Pandemic fatigue impedes mitigation of COVID-19 in Hong Kong

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Pandemic fatigue impedes mitigation of COVID-19 in Hong Kong

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ABSTRACT

Community-wide social distancing has been a cornerstone of pandemic control prior to mass vaccinations. The extent to which pandemic fatigue is undermining adherence to such measures and accelerating transmission remains unclear. Using large-scale weekly telephone surveys and mobility data, we characterize the evolution of risk perception and protective behaviours in Hong Kong. We estimate a 1.5% to 5.5% reduction in population compliance with protective policies for the fourth wave (October 2020 to January 2021) versus the third wave (July to August 2020), inducing prolonged disease circulation with increased infections. Mathematical models incorporating population protective behaviours estimates that the fourth wave would have been 14% smaller if not for pandemic fatigue. Mitigating pandemic fatigue is essential in maintaining population protective behaviours for controlling COVID-19.

The COVID-19 pandemic has caused significant health, social, and economic burden globally. In response, countries enacted public health and social measures (PHSMs), including unprecedented movement restrictions, to control transmission [1]. This has led to loss of employment, education, exercise opportunities, and other important social and cultural activities [2]. Pandemic fatigue is a natural response to a prolonged public health crisis due to complex interplay of cultural and social factors (e.g., the risk perception of threats) [3,4]. Recent studies suggest the gradual emergence of pandemic fatigue in many countries as demotivation to follow recommended mitigation behaviours [1,5–7].

Hong Kong has implemented stringent social distancing measures to curb four COVID-19 epidemic waves since January 2020. Similar PHSMs were used to contain transmission and bring case numbers down to low levels in each wave, including masks in all public areas, closure of schools, bars and social venues, work at home policies, and restaurant measures [8]. While the third wave between July and September was brought under control within 2 months, the fourth wave starting from the end of October 2020 has taken longer to bring under control and lasted at least 5 months. One of the potential reasons for the reduced impact of PHSMs on transmission in the fourth wave is pandemic fatigue [9].

To study the changing patterns of Hong Kong residents' risk perception and compliance with protective policies, and the associated impact on COVID-19 transmission, we conducted 40 rounds of weekly cross-sectional telephone surveys from 5 May 2020 through 15 February 2021. A total of more than 31,000 local adult residents have been interviewed via these surveys (see Methods). Such large-scale longitudinal data provides an opportunity to quantify risk perception and its impact on behavioural changes over time on the basis of disease-behaviour coupled framework that combines the analysis of risk perceptions, protective behaviours, transmission, and public reports (RPT-P), given in Fig. 1.

We first summarized the change in the risk perception and self-reported behaviours using the RPT-P framework. Comparing survey results during the fourth wave to those during the third wave, on average 7.2% to 7.7% fewer surveyed participants perceived the risk of infection and on average 1.5% to 5.5% fewer surveyed participants followed the physical distancing policies (e.g., avoiding social gathering and crowded places) during the fourth wave (Supplementary Table 4). This increase in pandemic fatigue is associated with a 25% increase in the median reproduction number for the fourth wave with respect to the third wave (Fig. 1 and Supplementary Table 4).

We next explored the interactive relationships among four key factors using the RPT-P framework driving the community transmission of COVID-19, including risk perception (e.g., perceived risk about being infected), self-reported protective behaviours (e.g., actions linking to reduced exposure), transmission (e.g., new infections over time), and public reports (e.g., public news of COVID-19 pandemic). We measured the impact of each factor using several indicators (summarized in Supplementary Table 2), and used the structural equation modeling to unravel the dependencies of these factors and the potential assumptions of their relationship (Fig. 1 and Supplementary Table 6). Furthermore, using each indicator of the four factors to predict the mean reproduction number in each week via linear regression, we found that, on average, an increase of 100 new cases per day corresponds to a 7% increase in people worrying about being infected, a 4% increase in people avoiding social gatherings, and a 0.36 decrease in the reproduction number (Supplementary Figure 1).

