Predicting onset risk of COVID-19 symptom to support healthy travel route planning in the new normal of long-term coexistence with SARS-CoV-2

Chengzhuo Tong, Wenzhong Shi and Anshu Zhang
Otto Poon Charitable Foundation Smart Cities Research Institute and Department of Land Surveying and Geo-Informatics, The Hong Kong Polytechnic University, Hong Kong, China

Zhicheng Shi
Research Institute for Smart Cities, School of Architecture and Urban Planning, Shenzhen University, China

Abstract
Due to the increased outdoor transmission risk of new SARS-COV-2 variants, the health of urban residents in daily travel is being threatened. In the new normal of long-term coexistence with SARS-CoV-2, how to avoid being infected by SARS-CoV-2 in daily travel has become a key issue. Hence, a spatiotemporal solution has been proposed to assist healthy travel route planning. Firstly, an enhanced urban-community-scale geographic model was proposed to predict daily COVID-19 symptom onset risk by incorporating the real-time effective reproduction numbers, and daily population variation of fully vaccinated. On-road onset risk predictions in the next following days were then extracted for searching healthy routes with the least onset risk values. The healthy route planning was further implemented in a mobile application. Hong Kong, one of the representative highly populated cities, has been chosen as an example to apply the spatiotemporal solution. The application results in the four epidemic waves of Hong Kong show that based on the high accurate prediction of COVID-19 symptom onset risk, the healthy route planning could reduce people's exposure to the COVID-19 symptoms onset risk. To sum, the proposed solution can be applied to support the healthy travel of residents in more cities in the new normalcy.

Keywords
healthy route planning, COVID-19, onset risk, spatiotemporal prediction

Corresponding author:
Wenzhong Shi, Otto Poon Charitable Foundation Smart Cities Research Institute and Department of Land Surveying and Geo-Informatics, The Hong Kong Polytechnic University, 181 Chatham Road South, Hung Hom, Hong Kong, China.
Email: john.wz.shi@polyu.edu.hk

Introduction

The COVID-19 pandemic has dealt a severe blow to global cities, with 90% of infections occurring in urban areas (Acuto et al., 2020). The accelerated COVID-19 vaccination has been enforced in global cities to contain further SARS-CoV-2 transmissions (Assiri et al., 2021; Batista et al., 2021; Castillo et al., 2021; Sah et al., 2021). However, the emergence and spread of SARS-CoV-2 variants (e.g. Omicron, Delta) may erode vaccine efficacy, potentially compromising efforts to control the pandemic (Harder et al., 2021; Khan et al., 2022). Under the new normal of long-term coexistence with SARS-CoV-2, global cities need more than ever to resort to advanced technology to help urban residents avoid being infected by SARS-CoV-2 while improving their daily travel (Jiang et al., 2021; Yue et al., 2021). According to a survey conducted in 7 countries including China and the United States, reducing the risk of infections is the priority for daily travel in the new normal, overtaking even destination time in importance (McKinsey & Company, 2020). Therefore, how to avoid the SARS-CoV-2 infection during daily travel to protect the health of residents has become a key issue.

In response to these above issues, based on the enhanced risk prediction of COVID-19 symptoms onset, a spatiotemporal solution was proposed to provide healthy route planning with the least exposure of COVID-19 symptoms onset risk for the daily travel of the public.

In order to assist people in healthy travel planning, it is necessary to be able to predict and identify the spatiotemporal risk hotspots of COVID-19 (Ghosh and Cartone, 2020; Sharifi and Khavarian-Garmsir, 2020). Since the outbreak of COVID-19, a series of studies on predicting and identifying risk hotspots have emerged (Das et al., 2021; Guo et al., 2021; Islam et al., 2021; Lak et al., 2021; Sannigrahi et al., 2020). For example, Jia et al. used a spatiotemporal risk source model to identify the areas within high transmission risk and statistically derive the geographical spread and growth pattern of COVID-19 in China (Jia et al., 2020). Feng et al. further compared transmission paths, outbreaks timelines and coping strategies of COVID-19 in China and the US (Feng, Z et al., 2020). It is helpful to understand the spatiotemporal characteristics, development dynamics and actual processes of COVID-19 in different countries. Moreover, Ma et al. explored the spatiotemporal clustering pattern and hot spots of COVID-19 cases at the city level (Ma et al., 2021).

The above-mentioned studies have improved our understanding of the spatiotemporal transmission dynamics of COVID-19. However, there are still three shortcomings that need to be resolved. A major shortcoming is that only a few studies have taken into account the effects of changes in the transmission capacity of new SARS-CoV-2 variants when estimating the spatiotemporal spread of COVID-19. Estimates of the growth rate, disease severity and impact of new SARS-CoV-2 variants are crucial in the new normal (Franceschi et al., 2021). Moreover, the existing research mainly focused on the city or regional scale (Bollen et al., 2021; Davies et al., 2021). Few studies considered the transmission of new SARS-CoV-2 variants at the community level. In addition, most existing models make predictions and analyses based on the diagnosis date (i.e. the date on which the cases are confirmed) in historical data. It has been found that COVID-19 patients are at their most infectious during the first week after the symptom onset (He et al., 2020; Kawasuji et al., 2020). Thus, if using findings based purely on the COVID-19 diagnosis dates, as opposed to the date of symptom onset, the key period for enabling the prevention of further COVID-19 infections may be missed. Therefore, in this study, to achieve a more accurate prediction for assisting healthy daily travel, it is necessary to adopt appropriate data-driven models and combine the new characteristics of COVID-19 transmission to analyse its transmission trends at the community level.

Shi et al. developed intercity-scale and urban-community-scale extended weighted kernel density estimation (WKDE) models to predict spatiotemporal COVID-19 symptom onset risk (Shi et al., 2021). The models perform retrospective analysis based on the spatiotemporal information of onset cases to predict the distribution of onset risk in terms of a future date. According to the transmission law of COVID-19, the dynamic human mobility data was introduced into the models to improve the accuracy

of prediction. The extended WKDE model predicts the COVID-19 symptom onset risk effectively and provides competitive advantages based on (Shi et al., 2021): (i) high viral load and transmissibility around the date of symptom onset and (ii) the delay between the onset dates and subsequent confirmation report dates. Therefore, the tracking of the COVID-19 symptom onset better reflects at the community level rather than the tracking COVID-19 confirmation.

However, the WKDE model at the urban-community-scale needs further improvement as regarding the new normal of long-term coexistence with SARS-CoV-2: (i) the protection from vaccination; (ii) the transmissibility of different SARS-COV-2 variants; and (iii) control measures and behaviour changes. As a result, this study enhanced the urban-community-scale WKDE model by introducing (i) the real-time effective reproduction number for local cases R_t (Shi et al., 2021) and (ii) the number V(t) of daily vaccinators who receive full protection.

The newly enhanced urban-community-scale WKDE model has been applied to predict the risk of COVID-19 symptom onset in each of the 291 tertiary planning units (TPUs) in Hong Kong (Figure 1). On-road onset risk prediction results were then extracted to assist the planning of healthy routes with the least COVID-19 symptom onset risk. The study was conducted based on a spatiotemporal dataset of 7184 local onset cases with community-level locations in Hong Kong from 18 January 2020 to 22 April 2021, including all four epidemic waves of COVID-19 epidemics in Hong Kong so far, caused by different SARS-CoV-2 variants, respectively.

