Preplanned Studies

Characterizing Human Collective Behaviors During COVID-19 — Hong Kong SAR, China, 2020

Zhanwei Du[1]; Xiao Zhang[2]; Lin Wang[3]; Sidan Yao[4]; Yuan Bai[1,2]; Qi Tan[1,2]; Xiaoke Xu[5]; Sen Pei[6]; Jingyi Xiao[1]; Tim K. Tsang[1]; Qiuyan Liao[1]; Eric H. Y. Lau[1,2]; Peng Wu[1,2]; Chao Gao[7,#]; Benjamin J. Cowling[1,2,#]

Summary

What is already known about this topic?

People are likely to engage in collective behaviors online during extreme events, such as the coronavirus disease 2019 (COVID-19) crisis, to express awareness, take action, and work through concerns.

What is added by this report?

This study offers a framework for evaluating interactions among individuals' emotions, perceptions, and online behaviors in Hong Kong Special Administrative Region (SAR) during the first two waves of COVID-19 (February to June 2020). Its results indicate a strong correlation between online behaviors, such as Google searches, and the real-time reproduction numbers. To validate the model's output of risk perception, this investigation conducted 10 rounds of cross-sectional telephone surveys on 8,593 local adult residents from February 1 through June 20 in 2020 to quantify risk perception levels over time.

What are the implications for public health practice?

Compared to the survey results, the estimates of the risk perception of individuals using our network-based mechanistic model capture 80% of the trend of people's risk perception (individuals who are worried about being infected) during the studied period. We may need to reinvigorate the public by involving people as part of the solution that reduced the risk to their lives.

Countries have adopted public health and social measures to control coronavirus disease 2019 (COVID-19) transmission, loss of jobs, education impediments, and other critical social and cultural activities affected during crises (*1*–*3*). During such extreme events, people are likely to engage in a miscellaneous set of behaviors (henceforth collective behavior), such as exchanging information in social situations (*4*). For instance, people are inclined to swiftly spread messages via social media about natural disasters in order to gain more knowledge and decrease unforeseen worries (*5*). Recent studies suggest people would likely similarly share such COVID-19 content on their social media (*6*–*7*).

The first COVID-19 case was confirmed in Hong Kong Special Administrative Region (SAR) on January 22, 2020 (*8*). Since then, Hong Kong has put in place strong measures to prevent COVID-19, including wearing masks in all public areas; the closure of schools, bars and social venues; work-at-home policies; and restaurant disease control measures (*9*). Alongside this, social media has predictably become an all-embracing part of daily life for rapid knowledge dissemination during the isolationism of the COVID-19 pandemic. These platforms have been used by Hong Kong people to, among other uses, express their emotions (e.g., depression) during the pandemic (*10*). To study human collective behaviors during the COVID-19 response, this study evaluates interactions among Hong Kong residents' emotions, perceptions, and behaviors using a network-based mechanistic model that links together external situations of COVID-19 prevalence and social networks (Figure 1A).

This study's stochastic, network-based, agent-based model incorporates environment, agents, local behaviors, and ever-updating rules by combining the mapping between multiagent systems and social networks (*11*). Following external situation reports, individuals perceive risks, experience different emotional reactions, and further change their behaviors — usually by following the strengthening process (i.e., risk perception drives emotional reactions, and emotional reactions affect collective behaviors, Figure 1A). Inversely, resulting behaviors should reduce individuals' emotions (e.g., anxiety and stress) and risk perception.

This study gives a general framework for network-based, agent-based models — extending this study's authors' prior proposed study of collective behaviors during extreme events (*5*). In this framework, each individual has a profile of six attributes, of which one is