We compared the self-reported behavioural changes in our survey data with mobility data. Considering the large user base of Google's products and the real-time data of Google's Community Mobility Reports [10], we performed a stepwise regression analysis to examine the correlation between each surveyed indicator of protective behaviours and daily mobility movement trends of Google. We found that Google's mobility indexes are highly correlated with our surveyed self-reported protective behaviours (Supplementary Figure 2 and Supplementary Table 5). For example, the mobility of retail and grocery can explain up to 87% for the variability in avoiding social gathering (Supplementary Table 5). Combining with Google's mobility indexes, our surveyed weekly snapshot of population behavioural change can be augmented into a more granular daily resolution (Subsection *Epidemic model* in Supplementary Information).

Based on the changing proportions of protective behaviours, avoidance of social gathering has the highest degree of determination (adjusted R^2) to explain the real-time reproduction number in Hong Kong (0.43; Supplementary Table 1). Therefore, avoidance of social gathering is expected to be an essential element for modeling COVID-19 transmission in Hong Kong. Our epidemic model with transmission forcing adjusted by the real-time change in population protective behaviours is able to nowcast the local incidence curve of the official surveillance report of symptomatic case counts (Fig. 2). Furthermore, an 1.7% and 6.3% increase in the percentage of people avoiding social gathering per day (which were determined as the ratio of median and 95% credible interval (CrI) upper during the third wave to median during the fourth wave, respectively, Supplementary Table 4) would reduce the size of the outbreak by 14% (95% CrI: -58%, 76%) and 39% (95% CrI: -15%, 86%), respectively, during the fourth wave between 31 October in 2020 and 15 January in 2020.

Our study has several limitations. First, we avoided modeling the influence of climate effects and new variants of SARS-CoV-2. We excluded the climate effects because of the low and non-significant correlation between real-time reproduction number and daily climate data [11] for air temperature, relative humidity, and air pressure in Hong Kong. We did not consider the new SARS-CoV-2 variants, because the first two imported cases caused by the new variant were detected at the later stage of the fourth wave [12] and all inbound international travelers were imposed with 14-day or 21-day hotel quarantine to minimize the risk of imported cases [8]. Second, although we analyzed self-reported behaviour and did not validate this against actual behaviours, self-reported surveys have been widely used to study human behaviour such as contact patterns [13] and hospital attendance [14]. Third, other social activities may affect the risk perception and protective behaviours. For example, family gatherings during the Winter Solstice and Christmas have been the social norm in Hong Kong for decades. Prolonged financial stress due to job loss and mask costs and distrust of government's policies such as the slow roll-out of vaccination schemes may also contribute to the emergence of pandemic fatigue in the fourth wave. Despite these limitations, the strong correlation between our surveyed behaviour data and Google mobility data suggests the capacity of our large-scale longitudinal survey in capturing the actual population behaviour change.

Informed by weekly cross-sectional telephone surveys, our results indicate signs of pandemic fatigue in Hong Kong by measuring public responses to pandemic interventions, which are impacted by people’s risk perception and resulting reproduction number changes. The real-time metric of behaviour changes can be refined by the Google mobility index, which provides a measurement of epidemiological transmission rate and links to the transmission rate to track the local cases reported. The observed pandemic fatigue reveals that compliance with public health advice declines when dire circumstances drag on, especially when new virus variants are reported worldwide, associated with increased transmissibility [15–17], and might be spreading without detection in countries with limited virus sequencing capacity [18].

The current pandemic-induced socio-political and economic crisis requires decision-makers’ attention that goes beyond the number of confirmed cases. The growing issue of pandemic fatigue reflects people’s social, emotional and mental health needs. While COVID-19 vaccines provide a pathway back to normality, PHSMs are essential to COVID-19 control until herd immunity is achieved via high vaccination coverage. To maintain compliance with PHSMs may require solutions to pandemic fatigue. These may only be identified if we engage people as part of the solution, understand their needs, acknowledge their hardship, and empower them to live their lives with reduced risk [1].