Methods

Data sources

In addition to asymptomatic cases, imported cases under mandatory quarantine, and cases with unknown location information, a total of 7184 local onset cases from 18 January 2020 to 22 April
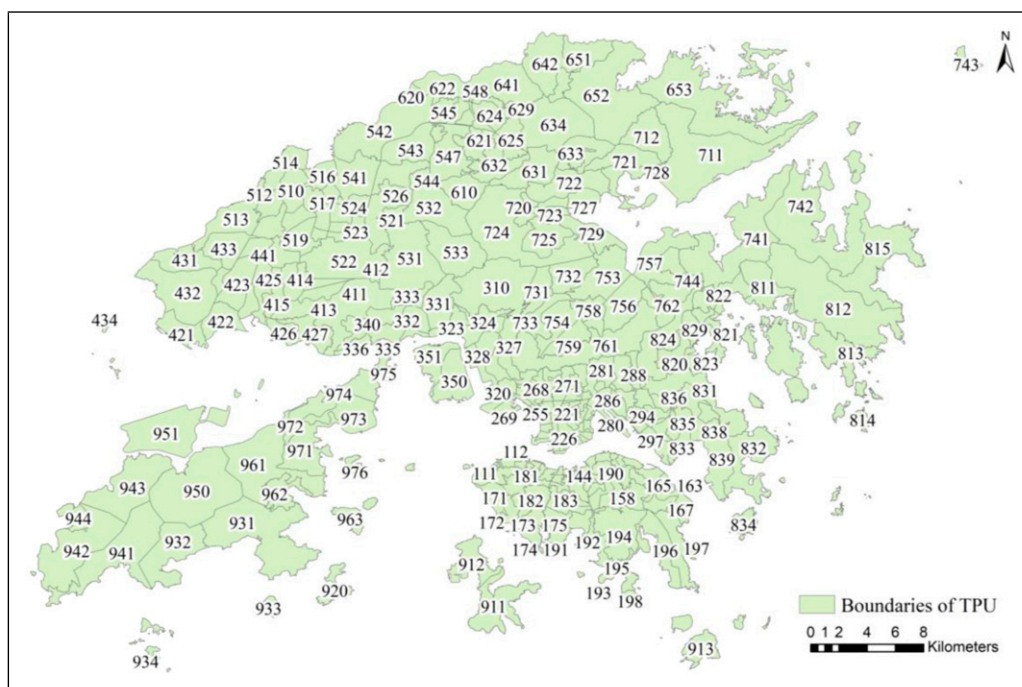

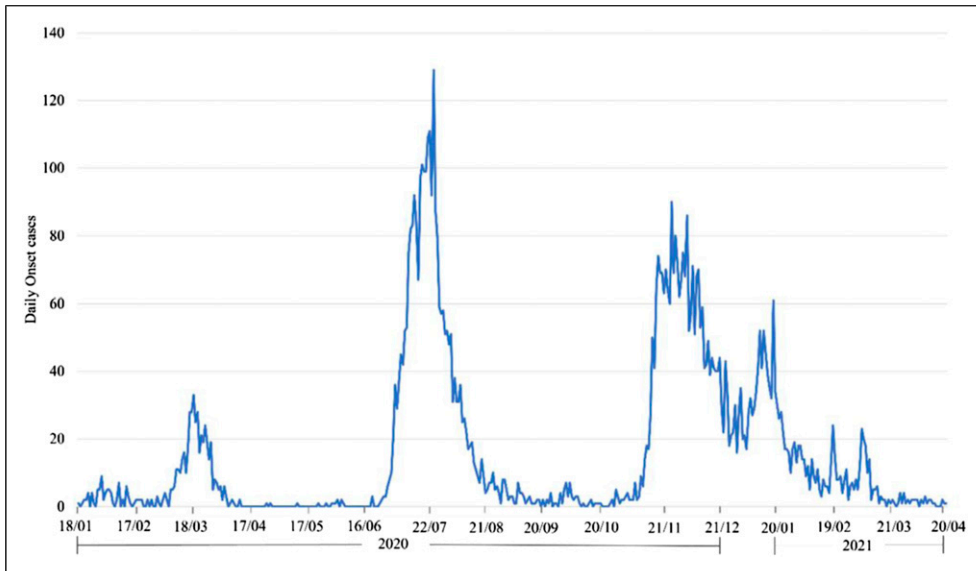**Figure 1.** The boundaries of 291 TPUs in Hong Kong.

Figure 2. The daily variation in COVID-19 symptom onset cases (The Centre for Health Protection, 2021) in Hong Kong from 18 January 2020 to 22 April 2021.

2021 have been used in this study (The Centre for Health Protection, 2021) (Figure 2). These local onset cases include information regarding the date of the onset and consequent report, as well as the community-level location of these onset cases prior to diagnosis. To measure the impact of full vaccination on the COVID-19 epidemic, daily data (The Government of the Hong Kong Special Administrative Region, 2021) on people with sufficient effective protection, after the second dose, were selected: (i) the daily number of people receiving the second dose of the BNT162b2 vaccine from 22 March 2021 to 15 April 2021 (The Government of the Hong Kong Special Administrative Region, 2021); (ii) the daily number of people receiving the second dose of the CoronaVac vaccine from 3 March 2021 to 8 April 2021 (The Government of the Hong Kong Special Administrative Region, 2021). The daily traffic volume data (i.e. number of vehicles per day) from 700 traffic detectors covered all Hong Kong strategic routes (Figure 3) from 18 January 2020 to 22 April 2021 were used in this study (Transport Department of Hong Kong, 2021). These traffic detectors cover 218 TPUs, accounting for 75%. In the 218 TPUs, the number of vehicles per day obtained by traffic detectors was used to represent the mobility within a specific TPU and the mobility from a specific TPU to other TPUs. The remaining 73 TPUs are in the countryside, including beaches, woodlands and mountain ranges. These areas are almost inaccessible areas. In the remaining 73 TPUs, the mobility within a specific TPU and the mobility from a specific TPU to other TPUs was set as 0. Moreover, the real-time effective reproductive number (R_t) for local cases during the same period was generated by an enhanced Susceptible-Infectious-Removed (SIR) model (Leung et al., 2021) (Figure 4).