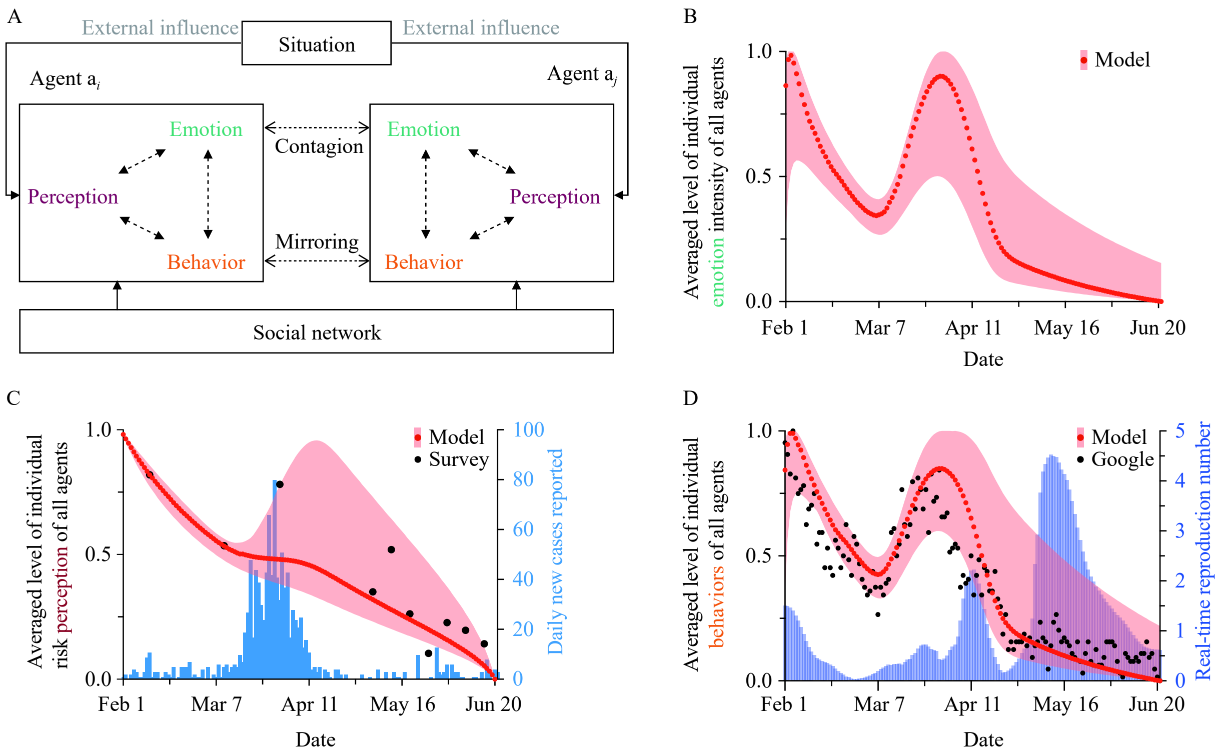

FIGURE 1. Reconstruction of human collective behaviors during the first and second waves of the coronavirus disease 2019 (COVID-19) pandemic in Hong Kong from February 1 to June 20 in 2020, using a human collective behavior model that incorporates daily external situation reports of new infections. (A) Structure of the individual-based model with influences from the external situation and individual-based social networks. (B) Results for daily individual emotional intensity levels. The red dots and shading indicate the median and 95% credibility interval (CrI) of square root of normalized averaged levels of individual emotional intensity across all agents in the model. (C) Results for daily individual risk perception levels. (D) Results for normalized daily search behavior levels.

Note: We projected the daily time series of the observed behaviors of individuals by tracking external situation reports of new infections. In response to the external situation reports, each individual can experience the strengthening process that first changes the perceived risk of infections and then changes the emotional reactions (e.g., anxiety and stress), which in turn leads to the adjustment of protective behaviors. Each individual will also experience the weakening process, in which the changes in protective behaviors can reduce the emotional reactions and perceived risk of infections. Due to daily interactions on social networks (e.g., messaging in Facebook), the emotion and behaviors of an individual can influence the emotions and behaviors of other connected individuals in the network, denoted as emotion contagion and behavior mirroring. These dotted lines denote the interactions of psychological factors within and between individuals. Our human collective behavior model is well matched to the observed time series in our survey data (black dots). The black dots indicate the normalized daily logarithmic percentage of individuals who are worried about being infected in our survey to indicate people's risk perception in Hong Kong. The red dots and shading indicate the median and 95% CrI of normalized averaged levels of individual risk perception across all agents in the model. The blue bars indicate daily new cases reported in Hong Kong. Our human collective behavior model incorporating the interactions among agents is well fitted to the observed time series data (black dots). The black dots indicate the observation of normalized daily Google search behaviors of residents in Hong Kong. The red dots and shading indicate the median and 95% CrI of averaged levels of individual behaviors across all agents in the model.