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Author contributions

ZD, LW, PW, LAM, and BJC: conceived the study, designed statistical and modelling methods, conducted analyses, interpreted results, wrote and revised the manuscript; SS, DL, TKT, JX, HG, BY, STA, SP, ICHF, EHYL, QL, and GML: collected and compiled data, interpreted results, and revised the manuscript.

Competing interests

GML and BJC are supported by the AIR@innoHK program of the Innovation and Technology Commission of the Hong Kong SAR Government.

Figure legends

Figure 1, The coupled disease-behaviour framework that combines the analysis of risk perceptions, protective behaviours, transmission, and public reports (RPT-R) during the third wave (July to August 2020) and the fourth wave (October 2020 to January 2021). (A) The RPT-R framework. Purple arrows indicate the interplay of risk perception, protective behaviours, transmission, and public reports. (B) Using 40 rounds of cross-sectional telephone surveys from May 2020 to February 2021, we estimated the percentages of participants following the protective behaviours or reporting higher levels of perceived risk or worry by asking participants whether they have taken specific measures in the past 7 days to prevent from contracting SARS-CoV-2 or likely feel susceptible and worried about being infected, respectively, associated with the estimated SARS-CoV-2 reproduction numbers and daily reported cases in Hong Kong (Supplementary Table 4). Error bars indicate the median and 95% CrI, respectively. The asterisk indicates the rejection of equal medians for the third wave versus the fourth wave at the 5% significance level using the two-sided Wilcoxon rank sum test [18].

Figure 2, Reconstruction of the third and fourth waves of the COVID-19 pandemic in Hong Kong, using an epidemic model that incorporates our weekly survey data together with Google's daily population mobility data. We projected the daily time series of the observed data by tracking the new infections (Supplementary Information *Epidemic model*). Black dots indicate the observed daily time series of confirmed cases by symptom onset that were reported by the Centre for Health Protection of Hong Kong (Supplementary Table 2). Back curve and gray shaded regions indicate the median and 95% credibility interval (CrI) of our reconstructed daily time series of confirmed cases by symptom onset date. (A) Results for the third wave from the early of July to the end of August 2020. (B) Results for the fourth wave from the end of October 2020 to the end of January 2021. Our standard model incorporating the infection forcing of population protective behaviour (black dots and gray bars) is well fitted to the observed time series data (red curve). The counterfactual scenario assuming a 5% increase in the proportion of population avoiding social gathering per day (blue curve and shaded region) suggests that mitigating pandemic fatigue can substantially reduce the number of new cases after the peak of the fourth wave at around the end of November 2020, which would avert 34% (95% CrI: -23%, 84%) of confirmed cases compared to that of standard model. (C) Structure of the epidemic model (see supplementary materials for details).

Supplementary Figure 1, Linear regression of surveyed indicators over 40 surveys between May 5, 2020 and February 8, 2021. We estimate the coefficients using linear regression for each indicator (stratified by factors in Supplementary Table 2) per 100 daily cases and only show those with adjusted R^2 larger than 0.3. The value on each edge indicates the coefficient of significant linear regression of the two lined factors across the 40 surveys (Supplementary Table 1).

Supplementary Figure 2, Linear Stepwise regression of Google mobility measures and protective behaviour proportions with information on coefficients in Supplementary Table 5. We examine the correlation between each type of surveyed protective behaviours and six daily mobility movement trends of Google by a stepwise regression analysis to add or remove predictors with the criterion of p-value for F test. Lines denote those selected mobility indexes for each behaviour.