An enhanced urban-community-scale WKDE model for predicting the onset risk of COVID-19 symptoms

As a further development of the original urban-community-scale WKDE model, the enhanced urban-community-scale WKDE model proposed in this study, included the following three steps (Shi et al., 2021; Shi et al., 2021; Tong et al., 2021; Tong et al., 2022): (i) making a retrospective
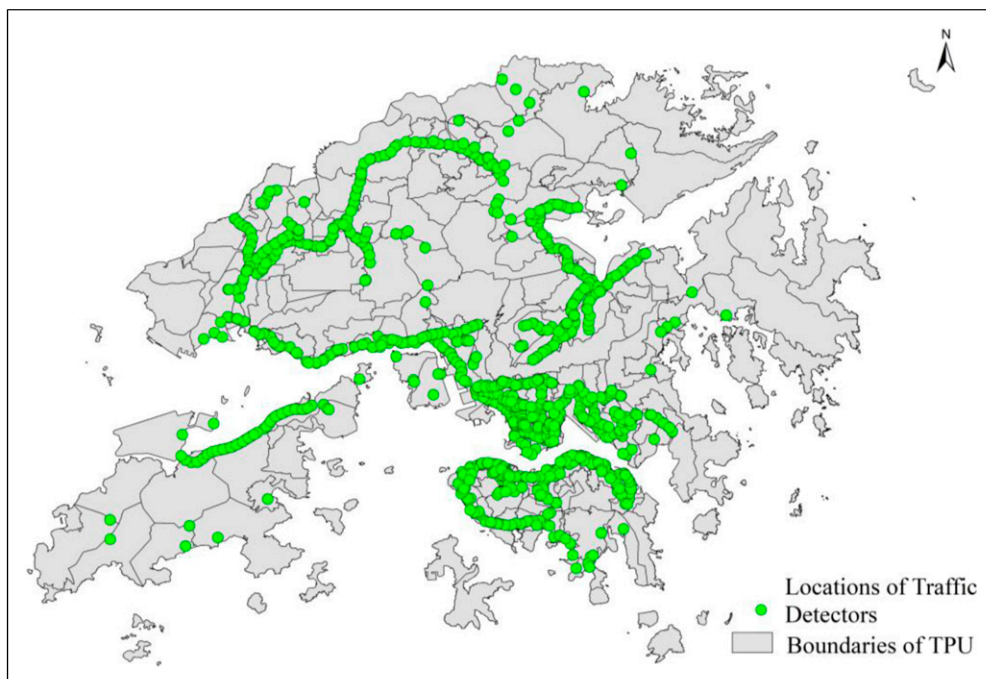
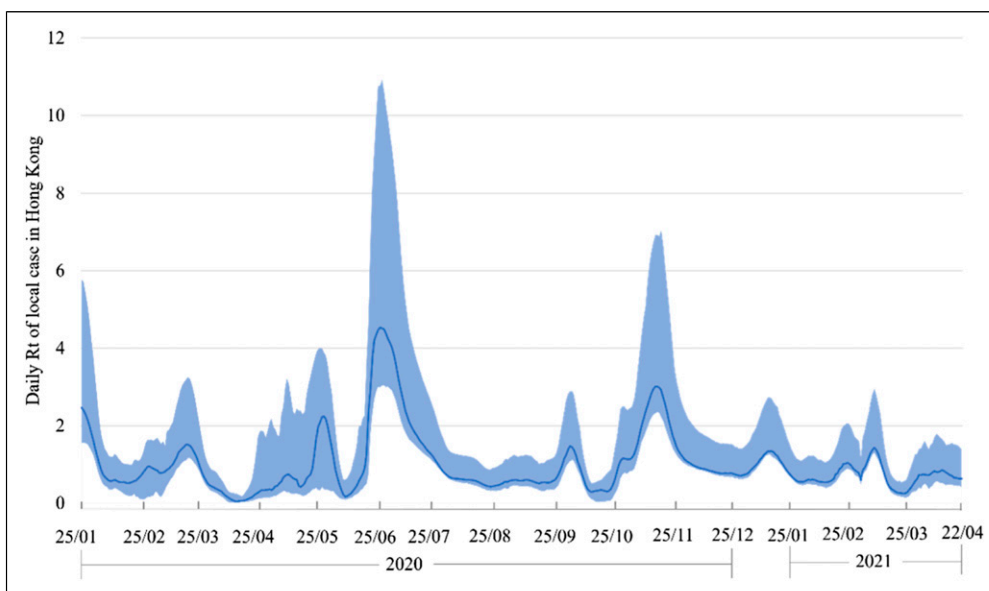**Figure 3.** Locations of traffic detectors in Hong Kong.

Figure 4. The daily variation in real-time effective reproductive number $R_t(t_i)$ (Leung et al., 2021; Shi et al., 2021) for local cases of Hong Kong from 18 January 2020 to 22 April 2021. An enhanced urban-community-scale WKDE model for predicting the onset risk of COVID-19 symptoms.

inference of the historical existence likelihood of the infection in each location in which an onset case has stayed, (ii) making inferences on the historical existence likelihood of the infection in each spatial location of the whole city area, and (iii) making onset risk predictions in the whole city area on a near-future day. The details of the three steps of the original extended WKDE model can be found at the previous study and applications (Shi et al., 2021).

The main improvement of the improved urban-community-scale WKDE model was seen as the historical existence likelihood of the infection in a spatial location at step (ii) and is formulated as follows (Shi et al., 2021; Shi et al., 2021)

$$P_{\text{Infection}}(S, ti) = n(t_i)^{-1} \sum_{j=1}^{n(t_i)} \frac{1}{Vt(ti)} Rt(ti) M_{inter\_TPU}(S, t_i) M_{\text{intra}\_TPU}(S, t_i) P_{Infection}(L_j, t_i) K_h(S - L_j)$$

$$(1)$$

where $P_{Infection}(S, t_i)$ is the probability of any infected person infecting others in a random location S in the city on day t_i. All 460 days in this study period (18 January 2020–22 April 2021) are in the order denoted as $t_1, t_2,\ldots t_{460}$. L_j is the j-th location among the places where onset cases remained. $P_{Infection}(L, t_i)$ denotes the probability that one onset case was infected on day t_i in location L. $K_h(S - L_j)$ denotes a Gaussian kernel between locations S and L_j (Scott, 1979; Shi, 2010). The values of $P_{Infection}(L_j, t_i)$, $K_h(S-L_j)$, and h have been determined in earlier model procedures (Shi et al., 2021; Shi et al., 2021). $R_t(t_i)$ denotes the real-time effective reproductive number for local cases in the city on day t_i.

$V_t(t_i)$ denotes the factor about the protection from vaccination in the city on day t_i, in the city on day t_i, calculated as follows

$$Vt(ti) = i^{-1} \sum_{k=1}^{i} vk \qquad (2)$$

where v_k denotes the daily number of persons fully vaccinated and hence protected in the city on day t_k prior to t_i. Before persons start to be fully vaccinated, the value of $V_t(t_i)$ is set equal to 1.

$M_{intra\_TPU}(S, t_i)$ denotes a human mobility factor within a TPU containing location S on day t_i, calculated as follows (Shi et al., 2021; Shi et al., 2021)

$$M_{intra\_TPU}(S, ti) = i^{-1} \sum_{k=1}^{i} Xk \qquad (3)$$

where X_k denotes the daily traffic flow within the TPU containing location S on day t_k prior to t_i.

$M_{interTPU}(S, t_i)$ denotes a human mobility factor from other TPUs to the TPU containing location S, calculated as follows (Shi et al., 2021; Shi et al., 2021)

$$M_{inter\_TPU}(S, ti) = i^{-1} \sum_{k=1}^{i} Yk \qquad (4)$$

where Y_k denotes the daily traffic flow from other TPUs to the TPU containing location S on day t_k prior to t_i.

Finally, the original onset risk prediction in each location was divided by the city's maximum predicted risk, on a specific date, and thereby standardized to a value of between 0 and 1. Different levels of onset risk were set as follows: low onset risk [0–0.2], low-medium onset risk [0.2–0.4], medium onset risk [0.4–0.6], medium-high onset risk [0.6–0.8] and high onset risk [0.8–1].

