

Pandemic fatigue impedes mitigation of COVID-19 in Hong Kong

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1 **Pandemic fatigue impedes mitigation of COVID-19 in Hong Kong**

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24

25 **ABSTRACT**

26 Community-wide social distancing has been a cornerstone of pandemic control prior to mass
27 vaccinations. The extent to which pandemic fatigue is undermining adherence to such measures
28 and accelerating transmission remains unclear. Using large-scale weekly telephone surveys and
29 mobility data, we characterize the evolution of risk perception and protective behaviours in Hong
30 Kong. We estimate a 1.5% to 5.5% reduction in population compliance with protective policies for
31 the fourth wave (October 2020 to January 2021) versus the third wave (July to August 2020),
32 inducing prolonged disease circulation with increased infections. Mathematical models
33 incorporating population protective behaviours estimates that the fourth wave would have been
34 14% smaller if not for pandemic fatigue. Mitigating pandemic fatigue is essential in maintaining
35 population protective behaviours for controlling COVID-19.

36

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

45

46 Hong Kong has implemented stringent social distancing measures to curb four COVID-19 epidemic
47 waves since January 2020. Similar PHSMs were used to contain transmission and bring case

48 numbers down to low levels in each wave, including masks in all public areas, closure of schools,
49 bars and social venues, work at home policies, and restaurant measures ⁸. While the third wave
50 between July and September was brought under control within 2 months, the fourth wave starting
51 from the end of October 2020 has taken longer to bring under control and lasted at least 5 months.
52 One of the potential reasons for the reduced impact of PHSMs on transmission in the fourth wave
53 is pandemic fatigue ⁹.

54

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

63

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

71

72 We next explored the interactive relationships among four key factors using the RPT-P framework
73 driving the community transmission of COVID-19, including risk perception (e.g., perceived risk
74 about being infected), self-reported protective behaviours (e.g., actions linking to reduced
75 exposure), transmission (e.g., new infections over time), and public reports (e.g., public news of
76 COVID-19 pandemic). We measured the impact of each factor using several indicators
77 (summarized in Supplementary Table 2), and used the structural equation modeling to unravel
78 the dependencies of these factors and the potential assumptions of their relationship (Fig. 1 and
79 Supplementary Table 6). Furthermore, using each indicator of the four factors to predict the mean
80 reproduction number in each week via linear regression, we found that, on average, an increase of
81 100 new cases per day corresponds to a 7% increase in people worrying about being infected, a
82 4% increase in people avoiding social gatherings, and a 0.36 decrease in the reproduction number
83 (Supplementary Figure 1).

84

85 We compared the self-reported behavioural changes in our survey data with mobility data.
86 Considering the large user base of Google's products and the real-time data of Google's Community
87 Mobility Reports ¹⁰, we performed a stepwise regression analysis to examine the correlation
88 between each surveyed indicator of protective behaviours and daily mobility movement trends of
89 Google. We found that Google's mobility indexes are highly correlated with our surveyed self-
90 reported protective behaviours (Supplementary Figure 2 and Supplementary Table 5). For
91 example, the mobility of retail and grocery can explain up to 87% for the variability in avoiding
92 social gathering (Supplementary Table 5). Combining with Google's mobility indexes, our

93 surveyed weekly snapshot of population behavioural change can be augmented into a more
94 granular daily resolution (Subsection *Epidemic model* in Supplementary Information).

95

96 Based on the changing proportions of protective behaviours, avoidance of social gathering has the
97 highest degree of determination (adjusted R^2) to explain the real-time reproduction number in
98 Hong Kong (0.43; Supplementary Table 1). Therefore, avoidance of social gathering is expected to
99 be an essential element for modeling COVID-19 transmission in Hong Kong. Our epidemic model
100 with transmission forcing adjusted by the real-time change in population protective behaviours is
101 able to nowcast the local incidence curve of the official surveillance report of symptomatic case
102 counts (Fig. 2). Furthermore, an 1.7% and 6.3% increase in the percentage of people avoiding
103 social gathering per day (which were determined as the ratio of median and 95% credible interval
104 (CrI) upper during the third wave to median during the fourth wave, respectively,
105 Supplementary Table 4) would reduce the size of the outbreak by 14% (95% CrI: -58%, 76%) and
106 39% (95% CrI: -15%, 86%), respectively, during the fourth wave between 31 October in 2020 and
107 15 January in 2020.