Supplementary Figure 3, Epidemiological model of COVID-19 transmission in Hong Kong. Upon infection, susceptible individuals (S) progress to being exposed (E). A fraction of cases become asymptomatic infectious (A) with lower infectiousness before recovering (R); the remaining cases progress to presymptomatic (P), where they are moderately infectious but not yet symptomatic, followed by symptomatic infectious (Y) and then either recover or die (R).

Supplementary Figure 4, Overview of survey and epidemic data. Weekly proportions of protective behaviour and risk perception from weekly cross-sectional telephone surveys, daily reported cases on average in a week by reporting date, and real-time reproduction number on average in a week (Supplementary Table 2).

Supplementary Figure 5, Google mobility data for each of the location categories. Google compares visitor daily numbers to specific categories of location to that during the baseline period (the 5-week period from January 3 to February 6, 2020) before the pandemic outbreak. Six Google mobility measures are collected to track how the numbers of visitors to places of (1) retail and recreation, (2) grocery and pharmacy stores, (3) transit stations, (4) workplaces, (5) residential areas, and (6) parks have changed compared to baseline days[4].

Table legends

Supplementary Table 1, Linear regression of self-reported protective behaviours and reproduction number over 40 surveys between May 5, 2020 and February 8, 2021. Using the real-time reproduction number estimations in Hong Kong [19], we estimate the mean reproduction number for each week from 5 May 2020 to 15 February 2021. The coefficient and intercept obtained from the linear regression analysis are summarized in this table. Each row corresponds to the regression between the weekly mean reproduction number (averaged over 7 days in each week) and one type of those proportions of protective behaviours.

Supplementary Table 2, Data sources towards COVID-19 of risk perceptions, behavioural responses, transmission, public reports, and Google mobility in Hong Kong.

Supplementary Table 3, Epidemiological parameters for the SARS-CoV-2 infection model.

Supplementary Table 4, Protective behaviours and risk perception in the surveys, associated with the reproduction number.

Supplementary Table 5, Stepwise regression of protective behaviours and Google mobility movement trends across different categories of places. We examine the correlation between each type of surveyed protective behaviours and six daily mobility movement trends of Google by a stepwise regression analysis to add or remove predictors with the criterion of p-value for F test.

Supplementary Table 6, Structural equation modeling of protective behaviours and risk perception in the surveys, associated with the reproduction number and public reports. We used the structural equation modeling [20] to unravel the dependencies and potential causal assumptions of these factors (Fig. 1), including risk perception, self-reported protective behaviours, transmission, and public reports, each with at least one measured variable. We estimate the t-statistic and p values, which denote the strong causal assumptions of these factors (a full report with more analyses in URL).

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Methods

Survey data

In each weekly survey from 5 May 2020 to 15 February 2021, we contacted either 500 or 1000 local residents through random digit dialing of landlines and mobile telephones, using age, gender, education, and employment information to weight the response frequencies to the adult population in Hong Kong [21]. More than 31,000 local residents were interviewed through these 40 cross-sectional telephone surveys. We asked each participant about the perception of the risk of being infected and the compliance with physical distancing measures. Specifically, to assess the risk perception, we asked whether the participant was aware of being susceptible to the COVID-19 and worried about being infected. To assess the physical distancing behaviour, we asked whether the participant complied with the recommended distancing policies including the avoidance of going to crowded places (e.g., Leisure venues and bars), staying at home as much as possible, avoidance of using public transportation, and avoidance of social gathering (e.g., dining together, weddings, funerals, religious services) Details about the surveyed questions are summarized in Supplementary Table 2 and shown in Supplementary Figure 4.

The survey enables us to estimate (1) the percentage of participants perceived the risk of infection; and (2) the percentage of participants engaged in physical distancing policies.

Epidemic data

We collect the daily reported cases by reporting date in Hong Kong from COVID-19 Dashboard by the Center for Systems Science and Engineering at Johns Hopkins University [22] and the real-time effective reproductive number for local cases and the daily symptomatic cases by onset date in Hong Kong from the real-time dashboard in School of Public Health, The University of Hong Kong [19], shown in Supplementary Figure 4.