Furthermore, a popular indicator for the prediction accuracy of the KDE model is the hit rate (Ohyama & Amemiya, 2018; Pezzuchi, 2008; Zhang & Cheng, 2020). The hit rate is defined as the percentage of all incidents (e.g. crimes) at a later Time 2, that are captured by the identified

hotspots created from data at an earlier Time 1 (Ohyama & Amemiya, 2018; Pezzuchi, 2008; Zhang & Cheng, 2020). Following the idea of a hit rate, the accuracy of the enhanced urban-community-scale WKDE model is set as the percentage of all actual onset cases on the date of prediction that occur in the areas with predicted onset risk higher than 0.8 ('hotspots') (Shi et al., 2021; Shi et al., 2021).

Route searching with least COVID-19 symptom onset risk

An undirected graph R = (V, E, W_{ONSET}), including V nodes, E related edges and the weights of edges – W_{ONSET}. The weight W_{ONSET} represented the COVID-19 symptom onset risk weight of the edges. The example weight calculation method was shown in Figure 5. V_1 and V_2 were connected by an edge E_1 located in three grids. In three grids, the predicted COVID-19 symptom onset risk is X_1, X_2 and X_3, respectively. The calculation formula for the weight W_{ONSET} is (Tong et al., 2021)

$$W_{ONSET} = d_{1,1} \times X_2 + d_{1,2} \times X_1 + d_{1,3} \times X_3 \tag{5}$$

where $d_{1,1}$ is the length of edge E_1 in grid 2, $d_{1,2}$ is the length of edge E_1 in grid 1 and $d_{1,3}$ is the length of edge E_1 in grid 3.
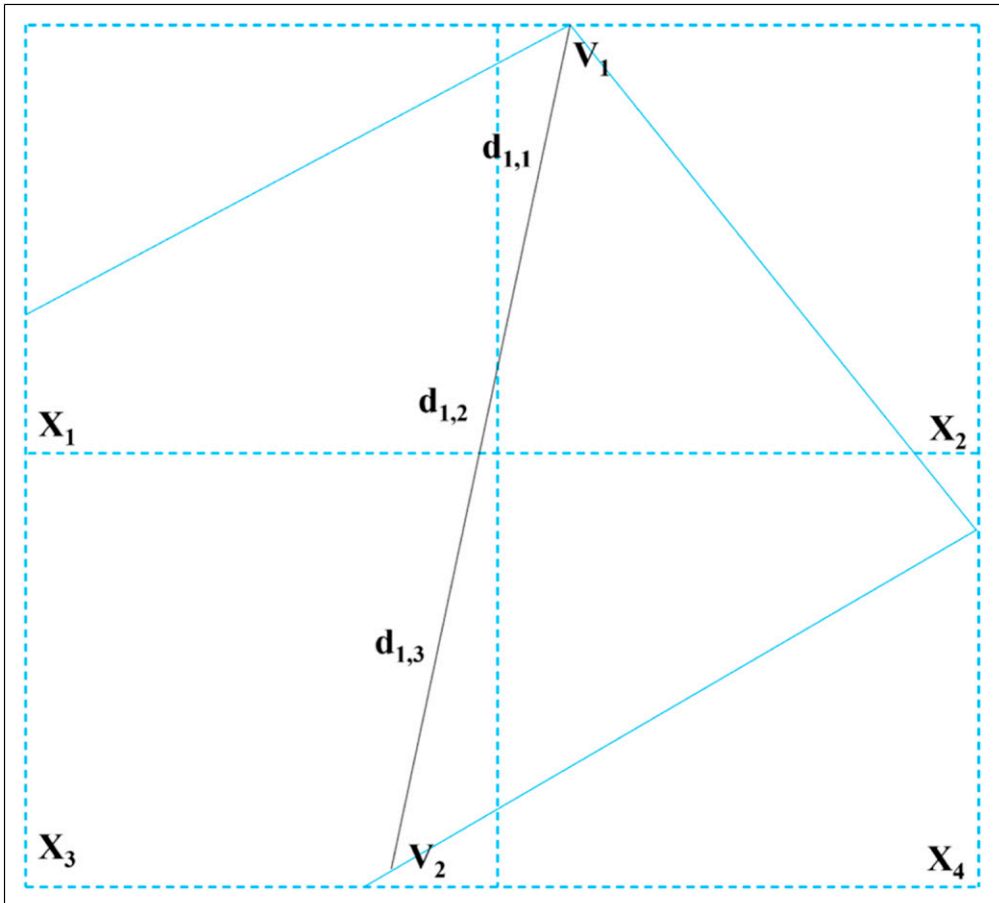

Figure 5. The example weight calculation method.

Based on the example weight calculation method, the COVID-19 symptom onset risk weight of all edges in the road network of the whole city could be obtained. The widely used A* pathfinding algorithm (Hasenfratz, 2015; Hasenfratz et al., 2015) was used to search the least-cost path between two nodes of the road network according to the two weight metrics introduced. A* requires each node $v_i \in V$ to make a heuristic estimate h (v_i) of the cost involved in getting from node vi to the target node. A* is only guaranteed to compute the optimality of the path if an acceptable heuristic is used, that is, if the heuristic never overestimates the cost of reaching the goal node. To calculate the optimal path with less onset risk, we used the product of the line-of-sight distance and the minimum onset risk within the modelled area. With the help of these admissible heuristics, A* could be used to perform goal-directed exploration and quickly find the least-cost path.

Results

Prediction accuracy of COVID-19 symptom onset risk by the enhanced urban-community-scale WKDE model

Based on the onset cases data in 291 TPUs of Hong Kong from 18 January 2020 to 22 April 2021, the daily spatiotemporal onset risk prediction of COVID-19 symptom was obtained by the enhanced urban-community-scale WKDE model developed in this study. The data of i) the real-time effective reproduction number (R_t) for local cases (K. Leung et al., 2021; Shi et al., 2021) and ii) the number of persons fully vaccinated for BNT162b2 and CoronaVac vaccines (The Government of the Hong Kong Special Administrative Region, 2021) was used in the enhanced model. During the following 7 days when predicting the onset risk, the prediction accuracy (Shi et al., 2021; Shi et al., 2021) of the urban-community-scale WKDE model was over 75% (Figure 6). The enhanced urban-community-scale WKDE model achieved higher accuracy than the original extended WKDE model (Figure 6). The average prediction accuracy of the enhanced urban-community-scale WKDE
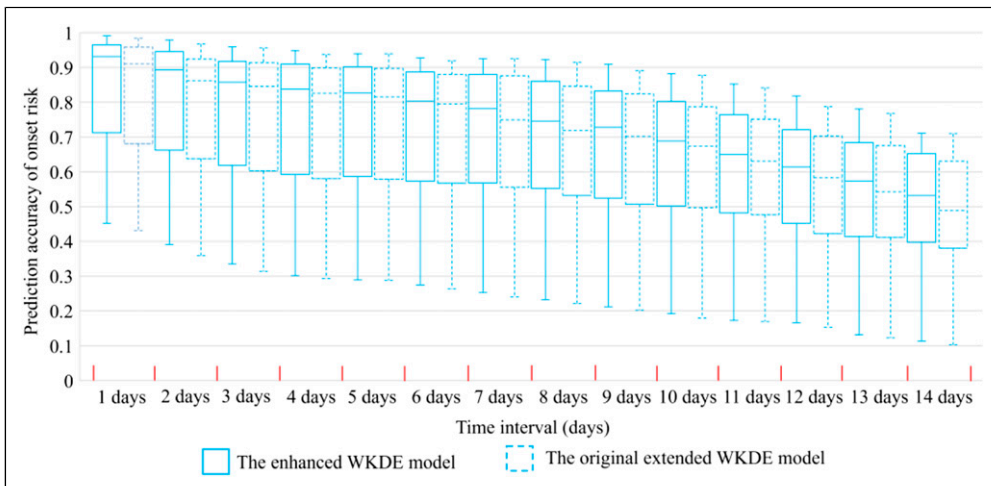