individual behavior, two psychological factors (emotional intensity and risk perception) and three intrinsic characteristics (personality characteristics, open level, and expression level). This study then projected the population-scale human collective behaviors by the overall behaviors of all agents in the study's multiagent system. More details of methods and data can be found in the Supplementary Material (available in http://weekly.chinacdc.cn). Lastly, although this study analyzed the model with a focus on Hong Kong, the results can be applied to other cities in general. All analyses were conducted by Matlab software (version R2020a, The MathWorks Inc., Natick, MA, USA).

Following reports of external situations, individuals perceive modified risks, experience different emotional reactions, and change their behaviors. Those resulting protective behaviors inversely reduce people's anxiety and perceptions of susceptibility, resulting in less decreases in perceived risk during March and April 2020 (Figure 1C and D). This study then projected the daily time series of the observed behaviors of individuals by tracking external situation reports of new infections (Figure 1B–D). When comparing observed behaviors of Google search data, this study's human collective behavior model incorporating the interactions among agents is well fitted. About 79% of the observed Google search data are included in the 95% credibility interval (CrI) ranging of normalized averaged levels of individual behaviors across all agents in the model (Figure 1D). The Pearson's linear correlation coefficient between the real-time reproduction number (R_t) and the averaged levels of individual behaviors is −0.40 with a P-value of 0.0001. After the individual behavior reached its bottom, R_t began to increase after April 23, 2020.

To validate the model output of risk perception, this investigation conducted 10 rounds of cross-sectional telephone surveys from February 1 through June 20 in 2020. A total of 8,593 local adult residents have been interviewed via these surveys (Supplementary Material). Such large-scale longitudinal data provides an opportunity to quantify risk perception levels over time. This study estimates the daily time series of the risk perception of individuals using the network-based mechanistic model informed by external situation reports of new infections. Compared to the survey results, the estimated values of median and 95% CrI capture 80% (8 out of 10 surveys) of the trend of people's risk perception (individuals who worried about being infected) during the studied period (Figure 1C). The average level of individual risk perception continues to decrease, but slows down as case numbers start to soar in March 2020.

DISCUSSION

Hong Kong has been following a zero-COVID strategy, through which it has implemented stringent social distancing measures (including unprecedented movement restrictions, quarantines on inbound travellers, universal masking, closure of schools, bars and social venues, work-at-home policies, and restaurant measures) to curb COVID-19 transmission since January 2020 and bring case numbers down to low levels in each wave (*9*,*12*–*13*). Given the continued threat of COVID-19 in Hong Kong (*14*), pandemic fatigue is a natural response due to the complex interplay of cultural and social factors (e.g., the risk perception of threats) (*15*–*18*), which has been observed in many countries (*19*–*22*). This study's results of decreasing individual risk perception indicate that the gradual emergence of pandemic fatigue in Hong Kong arose as demotivation from a series of related behaviors.

The theory behind this study is the interplay of human psychological factors and external influences on psychological factors, as indicated in Figure 1 (*5*). This study has several limitations. First, it analyzed self-reported behavior but did not validate this against actual behaviors — although self-reported surveys have been widely used to study human behavior, such as contact patterns (*23*) and hospital attendance (*24*). Second, this study focuses on the period of the first two waves in Hong Kong, which are taken as extreme events, rather than subsequent waves. Informed by the daily Google search interest in Google Trend for COVID-19 in Hong Kong, this study finds it has decreased 20% to 50% on average since the third wave, perhaps due to people having gained enough knowledge and having gotten used to the COVID-19 situation. Third, other social activities may affect the risk perception and protective behaviors. Prolonged financial stress due to job loss, mask costs, and the distrust of governmental policies may also contribute to the emergence of pandemic fatigue in the studied period. Fourth, the risk perception is represented in this study by the proportion of weekly surveyed residents who are beyond moderately worried, while in reality, it is a complex concept involving many emotions-including anxiety, depression, post-traumatic stress disorder, and psychological stress triggered by extreme events (e.g., COVID-19, weather disasters) (*25*–*26*). Importantly, excepting worry, other sentiments related to risk perception may have different temporal dynamics and attributes. This study caveats researchers to be cautious about their conclusions when using the framework in this study. Fifth, this study runs 100 stochastic simulations and uses medians of risk perception across all agents across simulations to calibrate the model (Supplementary Material, section parameter calibration). More simulations may have a direct impact on the range of simulation outputs, but a limited impact on the medians. As such, this study reminds researchers to be careful when they use the range of the study model, rather than only medians. Despite these limitations, the close matching of model output with human collective behavior of Google search data and surveyed risk perception data suggests that the capacity of individual-based human collective behavior model in capturing the actual population behaviors.