Mobility data

To estimate the dynamic of people traveling in the COVID-19 pandemic, we obtained the daily mobility data from the Google community mobility reports in Hong Kong [10]. Based on visitors' daily numbers to specific categories of location (e.g. grocery stores; parks; train stations), Google compares it to baseline period (the 5-week period from January 3 to February 6, 2020) before the pandemic outbreak and reports six mobility categories to indicate how the numbers of visitors in Hong Kong to places of (1) retail and recreation (restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters), (2) grocery and pharmacy stores (grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies), (3) transit stations (public transport hubs such as subway, bus, and train stations), (4) workplaces, (5) residential areas, and (6) parks (local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens) have changed [10], as shown in Supplementary Figure 5.

Epidemic model

We simulate the transmission of COVID-19 using a compartmental model, in which the health status of each individual can be susceptible (S), exposed (E), asymptomatic (A), presymptomatic (P), symptomatic (Y), or recovery/death (R) at any time (Supplementary Figure 3). After infection, an individual remains in an exposed state (E) for a non-infectious incubation period, which is on average $1/\sigma$ days. Then, the exposed individual (E) becomes asymptomatic (A) or pre-symptomatic (P) with probabilities of $1 - p_{sym}$ and p_{sym}, respectively. The asymptomatic case (A) has a reduced ability to infect others, and is recovered/died (R) after an asymptomatic infectious period, which is on average $1/\hat{\gamma}$ days. Pre-symptomatic case also has a reduced ability to infect others. Pre-symptomatic case (P) becomes symptomatic at a rate ϵ, after which will recover/die at a rate γ. Recovered individuals are assumed to be immunized against re-infection throughout the duration of simulation (3 months). Details about the parameterization are summarized in Supplementary Table 3.

The infectiousness of a case depends on the infection status (i.e., pre-symptomatic, asymptomatic or symptomatic). Compared to symptomatic cases, the infectiousness of asymptomatic and pre-symptomatic cases is reduced by a factor of $\hat{\omega}$ and ω, respectively. Let β be the transmission rate between each pair of susceptible and infectious individuals, which accounts for the influence of protective behaviours by formulating as

$\beta = \alpha(d)\ \Phi(d) + \rho + \xi(d)$. Here $\Phi(d)$ is the daily percentage of people avoiding social gathering, $\alpha(d)$ the coefficient of $\Phi(d)$, and ρ the intercept at day *d*. $\xi(d)$ denotes the noise uniformly distributed between -0.1 and 0.1. To avoid overfitting due to the multicollinearity between surveyed indicators, we only incorporate the data for the avoidance of social gathering. We build compartments to model the transitions between the states: susceptible (*S*), exposed (*E*), pre-symptomatic infectious (*P*), symptomatic infectious (*Y*), asymptomatic infectious (*A*), recovered (*R*).

Let *S*(*t*), *E*(*t*), *A*(*t*), *P*(*t*), *Y*(*t*), and *R*(*t*) denote the number of susceptible, exposed, asymptomatic, presymptomatic, symptomatic, and recovery/death individuals at time *t*, respectively. The total population size is *N* = *S*+*E*+*A*+*P*+*Y*+*R*. We use the following ordinary differential equations to simulate the transmission of COVID-19:

$$S(t+1) = S(t) - \beta S(t)\ (\hat{\omega} A(t) + \omega P(t) + Y(t))/N$$

$$E(t+1) = E(t) + \beta S(t)\ (\hat{\omega} A(t) + \omega P(t) + Y(t))/N - \sigma E(t)$$