Figure 6. Accuracy (Shi et al., 2021) of the predicted risk of COVID-19 symptom onset by the enhanced urban-community-scale WKDE model compared with the original extended WKDE model. Daily prediction of COVID-19 symptom onset risk by the enhanced urban-community-scale WKDE model.

model in the future 14 days was 2.29% higher than that of the original extended WKDE model (Figure 6).

Daily prediction of COVID-19 symptom onset risk by the enhanced urban-community-scale WKDE model

Based on the urban-community-scale WKDE model, the daily spatiotemporal onset risk of COVID-19 symptom in the four epidemic waves was predicted (Figure 7). It can be seen that in the whole four epidemic waves, high-onset-risk communities were always concentrated in communities with high traffic flow (Figures 6(a)–(f)), such as Central & Western (e.g. TPU_116, TPU_141 and TPU_181), Wan Chai (e.g. TPU_124, TPU_145 and TPU_184), Kowloon City (e.g. TPU_215,
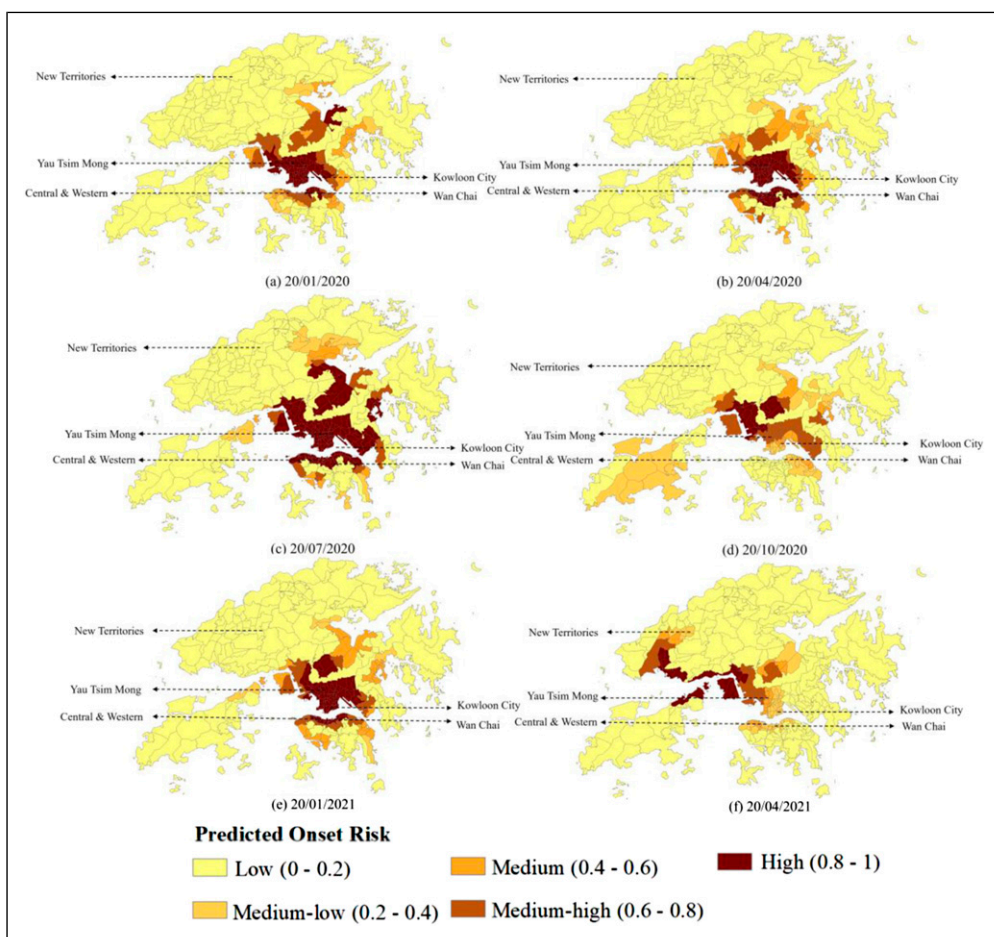