The current socio-political and economic dilemma caused by a pandemic call for decision-makers to focus beyond the number of cases reported. The fluctuation of human collective behaviors online reflects people's social, emotional, and mental health needs, impacted by external situations. To maintain people's risk perception of COVID-19 on a high level, global leadership may need to reinvigorate the public by engaging people as part of the solution, understanding their needs, acknowledging their hardship, and empowering them to live their lives with reduced risk (*19*,*27*).

Conflicts of interest: BJC consults for AstraZeneca, Fosun Pharma, GlaxoSmithKline, Moderna, Pfizer, Roche and Sanofi Pasteur. BJC is supported by the AIR@innoHK program of the Innovation and Technology Commission of the Hong Kong SAR Government. No other conflicts of interest reported.

Funding: Supported by the Key Program for International Science and Technology Cooperation Projects of China (No. 2022YFE0112300), AIR@InnoHK administered by Innovation and Technology Commission of the Research Grants Council of the Hong Kong SAR Government, the Health and Medical Research Fund, Food and Health Bureau, Government of the Hong Kong Special Administrative Region (Grant No. COVID190118, 21200632), the Research Grants Council of the Hong Kong Special Administrative Region, China (GRF 17110221), National Natural Science Foundation of China (Grant No. 72104208). The weekly telephone surveys were supported by the Government of the Hong Kong Special Administrative Region.

doi: 10.46234/ccdcw2023.014

[#] Corresponding authors: Benjamin J. Cowling, bcowling@hku.hk; Chao Gao, cgao@nwpu.edu.cn.

[1] WHO Collaborating Centre for Infectious Disease Epidemiology and Control, School of Public Health, Li Ka Shing Faculty of Medicine, The University of Hong Kong, Hong Kong Special Administrative Region, China; [2] Laboratory of Data Discovery for Health, Hong Kong Science and Technology Park, New Territories, Hong Kong Special Administrative Region, China; [3] Department of Genetics, University of Cambridge, Cambridge, CB2 3EH, UK; [4] Institute of High Performance Computing (IHPC), Agency for Science, Technology and Research (A*STAR), Singapore; [5] College of Information and Communication Engineering, Dalian Minzu University, Dalian City, Liaoning Province, China; [6] Department of Environmental Health Sciences, Mailman School of Public Health, Columbia University, New York City, NY, USA; [7] School of Artificial Intelligence, Optics, and Electronics (iOpen), Northwestern Polytechnical University, Xi'an City, Shaanxi Province, China.