$$P(t+1) = P(t) + \sigma p_{sym} E(t) - \epsilon P(t)$$

$$A(t+1) = A(t) + \sigma(1 - p_{sym})E(t) - \hat{\gamma} A(t)$$

$$Y(t+1) = Y(t) + \epsilon P(t) - \gamma Y(t)$$

$$R(t+1) = R(t) + \hat{\gamma} A(t) + \gamma Y(t)$$

We estimate the transmission rate β by fitting the daily reported local symptomatic cases [19] via the Ensemble Adjustment Kalman Filter (EAKF) algorithm [23] with 10,000 particles. To account for the reporting delay of local confirmed cases at day⍰, we assume the new infections $\beta S(t)\ (\hat{\omega} A(t) + \omega P(t))$ with the proportion p_{sym} following the normal distribution with mean $I^Y(d + 1/\sigma + 1/\epsilon)$ and standard deviation $\sqrt{\frac{\Sigma_{i=1}^{3}(\ I^Y(d+1/\sigma+1/\epsilon\ -i))^2}{10}}$. In our study, we aligned the reconstructed daily time series of exposed cases to the observed data by 5 days (as $1/\sigma + 1/\epsilon$) to track the new infections.

To estimate the outbreak size averted in the fourth wave between 31 October in 2020 and 15 January in 2021, we introduce the epidemic model with values of $\alpha(d)$, calibrated by the EAKF algorithm informed by local cases. Accordingly, we estimate the median symptomatic incidence across scenarios with increases in the percentage of people avoiding social gathering per day.

Ethics approval

Data collection and analysis were required by the National Health Commission of the People's Republic of China to be part of a continuing public health outbreak investigation.

Data availability

All data are available in the supplementary materials and will be posted online.

Code availability

The computer code and simulated data will be made available to anyone for any purpose upon request to the corresponding author following publication.