108

109 Our study has several limitations. First, we avoided modeling the influence of climate effects and
110 new variants of SARS-CoV-2. We excluded the climate effects because of the low and non-
111 significant correlation between real-time reproduction number and daily climate data ¹¹ for air
112 temperature, relative humidity, and air pressure in Hong Kong. We did not consider the new
113 SARS-CoV-2 variants, because the first two imported cases caused by the new variant were
114 detected at the later stage of the fourth wave ¹² and all inbound international travelers were
115 imposed with 14-day or 21-day hotel quarantine to minimize the risk of imported cases ⁸. Second,

116 although we analyzed self-reported behaviour and did not validate this against actual behaviours,
117 self-reported surveys have been widely used to study human behaviour such as contact patterns ¹³
118 and hospital attendance ¹⁴. Third, other social activities may affect the risk perception and
119 protective behaviours. For example, family gatherings during the Winter Solstice and Christmas
120 have been the social norm in Hong Kong for decades. Prolonged financial stress due to job loss and
121 mask costs and distrust of government's policies such as the slow roll-out of vaccination schemes
122 may also contribute to the emergence of pandemic fatigue in the fourth wave. Despite these
123 limitations, the strong correlation between our surveyed behaviour data and Google mobility data
124 suggests the capacity of our large-scale longitudinal survey in capturing the actual population
125 behaviour change.

126

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

136

137 The current pandemic-induced socio-political and economic crisis requires decision-makers'
138 attention that goes beyond the number of confirmed cases. The growing issue of pandemic fatigue

139 reflects people's social, emotional and mental health needs. While COVID-19 vaccines provide a
140 pathway back to normality, PHSMs are essential to COVID-19 control until herd immunity is
141 achieved via high vaccination coverage. To maintain compliance with PHSMs may require
142 solutions to pandemic fatigue. These may only be identified if we engage people as part of the
143 solution, understand their needs, acknowledge their hardship, and empower them to live their
144 lives with reduced risk¹.

145

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149 Research Fund from the Government of the Hong Kong Special Administrative Region (BJC).

150 **Author contributions**

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

155 **Competing interests**

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158 Commission of the Hong Kong SAR Government.

159 **Figure legends**

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

173
174 **Figure 2**, Reconstruction of the third and fourth waves of the COVID-19 pandemic in Hong Kong,
175 using an epidemic model that incorporates our weekly survey data together with Google's daily
176 population mobility data. We projected the daily time series of the observed data by tracking the
177 new infections (Supplementary Information *Epidemic model*). Black dots indicate the observed
178 daily time series of confirmed cases by symptom onset that were reported by the Centre for
179 Health Protection of Hong Kong (Supplementary Table 2). Back curve and gray shaded regions
180 indicate the median and 95% credibility interval (CrI) of our reconstructed daily time series of
181 confirmed cases by symptom onset date. (A) Results for the third wave from the early of July to
182 the end of August 2020. (B) Results for the fourth wave from the end of October 2020 to the end of
183 January 2021. Our standard model incorporating the infection forcing of population protective
184 behaviour (black dots and gray bars) is well fitted to the observed time series data (red curve).
185 The counterfactual scenario assuming a 5% increase in the proportion of population avoiding
186 social gathering per day (blue curve and shaded region) suggests that mitigating pandemic fatigue

187 can substantially reduce the number of new cases after the peak of the fourth wave at around the
188 end of November 2020, which would avert 34% (95% CrI: -23%, 84%) of confirmed cases
189 compared to that of standard model. (C) Structure of the epidemic model (see supplementary
190 materials for details).

191
192 **Supplementary Figure 1**, Linear regression of surveyed indicators over 40 surveys between May
193 5, 2020 and February 8, 2021. We estimate the coefficients using linear regression for each
194 indicator (stratified by factors in Supplementary Table 2) per 100 daily cases and only show those
195 with adjusted R^2 larger than 0.3. The value on each edge indicates the coefficient of significant
196 linear regression of the two lined factors across the 40 surveys (Supplementary Table 1).