Figure 7. Predicted risk of original COVID-19 symptom onset risk across Hong Kong in all four epidemic waves from 18 January 2020 to 22 April 2021. (a) Predicted risk of original COVID-19 symptom onset risk across Hong Kong on 20 January 2020 in the first epidemic wave. (b) Predicted risk of original COVID-19 symptom onset risk across Hong Kong on 20 April 2020 in the second epidemic wave. (c–d) Predicted risk of original COVID-19 symptom onset risk across Hong Kong on 20 July 2020 and 20 October 2020 in the third epidemic wave. (e–f) Predicted risk of original COVID-19 symptom onset risk across Hong Kong on 20 January 2021 and 20 April 2021 in the fourth epidemic wave.
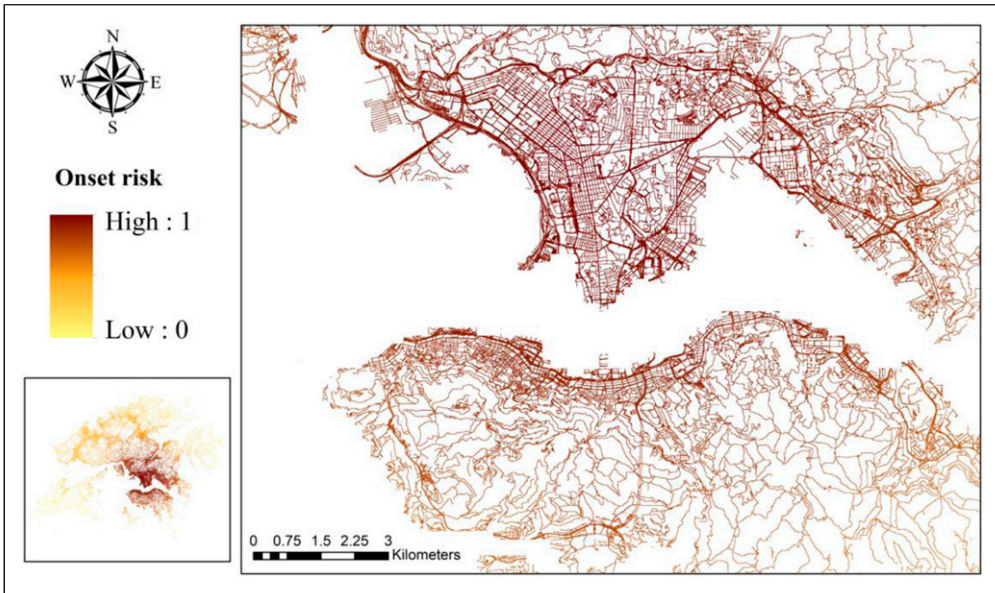
Figure 8. Predicted risk of original COVID-19 symptom onset risk on all roads of Hong Kong(a-o) on 20 January 2021. Healthy route planning app with less COVID-19 symptom onset risk.
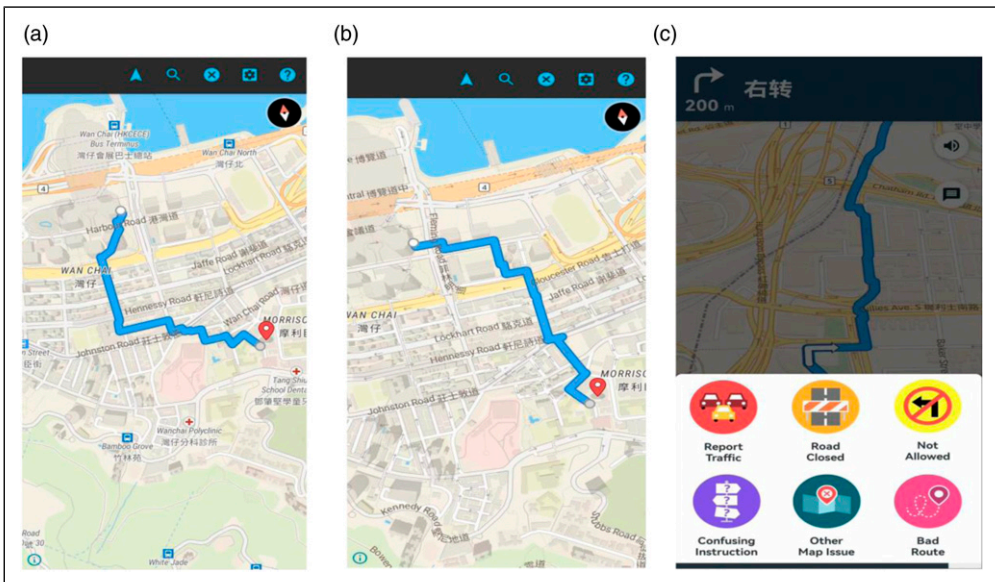

Figure 9. Introduction interface and the example of healthy travel route planning and the shortest route planning of the mobile application. (a) An example of the healthy travel route for COVID-19 symptom onset risk in Hong Kong. (b) An example of the shortest route in Hong Kong. (c) The feedback interface in the navigation process of the mobile application.

TPU_226 and TPU_236) and Yau Tsim Mong (e.g. TPU_221, TPU_251 and TPU_253). In remote areas of the New Territories or other areas with inconvenient transportation (e.g. TPU_652, TPU_653, TPU_711 and TPU_712), the COVID-19 onset risk was relatively low. Moreover, the spatiotemporal variation trend of COVID-19 onset risk from 18 January 2020 to 22 April 2021 could be also obtained. Furthermore, we further extracted the daily distribution of COVID-19 risk on each road in Hong Kong. As a result, COVID-19 onset risk information on 70,788 roads covering the whole of Hong Kong could be obtained (Figure 8). These would be used for healthy travel path planning.

Healthy route planning app with less COVID-19 symptom onset risk

Based on the on-road predictions of COVID-19 symptom onset risk, a mobile application for healthy travel route planning was developed, to provide the healthy travel routes with the least

Table 1. COVID-19 onset risk reduction on typical healthy routes compared with shortest routes in Hong Kong.

Area	Route	Healthy route (km)	Shortest route (km)	COVID-19 onset risk reduction (%)		
				Community transmission	Sporadic cases or clusters of local onset cases	No local onset cases
Wan Chai	Hopewell Centre – Causeway Bay Station	1.4	1.3	5.47	8.86	4.93
	Exhibition Centre – Times Square	2.3	1.9	8.53	13.75	7.68
	Harbour Centre, – Wan Chai Market	1.0	0.95	3.32	5.03	2.65
	Nabe One – Lee theatre	0.65	0.5	2.14	3.17	2.06
	Hong Kong Arts Centre – Victoria park swimming pool	2.6	2.5	6.95	10.32	6.49
Tsim Sha Tsui	Kowloon park – Peninsula Centre Arcade	1.2	1.1	4.36	7.49	4.97
	Hong Kong Heritage Discovery Centre, Haiphong road Kowloon park, Tsim Sha Tsui – HKCC creative market	1.0	0.85	5.01	7.98	4.94
	K11 Art Mall – urban council centenary garden	0.65	0.6	1.98	2.74	1.87
	Kowloon Shangri-La – Hong Kong Science museum	0.8	0.7	4.25	6.82	3.97
	Mody Road Garden – 1881 Heritage	1.6	1.2	10.51	16.24	9.19
Tuen Mun	Tuen Mun Town Plaza – Siu On Court Ting Lok House	0.9	0.8	5.17	8.49	4.86
	V city – Siu Lun Court	1.9	1.7	7.87	11.01	7.61
	San Hui playground public toilet - Tuen Mun station	0.95	0.9	4.6	7.65	4.15
	On Ting estate – Town Centre	0.75	0.65	3.82	6.13	3.54
	Rose Dale Gardens shopping mall – Chi Lok Fa Yuen	1.8	1.3	12.43	19.78	11.96

COVID-19 symptom onset risk in Hong Kong (Figure 9). In the process, it was assumed that the travel time between the edges of travel routes was proportional to the distance, and that the intensity of onset risk was proportional to the exposure time. Therefore, the onset risk value of each pixel along the edge was multiplied by the length of the edge located in each pixel, to directly gain the onset-risk-weighted value of each route. The healthy route between the starting point and the endpoint was then searched. A typical example is shown in Figures 9(a) and (b). The example indicates the healthy route from the 6 Salvation Army St, Morrison Hill to the Convention Plaza Office Tower, 1 Harbour Rd, Wan Chai (the route in Figure 9(a) indicates the least onset risk route, while the route in Figure 9(b) indicates the shortest route). Thus, the healthy route was 200m longer than that of the shortest route, while the healthy route regarding avoidance of COVID-19 onset risk has been decreased by 21.4%.

Compared with the shortest routes, reduction percentages of COVID-19 onset risk on the healthy routes were explored under three main epidemiological scenarios. In the three travel hotspot areas in Hong Kong-Wan Chai, Tsim Sha Tsui and Tuen Mun, 50 routes longer than 0.5 km were randomly selected. We require a minimum straight-line distance of 0.5 km between source and destination nodes to prevent very short routes where with high probability the shortest and health-optimal routes are identical. Some typical examples are shown in Table 1. The results show that in the most common scenario of sporadic cases or clusters of local onset cases, the average reduction percentage of onset risk was the highest reaching an average of 11.28%. In the two scenarios of community transmission and no local onset cases, the onset risk was reduced by 6.87% and 6.12%, respectively. In particular, during the navigation process, a specific function is added to allow the user to provide feedback on the situation encountered during their travel (Figure 9(c)). For example, when users find that there are more people travelling on the planned healthy route, they can click on the feedback function to give feedback. This application will re-plan to provide an alternative route to users.