Figures

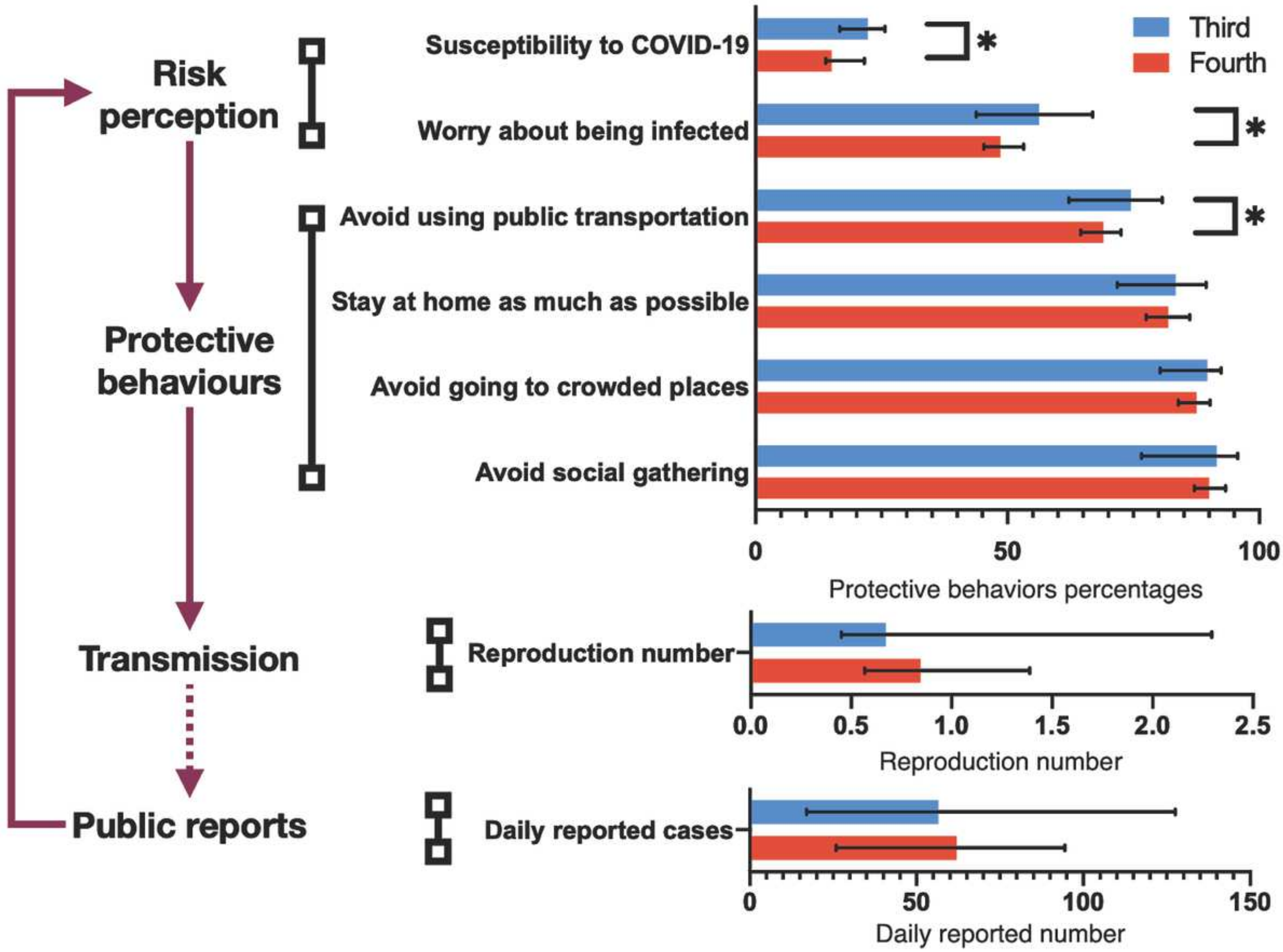

Figure 1

The coupled disease-behaviour framework that combines the analysis of risk perceptions, protective behaviours, transmission, and public reports (RPT-R) during the third wave (July to August 2020) and the fourth wave (October 2020 to January 2021). (A) The RPT-R framework. Purple arrows indicate the interplay of risk perception, protective behaviours, transmission, and public reports. (B) Using 40 rounds of cross-sectional telephone surveys from May 2020 to February 2021, we estimated the percentages of participants following the protective behaviours or reporting higher levels of perceived risk or worry by asking participants whether they have taken specific measures in the past 7 days to prevent from contracting SARS-CoV-2 or likely feel susceptible and worried about being infected, respectively, associated with the estimated SARS-CoV-2 reproduction numbers and daily reported cases in Hong Kong (Supplementary Table 4). Error bars indicate the median and 95% CrI, respectively. The asterisk indicates the rejection of equal medians for the third wave versus the fourth wave at the 5% significance level using the two-sided Wilcoxon rank sum test 18.