197
198 **Supplementary Figure 2**, Linear Stepwise regression of Google mobility measures and protective
199 behaviour proportions with information on coefficients in Supplementary Table 5. We examine
200 the correlation between each type of surveyed protective behaviours and six daily mobility
201 movement trends of Google by a stepwise regression analysis to add or remove predictors with
202 the criterion of p-value for F test. Lines denote those selected mobility indexes for each behaviour.

203
204 **Supplementary Figure 3**, Epidemiological model of COVID-19 transmission in Hong Kong. Upon
205 infection, susceptible individuals (S) progress to being exposed (E). A fraction of cases become
206 asymptomatic infectious (A) with lower infectiousness before recovering (R); the remaining cases
207 progress to presymptomatic (P), where they are moderately infectious but not yet symptomatic,
208 followed by symptomatic infectious (Y) and then either recover or die (R).

209
210 **Supplementary Figure 4**, Overview of survey and epidemic data. Weekly proportions of
211 protective behaviour and risk perception from weekly cross-sectional telephone surveys, daily
212 reported cases on average in a week by reporting date, and real-time reproduction number on
213 average in a week (Supplementary Table 2).

214
215 **Supplementary Figure 5**, Google mobility data for each of the location categories. Google
216 compares visitor daily numbers to specific categories of location to that during the baseline period
217 (the 5-week period from January 3 to February 6, 2020) before the pandemic outbreak. Six Google
218 mobility measures are collected to track how the numbers of visitors to places of (1) retail and
219 recreation, (2) grocery and pharmacy stores, (3) transit stations, (4) workplaces, (5) residential
220 areas, and (6) parks have changed compared to baseline days⁴.

221
222

223 *Table legends*

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

231

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

234

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

236

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

239

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

244

245 **Supplementary Table 6**, Structural equation modeling of protective behaviours and risk
246 perception in the surveys, associated with the reproduction number and public reports. We used
247 the structural equation modeling²⁰ to unravel the dependencies and potential causal assumptions
248 of these factors (Fig. 1), including risk perception, self-reported protective behaviours,
249 transmission, and public reports, each with at least one measured variable. We estimate the t-
250 statistic and p values, which denote the strong causal assumptions of these factors (a full report
251 with more analyses in [URL](#)).

252

253

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255

256

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299 **Methods**

300 ***Survey data***

301 In each weekly survey from 5 May 2020 to 15 February 2021, we contacted either 500 or
302 1000 local residents through random digit dialing of landlines and mobile telephones,
303 using age, gender, education, and employment information to weight the response
304 frequencies to the adult population in Hong Kong ²¹. More than 31,000 local residents were
305 interviewed through these 40 cross-sectional telephone surveys. We asked each participant
306 about the perception of the risk of being infected and the compliance with physical
307 distancing measures. Specifically, to assess the risk perception, we asked whether the
308 participant was aware of being susceptible to the COVID-19 and worried about being
309 infected. To assess the physical distancing behaviour, we asked whether the participant
310 complied with the recommended distancing policies including the avoidance of going to
311 crowded places (e.g., Leisure venues and bars), staying at home as much as possible,
312 avoidance of using public transportation, and avoidance of social gathering (e.g., dining
313 together, weddings, funerals, religious services) Details about the surveyed questions are
314 summarized in Supplementary Table 2 and shown in Supplementary Figure 4.

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

317 ***Epidemic data***

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

323 ***Mobility data***

324 To estimate the dynamic of people traveling in the COVID-19 pandemic, we obtained the
325 daily mobility data from the Google community mobility reports in Hong Kong ¹⁰. Based on
326 visitors' daily numbers to specific categories of location (e.g. grocery stores; parks; train

327 stations), Google compares it to baseline period (the 5-week period from January 3 to
328 February 6, 2020) before the pandemic outbreak and reports six mobility categories to
329 indicate how the numbers of visitors in Hong Kong to places of (1) retail and recreation
330 (restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie
331 theaters), (2) grocery and pharmacy stores (grocery markets, food warehouses, farmers
332 markets, specialty food shops, drug stores, and pharmacies), (3) transit stations (public
333 transport hubs such as subway, bus, and train stations), (4) workplaces, (5) residential
334 areas, and (6) parks (local parks, national parks, public beaches, marinas, dog parks, plazas,
335 and public gardens) have changed ¹⁰, as shown in Supplementary Figure 5.

