. **Jingbo Liang:** Conceptualization; Data curation; Writing – review & editing. **Md Pear Hossain:** Formal analysis; Writing – review & editing.

Declaration of interests

All authors declare no competing interests.

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Evidence before this study

What public health and environmental factors contribute to driving or containing a SARS-CoV-2 Omicron outbreak remains largely unknown. A better understanding of these factors is of great importance in providing a path to normalcy without seriously harming people's lives, especially for 'zero-COVID' countries. We searched PubMed for research articles published in English from 1 February 2020 to 26 August 2022, with the following keywords: (COVID-19 OR SARS-CoV-2) AND (modelling OR Modeling) AND (transmission) AND (zero-COVID OR zero-Infections) NOT (Review [Publication Type]). We found only 3 modelling studies but their projections were made based the small-scaled outbreaks in a zero-COVID country, which were contained using strict non-pharmaceutical interventions (NPIs). None of them considered the change in social distancing, the use of rapid antigen test (RAT), the increase in

vaccine uptake and the variation of weather conditions during a significant outbreak.

Added value of this study

Our modelling quantified the impacts of social distancing regulations, RAT use, vaccine booster doses and temperature variations on the disease dynamics throughout a significant outbreak leading to more than a million of infected cases in a zero-COVID region. We combined comprehensive data during this outbreak including Google mobility, vaccination rates, vaccine-induced serological responses, cases confirmed either by PCR or RAT, and the proportion of cases that are contact-traced to calibrate the model. The results showed that although NPIs and vaccination were crucial in mitigating the spread of the disease, the large variation in temperature appeared to affect the R_e substantially. Quantifying the impacts of public health interventions during different temperature conditions can help to inform more cost-effective preventive strategies to reduce the number of cases.

Implications of all the available evidence

Avoiding a significant outbreak in cold conditions appears to be difficult in a highly susceptible populations (countries that adopt zero-COVID). Without strict NPIs (such as lockdowns), once the next outbreak occurs, preventing and preparing for a surge in the transmission of COVID-19 following a rapid temperature decrease is critical in reducing a large number of infections and hence the risk of healthcare collapse.

Appendix A. Supporting information

Supplementary data (including the access to the source codes) associated with this article can be found in the online version at doi:10.1016/j.jiph.2022.10.026.

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