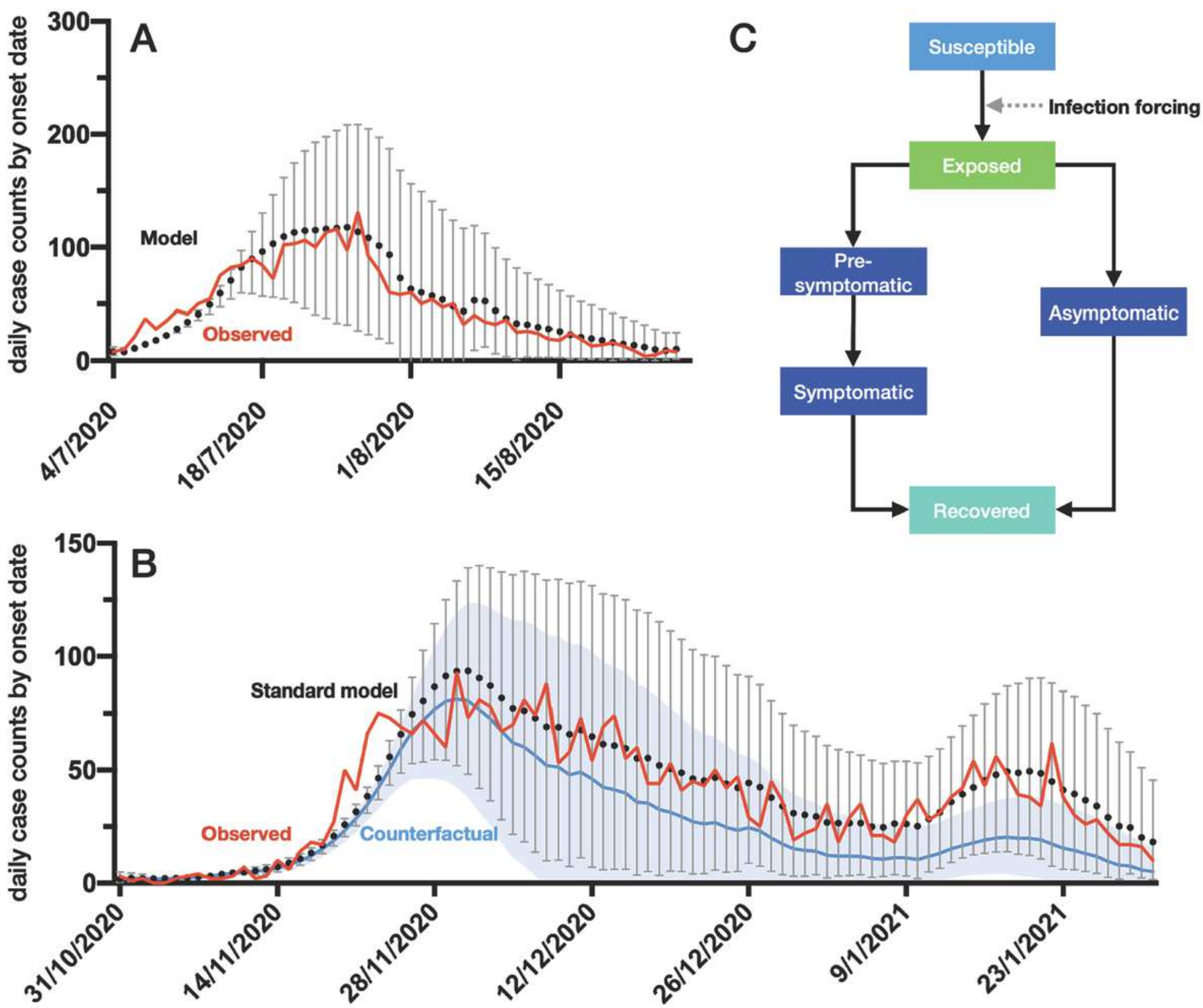

Figure 2

Reconstruction of the third and fourth waves of the COVID-19 pandemic in Hong Kong, using an epidemic model that incorporates our weekly survey data together with Google's daily population mobility data. We projected the daily time series of the observed data by tracking the new infections (Supplementary Information Epidemic model). Black dots indicate the observed daily time series of confirmed cases by symptom onset that were reported by the Centre for Health Protection of Hong Kong (Supplementary Table 2). Back curve and gray shaded regions indicate the median and 95% credibility interval (CrI) of our reconstructed daily time series of confirmed cases by symptom onset date. (A) Results for the third wave from the early of July to the end of August 2020. (B) Results for the fourth wave from the end of October 2020 to the end of January 2021. Our standard model incorporating the infection forcing of population protective behaviour (black dots and gray bars) is well fitted to the observed time series data (red curve). The counterfactual scenario assuming a 5% increase in the proportion of population avoiding social gathering per day (blue curve and shaded region) suggests that mitigating pandemic fatigue can substantially reduce the number of new cases after the peak of the fourth wave at around the end of November 2020, which would avert 34% (95% CrI: -23%, 84%) of confirmed cases compared to that of standard model. (C) Structure of the epidemic model (see supplementary materials for details).

Supplementary Files

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