336

337 ***Epidemic model***

338 We simulate the transmission of COVID-19 using a compartmental model, in which the
339 health status of each individual can be susceptible (S), exposed (E), asymptomatic (A),
340 presymptomatic (P), symptomatic (Y), or recovery/death (R) at any time
341 (Supplementary Figure 3). After infection, an individual remains in an exposed state (E) for
342 a non-infectious incubation period, which is on average $1/\sigma$ days. Then, the exposed
343 individual (E) becomes asymptomatic (A) or pre-symptomatic (P) with probabilities of
344 $1 - p_{sym}$ and p_{sym} , respectively. The asymptomatic case (A) has a reduced ability to infect
345 others, and is recovered/died (R) after an asymptomatic infectious period, which is on
346 average $1/\hat{\gamma}$ days. Pre-symptomatic case also has a reduced ability to infect others. Pre-
347 symptomatic case (P) becomes symptomatic at a rate ϵ , after which will recover/die at a
348 rate γ . Recovered individuals are assumed to be immunized against re-infection throughout
349 the duration of simulation (3 months). Details about the parameterization are summarized
350 in Supplementary Table 3.

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

356 $\beta = \alpha(d) \Phi(d) + \rho + \xi(d)$. Here $\Phi(d)$ is the daily percentage of people avoiding social
 357 gathering, $\alpha(d)$ the coefficient of $\Phi(d)$, and ρ the intercept at day d . $\xi(d)$ denotes the noise
 358 uniformly distributed between -0.1 and 0.1. To avoid overfitting due to the
 359 multicollinearity between surveyed indicators, we only incorporate the data for the
 360 avoidance of social gathering. We build compartments to model the transitions between
 361 the states: susceptible (S), exposed (E), pre-symptomatic infectious (P), symptomatic
 362 infectious (Y), asymptomatic infectious (A), recovered (R).

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

$$367 \quad S(t + 1) = S(t) - \beta S(t) (\hat{\omega}A(t) + \omega P(t) + Y(t))/N$$

$$368 \quad E(t + 1) = E(t) + \beta S(t) (\hat{\omega}A(t) + \omega P(t) + Y(t))/N - \sigma E(t)$$

$$369 \quad P(t + 1) = P(t) + \sigma p_{sym} E(t) - \epsilon P(t)$$

$$370 \quad A(t + 1) = A(t) + \sigma(1 - p_{sym})E(t) - \hat{\gamma}A(t)$$

$$371 \quad Y(t + 1) = Y(t) + \epsilon P(t) - \gamma Y(t)$$

$$372 \quad R(t + 1) = R(t) + \hat{\gamma}A(t) + \gamma Y(t)$$

373 We estimate the transmission rate β by fitting the daily reported local symptomatic cases ¹⁹
 374 via the Ensemble Adjustment Kalman Filter (EAKF) algorithm ²³ with 10,000 particles. To
 375 account for the reporting delay of local confirmed cases at day \bar{d} , we assume the new
 376 infections $\beta S(t) (\hat{\omega}A(t) + \omega P(t))$ with the proportion p_{sym} following the normal
 377 distribution with mean $I^Y(d + 1/\sigma + 1/\epsilon)$ and standard deviation

378 $\sqrt{\frac{\sum_{i=1}^3 (I^Y(d+1/\sigma+1/\epsilon - i))^2}{10}}$. In our study, we aligned the reconstructed daily time series of
 379 exposed cases to the observed data by 5 days (as $1/\sigma + 1/\epsilon$) to track the new infections.

380 To estimate the outbreak size averted in the fourth wave between 31 October in 2020 and
381 15 January in 2021, we introduce the epidemic model with values of $\alpha^{(d)}$, calibrated by the
382 EAKF algorithm informed by local cases. Accordingly, we estimate the median symptomatic
383 incidence across scenarios with increases in the percentage of people avoiding social
384 gathering per day.