Conclusion

Since the beginning of the COVID-19 pandemic, the demand for healthy travel has increased significantly for the public. Therefore, an urgent challenge is how to ensure people's safe and healthy travel in daily travel under the new normal of long-term coexistance with SARS-CoV-2. The emergence of new SARS-CoV-2 variants has increased this challenge, especially the SARS-CoV-2 variant Omicron, which is the most transmissible and most easily spread to date (Torjesen, 2021; United Nations International Children's Emergency Fund, 2022). In this study, a spatiotemporal solution that supports healthy travel has been proposed and applied in Hong Kong, for the first time.

The results of the application of the proposed solution in Hong Kong reflect its characteristics in the following aspects:

(1) Based on the enhanced urban-community-level WKDE model, the daily COVID-19 onset risk in each community location of Hong Kong for the next few days can be predicted. In the prediction in the four epidemic waves, the enhanced urban-community-level model has achieved a high prediction accuracy with over 75% in the future 7 days. Therefore, the model can accurately predict the spatiotemporal distribution of COVID-19 symptom onset risk under the new normal.

(2) Different from the existing path planning applications that mainly consider time and distance costs, a healthy route planning application that can provide the healthy travel route with the least COVID-19 symptom onset risk was further developed in this solution. This can help the public plan in advance for their healthy travel in the next few days. The application results in the four epidemic wave in Hong Kong show that compared with traditionally used shortest path routes, healthy routes could effectively reduce people's exposure to the risk of COVID-19 symptoms onset. The mobile

application helps people in Hong Kong in their planning of daily activities by providing healthy routes to ensure their health.

The authors acknowledge several limitations of this study. Firstly, enough official data in Hong Kong provides more detailed sufficient information than most other regions of the world to support the spatiotemporal solution of healthy route planning with less COVID-19 onset risk. Thus, the applicability of this solution in other parts of the world will depend on the availability of data indicating the spatiotemporal distribution of COVID-19 cases in the corresponding regions. Such COVID-19 spatiotemporal distribution data is available in many regions, for example, the data in Taiwan, South Africa, Japan and Malaysia have been used to explore COVID-19 onset risk prediction (Tong et al., 2022; Tong et al., 2021). Secondly, due to traffic data accessibility in Hong Kong, human mobility within and between communities in Hong Kong was estimated based on the vehicle traffic flow on main strategic routes, which does not fully include other traffic modes or in on smaller roads. We plan to seek for aggregate cellphone tracking data with higher data coverage in future to replace the existing human mobility data. Thirdly, in the current application, when the user prepares to be in a stopped state while travelling, the user still needs to exit the navigation through their operation. This will cause inconvenience to the user. Therefore, we considered adding an automatic check-out function based on an intelligent behaviour detection module from only inertial sensor data from the mobile phone's accelerometer (Peng et al., 2021). Fourth, this mobile application does not deal well with the problem of traffic congestion caused by the congestion of users on the same healthy route in the route planning. Based on the principles of game theory and the experience of existing path planning applications like Google Map, we will further try to integrate the traffic speed, volume and road occupancy into the healthy route planning to provide the best alternative route to balance the traffic volume. Furthermore, with the need for mobile contact avoidance navigation in the dynamic and heterogeneous (indoor and outdoor) environments, the novel route discovering algorithm like ASTRO (Accessible Spatio-Temporal Route Optimization) could be introduced and explored to improve the performance of the mobile application (Anastasiou et al., 2021; Li et al., 2021).

Despite the above limitations, this study plays key roles in the following aspects:

(i) To support the healthy route planning by the proposed solution, especially for unvaccinated elderly people. There are still more than 390,000 elderly people over 60 in Hong Kong who are not fully vaccinated. Elders who are not fully vaccinated are more than 10 times more likely to die from COVID-19 infection than those who have full vaccinated. Omicron further increases the death risk for such individuals. Therefore, the mobile application of the health path planning can reduce the risk of infection in the daily outdoor activities of the elderly to further protect their health.

(ii) To support precise epidemic prevention and control by the enhanced urban-community-level prediction method of onset risk. The pandemic is still not over, and the health and economic toll continue to mount. It is clear that COVID-19 will be with us for a long time to come. The urban-community-scale onset risk prediction method proposed in this study can support reliable monitoring of the spatiotemporal spread of the virus. It will help the public health department to take differentiated and precise epidemic control measures in communities within different risk levels. Thus, the impact on social-economic activities can also be reduced. Moreover, this method can also be used as a key part of the real-time early warning platform of the epidemic to provide more support for people's daily life.

Faced with the situation that may need to coexist with SARS-CoV-2 in the future, this study can be used to help urban residents in more cities travel healthier. Furthermore, we hope to promote the health-related Sustainable Development Goal (SDG3) – Ensure healthy lives and promote well-being for all at all ages.

ORCID iDs

Wenzhong Shi https://orcid.org/0000-0002-3886-7027

References

Acuto M, Larcom S, Keil R, et al. (2020) Seeing COVID-19 through an urban lens. *Nature Sustainability* 3: 977–978.

Anastasiou C, Costa C, Chrysanthis P K, et al. (2021) ASTRO: Reducing COVID-19 Exposure through Contact Prediction and Avoidance. *ACM Transactions on Spatial Algorithms and Systems (TSAS)* 8(2): 1–31.

Assiri A, Al-Tawfiq J A, Alkhalifa M, et al. (2021) Launching COVID-19 vaccination in Saudi Arabia: Lessons learned, and the way forward. *Travel Medicine and Infectious Disease* 43: 102119.

Batista C, Shoham S, Ergonul O, et al. (2021) Urgent needs to accelerate the race for COVID-19 therapeutics. *EClinicalMedicine* 36: 100911.

Bollen N, Artesi M, Durkin K, et al. (2021) Exploiting genomic surveillance to map the spatio-temporal dispersal of SARS-CoV-2 spike mutations in Belgium across 2020. *Scientific Reports* 11: 1–8.

Castillo J C, Ahuja A, Athey S, et al. (2021) Market design to accelerate COVID-19 vaccine supply. *Science* 371: 1107–1109.

Das A, Ghosh S, Das K, et al. (2021) Living environment matters: Unravelling the spatial clustering of COVID-19 hotspots in Kolkata megacity, India. *Sustainable Cities and Society* 65: 102577.

Davies N G, Jarvis C I, vanZandvoort K, et al. (2021) Increased mortality in community-tested cases of SARS-CoV-2 lineage B.1.1.7. *Nature* 593: 270–274.

Feng Z., Xiao C., Li P, et al. (2020) Comparison of spatio-temporal transmission characteristics of COVID-19 and its mitigation strategies in China and the US. *Journal of Geographical Sciences* 30: 1963.

Franceschi V B, Ferrareze P A G, Zimerman R A, et al. (2021) Mutation hotspots and spatiotemporal distribution of SARS-CoV-2 lineages in Brazil, February 2020-2021. *Virus Research* 304: 198532.

Ghosh P and Cartone A (2020) A Spatio-temporal analysis of COVID-19 outbreak in Italy. *Regional Science Policy and Practice* 12: 1047–1062.