Submitted: October 08, 2022; Accepted: January 11, 2023

REFERENCES

1. World Health Organization. Survey tool and guidance: rapid, simple, flexible behavioural insights on COVID-19. 2020. https://www.medbox.org/document/survey-tool-and-guidance-rapid-simple-flexible-behavioural-insights-on-covid-19#GO. [2023-1-9].
2. Bai Y, Xu MD, Liu CF, Shen MW, Wang L, Tian LW, et al. Travel-related importation and exportation risks of SARS-CoV-2 Omicron variant in 367 prefectures (cities) — China, 2022. China CDC Wkly 2022;4(40):885 – 9. http://dx.doi.org/10.46234/ccdcw2022.184.
3. Bai Y, Du ZW, Xu MD, Wang L, Wu P, Lau EHY, et al. International risk of SARS-CoV-2 Omicron variant importations originating in South Africa. J Travel Med 2022;29(6):taac073. http://dx.doi.org/10.1093/jtm/taac073.
4. Adar E, Weld DS, Bershad BN, Gribble SS. Why we search: visualizing and predicting user behavior. In: Proceedings of the 16th international conference on world wide web (WWW'07). ACM, 2007;161-70. http://dx.doi.org/10.1145/1242572.1242595.
5. Gao C, Liu JM. Network-based modeling for characterizing human collective behaviors during extreme events. IEEE Trans Syst Man Cybern: Syst 2017;47(1):171 – 83. http://dx.doi.org/10.1109/TSMC.2016.2608658.
6. World Health Organization. Social media & COVID-19: a global study of digital crisis interaction among Gen Z and Millennials. 2021. https://www.who.int/news-room/feature-stories/detail/social-media-covid-19-a-global-study-of-digital-crisis-interaction-among-gen-z-and-millennials. [2023-1-9].
7. Tsao SF, Chen H, Tisseverasinghe T, Yang Y, Li LH, Butt ZA. What social media told us in the time of COVID-19: a scoping review. Lancet Digit Health 2021;3(3):e175 – 94. http://dx.doi.org/10.1016/S2589-7500(20)30315-0.
8. CHP investigates highly suspected imported case of novel coronavirus infection. 2020. https://www.info.gov.hk/gia/general/202001/22/P2020012200982.htm. [2023-1-9].
9. The government of the Hong Kong special administrative region. Together, we fight the virus. https://www.coronavirus.gov.hk/eng/index.html. [2023-1-9].
10. Yang X, Yip BHK, Mak ADP, Zhang DX, Lee EKP, Wong SYS. The differential effects of social media on depressive symptoms and suicidal ideation among the younger and older adult population in Hong Kong during the COVID-19 pandemic: population-based cross-sectional survey study. JMIR Public Health Surveill 2021;7(5):e24623. http://dx.doi.org/10.2196/24623.
11. Jiang YC, Hu J, Lin DH. Decision making of networked multiagent systems for interaction structures. IEEE Trans Syst Man Cybern Part A: Syst Humans 2011;41(6):1107 – 21. http://dx.doi.org/10.1109/TSMCA.2011.2114343.
12. Du ZW, Wang CY, Liu CF, Bai Y, Pei S, Adam DC, et al. Systematic review and meta-analyses of superspreading of SARS-CoV-2 infections. Transbound Emerg Dis 2022;69(5):e3007 – 14. http://dx.doi.org/10.1111/tbed.14655.
13. Du ZW, Wang SQ, Bai Y, Gao C, Lau EHY, Cowling BJ. Within-host dynamics of SARS-CoV-2 infection: a systematic review and meta-analysis. Transbound Emerg Dis 2022. http://dx.doi.org/10.1111/tbed.14673.
14. Wang SQ, Zhang FD, Wang Z, Du ZW, Gao C. Reproduction numbers of SARS-CoV-2 Omicron subvariants. J Travel Med 2022;29(8):taac108. http://dx.doi.org/10.1093/jtm/taac108.
15. Morrison M, Parton K, Hine DW. Increasing belief but issue fatigue: changes in Australian Household Climate Change Segments between 2011 and 2016. PLoS One 2018;13(6):e0197988. http://dx.doi.org/10.1371/journal.pone.0197988.
16. Masten AS, Motti-Stefanidi F. Multisystem resilience for children and youth in disaster: reflections in the context of COVID-19. Adv Res Sci 2020;1(2):95 – 106. http://dx.doi.org/10.1007/s42844-020-00010-w.