385

386

387

388

389 ***Ethics approval***

390 Data collection and analysis were required by the National Health Commission of the
391 People's Republic of China to be part of a continuing public health outbreak investigation.
392

393 ***Data availability***

394 All data are available in the supplementary materials and will be posted online.
395

396 ***Code availability***

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

Figures

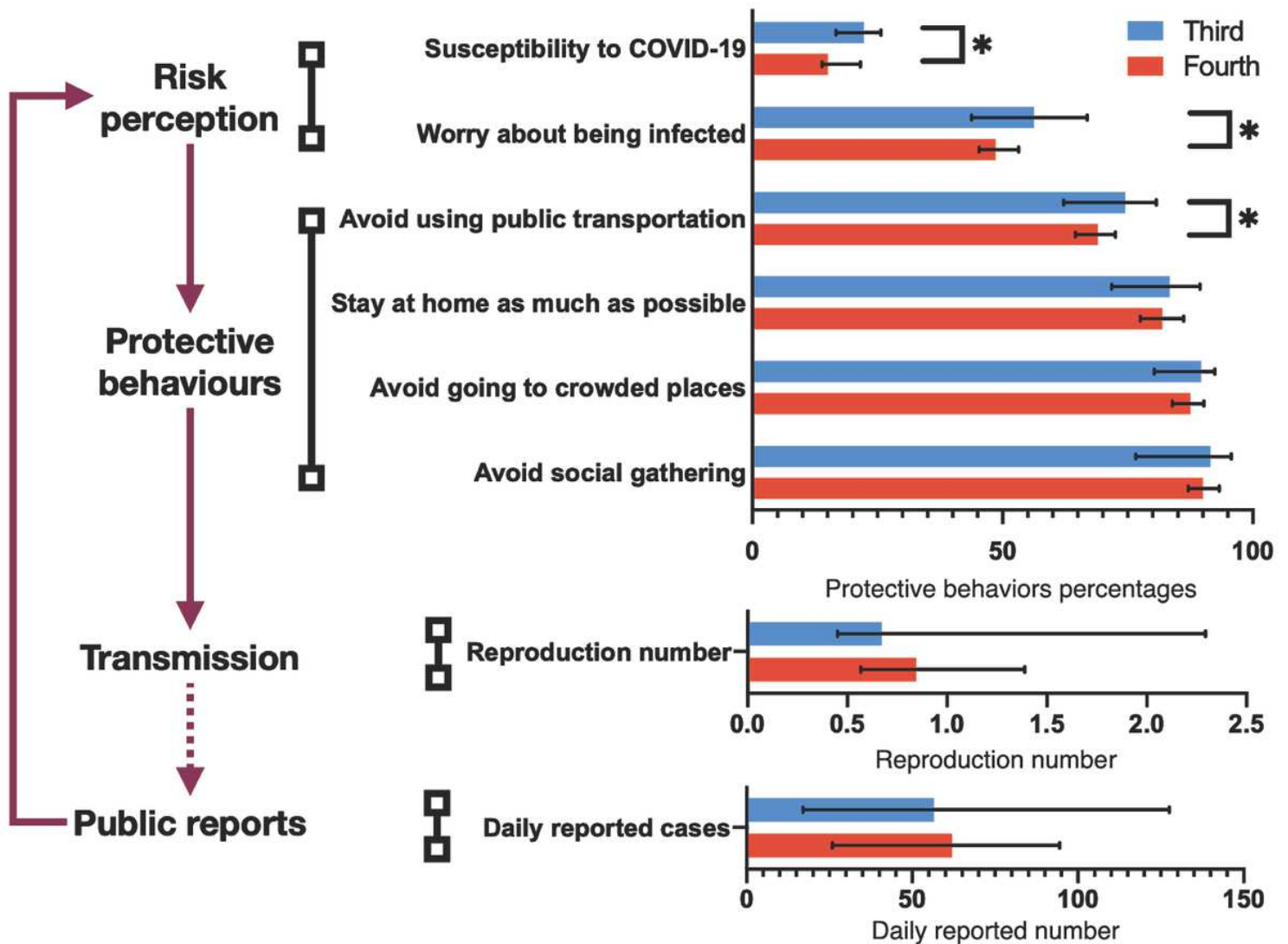


Figure 1

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.