Guo Y, Qian H, Sun Z, et al. (2021) Assessing and controlling infection risk with Wells-Riley model and spatial flow impact factor (SFIF). *Sustainable Cities and Society* 67: 102719.

Harder T, Külper-Schiek W, Reda S, et al. (2021) second interim results of a living systematic review and meta-analysis, 1 January to 25 August 2021. *Effectiveness of COVID-19 Vaccines Against SARS-CoV-2 Infection with the Delta (B.1.617.2) variantEurosurveillance* 26: 1–10.

Hasenfratz D (2015) Enabling Large-Scale Urban Air Quality Monitoring with Mobile Sensor Nodes. Doctoral Thesis. *ETH-Zürich*.

Hasenfratz D, Arn T, de Concini I, et al. (2015) Health-optimal routing in urban areas. In *Proceedings of the 14th International Conference on Information Processing in Sensor Networks*, pp. 398–399.

He X, Lau E H Y, Wu P, et al. (2020) Temporal dynamics in viral shedding and transmissibility of COVID-19. *Nature Medicine* 26: 672–675.

Islam A, Sayeed M A, Rahman M K, et al. (2021) Geospatial dynamics of COVID-19 clusters and hotspots in Bangladesh. *Transboundary and Emerging Diseases*: 1–15.

Jia J S, Lu X, Yuan Y, et al. (2020) Population flow drives spatio-temporal distribution of COVID-19 in China. *Nature* 582: 389–394.

Jiang P, Fu X, Fan Y Van, et al. (2021) Spatial-temporal potential exposure risk analytics and urban sustainability impacts related to COVID-19 mitigation: A perspective from car mobility behaviour. *Journal of Cleaner Production* 279: 123673.

Kawasuji H, Takegoshi Y, Kaneda M, et al. (2020) Transmissibility of COVID-19 depends on the viral load around onset in adult and symptomatic patients. *PLoS ONE* 15: 1–8.

KhanN A, Al-Thani H and El-Menyar A (2022) The emergence of new SARS-CoV-2 variant (Omicron) and increasing calls for COVID-19 vaccine boosters-The debate continues. *Travel Medicine and Infectious Disease* 45: 102246.

Lak A, Hakimian P and Sharifi A (2021) An evaluative model for assessing pandemic resilience at the neighborhood level: The case of Tehran. *Sustainable Cities and Society* 75: 103410.

Leung K, Wu JT and Leung GM (2021) Real-time tracking and prediction of COVID-19 infection using digital proxies of population mobility and mixing. *Nature Communications* 12: 1–8.

Li J, Wang X, He Z, et al. (2021) A personalized activity-based spatiotemporal risk mapping approach to the COVID-19 pandemic. *Cartography and Geographic Information Science* 48(4): 275–291.

Ma Q, Gao J, Zhang W, et al. (2021) Spatio-temporal distribution characteristics of COVID-19 in China: a city-level modeling study. *BMC Infectious Diseases* 21: 1–14.

McKinsey and Company (2020) *Five COVID-19 Aftershocks Reshaping Mobility's Future*. McKinsey and Company. https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/five-covid-19-aftershocks-reshaping-mobilitys-future

Ohyama T and Amemiya M (2018) Applying Crime Prediction Techniques to Japan: A Comparison Between Risk Terrain Modeling and Other Methods. *European Journal on Criminal Policy and Research* 24: 469–487.

Pezzuchi G (2008) A Brief Commentary on 'The Utility of Hotspot Mapping for Predicting Spatial Patterns of Crime. *Security Journal* 21: 291–292.

Peng Z, Huang J, Wang H, et al. (2021) BU-trace: A permissionless mobile system for privacy-preserving intelligent contact tracing. In *International Conference on Database Systems for Advanced Applications*. Cham: Springer, pp. 381–397.

Sah R, Khatiwada AP, Shrestha S, et al. (2021) COVID-19 vaccination campaign in Nepal, emerging UK variant and futuristic vaccination strategies to combat the ongoing pandemic. *Travel Medicine and Infectious Disease* 41: 102037.

Sannigrahi S, Pilla F, Basu B, et al. (2020) Examining the association between socio-demographic composition and COVID-19 fatalities in the European region using spatial regression approach. *Sustainable Cities and Society* 62: 102418.

Scott DW (1979) On optimal and data-based histograms. *Biometrika* 66: 605–610.

Sharifi A and Khavarian-Garmsir AR (2020) The COVID-19 pandemic: Impacts on cities and major lessons for urban planning, design, and management. *Science of the Total Environment* 749: 1–3.

Shi W, Tong C, Zhang A, et al. (2021) A spatial and dynamic solution for allocation of COVID-19 vaccines when supply is limited. *Communications Medicine* 1: 23.

Shi W, Tong C, Zhang A, et al. (2021) An extended Weight Kernel Density Estimation model forecasts COVID-19 onset risk and identifies spatiotemporal variations of lockdown effects in China. *Communications Biology* 4: 126.

Shi X (2010) Selection of bandwidth type and adjustment side in kernel density estimation over in-homogeneous backgrounds. *International Journal of Geographical Information Science* 24: 643–660.

The Centre for Health Protection (2021) *Onset Cases in Hong Kong*. The Centre for Health Protection. https://www.chp.gov.hk/en/media/116/index.html#

The Government of the Hong Kong Special Administrative Region (2021) *Hong Kong Vaccination Dashboard*. The Government of the Hong Kong Special Administrative Region. https://www.covidvaccine.gov.hk/en/dashboard

Tong C, Shi Z, Shi W, et al. (2021) Mapping Microscale PM2.5 Distribution on Walkable Roads in a High-Density City. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 14: 6855–6870.

Tong C, Shi W, Zhang A, et al. (2021) Tracking and Controlling the Spatiotemporal Spread of SARS-CoV-2 Lineage B.1.1.7 in COVID-19 Reopenings. *Geohealth* 5(12): e2021GH000517.

Tong C, Shi W, Zhang A, et al. (2022) Tracking and controlling the spatiotemporal spread of SARS-CoV-2 Omicron variant in South Africa. *Travel Medicine and Infectious Disease* 46: 102252.

Torjesen I (2021) Covid-19: Omicron may be more transmissible than other variants and partly resistant to existing vaccines, scientists fear. *BMJ* 375: n2943.

Transport Department of Hong Kong (2021) *Traffic Speed, Volume and Road Occupancy from 700 Traffic Detectors on Strategic Routes/Major Roads in Hong Kong*. Transport Department of Hong Kong. https://data.gov.hk/en-data/dataset/hk-td-sm_4-traffic-data-strategic-major-roads

United Nations International Children's Emergency Fund (2022) *What We Know about the Omicron Variant*. United Nations International Children's Emergency Fund. https://www.unicef.org/coronavirus/what-we-know-about-omicron-variant

Yue S, Zhang J, Cao M, et al. (2021) Knowledge, Attitudes and Practices of COVID-19 Among Urban and Rural Residents in China: A Cross-sectional Study. *Journal of Community Health* 46: 286–291.

Zhang Y and Cheng T (2020) Graph deep learning model for network-based predictive hotspot mapping of sparse spatio-temporal events. *Computers, Environment and Urban Systems* 79: 101403.