17. Du ZW, Wang L, Shan SW, Lam D, Tsang TK, Xiao JY, et al. Pandemic fatigue impedes mitigation of COVID-19 in Hong Kong. Proc Natl Acad Sci USA 2022;119(48):e2213313119. http://dx.doi.org/10.1073/pnas.2213313119.
18. Gao C, Liu JM. Uncovering spatiotemporal characteristics of human online behaviors during extreme events. PLoS One 2015;10(10):e0138673. http://dx.doi.org/10.1371/journal.pone.0138673.
19. Habersaat KB, Scheel AE. Pandemic fatigue - Reinvigorating the public to prevent COVID-19. World Health Organization-Regional Office for Europe. 2020. https://www.preventionweb.net/publications/view/74208. [2023-1-9].
20. Ilesanmi OS, Bello AE, Afolabi AA. COVID-19 pandemic response fatigue in Africa: causes, consequences, and counter-measures. Pan Afr Med J 2020;37(Suppl 1):37. http://dx.doi.org/10.11604/pamj.supp.2020.37.37.26742.
21. World Health Organization. Statement - Rising COVID-19 fatigue and a pan-regional response. 2020. https://www.who.int/europe/news/item/06-10-2020-statement-rising-covid-19-fatigue-and-a-pan-regional-response. [2023-1-9].
22. Crane MA, Shermock KM, Omer SB, Romley JA. Change in reported adherence to nonpharmaceutical interventions during the COVID-19 pandemic, April-November 2020. JAMA 2021;325(9):883 – 5. http://dx.doi.org/10.1001/jama.2021.0286.
23. Mossong J, Hens N, Jit M, Beutels P, Auranen K, Mikolajczyk R, et al. Social contacts and mixing patterns relevant to the spread of infectious diseases. PLoS Med 2008;5(3):e74. http://dx.doi.org/10.1371/journal.pmed.0050074.
24. Hegde ST, Salje H, Sazzad HMS, Hossain MJ, Rahman M, Daszak P, et al. Using healthcare-seeking behaviour to estimate the number of Nipah outbreaks missed by hospital-based surveillance in Bangladesh. Int J Epidemiol 2019;48(4):1219 – 27. http://dx.doi.org/10.1093/ije/dyz057.
25. Yu SB, Eisenman D, Han ZQ. Temporal dynamics of public emotions during the COVID-19 pandemic at the epicenter of the outbreak: sentiment analysis of weibo posts from Wuhan. J Med Internet Res 2021;23(3):e27078. http://dx.doi.org/10.2196/27078.
26. Han ZQ, Shen MF, Liu HB, Peng YF. Topical and emotional expressions regarding extreme weather disasters on social media: a comparison of posts from official media and the public. Humanit Soc Sci Commun 2022;9(1):421. http://dx.doi.org/10.1057/S41599-022-01457-1.
27. Du ZW, Tian LW, Jin DY. Understanding the impact of rapid antigen tests on SARS-CoV-2 transmission in the fifth wave of COVID-19 in Hong Kong in early 2022. Emerg Microbes Infect 2022;11(1):1394 – 401. http://dx.doi.org/10.1080/22221751.2022.2076616.

SUPPLEMENTARY MATERIAL

Data

Epidemic data. This study collected the daily data of all newly confirmed coronavirus cases (by reporting date) in Hong Kong from January 31 to June 28, 2020 (*1*) to denote the impact of external situations on Hong Kong residents.

Google search data. This study collected the daily data of search interest for the disease of COVID-19 in Hong Kong during the period of January 31 to June 28, 2020 from Google Trend (*2*) using URL (https://trends.google.com/trends/explore?geo=HK&q=coronavirus) to denote the online behavior dynamics of Hong Kong residents. This study normalized the daily values between 0 and 1 and used them for model parameter calibration.

Survey data. In each monthly/weekly survey from February 1 to June 20 in 2020, this study contacted either 500 or 1,000 local residents through random digit dialing of landlines and mobile telephones (using age, gender, education, and employment information to weight response frequencies relative to the adult population in Hong Kong) (*3*). Then, 8,593 local residents were interviewed through these 10 cross-sectional telephone surveys. During these calls, this study asked each participant about their perception of the risk of being infected by COVID-19. Specifically, to assess the risk perception, participants were asked whether they were worried about being infected with COVID-19 (with a spectrum of response options including: not at all, mildly, moderately, very much, and extremely worried). Then, this study defined the overall risk perception each week as the proportion of weekly surveyed residents who are beyond moderately worried.

Methods

General formulation for modeling collective behaviors. Combining the mapping between multiagent systems and social networks (*4*), we extend multiagent systems to a network-based agent-based model, which contains three basic parts: 1) an environment for both serving as a platform and communication channels for agents, 2) autonomous agents that react to each other in their local environment based on local behaviors and updating rules involved in their own decision-making process, following the general framework of collective behaviors during extreme events (*5*).