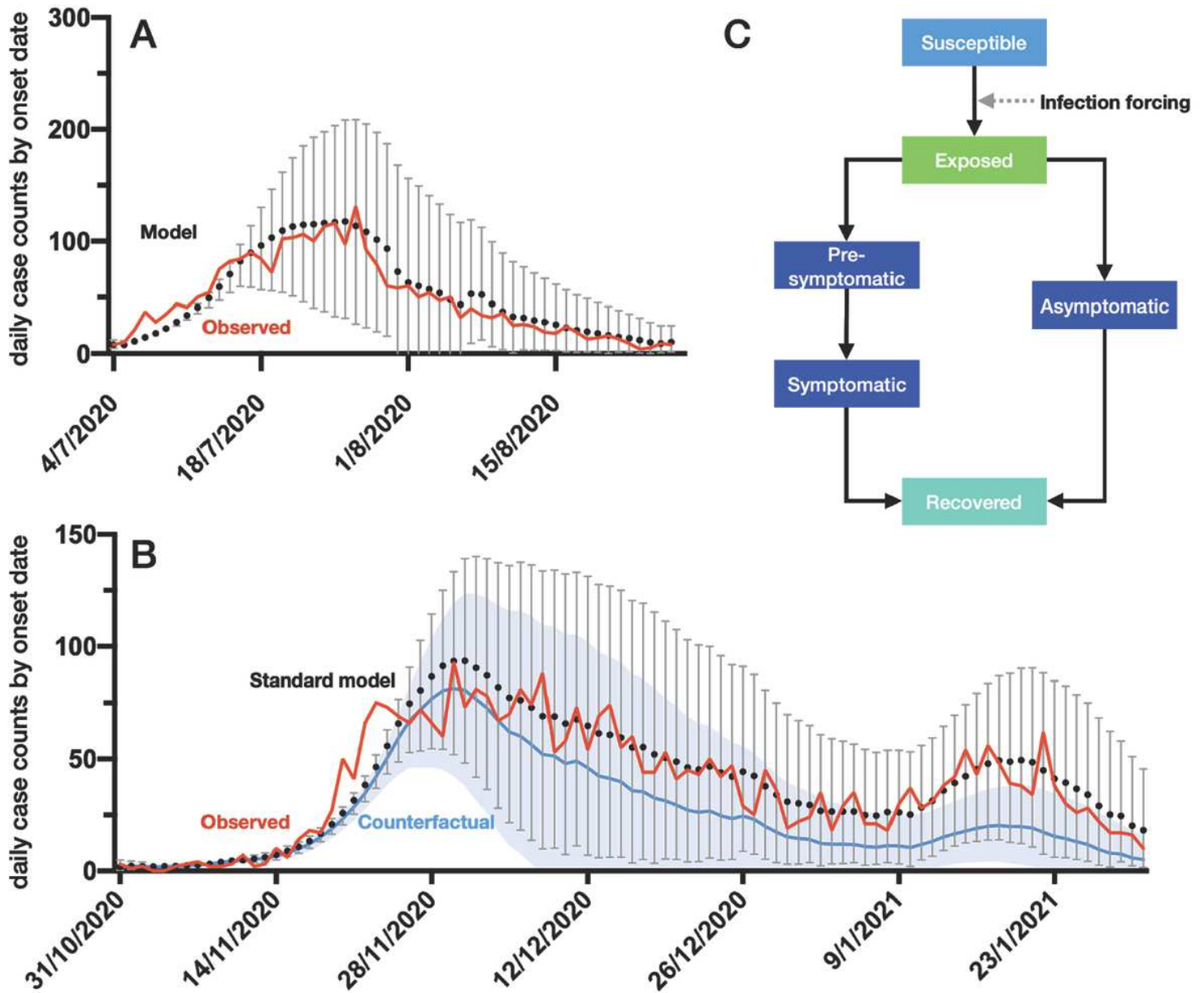


Figure 2

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

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryMaterials.pdf](#)