Modeling human responses, especially two types of feedback loops underlying the decision-making process in an uncertain environment, is an open and non-equilibrium system. Through implicitly incorporating certain global influences or biases (e.g., uncertainty reduction theory in our study) into local behaviors, the whole system can achieve a desired global state (i.e., collective regulation of information-related behaviors and anxious emotion in our study). Here, we would highlight the effects of two conditions on collective regulation based on the methodology of complex behavior characterization.

As a sufficient condition to realize self-organized computation, agents should implicitly incorporate certain global influences into local autonomy. When agents perform certain behaviors in an uncertainty situation, their profiles (measured by parameters) can be dynamically updated based on the interactions with other agents. Each local agent $a_i$makes a decision for a certain behavior in terms of a design-making mechanism for each neighbor of a_i. Before a_i makes a decision, it will first estimate the influences from its neighbors a_j because of the content diffusion. Then, a_i makes a decision by aggregating all impact factors in order to implement the exploit or explore behaviors with different probabilities based on their own decision-making mechanism.

Modeling collective behaviors during extreme events. Following external situation reports, individuals perceive risks, experience different emotional reactions, and further affect their behaviors following the strengthening process. Inversely, resulting behaviors would reduce individuals' emotions (e.g., anxiety and stress) and risk perception, with respect to the weakening process.

In our case study of Hong Kong, we consider 1,000 agents with weighted links. Each agent has a profile of six attributes, including individual behavior (*IB*), emotional intensity (*EI*), risk perception (*RP*), personality characteristic (*PC*), open level (*OL*) and expression level (*EL*), represented by $ib_i(t)$, $ei_i(t)$, $rp_i(t)$, $pc_i(t)$, $ol_i(t)$, and $el_i(t)$, respectively, which are all in the range between 0 and 1 for agent a_i at time step t. Agent a_i with larger $ib_i(t)$ and $ei_i(t)$ would perform more behaviors and emotions to other agents respectively. $rp_i(t)$ indicates how sensitive agent a_i is to external situation at time step t. $pc_i(t)$, $ol_i(t)$, and $el_i(t)$ characterize how much this agent would weaken the impact of negative information, be impacted by other agents, and affect others, respectively. The collective responses, represented by $ib_c(t)$, $ei_c(t)$, and $rp_c(t)$ at time step t, denote the mean estimates of $ib_i(t)$, $ei_i(t)$, and $rp_i(t)$ of all agents.

Given IB and EI have the same updating equations, we use S to denote IB or EI, and s to represent the ib or ei. Agents are affected by the local environment/social network (denoted as F_{SN}) and the psychological mechanism after obtaining the latest public news (denoted as F_{PM}). The agent a_i is updated over time by

$$s_i(t+1) = \eta F_{\mathrm{SN}}(s_i(t)) + (1-\eta) F_{\mathrm{PM}}(s_i(t)), \tag{1}$$

$$F_{\mathrm{SN}}(s_i(t)) = \sum_{j \neq i} w_{ij} \times \left[f(\bar{s}_i(t), s_i(t)) - s_i(t)\right], \tag{2}$$

where η is a scaling factor. w_{ij} indicates the link weight between agents a_i and a_j. $\bar{s}_i(t)$ represent the normalized diffusion strength of the neighbors of agent a_i at time step t, estimated by

$$\bar{s}_i(t) = \frac{\sum_{j \neq i} w_{ij} \times s_j(t)}{\sum_{j \neq i} w_{ij}}. \tag{3}$$

The coupling function $f(\bar{s}_i(t), s_i(t))$ is typically used to estimate the influence of selective parameters on a decision-making process (*6*):

$$f(\bar{s}_i(t), s_i(t)) = rp_i(t) \times [1 - (1-\bar{s}_i(t)) \times (1 - s_i(t))] + (1 - rp_i(t)) \times \bar{s}_i(t) \times s_i(t). \tag{4}$$

$F_{\mathrm{PM}}(ib_i(t+1))$ and $F_{\mathrm{PM}}(ei_i(t+1))$ are estimated by:

$$F_{\mathrm{PM}}(ib_i(t+1)) = \sqrt{ib_i(t-1)}\left[1 - (1 - I(u)) \times (1 - ei_i(t)) \times (1 - rp_i(t))\right], \tag{5}$$

$$F_{\mathrm{PM}}(ei_i(t+1)) = \sqrt{ei_i(t-1)}\left[1 - (1 - I(u)) \times ib_i(t) \times (1 - rp_i(t))\right], \tag{6}$$

where $u = (r(t))^{\beta}$ and β is a scaling factor. Higher RP and external influence $I(u)$ denote the impact of public reports $r(t)$ on agents, thus capturing the gradually unfolding COVID-19 events in the studied period. We give the square root to $ib_i(t-1)$ and $ei_i(t-1)$, resulting in better fitting performance than not. $I(u)$ is given by:

$$I(u) = \frac{\ln(1+\lambda u)}{1+\lambda}. \tag{7}$$

The RP of agents is affected by EI and the external related information and the constant ν is used to measure the weight of these two factors. $rp_i(t+1)$ is updated as:

$$rp_i(t+1) = (1-\nu) F_{rp} + \nu \frac{1}{1 + e^{-\delta(ei_i(t) - \tau)}} F_{rp}, \tag{8}$$

where the value of the second part of the formula will rise rapidly when $ei_i(t)$ exceeds the threshold τ. The F_{rp} is used to measure the impact of external information on the RP of agent a_i. $I(u)$ would increase individuals' risk perception and reduce uncertainty of extreme events. And pessimists (i.e., pc_i is low) will amplify the impact of negative public news (i.e., p is low), and vice versa. F_{rp} is therefore expressed as follows:

$$F_{rp} = rp_i(t) \times \left[1 - ib_i(t) \times (1 - I(u)) \times \left(1 - pc_i \times p - (1 - pc_i) \times (1 - p)\right)\right]. \tag{9}$$

The strengthening and weakening processes are reflected by the positive and negative relationships in the above equations.

Parameter calibration. To reduce the impact of data noise, we would fit a curve $r_f(t)$ from model to the external situation reports following ref. (*2*). To introduce the stochasticity into simulations, $r_f(t)$ is based on $r(t)$ with random noise following the uniform distribution $u(-\phi, \phi)$:

$$r_f(t) = r(t) + u(-\phi, \phi). \tag{10}$$

We ran 100 simulations, each with a different time series of $r(t)$ following this sampling method. β is chosen as the best value of resulting in the least root mean square deviation between the normalized daily Google search behaviors in Hong Kong and the medians of normalized averaged levels of individual risk perception across all agents across 100 stochastic simulations. ϕ is chosen as 0.14 by experience to balance the width of 95% CrI of individual behaviors in the model.

REFERENCES

1. Our World in Data. Coronavirus (COVID-19) cases. http://ourworldindata.org/covid-cases. [2023-1-9].
2. Google. Google trends. https://trends.google.com/trends/explore?date=2020-01-31%202020-06-28&geo=HK&q=%2Fm%2F01cpyy. [2023-1-9].
3. Cowling BJ, Ali ST, Ng TWY, Tsang TK, Li JCM, Fong MW, et al. Impact assessment of non-pharmaceutical interventions against coronavirus disease 2019 and influenza in Hong Kong: an observational study. Lancet Public Health 2020;5(5):e279 – 88. http://dx.doi.org/10.1016/S2468-2667(20)30090-6.
4. Jiang YC, Hu J, Lin DH. Decision making of networked multiagent systems for interaction structures. IEEE Trans Syst Man Cybern Part A: Syst Humans 2011;41(6):1107 – 21. http://dx.doi.org/10.1109/TSMCA.2011.2114343.
5. Gao C, Liu JM. Network-based modeling for characterizing human collective behaviors during extreme events. IEEE Trans Syst Man Cybern: Syst 2017;47(1):171 – 83. http://dx.doi.org/10.1109/TSMC.2016.2608658.
6. Lanham MJ, Morgan GP, Carley KM. Social network modeling and agent-based simulation in support of crisis de-escalation. IEEE Trans Syst Man Cybern: Syst 2014;44(1):103 – 10. http://dx.doi.org/10.1109/TSMCC.2012.2230255.